VILNIUS UNIVERSITY
BUSINESS SCHOOL

DEEP TECH ENTREPRENEURSHIP PROGRAMME

Kornelijus Ruskonis

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MASTER'S THESIS

Rinkos laiko parinkimas aukštųjų technologijų srityje: startuolių sėkmės strategijos	Market Timing in Deep-Tech: Strategies for Startup Success

Supervisor Prof. Dr. Saule Mačiukaitė-Žvinienė

Vilnius, 2025

Contents

Summary

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Scope of Master’s thesis (project) – 81 pages.

Number of tables used in Master’s thesis – 14 pcs. tables

Number of figures used in the Master’s thesis - 4 pcs. figures

Number of bibliography and references - 98 pcs. references

The Master’s thesis described in brief:

In this Master's Thesis, we investigate timing for markets by startups using deep technologies and analyze whether and to what extent the relationship between internal organizational aspects (factors) and external market elements (conditions), affect market fit and start-up success. The research is focused on start-ups that rely on scientific basis and therefore are characterized by high uncertainty, very long product development time frames, as well as strong regulatory and ecosystem dependency. The research provides an integrated theoretical-experimental explanation of why successful commercialization in deep-technological environments depend on coordinating timing of market entry rather than uncoordinated individual strategic decisions.

Problem, objective and tasks of the Master’s thesis:

The research problem addresses the limited understanding of how deep-tech startups align internal capabilities with external conditions to achieve market fit and success. The objective of the thesis is to evaluate the impact of market timing, internal alignment, and adaptation on startup success through the mediating role of market fit. The tasks include examining theoretical approaches to market timing in deep-tech ventures, identifying key internal and external factors affecting market

fit, developing a research model based on contingency theory, conducting empirical research, and integrating quantitative and qualitative findings.

Research methods used in the Master’s thesis:

The research applies a mixed-method design. A systematic analysis of scientific literature provides the theoretical foundation. Quantitative data are collected through an online questionnaire survey of deep-tech startup employees. Qualitative data are gathered through semi-structured interviews with founders and senior decision-makers. Triangulation is used to integrate results from both methods.

Research and results obtained:

Quantitative research found significant positive correlation between internal alignment, adaptability & responsiveness to the perceived market fit. Although, market timing is less connected to internal alignment. The qualitative results of the study also revealed that the founders see the timing as an ongoing, iterative, and adaptive process based on market information. Additionally, triangulation confirms that the findings are consistent across all methods used in this study.

Conclusions of the Master’s thesis:

Timing can function as a process of constant, iterative alignment between a deep-tech startup's team and its target markets. A market's "fit" mediates all timing- related influences on the success of a deep-tech startup. Whether or not a deep-tech startup successfully converts outside opportunity into actual results depends on the internal alignment and adaptability of its team.

Santrauka

VILNIAUS UNIVERSITETO VERSLO MOKYKLA

AUKŠTŪJŲ TECHNOLOGIJŲ VERSLO PROGRAMA

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Vadovė Prof. Dr. Saulė Mačiukaitė-Žvinienė

Vilnius, 2025

Magistro baigiamojo darbo apimtis - 81 puslapiai.

Magistro baigiamajame darbe panaudotų lentelių skaičius - 14 vnt.

Magistro baigiamajame darbe panaudotų paveikslų skaičius - 4 vnt.

Naudotų literatūros šaltinių ir nuorodų skaičius - 98 vnt.

Magistro darbo santrauka:

Šiame magistro darbe nagrinėjamas rinkos laiko parinkimas aukštūjų technologijų startuoliuose ir analizuojama, kaip vidinių organizacinių veiksnių ir išorinių rinkos sąlygų suderinamumas daro įtaką rinkos atitikčiai ir startuolio sėkmei. Tyrimas orientuotas į mokslo žiniomis grįstus startuolius, veikiančius didelio neapibrėžtumo, ilgų technologijų kūrimo ciklų bei stiprios reguliacinės ir ekosisteminės priklausomybės sąlygomis. Integruojant teorinius ir empirinius duomenis, darbe pateikiamas nuoseklus paaiškinimas, kodėl sėkminga komercializacija aukštosios technologijos kontekste priklauso nuo suderinto laiko planavimo, o ne nuo pavienių strateginių sprendimų.

Magistro darbo problema, tikslas ir uždaviniai:

Tyrimo problema siejama su ribotu supratimu, kaip aukštosios technologijos startuoliai suderina vidinius gebėjimus su išorinėmis sąlygomis, siekdami rinkos atitikčiai ir sėkmei. Darbo tikslas – įvertinti rinkos laiko parinkimo, vidinio suderinamumo ir prisitaikymo įtaką startuolio sėkmei per

tarpinį rinkos atitikties vaidmenį. Uždaviniai apima rinkos laiko parinkimo teorinių požiūrių analizę aukštosios technologijos kontekste, pagrindinių vidinių ir išorinių veiksnių, darančių įtaką rinkos atitikčiai, identifikavimą, tyrimo modelio, pagrįsto kontingencijos teorija, sukūrimą, empirinio tyrimo atlikimą bei kiekybinių ir kokybinių rezultatų integravimą.

Magistro darbe taikyti tyrimo metodai:

Tyrime taikomas mišrus tyrimo dizainas. Teorinį pagrindą sudaro sisteminė mokslinės literatūros analizė. Kiekybiniai duomenys renkami taikant internetinę anketinę apklausą, skirtą giliosios technologijos startuolių darbuotojams. Kokybiniai duomenys surinkti pusiau struktūruotų interviu su steigėjais ir aukščiausio lygmens sprendimų priėmėjais metu. Tyrimo rezultatams apjungti taikyta trianguliacija.

Tyrimo rezultatai:

Kiekybinė analizė atskleidė teigiamus ryšius tarp vidinio suderinamumo, prisitaikymo ir reagavimo bei suvokiamos rinkos atitikties. Rinkos laiko parinkimas pasižymi silpnesniu poveikiu, kai nėra vidinės koordinacijos. Kokybiniai duomenys parodė, kad steigėjai rinkos laiką vertina kaip etapais vykstantį ir adaptyvų procesą, grindžiamą validacijos signalais. Trianguliacija patvirtino rezultatų nuoseklumą.

Magistro darbo išvados:

Daroma išvada, kad rinkos laiko parinkimas aukštosios technologijos startuoliuose yra nuolatinis suderinamumo procesas. Rinkos atitiktis tarpininkauja ryšiui tarp su laiku susijusių veiksnių ir startuolio sėkmės. Vidinis suderinamumas ir prisitaikymas lemia, ar išorinės galimybės virsta realiais veiklos rezultatais.

Introduction

Novelty and relevance of the research topic: With increasing importance, deep tech start-ups are playing an important role in innovation, technology development and in social development. As they depend heavily on scientific/technological innovations (i.e., they are based on scientific/engineering innovations), they have long R&D periods and high capital requirements; as a result, their position is very different from that of digital start-ups. The position of deep tech start-ups is characterized by strong technological uncertainties, strict legal conditions and, due to their dependency on the support of external stakeholders like investors, partners and public institutions, market timing is one of the most significant strategic problems of deep tech start-ups.

The scientific literature is abundant regarding market timing, technological maturity, venture capital timing, regulatory impacts and the dynamics of an ecosystem. However, research generally analyzes each of these variables in isolation. Research is limited in its ability to illustrate how deep tech start-ups link their internal organization and external market conditions to create market fit and ultimately succeed. As such this thesis will examine a less researched question as it relates to an internal/external integration of alignment (and adaptation) and external market timing through a singular analytical lens. It will do so from a contingency viewpoint and focus on internal alignment verses isolated variables. The research will employ a mixed method approach in a context that is characterized by an abundance of fragmented empirical evidence. Data collected directly from deep-tech start-up employees/founders will provide new insight to existing theory and further relate the concept of timing, alignment, and market fit in a single model.

Deep Tech Startups are failing at a very high rate despite having a solid foundation in technology. This is because many of these companies fail to properly prepare themselves for commercialization. Founders often find that they have miscalculated their timing and/or failed to create an internal coordination process to move through each stage of commercialization as well as to interpret external (market) signals appropriately. The interplay between internal and external factors can provide value to founders, investors, and policymakers wishing to reduce the amount of failure occurring during commercialization and increase the overall success of startups.

Research problem: There is insufficient understanding of how deep-tech startups align internal organizational capabilities with external market conditions to achieve market fit and startup success.

Research Aim: The subject matter of the research is the alignment between internal organizational factors and external market timing conditions and their influence on market fit and startup success in deep-tech startups.

Research objective: To evaluate how alignment between internal organizational factors and external market timing conditions influences market fit and startup success in deep-tech startups.

Research tasks:

1. To examine theoretical approaches to market timing, market fit, and startup success in the context of deep-tech ventures.
2. To systematize internal and external factors influencing market timing based on Contingency Theory.
3. To evaluate the impact of market timing, internal alignment, and adaptation and responsiveness on market fit using quantitative research.
4. To explore founder and senior manager perspectives on timing and alignment through qualitative interviews.
5. To integrate quantitative and qualitative findings to assess how alignment influences startup success.

Research methods:

The research applies systematic analysis and synthesis of scientific literature. Quantitative research is conducted using an online questionnaire survey. Qualitative research is conducted through semi-structured interviews with founders and senior managers. Statistical data analysis is performed using IBM SPSS Statistics. Methodological triangulation is applied to integrate and validate findings from both research methods.

Research limitations and difficulties:

The research relies on non-probability sampling methods due to the narrow and hard-to-reach target group of deep tech startup founders and employees. Access to participants required self-selection, which limited sample size and reduced representativeness. As a result, survey data reflect subjective perceptions, while interview data depend on participant interpretation. Both survey and interview data rely on self-reported perceptions of timing, internal alignment, and performance rather than objective indicators. This increases the risk of recall bias and socially desirable responses. The study also focuses on startups operating within specific technological and institutional contexts. The findings therefore apply mainly to similar deep tech environments and should not be directly transferred to non-deep tech ventures or different ecosystem settings. These limitations were addressed through mixed-method triangulation, which strengthened reliability and depth of analysis.

Structure of the thesis:

The thesis consists of three main parts. The first part presents the theoretical foundations of market timing in deep-tech startups, including technological readiness, market signals, regulatory conditions, and ecosystem dynamics. The second part describes the research methodology, data collection instruments, sampling, and analysis procedures. The third part presents the empirical research results, including quantitative analysis, qualitative findings, and triangulation. The final chapter provides conclusions and research-based recommendations for theory and practice.

Scientific and practical value of the research:

This study provides practical use as it will allow founders and managers of deep-technology companies to make timing decisions based on their findings for internal process alignment with external market conditions. The study's theory supports both timing decision making (i.e., when to enter a market) and internal process coordination (i.e., how to operate) and adaptability in deep-technology ventures. Research adds new insight by showing market timing in deep-tech startups depends on internal alignment, not only external market conditions. Existing research often treats timing as a decision based on market maturity or technology readiness. This research shows entry timing leads to success only when internal structures, decision processes, and team coordination align with external conditions. The findings explain why startups entering similar markets at similar times achieve different outcomes.

1. THEORETICAL FOUNDATIONS OF MARKET TIMING IN DEEP-TECH STARTUPS

1.1 Conceptualizing Market Timing and Deep-Tech Startups

1.1.1 Meaning and Evolution of Market Timing

This chapter explains how the idea of market timing developed, how it is understood in entrepreneurship, and why it matters for deep-tech startups. It introduces the core concepts that guide the rest of the thesis and prepares the ground for the empirical work that follows. These foundations are needed because the research examines how startup founders and employees judge the right moment for market entry, so the chapter defines the meaning of timing, how it evolved, and why it shapes success in sectors where technology moves fast.

The term market timing originated in corporate finance, where it refers to the practice of issuing or selling shares at high prices and repurchasing at low prices. With the inattention of using temporary fluctuations in the cost of equity or shares relative to the cost of other forms of capital in the market (Baker & Wurgler, 2002). As the business environment evolved, this concept could be extended well beyond the financial markets. One could incorporate business and entrepreneurship to determine the timing of market entry or exit. This link from finance to entrepreneurship is important for the thesis because it shows that timing is not only a financial act but a strategic judgment. This helps explain why empirical research focuses on how founders and employees sense the right moment to act.

For ventures based on deeper scientific or engineering innovations (such as many deep-tech startups), the challenge of market timing becomes very important. These firms must not only advance their technological development (over long, sequential product or prototype cycles) but also wait for the convergence of market acceptance, regulatory maturity, enabling infrastructure, and investor confidence. If the timing is mis-aligned despite great technology used, the startup may fail. However, well-timed market entry can secure advantages in the market, it may include attracting early funding, and accelerate the launch (Argaw et al., 2024; McDonald & Eisenhardt, 2020). This point is central for the empirical work because the interviews and survey explore how deep-tech actors read market and regulatory signals, how they judge readiness, and how they plan timing under uncertainty.

In entrepreneurship, market timing refers to the deliberate choice of when to introduce a product, technology, or business model to a target market, based on an assessment of internal readiness and external conditions. It is not simply a reactive response to external conditions, but rather a coordination of internal and external readiness signals (Flint, 2019; Argaw et al., 2024). As research indicates, the difference between success and failure for new ventures may rely less on "what" they offer and more on when they choose to offer it, if the market is ready for it (Argaw et al., 2024). This final link shows why the thesis examines both founders and employees. Timing depends on how people inside the startup coordinate their actions and prepare the organization for market entry, which is the core focus of the empirical part.

In summary, the evolution of the market timing concept from financial decision-making to entrepreneurial strategy highlights why deep-tech ventures must manage timing deliberately. Their long development cycles, strong regulatory exposure, and dependence on ecosystem maturity make the choice of when to enter the market a central determinant of performance. These foundations provide the basis for empirical research, which examines how timing decisions are understood and coordinated inside deep-tech startups.

1.1.2 Deep-Tech Startup Ecosystem

Deep tech refers to ventures built on advanced scientific or engineering discoveries that require significant research, specialized knowledge, and long development cycles to reach the market. These technologies are rooted in fundamental breakthroughs in fields such as artificial intelligence, robotics, quantum computing, advanced materials, and biotechnology, and they often demand extensive validation before commercial use (Basilio Ruiz de Apodaca, Dionisio et al., 2023). By contrast, the so-called digital unicorns are typically built upon consumer-oriented business models that rely on a digital architecture and established technologies, rather than novel technological breakthroughs and research (Urbinati et al., 2019). While digital unicorns garnered attention for their rapid scaling and large valuations, ventures based on deep technologies did not receive as much attention and focus from funding programs, venture capitalists, and policy makers until quite recently (Dionisio, 2023).

In contrast to digital startups, deep-tech ventures frequently require a complex integration of hardware and software components, meaning that while they may deliver distinctive and novel solutions, they must also contend with finding compatible technological architectures, which has much higher operational complexity, than in purely digital models (Kames et al., 2023). These conditions also influence when such ventures can credibly approach the market or investors.

Figure 1.1.2

Operational complexity and Innovation scope: the of hardware start-ups

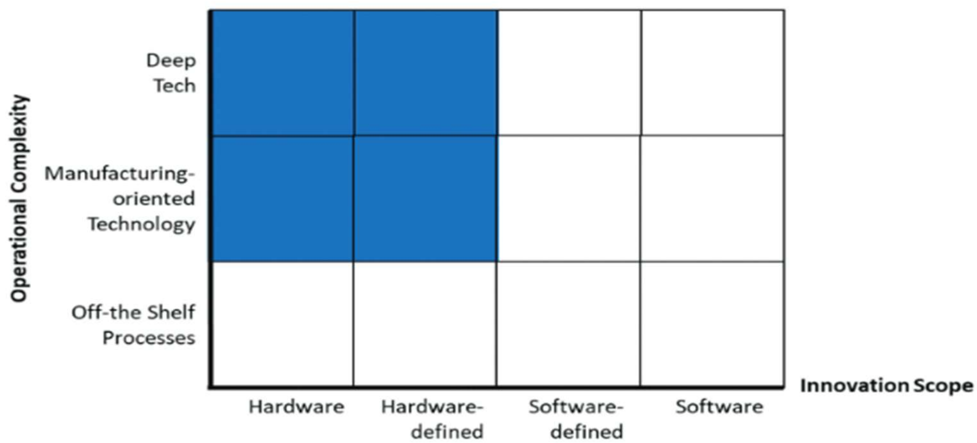


Figure 2. Operational complexity and innovation scope: the case of hardware start-ups.

Source: Based on Kames et al. (2023), p. 5

Deep tech ventures in Europe have a lot of potential to dominate the future market, but more importantly, have a variety of characteristics with respect to time, capital intensity and uncertainty that require new or adapted approaches to their founding, growth, and support, not only in their early stages, but also when entering beyond series B financing (Bobier et al., 2022). This contrast is important because deep-tech and digital startups face different development trajectories and therefore require different timing strategies.

Rather than relying exclusively on business-model a innovation, deep-tech startups draw their competitive advantage by proposing solutions to problems using advanced technologies (AI, Biotechnology, etc.). Often, these ventures originate as spin-offs from research institutions or collaborate closely with research infrastructures (Dionisio, 2023). However, because the technology base used in a startup can be challenging for many investors to comprehend and evaluate (Aaltonen & Kurvinen, 2025). For this reason, deep-tech entrepreneurs must often secure early supporters to finance their startup, so they would not run out of money and go out of business.

Unlike many digital startups that adopt lean, rapid development cycles tailored to shifting consumer requirements, deep-tech firms typically run through extended and sequential development cycles (Dionisio, 2023). Moreover, while digital technologies often deliver end-user applications directly, deep technologies tend to represent enabling or intermediate components, foundational technologies that support or feed the creation of end user applications, and thus the entrepreneur's task is to identify and commercialize how these foundational technologies can serve end users (Bresnahan & Trajtenberg, 1995; Dionisio, 2023). Collectively, these characteristics contribute to the expectation that deep tech ventures involve high risks and uncertainty.

These ecosystem characteristics long development cycles, high uncertainty, scientific complexity, and dependence on external infrastructure shape how deep-tech startups plan their entry into the market. Timing depends not only on internal technological readiness but also on when regulators, investors, and potential customers is prepared to adopt or validate the technology. As a result, deep-tech market timing is slower, more dependent on external signals, and more sensitive to ecosystem alignment than timing in purely digital ventures.

1.1.3 The Role of Venture Capital Timing in Startup Success

Technological innovations are a fundamental driver of economic growth. Venture Capital firms play a crucial role in the success of these new deep-tech startups as they are funding these companies in hopes of reaching greater success and profit (Hsu, H. C. S., 2013). The timing of venture capital investment represents one of the most critical points of startup performance, influencing progression of innovation, market entry dynamics, and the sustainability of the new business. In deep-tech startups, technology is very important and often originates from scientific discovery and requires lengthy R&D cycles; financial timing is extremely important for these ventures as technological advancements change fast. Venture capitalists not only support financially but also shape strategic direction, network access, and scaling capabilities (Gompers et al., 2004). Understanding when venture capital should enter the startup lifecycle is a vital part of the market ecosystem, like understanding how the startup operates in an entrepreneurial landscape. To guide the reader, it is important to note that VC timing functions as a strategic tool rather than a simple funding decision, shaping how a startup moves from research to commercialization.

Venture capital timing has the most impact when it is synchronized with the technological and market readiness of the startup. Early-stage ventures need a lot of funding for R&D but are exposed to the risk of failing with the market not being ready for the technology yet. "Venture capital firms avoid the early stages of technology-driven ventures, when technologies are uncertain and market needs largely unknown (Dimov et al., 2007), that is, they primarily invest in technology-driven ventures that have already reached a TRL of 8 or higher" (Romme et al., 2023). On the other hand, investments made later in the lifecycle of high-tech ventures tend to generate higher revenue growth but diminish R&D intensity. The timing of capital deployment can shift startups' strategic focus from innovation to commercialization. "On the contrary, Lin et al. (2020) pointed out that venture capital involved in the later stage of enterprise is more focused on marketing and commercial activities, as well as innovation output expansion, so it is not conducive to encouraging innovation" (Li & Zhao, 2022). Companies in deep-tech fields, that may include biotechnology, quantum computing, or artificial intelligence, need early funding for foundational development. This is highly risky if technological maturity and willingness to buy is not established by the startup. However, delayed funding may result in missed market opportunities, as competitors with faster access to capital can commercialize similar technologies and take the business out of these low funded startups. "Therefore, exploitative learning for corporate parents is less likely to occur with early-stage investments as these will entail uncertainty about the value of transferred knowledge (e.g. technological maturity of a product, willingness-to-buy of potential customers)" (Frey & Kanbach, 2023). The timing of venture capital has to be aligned with the internal technological course and, at the same time, be in line with the market adoption aspect of it. This section shows how VC timing interacts with both technology readiness and market maturity, forming a dual condition that determines how useful the capital becomes once deployed.

Beyond firm-level considerations, venture capital timing depends on the macroeconomic and industry cycles. The term vintage year is used to group funds, generally referring to the year they began (Kaplan et al., 2016). The correlation with investment performance is that periods (vintage years) of abnormally high fundraising levels are followed by periods of low subsequent performance for both buyout and venture capital (Harris, Jenkinson, Kaplan, & Stucke, 2020). Deep-tech startups are very sensitive to the market cycles as the exit predictions are longer and can be influenced by market liquidity and regulatory approval. "Reported unicorn post-money valuations average 48% above fair value, with 14 being more than 100% above" (Gornal et al., 2020). This just shows that during hype periods VC capital firms tend to over valuate startups and give them a unstable growth expectation. On the other hand, according to Romme et al. (2023), it could be challenging for deep tech ventures to overcome the lack of finances during the times of uncertainty as they fail to bridge the gap between research and profitability. Their research shows that the alignment of venture capital deployment with industry maturity and macroeconomic cycles is crucial for making sustainable startup success possible. This transition highlights the broader setting in which VC timing operates, showing how startup-level timing choices mirror the cyclical behavior of investment markets.

The timing of VC entry shapes the startup governing structure and innovation strategies. Venture capital participation at the early stages of startup financing, most commonly at the Pre-Seed and Seed stages, often involves high levels of investor influence and a strong focus on verifying the fundamental technological plausibility of the venture (Schmitz & Karpenko, 2024). This involvement is very important as it can give coaching and structure for the startups when they just begin their journey. For example, the French investment bank Bpifrance's Plan Deeptech provided coaching and tailored diagnostics to 270 deep tech startups in 2020, alongside innovation funding (Nedayvoda et al., 2021). However, early investment can include pressure and constraints connected to performance and development time frame that are usually longer for these deep-tech ventures. Some KPIs can even be counterproductive "For nascent deep-tech ventures, for example, KPIs focused on short-term P&L impact can be counterproductive" (Harlé et al., 2017). As we can see, for newly established startups funding and timing is very important as then they need to develop their technology as well as scale their business. That is why finding an investor with the right expectations is crucial. If the KPIs connected with the investors' view include profit gain, this could be setting up a new venture for disaster. As this means that the investor came in at the wrong time, and they are expecting to get into a later stage startup, that would pursue profits. Therefore, determining optimal VC entry points requires balancing the benefits of early innovation support with the stability of later-stage scaling. This section shows that VC timing not only affects funding but also shapes internal governance and expectations, which can strongly influence the company's pace of development.

The timing of venture capital funding even further interacts with startup market dynamics. The entry of VCs into a startup is rarely an isolated event, it typically occurs within syndicated networks that combine multiple investors' expertise and risk appetite (Lerner, 2009). The entry timing of these investment groups affects startups access to strategic knowledge, market partnerships, and more financing opportunities. In deep-tech environment, venture capital involvement at the very right time can unlock connections with academic institutions, government bodies, and business partners. "Knowledge transfer between academia and industry is considered an important driver of innovation and economic growth as it eases the commercialization of new scientific knowledge within firms" (De Wit-De Vries et al., 2018). This just shows that if timed correctly one can receive not only funding but also great knowledge that can help a startup reach commercialization of technology. On the other hand, delayed VC involvement may result in startups operating in isolation during the crucial development phase, missing the much-needed help that could optimize their time-to-market expectations. The strategic timing of venture capital engagement creates the alignment of financial backing, technological proficiency, and market positioning, enhancing the speed of commercialization. This connection highlights how VC timing determines access to external knowledge flows, which is especially important for deep-tech startups facing long development cycles.

Timing of Venture Capital Involvement Affects the Success of Startups Through Three Primary Channels:

(1) Technology Readiness,

(2) Market Maturity,

(3) Access to External Knowledge & Networks.

If all of these factors are aligned, then venture capital will support both quicker development and commercialization and faster scaling. If however, one or more of the factors are misaligned, the risk of failure for the start-up increases exponentially.

To summarize, the timing of venture capital is a critical component to determine. Whether a deep-tech startup will be successful and timing is especially important in deep tech sectors with long development times and unpredictable market maturation processes; achieving optimal timing alignment between technological readiness, market readiness, and the cycles of venture capital investment. While early stage funding can inspire creativity and scientific breakthroughs, there are risks associated with such funding (e.g. Financial exposure); on the other hand, late-stage funding supports commercialization efforts but may limit innovation. In addition to influencing internal dynamics, venture capital timing also influences interactions between financial and technological ecosystems, ultimately determining how science is translated into marketable products. Understanding and executing the right moment of investment for founders and investors of deep-tech companies is often the difference between success and failure. In addition to influencing the internal dynamics of a start-up, venture capital timing also influences startup market timing. Early-stage capital can accelerate entry to the market, while late-stage capital can slow it down. Venture capital expectations can determine when a product reaches the market and how quickly a company can scale. Therefore, venture capital timing and market timing operate synergistically to create a shared strategic window that ultimately determines if a deep-tech start-up can successfully enter the market at the right time.

1.2 Factors Influencing Market Timing in Deep-Tech Startups

1.2.1 Technological Readiness and Innovation Cycles

Technological readiness is one of the biggest factors that influences market timing decisions in deep-tech startups. "Unlike ‘web and app’ propositions, high-tech hardware ventures have to think about building a scalable supply-chain, creating IPR, and building global distribution channels for tangible products" (Romme et al., 2023). These deep tech startups operate with uncertainty, high capital intensity and as mentioned by the author has to think of more different aspect of startup. As a result, the decision of when to enter the market for a deep tech startup is tied very closely to the maturity of the technology that they are using as well as its alignment with the market adoption and commercialization cycles. To evaluate such market readiness, scholars and entrepreneurs employ models such as the Technology Readiness Level (TRL) framework, the Technology S-curve, and the Gartner Hype Cycle. Together, these three models show how technological maturity, expectations, and dispersion interact to determine optimal market timing for emerging innovations.

The Technology Readiness Level or how it is usually shortened to TRL, framework, originally developed by NASA, provides a systematic approach to assessing the maturity of a given technology, from early research (TRL 1 - 3) to system demonstration and commercial deployment (TRL 8 - 9) (Mankins, 2009). Deep-tech startups frequently operate at low TRLs for extended periods due to scientific uncertainty and the need for rigorous validation as well as research. For market timing, TRL indicates when a technology becomes credible enough for pilots, customer trials, or regulatory engagement. Entering before this point raises technical risk, while delaying past readiness risks losing strategic momentum. Successful adaptation to the market of new technologies depends on establishing a strong connection between technology development and market context, that forms the rational integration of Technology Readiness Level analysis for market adoption. TRL therefore guides when a startup should shift from research to external validation, which directly affects timing decisions. In deep-tech ventures, aligning investment and market-entry strategies with these timing dynamics can significantly increase scalability, as technology risk decrease and measurable demand begins to appear (Engel-Cox et al., 2022).

A second model that is crucial to understanding technological readiness is the technology S-curve, which describes forecasting technology trends drawn from the perspectives of both Product and Process (Masuda & Haruyama, 2021). The S-curve informs timing by indicating when performance meets early customer needs and when improvement begins to slow. Deep tech teams judge their place on this curve to decide if more research is useful or if the focus should shift to scaling. Benson and Magee state that acceleration in adoption begins when the improving technology reaches the level needed to meet early user needs, which they describe as the moment when “the performance of an improving new technology reaches a level adequate to satisfy some customers” (Benson & Magee, 2018, p. 5). The model helps teams avoid premature entry and also avoid losing position to faster competitors. Deep-tech entrepreneurs balance further progress with timely market entry, so they are not overtaken by faster improvement cycles.

The Gartner Hype Cycle adds an important layer because it highlights how expectations influence investor attention and customer readiness across the lifecycle. Studies based on Gartner data show that many technologies follow expectation-driven paths where early enthusiasm falls before adoption becomes more stable (Dedehayir & Steinert, 2016). For timing decisions, this framework shows whether it is wiser to launch during high visibility or after expectations stabilize. A launch during the early surge of attention can create visibility but also brings the risk of negative reactions once results take longer to appear. A launch later, when evidence of real performance starts to build, often supports more durable growth and clearer value signals (Leiponen & Thomas, 2019).

R&D intensity affects how a deep tech venture moves toward getting a product ready for real customers. It also influences how quickly the company advances through the Technology Readiness Level stages and the S curve. A strong focus on R&D helps the technology mature, but the work still needs to match what the market is asking for and what the firm can afford at each step. Chukhray et al (2022), state that "the level of novelty and the degree of technological readiness for the commercialization of a R&D product and, on the other hand, how much the consumer is receptive to it, and, then again, how the added value of the product will develop under market effects." This underlines the link between maturity and demand. The balance between exploratory and exploitative R&D determines when a technology becomes compelling enough for concrete market action. Capatina et al. highlight this issue by noting that "Deep tech firms spend a lot of time in innovation labs before being capable of bringing tech to market and achieving real market adoption." Together these points show how technological readiness, R&D focus, and market conditions shape effective market timing for deep tech startups.

Across all three frameworks, timing depends on aligning internal readiness (TRL), performance trajectory (S-curve), and external expectations (Hype Cycle). TRL shows when a technology becomes credible, the S-curve indicates when it meets user needs, and the Hype Cycle reflects market attention and acceptance. Deep-tech ventures make timing decisions by integrating these three views rather than relying on one model alone.

For deep-tech ventures, technological maturity grows slowly while expectations change quickly. Market timing becomes a strategic exercise in identifying the moment when performance, readiness, and external conditions align. These frameworks guide the empirical analysis in this thesis by showing how startups read technological signals when planning their entry strategy.

1.2.2 Market Signals and Customer Demand

Understanding and illustrating market signals is a central task for determining the right market entry moment in deep tech ventures. These ventures work under constant uncertainty shaped by long R&D cycles, complex technologies, and unclear market readiness. Research notes that “entrepreneurs often depend on external funding to develop and grow their ventures” (Steigenberger, Garz and Cyron, 2025, p. 1832). This dependence increases the importance of clear signals that lower information gaps between founders and investors. These signals help outside stakeholders assess emerging consumer needs, technology acceptance, and the reliability of a startup progress. The challenge is reinforced by the fact that “new ventures often operate in highly dynamic, unpredictable, complex environments which affect the level of information asymmetry” (Bafera and Kleinert, 2022, p. 2432). For deep tech ventures, these signals shape when a product reaches the market and how well the firm secures the support needed to move the product toward real sales. Signals therefore act as timing indicators, helping founders judge whether conditions support an immediate market entry or whether they should delay until uncertainty decreases.

Deep technology companies rely on early investor support, customer engagement and ultimately pilot user adoption in order to determine when to bring their products to the larger marketplace. As stated by Capatina et al. (2024), deep technology startups "must demonstrate the technological usefulness to scale from the laboratory to pilot customers." The researchers further identified the ability to attract pilot customers will improve the customer value proposition and support scaling efforts. Research conducted by Dionisio et al. (2023) provides additional evidence supporting these views. Dionisio et al. described how deep technology startup ventures have long/slow and sequential development cycles; they also noted that due to the difficulty of understanding and assessing deep technologies, entrepreneurs must establish early supporters to be able to pursue commercialization. Early adopters and early supporters send an indication of unrealized demand and provide guidance to both entrepreneurs and investors regarding the optimal time to transition from technical development into the broader marketplace. Therefore, early consumer and customer feedback serve as "go" signals, while lack of this type of feedback can signal the need to delay commercialization.

Startups face information gaps when they seek funding. Investors look for signals that reduce uncertainty, so founders use observable actions to show progress and quality of the product they are making. “Signals alleviate information issues in both public offerings and private equity deals” (Colombo et al., 2019). This highlights the role of positive signals in early financing by investors. Research on equity crowdfunding shows how early investor actions influence later decisions.

“Investments during the first days of online offerings are likely to affect subsequent bids” (Meoli and Vismara, 2021). This only confirms that visible and timely signals shape investor behavior. Deep tech founders wait for technical validation before they start raising equity. Strong signals reduce investor uncertainty and help them judge the project correctly. When these deep tech venture owners time their steps well, they match investor's focus on recent and verified information which allows them to give higher valuations and more funds. In this way, investor behavior directly communicates whether a startup should accelerate market steps or postpone them until stronger validation is available.

Open innovation partnerships strengthen the reliability of market signals by adding external feedback to R&D and commercialization work. University, industry, and government collaborations help startups to test their technologies and develop use cases before entering larger markets. Research shows that “the partnership structure most likely to further economic and broader societal goals is the living lab with the inherent focus on open innovation and co-creation” (Burbridge & Morrison, 2021). These collaborations act as endorsement signals that increase investor trust by showing credible progress. Public programs reinforce this effect through external validation. “Government awards to private parties certify the quality of the company, help the company become established, and enable the company to secure other sources of funds” (Colombo et al., 2016). Strong external validation typically signals readiness to scale or enter new markets, while a lack of such validation may prompt founders to delay entry and continue refining their technology.

Relational and behavioral signals reduce information gaps between founders and investors. These signals come up through early interactions where both sides investors and founders learn about each other's intentions and reliability. Research shows that “relationships are conduits through which financial and social resources flow, promoting the growth of new ventures” (Huang & Knight, 2017, p. 81). These early interactions help build familiarity and trust that lower uncertainty during later funding stages. Evidence also shows that “misunderstanding and uncertainty are negatively related to trust” (Nagel et al., 2019, p. 263). Deep tech founders use these early exchanges to assess investor interest, strengthen engagement, and create competitive signals by widening their pool of potential investors. When these relationship-building steps align with technical development milestones, they increase investor confidence and support stronger funding outcomes.

The challenge for deep tech startups lies in matching the strategies of signals with how fast the technology and market develop. These deep-tech ventures face mixed risks, long timelines, and uncertain market readiness, which increases the need for clear and credible signals over extended periods of time. The evidence found in a paper shows that "deep tech startups, which face both technological and commercialization challenges, may find it difficult to attract adequate investment" (Arora et al., 2024). This just reinforces the need for strong fixed signals for investors such as patents, certifications, and published results, together with dynamic indicators like customer pilots, partnerships, and visible investor engagement. Investors also remain cautious because "entrepreneurs tend to be too optimistic or have a natural incentive to exaggerate their prospects and the potential value of their firm" (Mohammadi & Shafi, 2017, p. 276). Founders with prior success or ties to reputable institutions reduce this uncertainty because reputational capital serves as an initial trust signal. The timing of these signals, when results are shown, when partners join, and when investors are approached, shapes how well the startup aligns its technological progress with credible market demand. Weak or inconsistent signals push firms toward delaying market entry, while strong and consistent signals indicate that conditions are aligning for commercialization.

Taken together, market signals help deep-tech entrepreneurs decide not only how to enter the market but when. Customer traction, investor engagement, external validation, and relational trust operate as timing cues that guide founders toward either accelerating commercialization or postponing it until uncertainty declines. Startups that actively interpret these signals improve their ability to synchronize technology maturity with market readiness, which is central to achieving the right moment of entry in deep-tech industries.

1.2.3 Regulatory Environment and Institutional Factors

The regulatory environment shapes market timing in deep tech. These ventures develop in sectors where compliance, certification, and government oversight guide how fast a technology moves from the invention to the market. Research notes that "science and technology based innovations… often have not managed to become part of social life, even when there was an expectation that they might address important social challenges" (Borrás and Edler, 2020). This highlights the role of institutional system and how it is shaping when technology becomes ready for adoption. Regulation affects the feasibility of market entry and sets the momentum for commercialization. Public views and rules affect how fast a new technology moves forward. As noted, "misplaced hopes or fears could lead to misguided regulation" (Cave et al., 2019). Deep-tech founders need to read these signals and plan around policy support, approval steps, and industry rules so they can match their progress with expected demand. This set of factors acts as regulatory barriers that may slow entry or force firms to postpone commercialization until conditions stabilize.

Government policies and regulations shape how fast deep tech solutions reach the market. Some rules or policies given by the government hold back actual commercialization, while others support new innovative activity. Evidence from the bioeconomy shows that "As a result, regulation has the potential to both enable and constrain bioeconomy development" (Pender et al., 2024). This finding shows how regulatory frameworks work as both barriers and drivers for deep tech ventures, depending on their structure and focus. Authors also describe how effective regulation must support sustainability, manage competing interests, and provide coherence and innovation support across sectors (Pender et al., 2024). For deep tech entrepreneurs in various fields such as clean energy and industrial biotechnology, this means that market entry timing decisions depend on researching where regulation will restrict their activity and where it will create them new market openings. When rules encourage experimentation or provide incentives, they signal a favorable entry moment; when they tighten, firms must delay until compliance becomes achievable.

Industry standards shape how deep tech technologies develop because they provide shared expectations for governance and technical practice. The paper notes that "A wide range of UN institutions have begun to undertake some activities on AI… including the International Organisation for Standardisation (ISO)" (Cihon, Maas, and Kemp, 2020, p. 228). This work goes alongside international efforts to update legal frameworks for autonomous systems, including changes to the Vienna Convention on Road Traffic that address autonomous vehicles. Deep tech venture entrepreneurs follow these developments to match their progress with the institutional processes that form future requirements and compliance expectations, these changes might help the future deep tech startups reach better and faster results. Standards therefore act as alignment signals, showing when a technology fits emerging compliance expectations and when firms should delay to avoid misalignment.

Market entry timing depends on how entrepreneurs sequence their strategic steps under uncertainty. The paper notes that “entrepreneurs face multiple potential strategies for commercializing their idea but due to the constraint of limited resources, cannot pursue them all at once” (Gans, Stern and Wu, 2019). This forces them to choose when to commit and when to delay their actions. Early moves without enough information can cause the risk of wasted resources or strategic lock in place, while long delays reduce the chance to benefit from early demand in the market. Entrepreneurs in deep tech take time to check their assumptions and look at early market signals. They wait to form partnerships or release a product until they know more about how the technology will perform. This staged approach reflects how institutional uncertainty shapes the pace and sequence of commercialization.

In fields like autonomous systems and advanced robotics, slow regulatory change creates uncertainty for founders who plan their market entry. The text notes that “The delay in government responses to emerging technologies, often called the 'pacing problem' ... creates a clear, even if interim, role for other actors in improving AI corporate governance in the public interest as AI research and development continues” (Cihon et al., 2021). This puts more pressure on firms to judge how their work fits within the rules that are still taking shape. The challenge grows because “The dynamism of emerging technologies such as AI is especially challenging for the development and enactment of detailed and rigorous 'hard' laws” (Eyert et al., 2020). These conditions shape the market timing choices for deep tech ventures. Many wait to speak with customers or investors until they see more stable signals about their technology from regulators. Others use controlled testing environments to show how they meet current expectations. These steps help them move toward the market at a pace that fits the changing policy setting. Such pacing gaps create timing windows where firms either advance ahead of regulation or strategically pause until the legal environment matures enough to support adoption.

Deep tech startups work across regions where different rules shape when they enter the market. In regulated fields such as medical and biotech, approval speed varies across agencies. As one study notes, “Our analysis of novel therapeutics approved between 2001 and 2010 shows that the FDA has provided more rapid reviews of applications involving novel therapeutics than have the EMA and Health Canada and that the vast majority of the novel therapeutics first received approval for use in the United States. These findings contradict recent criticisms of the speed of review by the FDA and question whether review speed is justified as an emphasis for PDUFA V, particularly since the FDA continues to outpace its European and Canadian peers" (Downing et al., 2012). These differences create lobsided openings for market entry. A similar split appears in the field of artificial intelligence. "The United States AI regulatory mechanism is led by the private sector, and the companies lead the innovation and development of AI within the broad risk management spectrum set by the government. This shows that the US government's understanding of the AI relies heavily on the private sector's approach to institutionalize and operationalize AI ethics and its societal dimension" (Sharma, 2023). These differences mean firms may enter one region early while delaying in another, turning regulatory variation into a sequencing strategy for global expansion.

Navigating different regulatory systems across countries takes planning. Standards shape how technologies grow and when firms move into new markets. As stated in the literature, "As formal standards and regulations shape the paths of further technological developments, it is highly important to understand their influence and functionality in order to increase economic growth and welfare" (Blind et al., 2016). This means entrepreneurs who track standards early can prepare for smoother approval steps and earlier market entry. Work across borders adds another layer. "Corporations that work across jurisdictions often follow the regulations of the most stringent jurisdiction across all jurisdictions to gain the efficiencies of a single standardized compliance operation" (Cihon et al., 2021). Deep tech businesses often take the same approach to reduce the risk and build credibility with investors. Being engaged in different policy groups or public partnerships helps startups stay aligned with future rules and plan their expansion to the markets with fewer delays.

Deep tech entrepreneurs work within broader institutional settings that include cultural norms, legal systems, and public funding rules. These settings shape when they bring new products to the market. Work with AI shows how social expectations matter, since "Corporate applications of AI touch on many important public issues, including social justice, economic vitality, and international security" (Cihon et al., 2021). This means that companies must show that their work aligns with public concerns, not only with formal rules. They also need to follow clear practices of responsible conduct. As noted in the same text, “Industry best practices and standards formulated by industry consortia can fill in the details of good conduct. Additionally, regulatory agencies and courts handling liability cases sometimes treat compliance with industry best practices and standards as satisfactory, such that corporations meeting these practices or standards avoid regulatory fines or court judgments of liability to which they would otherwise be subject” (Cihon et al., 2021). For founders, this shapes timing. They must plan when to launch based on formal requirements and on the expectations of society and investors.

Because governments understand it will take a long time for deep-tech innovation to mature, and because it will require consistent and stable support; there is growing interest in policy instruments that provide low-risk conditions for firms to introduce new technologies into the marketplace. As noted by researchers; "This leads to a greater relevance and attractiveness of adapting the existing regulatory framework in order to support private innovation activities" (European Commission, 2016) (Blind et al., 2017). In addition to providing supportive policies, the use of public funding tools (such as grants, R&D programs, etc.) and test environments create clearer signals and can reduce the uncertainty associated with innovation for founders. Policymakers are also being asked to develop guidance for rapidly evolving areas like AI. "The increasing call for regulation of AI has also highlighted the policymakers' roles in defining the trajectory of new and emerging technologies, and to understand the differences between the decentralized and centralized approaches to regulatory frameworks" (Sharma, 2023). The changes to the landscape of government support for deep-tech innovation matter to founders. Founders of deep-tech companies plan their development milestones and their market entry plans based on the availability of supportive government policies, the national priorities of the country where they operate, and the direction of government policies related to the new technologies they are developing. Companies that react to supportive policies early on in their lifecycle are able to establish themselves as leaders in the market as they transition from a research focus to a commercial focus. Therefore, supportive government policies serve as accelerators of commercialization, while restrictive or unclear government policies act as barriers to commercialization and cause firms to delay their commercialization until the level of regulatory certainty increases.

In this layered (regulatory and institutional) framework, timing is a reflection of how well an organization understands the rules and standards that govern their space, as well as the time gaps between societal expectations, regional differences, and pacing. The barriers to entry in a space cause companies to enter at slower rates than they would have othrwise, while enablers create opportunities for early movers to scale quickly. When there is institutional alignment, organizations are better able to synchronize their internal goals with the demands of the environment, thus, understanding the elements above help us understand why timing is more than just when a company has developed its product (technology), it also requires understanding the regulations and institutions that will be involved in the deployment of the product.

1.3 Strategic Approaches to Market Timing in Deep-Tech Startups

1.3.1 Market Entry Strategies

Market entry strategy determines how deep-tech startups time their move into the market. Two dominant strategies discussed in the literature are the first-mover and late-mover approaches. First-mover advantage refers to the competitive benefits gained by entering a market before others, such as technological leadership, early customer adoption, and influence over standards. "Early entrants may be able to preempt resources of various types. These include superior positions in geographic space (e.g., prime physical locations), technology space (e.g., patents), or customer perceptual space" (Lieberman & Montgomery, 1998) Late-mover advantage refers to benefits gained by entering later, such as learning from early entrants, reducing uncertainty, and avoiding technological or regulatory dead ends. "But pioneers often miss the best opportunities, which are obscured by technological and market uncertainties. In effect, early entrants may acquire the 'wrong' resources, which prove to be of limited value as the market evolves" (Lieberman & Montgomery, 1998)

In the case of deep-tech startups, the question of entry as first or late movers is very strategic, since their innovations usually come from scientific discoveries and long development and validation cycles. "Deep tech startups in particular identify market niches in which no established players are present and aim to disrupt existing or create new markets with deep technology innovations. In this context, deep tech startups face the challenge of not only developing their organization but also developing their technology and building a market in parallel." (Schuh et al, 2022) A first-mover strategy can, therefore, allow such ventures to establish technological leadership, secure intellectual property rights, and influence emerging industry standards (Lieberman & Montgomery, 1998). Early entrants into fields like quantum computing, new materials, or biotechnology are perceived to gain legitimacy and interest from strategic investors through their perceived pioneering status. First movers, however, face some significant hurdles. They have to bear the costs of educating the market, building infrastructures, and taking on technological uncertainties, very often before demand is fully realized. This means first-mover advantage and first-mover risk are deeply tied to timing: firms must enter early enough to lead, but not so early that they arrive before the market is capable of adopting their solution.

By contrast, late-mover deep-tech firms can leverage prior technological diffusion and market learning. They can refine existing innovations, adopt improved production methods, and target better-defined customer needs, thus lowering uncertainty and commercialization costs (Te Kič et al, 2024). Later entrants benefit from accumulated industry knowledge: they can align their strategies with established technical standards, clearer market expectations, and visible competitive patterns, enabling them to position their operations more effectively and improve their chances of long-term survival (Mitchell, 1991). In deep-tech ecosystems, where the time from invention to commercialization may span years, strategic patience can allow ventures to enter at the right technological and regulatory maturity stage, thereby avoiding the "valley of death" often faced by early pioneers. Ultimately, for deep-tech founders, optimal entry timing depends on balancing the potential for early technological dominance with the risks of premature market exposure. Late-mover strategies therefore reduce technological and regulatory uncertainty, but the trade-off is the risk of missing early influence or losing strategic ground to stronger competitors.

Deep-tech startups most often represent what is called disruptive innovation-scientific or engineering breakpoints that develop new market segments or redefine mature ones. In these endeavors, timing in relation to the market can make or break a disruptive possibility. "The lack of correlation between firm internal features and enhanced foresight capabilities proves that rapid technological advances outpace market readiness or customer adoption, claiming to replace "learning from the past" with "learning from the future" "(Capatina, 2024). Since deep technologies, such as AI, robotics, and synthetic biology, often rely on conditions within the ecosystem-for instance, timing in regulatory environments, manufacturing partners, and the general public-commercialization failure may occur even in the most technologically superior cases when the timing is off. This again reinforces that both first-mover and late-mover strategies succeed only when aligned with ecosystem timing.

Empirical studies of successful deep-tech companies, such as SpaceX, DeepMind, and QuantumScape, show that timely market entry-that is, when technological maturity coincides with investor confidence and customer readiness-allows firms to capture a share of early markets and draw strategic partnerships. These usually start by entering highly focused applications or pilot markets, followed by the rest of the broader sectors. “Through the involvement and close collaboration with pilot customers, the practicality of the product must be demonstrated while identifying a viable business model that ensures commercialization” (Schuh, 2022). This gradual entry process blends the benefits of early presence with controlled risk, illustrating that timing is not a single decision but a sequence of staged moves.

Whether to seek a niche market or broad-market appeal from inception is another critical strategic dilemma for deep-tech entrepreneurs. This approach allows startups to address a well-defined problem where the value of their technological solution is highly differentiated, especially in B2B or high-precision industrial settings. “Opportunities in deep-technology are typically less risky than those in strictly digital fields. When tackling a fundamental issue that has often been overlooked for many years, there will inevitably be a demand.” (Nguyen 2024) Through this route, the barriers to entry are more manageable, the validation happens more quickly, and there is an opportunity to co-create the product with pioneering users who will use the offering-oftentimes research institutions or specialized industries. Such a direction also minimizes the financial and operational risks during the early stages of development when resources are scanty, and product cycles are long.

On the other hand, some deep-tech startups would prefer a broad-market strategy in the event that the technology assumes platform characteristics or scalability across sectors, as witnessed by AI chips and renewable energy systems. At any rate, this approach requires an enormous amount of capital, solid supply-chain capabilities, and extensive commercialization infrastructure. Strategic choices will thus depend on the firm's technological maturity, investor support, and capacity to adapt across multiple markets. “Deep tech ventures generate and preserve “optionality”, that is, the leverage of science and technology to address the widest possible set of problems, while also finding a path to profitable scale and scope." (Murray & Frolund, 2023) Essentially, deep-tech entry strategies will balance scientific excellence with pragmatic market targeting in the effort to surmount the high risks related to deep-technology commercialization through a balance of focus, scalability, and timing.

Across these strategies, market timing emerges as the central coordinating factor. First-mover strategies rely on early readiness and the ability to shape markets, while late-mover strategies depend on learning effects and reduced uncertainty. Niche entry enables controlled timing through focused validation, whereas broad-market entry depends on timing windows created by ecosystem maturity and investor momentum. For deep-tech ventures, choosing when and how to enter is not a binary choice but a dynamic process that aligns technological maturity, market formation, and strategic positioning – the core focus of this thesis.

1.3.2 Timing as a Competitive Strategy

In deep-tech ventures, innovation is contingent on scientific or engineering breakthroughs; the environment is characterised by high uncertainty, long development-cycles and deep interdependencies across technology, regulation and markets. It is in this context that the ability to anticipate, envision, and prepare for multiple plausible future states-strategic foresight-and scenario planning become critical competitive tools. "Deep tech startups operate at the forefront of technological innovation, developing cutting-edge solutions that often address complex challenges and untapped market needs." (Capatina, 2024) "However, their success hinges not only on their technological prowess but also on their ability to anticipate and navigate future trends and market dynamics" (Romme et al., 2023). For example, firms that engage in systematic horizon-scanning, build contrasting future scenarios, monitor early signposts and adapt their road-maps accordingly are better situated to synchronise their technological readiness with market and regulatory readiness.

By employing a proactive approach to timing with the use of forward-looking methods, deep-tech start-ups can determine when a technology reaches a 'readiness' point, when an infrastructure will be available or a standard will exist, or when there will be enough consumer interest to warrant entering the market. In doing so, by considering several possible future outcomes, these start-up's will be able to take their decision-making about when to enter the market and turn it from being a "gambit" into a "strategic lever." Simply put; timing is not just about when to enter a market, but also about shaping the window in which one can enter. Evidence collected in the field of deep-tech demonstrates that technologically advanced companies can still fail due to poor timing. As an example, Gbadegeshin (2022) found that when the technological readiness of a product, market adoption and regulatory systems did not align, companies became stuck in what is referred to as the "valley of death," (the space between development and commercialization), while developing their products.

Deep-tech firms that enter the market when the necessary infrastructure is in place and investor confidence is high often gain a strong first-mover or early-mover advantage. Research shows that companies with careful foresight, scenario planning, and coordinated strategies for market readiness tend to outperform their peers in commercializing disruptive technologies. (Capatina et al., 2024). These examples highlight that market timing is more than a tactical choice; it is a strategic factor that can determine the success or failure of a venture. The moment a company launches - relative to technology maturity, regulatory conditions, and the readiness of the ecosystem - can make all the difference.

Deep-tech startups will have to walk a tightrope between agility and patience. They have to be agile enough for pivoting and iterating, quickly responding to shifting market signals. They must be patient enough to give time for technology development, regulatory approval, and setting industry standards in place. Moving too slowly will cause them to miss the window for an optimal entry, whereby their competitors establish commanding positions in the ecosystem Moving too early, however, results in wasted resources, low adoptions, and even failures, which may happen notwithstanding having a technically better product. “Misinformed or ill-timed strategic bets on losing technologies might result in significant company write-offs and, in the worst-case scenario, even jeopardize the company’s existence” (Aaltonen & Kurvinen, 2025).

Timing in deep tech, therefore, is very much a strategic exercise in pacing. Startups have to make careful decisions about when to accelerate development, when to wait, when to run pilot projects, and when to scale operations. This means continuous monitoring of TRLs, MRLs, regulatory trends, and investor sentiment. Those startups that can develop mechanisms for foresight, flexible adaptation, and staged entry thus demonstrate a better capability to cope with uncertainties and seize opportunities at just the right moment, maximizing their chances for long-term success. “Successful startups identify the optimal moment at which the market demand is ready for their solution. This factor includes an understanding of market trends, competitor movement and consumer readiness” (Argaw et al., 2024). In deep tech, such strategic timing of entry is not luck but an act of balancing readiness, flexibility, and patience in order to keep the competitive edge in a complex, fast-evolving industry.

Across these arguments, timing emerges as a strategic capability shaped by how well deep-tech founders use foresight to anticipate future conditions, interpret lessons from past success and failure, and maintain the right balance between agility and patience. The cases discussed in the literature show that ventures succeed when they can act early enough to benefit from emerging opportunities yet delay when signals indicate that the market or regulatory setting is not ready. The key determinants of timing, therefore, rest in a startup’s ability to forecast how its environment will evolve, to adjust its pace of development accordingly, and to avoid premature or delayed entry. In this way, timing becomes a competitive strategy grounded in informed judgment rather than chance.

1.3.3 Pivoting in deep-tech startups

Pivoting in deep-tech refers to a deliberate strategic shift in technology, target market, or commercialization path when new information shows that the original course is no longer optimal. Because deep-tech technologies require long development cycles and strict validation, the timing of these pivots is often as important as the pivot itself. The ability to pivot, or strategically adjust business direction, technological focus, or commercialization timing in response to both internal and external signals, would be the last determining factor for survival and growth among deep-tech startups. “Whereas shallow-tech startups might pivot quickly in the face of an obstacle, deep-tech startups often must navigate complex technical terrains.” (Aaltonen & Kurvinen, 2025). Compared with digital startups, where pivots are rapid and market-driven, pivots within deep-tech ventures are much slower and complex due to high technological path-dependency, capital intensity, and regulatory constraints. This makes pivot timing especially critical, because reacting too early or too late can significantly influence whether a startup progresses or stalls.

Deep-tech founders need to iteratively reassess market timing strategies by aligning their commercialization plans with evolving levels of technology readiness, investor sentiment, policy incentives, or market priority shifts. “Responsiveness is essential in dynamic startup environments. To thrive, startups need to be responsive and resilient in order to navigate through challenges and changes in the business environment” (Argaw et al., 2024). Technical pivots occur when teams adjust core technological components or development paths once they learn that the current approach cannot reach performance, cost, or scalability thresholds within the desired timeframe. Some ventures, for instance, wait for the right time to enter the market in order to coordinate with the development of industry standards. Others, however, enter prematurely due to unforeseen external catalysts, such as geopolitical changes or sustainability legislation, thus opening a very unexpected "window of opportunity." From this perspective, strategic pivoting represents a learning process and a resilience mechanism that allows deep-tech ventures to handle uncertainty and maintain the relevance of their technologies. Here, timing determines whether a technical pivot accelerates readiness or forces costly redesign.

The development of many deep-tech startups has as a critical inflection point their transition from prototype toward market-a transition that has been infamously coined the "commercialization valley of death." During this stage, the technological maturity needs to be in sync with market and ecosystem readiness. Entering the market too early can expose the firm to unverified assumptions, underdeveloped infrastructure, or unmet performance standards; entering too late risks losing first-mover advantages and investor momentum (Gbadegeshin, 2022). Market pivots involve changing target users, value propositions, or application domains when early pilots reveal a mismatch between expected and actual demand. The timing of this pivot determines whether the company escapes the valley of death or becomes stuck in it. A structured validation mechanism, such as a pilot program, testbed, and co-development partnership, enhances the chances of deep-tech startups timing their entry well. Strategic alliances with industrial partners and public R&D consortia can facilitate prototype polishing while garnering market acceptance. “Within the deep-tech industry context, the process of product development encompasses the development of prototypes that feature adequate functionality, along with conducting market research and collecting feedback. This process ultimately leads to achieving market readiness” (Nguyen 2024). Indeed, iterative testing at this stage has the beneficial effect of enabling founders to fine-tune the technological specifications and adjust them to industry-specific adoption barriers that may be unearthed along the way-prototype to commercialization thus becomes easier.

Regulatory pivots arise when founders adjust timing or product design to match evolving compliance requirements, approval pathways, or standards shifting their strategy in response to policy signals. “Dynamic capabilities, which are underpinned by organizational routines and managerial skills, are the firm's ability to integrate, build, and reconfigure internal competences to address, or in some cases to bring about, changes in the business environment” (Teece, 2018). As regulatory expectations change, founders may need to revise technical specifications, adjust testing protocols, or delay or accelerate commercialization steps to maintain compliance. These pivots reflect how startups interpret policy signals and reposition themselves to avoid regulatory barriers. Empirical studies also reveal that adaptable deep-tech startups have stronger investor attraction, higher technology-to-market conversion rates, and faster ecosystem integration when compared with rigid firms. Well-timed regulatory pivots help firms avoid costly redesigns or approval setbacks and ensure that commercialization proceeds in a alignment with emerging regulatory pathways. This is a delicate balance between deliberate delay and readiness to act-a factor distinguishing those deep-tech ventures which eventually succeed from those that fail due to technological lock-in or inflexibility. When timed well, regulatory pivots reduce compliance risk and maintain investor confidence; when mistimed, they undermine momentum, increase uncertainty, and weaken a startup’s position in the market.

In other words, deep-tech startups, whose operations are instilled with adaptability and structured mechanisms for pivoting, are more likely to overcome the intrinsic uncertainty of longer development cycles and manage the proper fit between technological breakthroughs and market opportunities. The findings highlight how enhanced foresight capabilities enable deep tech firms to leverage technology dominance with "desirable business agility, in order to adopt a virtuous cycle of capturing-market maker opportunities towards a future shaping builder" (Capatina et al., 2024).

Timing is at the heart of pivoting across technology, market and regulatory areas. Pivoting impacts whether or not a venture will be able to escape the "valley of death", capture emerging opportunities, or redeploy its resources prior to exhausting them. Those ventures which develop formalized systems to identify changes in their environment, validate their assumptions, and adjust their pace have enhanced ability to make good timing decisions. Thus, pivoting is not merely an adaptive process, but also a timing based strategic process which can lead to the long term success of ventures in deep tech ecosystems.

1.4 Success Factors in Market Timing for Deep-Tech Startups

1.4.1 Product/Market Fit and Startup Success

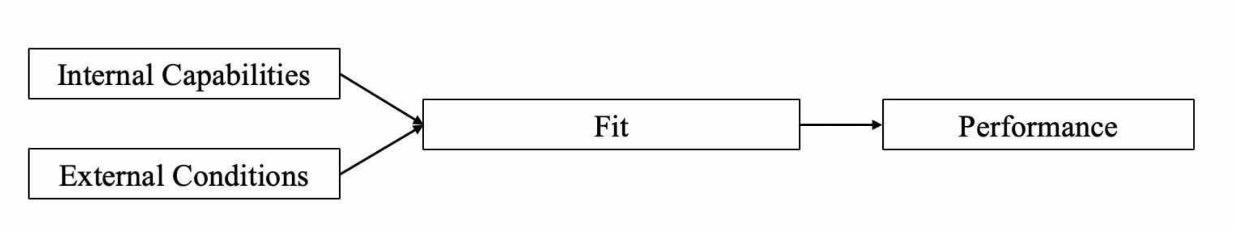
Startup success refers to the ability of a new venture to achieve sustainable growth, market acceptance, and profitability based on its strategic and operational goals. It is not defined only by financial outcomes but also by achieving stability, scalability, and a viable business model. According to James Okrah, Alexander Nepp, and Ebenezer Agbozo (2018), startup success is founded on two main elements: its consistency with innovation and a continuous flow of funds. Harjo et al., (2018) emphasize that success is multidimensional, combining financial performance with non-financial factors like customer satisfaction, product acceptance, and innovation outcomes. For deep-tech startups, success often includes the ability to commercialize advanced technologies, attract investment, and achieve long-term market presence despite high uncertainty and long development cycles.

A central condition connecting market timing to startup success is product/market fit. This concept describes the alignment between a product's value proposition and the needs of a well-defined market segment. Marc Andreesen (2007) defines product/market fit as "being in a good market with a product that can satisfy that market." His view is widely cited in startup research and practice. According to Andreesen, the interplay between three elements—team, product, and market - determines a startup's competitive potential. He emphasizes that the market is the most decisive of the three. In his words, when a great team meets a poor market, the market wins; when a poor team meets a great market, the market still wins; but when both are great, something special happens.

The logic of this position is that timing and readiness will not automatically lead to a successful outcome for a startup. A strong product or capable team will be unable to succeed in a poor market environment; however, within an attractive and growing market, those who can establish Product/Market Fit first will receive momentum and interest from investors and may successfully scale their business. The above position by Andreesen (2007) illustrates why strategic, market-based timing decisions are important; ultimately, success is dependent upon establishing a point where the market's demand conditions allow a product to attain traction.

1.4.1 Figure

Contingency theory model



Source: Made by authors, based on Donaldson (2001)

From a **Contingency Theory** perspective (refer to Figure 1.4.1), product/market fit reflects the degree of alignment, or “fit,” between external market conditions and internal organizational capabilities. Contingency Theory proposes that there is no single best way to organize or manage a firm; instead, effectiveness depends on the consistency between internal characteristics and the external environment (Lawrence and Lorsch, 1967; Donaldson, 2001). In other words, performance results from how well organizational structure, strategy, and processes adapt to contextual factors such as market dynamics, technological change, and competition. Applied to startups, this means that the right combination of internal readiness and external opportunity determines success. Startups that manage to align their product, team competencies, and timing with the market environment reach this equilibrium point and perform better. Therefore, achieving product/market fit can be viewed as both a performance driver and a validation of strategic fit.

In summary, startup success depends on achieving alignment between internal capabilities and external market conditions. Product/market fit serves as the connecting mechanism that links timing, readiness, and team competence to measurable outcomes such as growth, scalability, and market acceptance. Deep-tech startups operate in uncertain environments where success is not defined by innovation alone but by the ability to synchronize technological potential with real market demand. From a contingency perspective, this alignment represents the fit that drives organizational performance. When startups manage to time their entry effectively, develop products that satisfy existing needs, and adapt their internal processes to changing market conditions, they create the foundation for sustained success and competitive advantage.

1.4.2 Network Effects and Ecosystem Dynamics

For deep-tech startups, effective market timing rarely occurs in isolation, it is shaped by the broader innovation ecosystem in which these ventures operate. Because deep-tech innovation depends on long research cycles, capital-intensive prototyping, and cross-disciplinary expertise, strategic partnerships and alliances become crucial mechanisms for accelerating both technological maturation and market readiness (Adner, 2017). Ecosystem actors influence not only how fast a startup develops its technology but also how quickly it receives the signals needed to decide when to enter the market.

Strategic partnerships with universities, research institutes, established companies, or public agencies help startups share knowledge, access advanced infrastructure, and jointly develop new technologies. These collaborations reduce uncertainty and shorten the path from proof-of-concept to commercialization by aligning both technological progress and ecosystem readiness (Aaltonen & Kurvinen, 2025). Such partnerships accelerate timing by giving founders earlier validation, clearer performance benchmarks, and stronger evidence that customers or regulators will accept the innovation. Conversely, missing such partners can delay entry because key testing, certification, or data-gathering steps take longer to complete alone.

Alliances formed within industry clusters or innovation hubs also create strong network effects. In such environments, interconnected actors accelerate technology adoption, attract more investment, and help establish common standards (Nguyen, 2024). When deep-tech startups engage early in these ecosystems, they not only gain visibility and credibility but also improve their ability to time market entry accurately, thanks to ongoing market feedback and shared insights. Clusters speed up timing by exposing founders to user feedback and competitor activity earlier, but they can also delay timing if ecosystem norms encourage additional testing, verification, or incremental development before launch.

In emerging technological fields such as quantum computing and advanced robotics, the coordination of an entire innovation ecosystem is a critical determinant of successful market entry.

A venture may possess a technologically superior product yet fail to commercialize effectively in the absence of key partners. These partners are essential for validating practical applications, supplying complementary infrastructure, and facilitating regulatory approval. Consequently, deep-tech ecosystems function as "timing catalysts." They do not merely accelerate a startup's progress; they actively create the necessary market and infrastructural conditions that render a well-timed and scalable commercial launch feasible (Adner & Levinthal, 2001). Without this ecosystem coordination, timing decisions are slowed by uncertainty regarding interoperability, deployment pathways, or regulatory expectations.

Institutional mechanisms including accelerators, incubators, and venture-capital networks assume a strategically significant function in facilitating deep-tech ventures' capacity to identify and capitalize on optimal market-entry windows. Diverging from conventional startup accelerators, which prioritize rapid scaling and business model iteration, deep-tech programs are distinguished by their emphasis on readiness alignment (Thiel & Clarysse, 2021). This entails systematically advancing technologies toward commercialization through critical pathways such as technical validation, regulatory navigation, and targeted investor matchmaking. These structures accelerate timing by clarifying which milestones are necessary for launch and by connecting founders with partners who can remove bottlenecks.

These institutional supports aid founders in refining their market-timing strategies by delivering structured mentorship, facilitating pilot projects with corporate partners, and providing exposure to potential early adopters. Functioning as "market translators," these networks reinterpret scientific innovation into commercially viable solutions and provide critical insight into the appropriate timing for commercialization (Cohen & Hochberg, 2014). Illustrative of this approach, specialized deep-tech accelerators, such as Hello Tomorrow and the EIT Deep Tech Talent Initiative, enable startups to synchronize their technological milestones with evolving investor sentiment and pertinent policy trends, thereby optimizing their launch trajectory. They speed up timing when they validate market interest early, but they can also delay timing if additional refinement is recommended before investment or customer engagement.

Venture-capital (VC) networks further influence timing through staged funding mechanisms. Investors experienced in deep-tech domains often encourage founders to delay premature scaling until critical inflection points, such as verified product-market fit, regulatory approval, or ecosystem validation, are achieved (Gans & Stern, 2003). VC partners also facilitate introductions to corporate customers and supply-chain allies, thereby transforming financing relationships into strategic timing enablers. Thus, VC networks influence not only when capital becomes available but also when founders judge the market to be ready for entry.

A company's "market timing" is determined by both the strength of its network effect as well as the degree to which it participates in an ecosystem - through this the founder has access to a wider variety of signals, reduces information gap between the founding team, and accelerates technological and commercial validation. Network effects can speed up the market timing for a company because it creates opportunities for early "proof points", partnerships, and regulatory clarity; and slow down the market timing for a company if there are unmet requirements or if the network effects push the founding team to continue refining their product. The deep-tech startup will be able to successfully enter into the marketplace (and to be successful) when the founding team is able to decipher these ecosystem signals and the progress that the team is making on their product aligns with the "readiness" of the marketplace.

1.4.3 Case Studies of Deep-Tech Market Timing

Market timing has a significant impact in determining whether deep-tech startups would transform scientific breakthroughs into scalable businesses. Several case studies of deep-tech ventures show how alignment, or misalignment, between technological maturity, market readiness, and ecosystem support influences success trajectories (Gbadegeshin et al., 2022). To strengthen the link with the conceptual framework, each case is interpreted through four timing dimensions: technological readiness, market signals and customer demand, regulatory and infrastructure conditions, and ecosystem partnerships. This helps show how timing performance results from alignment across these factors.

NVIDIA stands as an example of effective strategic timing within the artificial intelligence (AI) hardware domain. At the beginning, NVIDIA focused on graphics processing for gaming, the company anticipated the growing need for high-performance computing to support data-intensive and machine-learning applications. The shift in NVIDIA's R&D focus toward general-purpose GPUs in the mid-2000s, precisely as AI algorithms began requiring large-scale parallel processing, allowed the company to synchronize its technological development with a major shift in computational demand. This foresight enabled the firm to transition from a niche graphics manufacturer to a foundational player in the global AI ecosystem. (VentureBeat, 2023) Its timing aligned not only with the maturation of deep-learning frameworks and cloud infrastructure but also with rising venture and enterprise investment in AI acceleration. At this moment, the technology had reached a high level of readiness for AI workloads, and early users such as researchers and cloud firms provided strong market signals. The regulatory environment and supporting ecosystem were stable, so all four timing dimensions aligned in NVIDIA's favor. The case highlights how strategic patience, coupled with ecosystem awareness, can position a hardware innovator at the core of a technological paradigm shift.

SpaceX offers another example of successful market timing in deep-tech startups. Founded in 2002, the company entered the aerospace sector at a moment when public-sector spending on space exploration was declining yet demand for commercial launch and satellite deployment services was expanding (Terzi et al., 2024). Elon Musk noticed that the space industry "had not really evolved in about fifty years. The aerospace companies had little competition and tended to make supremely expensive products that achieved maximum performance. They were building a Ferrari for every launch" (Vance, 2015, p. 114). This showed him that the industry's high costs and inefficiencies left room for a more disruptive approach. SpaceX developed reusable rockets right as the private space sector started to grow, proving that this approach could save money (U.S. International Trade Commission [USITC], 2023). By matching technological capabilities with market needs, SpaceX secured both commercial and government contracts and changed how space launches are economically structured (K Singh, 2022). The company's story highlights how coordinating innovation with industry trends and policy changes can turn external limitations into opportunities for breakthrough success. During this period, reusable launch systems showed credible technical progress, and satellite operators signaled clear demand for lower-cost launches. Approval pathways were predictable and supported by public programs, and the supply chain expanded, so the four timing dimensions reinforced each other.

The case of Better Place offers a critical lesson on the pivotal role of timing and ecosystem alignment in technological innovation. The venture's ambitious battery-swapping model for electric vehicles was launched in 2007, a period when the necessary conditions for its success were not yet established. The market suffered from low consumer adoption, a lack of unified technical standards, and insufficient cooperation from major automobile manufacturers (The Guardian, 2013). This disconnect stranded the company in a "valley of death," a phase where technological breakthroughs falter because the market and infrastructure are not prepared to sustain them. Therefore, despite considerable investment, Better Place's failure and subsequent bankruptcy in 2013 (Noel & Sovacool, 2016) underscore that commercial success is contingent not only on a venture's innovation and funding but also on the maturity of its external environment. At launch, the technology lacked standardization, market signals were weak because EV adoption was low, regulatory support for swapping networks was limited, and partner coordination was fragmented. These four dimensions did not align, which explains the failed timing outcome. It also highlights the importance of aligning technological ambition with ecosystem maturity, as even well-funded and innovative startups can fail when market timing is misjudged.

Figure 1.4.3

Comparative table of NVIDIA, SpaceX, and Better Place

	NVIDIA	SPACEX	better place
Technological readiness:	High GPU maturity for AI workloads	Demonstrated progress toward reusable launch systems	Low standardization and incomplete infrastructure
Market signals:	Strong early demand from researchers and cloud platforms	Clear demand from satellite operators and public agencies	Limited EV demand and uncertain customer acceptance
Regulatory conditions:	Neutral, with mature infrastructure	Predictable approval pathways with public-sector support	Weak support for battery-swap networks
Ecosystem support:	Strong developer and industry partnerships	Expanding supply chain and institutional partners	Fragmented coordination with automakers
Timing outcome:	Successful alignment	Successful alignment	Failed alignment

Source: Made by authors

Across the three cases, timing success depended on how well technological readiness aligned with demand signals, institutional conditions, and ecosystem support. NVIDIA and SpaceX acted when their technologies had reached credible maturity, when customers expressed clear interest, and when partners and institutions could support scaling. Better Place moved ahead under weak demand, low standardization, and limited partner engagement, which produced a timing gap the firm could not close. These cases show that deep-tech ventures succeed when internal progress and external readiness advance together, and they struggle when these elements diverge. “This emphasizes the need for timely decision-making and the ability to adapt to changing circumstances in order to seize opportunities before they become entrenched in the market.” (Corvello, 2023).

2. RESEARCH METHODOLOGY

2.1 Justification of the Research Method (Quantitative Survey)

This thesis uses a triangulation design. The goal is to answer research questions about market timing in science-based startups from two levels. The quantitative survey shows how employees understand timing, readiness, and adaptation in daily work. The qualitative interviews show how founders form timing decisions and how they read signals. The use of methodical triangulation helps researchers to minimise or offset the effects of weaknesses of the use of one research method with the strengths of other methods (Denzin, 1978; Sharif & Armitage, 2004).

A mixed approach is needed because the research questions involve both operational and strategic views. The survey answers questions linked to patterns inside teams. The interviews answer questions linked to timing logic at the founder level. Using both methods supports triangulation of results. Triangulation strengthens evidence because different methods confirm or extend each other.

The quantitative results show broad patterns. The qualitative results explain why these patterns appear. The integration of both stages provides a complete view of timing inside science-based startups.

Aim of the research: To evaluate the relationship between internal and external organizational factors and startup success, and to determine whether market fit mediates these relationships in deep-tech startups.

Research Problem: The lack of understanding of how deep-tech startups align internal capabilities and external market conditions to achieve success.

Research objectives:

1. To examine how internal and external factors, market timing, internal alignment, and adaptation affect startup success through the mediating role of market fit.
2. To explore how deep-tech startup founders perceive the importance of aligning internal capabilities with external market conditions in achieving market fit and success.

3. To assess whether the relationships identified quantitatively reflect the experiences and strategic decisions described by practitioners.
4. To apply Contingency Theory to explain how the alignment between internal and external factors determines performance outcomes in deep-tech startups.
5. To provide a comprehensive understanding of how alignment and timing influence success by combining statistical evidence with practical insights from startup experience.

Quantitative Method

The research method influences how well a study answers its questions. In this thesis, a quantitative survey is used to collect answers from employees who work in deep-tech or other technology-focused startups. The goal is to see how they understand market timing, how ready their company is for entry, and how flexible the organization is when conditions shift. Quantitative research aims to quantify the data and generalize findings from a sample of a study from varied perspectives (Ghanad, 2023). Quantitative data can be interpreted with statistical analysis, and since statistics are based on the principles of mathematics, the quantitative approach is viewed as scientifically objective and rational.

A structured questionnaire supports this thesis because it enables the collection of standardized answers from a wider group of respondents. It helps measure how employees perceive timing decisions made inside their firms. It also allows the researcher to compare responses across roles, teams, and companies. “Questionnaires offer an objective means of collecting information about people's knowledge, beliefs, attitudes, and behavior” (Boynton & Greenhalgh, 2004).

This method addresses the research questions that examine how employees understand timing, how coordinated the internal processes are, and how they interpret external signals. It also supports testing hypotheses about relationships between these constructs.

The survey method is practical. It is cost-effective, easy to distribute, and familiar to respondents. It gives anonymity and privacy, which often encourages honest answers about internal processes. “Some people will undoubtedly feel freer, in an anonymous style of responding” (Gillham, 2008). Since market timing can involve sensitive organizational topics, anonymity is important.

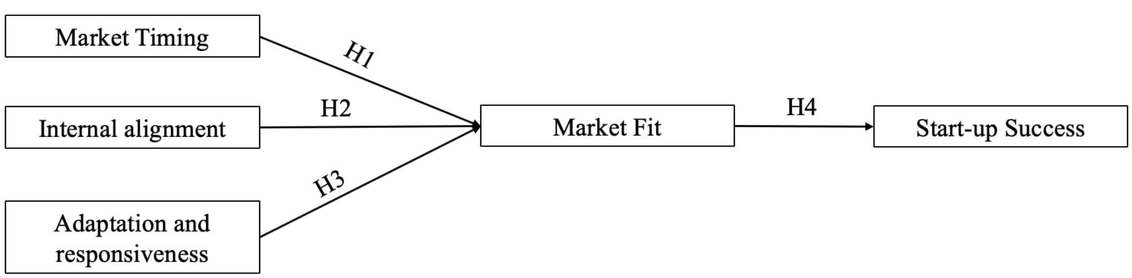
Closed questions and scaled responses support structured analysis. “Analysis of answers to closed questions is relatively straightforward” (Gillham, 2008). SPSS is used for statistical analysis because the researcher has experience with the software.

The research model is developed based on Contingency Theory (Donaldson, 2001). This theory was selected as the theoretical foundation because it explains how organizational performance depends on the alignment between internal and external factors. Using this perspective allows the model to integrate both internal organizational and external market dimensions, providing a more comprehensive understanding of how deep-tech startups achieve success.

In the theoretical part, key constructs derived from Contingency Theory were analyzed to identify the factors that influence startup performance. Based on this theoretical framework, the empirical research model (see **Figure 2.1.1**) includes five constructs. Market Timing which represents external factors, while Internal Alignment and Adaptation and Responsiveness represent internal factors. Market Fit serves as the mediating variable linking internal and external conditions, and Startup Success is the dependent variable.

Figure 2.1.1

Research model



Source: Made by authors, based on Donaldson (2001)

In the first part of the analysis, when examining the theoretical foundations of Contingency Theory, it was established that organizational performance depends on the alignment between internal factors and external environmental conditions (Donaldson, 2001). Internal factors include managerial decisions and strategic planning, while external factors represent market dynamics and readiness. Studies indicate that strategic timing decisions are often directly related to how effectively a company can match its internal readiness with external opportunities. Adner and Levinthal (2001) argue that correct market timing increases the perceived relevance of a product, leading to higher market acceptance. Similarly, startups entering the market when customer demand and technological readiness coincide are more likely to achieve market fit. Based on these theoretical insights and prior empirical findings, the following hypothesis is proposed:

H1: *Market timing has a positive impact on Market fit.*

Internal alignment is a key organizational factor influencing the ability of startups to achieve market fit. According to Schuh (2022), internal coordination between departments ensures that different functional units, such as R&D, marketing, and management, operate toward a shared strategic goal. When communication is clear and objectives are synchronized, organizations can respond to market signals more effectively. Firms with strong internal alignment are better able to balance innovation with market exploitation, leading to improved adaptability and competitive positioning. Additionally, Capatina (2024) emphasizes that aligned teams accumulate and share market knowledge faster, translating it into customer-focused solutions. In the context of deep-tech startups, internal alignment ensures that technological development, commercialization strategy, and market understanding progress cohesively. This unity of effort allows the company to tailor its offerings to fit emerging market needs. Therefore, the following hypothesis is proposed:

H2: *Internal alignment has a positive impact on Market fit.*

Adaptation and responsiveness are essential capabilities that enable startups to align with changing market conditions and achieve market fit. According to Teece, Pisano, and Shuen (1997), adaptive organizations develop dynamic capabilities that allow them to sense opportunities, seize them quickly, and reconfigure their resources to maintain competitiveness. Eisenhardt and Martin (2000) further explain that responsiveness involves the ability to integrate market feedback into decision-making and adjust strategies with speed and precision. For deep-tech startups operating in uncertain environments, adaptation often means modifying product features, business models, or communication strategies based on evolving customer and investor expectations. Zahra, Sapienza, and Davidsson (2006) found that firms demonstrating higher responsiveness are more successful at matching their innovations to emerging market needs. When startups react effectively to external signals, they reduce uncertainty, improve customer relevance, and increase the likelihood of achieving product–market fit. Therefore, the following hypothesis is proposed:

H3: *Adaptation and responsiveness have a positive impact on Market fit.*

Market fit is one of the most important determinants of startup success. Marc Andreesen (2007) defines product–market fit as "being in a good market with a product that can satisfy that market," emphasizing that ventures succeed only when customer needs and the product's value proposition align. When market fit is achieved, startups gain traction, attract investment, and experience scalable growth. According to Ries (2011), market fit marks the transition from the search phase to the growth phase, allowing firms to build a sustainable business model. Empirical research supports this link: Danneels and Kleinschmidt (2001) found that firms with a strong fit between product offerings and market expectations outperform competitors in both profitability and customer retention. In deep-tech contexts, achieving market fit validates technological feasibility and commercial relevance simultaneously, reducing uncertainty and improving long-term survival. Therefore, the following hypothesis is proposed:

H4: *Market fit has a positive impact on Start-up Success.*

Questionnaire Design

Data Collection Instrument. To identify relationships between variables and test the proposed hypotheses, a quantitative research approach was selected. The study employed an online questionnaire survey as the main data collection method. The questionnaire was created and administered using the "Google Forms" platform, chosen for its accessibility, user-friendly interface, and ability to organize and export responses efficiently. This tool allowed the design of Likert-scale questions aligned with each research construct, ensuring clear measurement of market timing, internal alignment, adaptation and responsiveness, market fit, and startup success. The survey was distributed online through LinkedIn groups, startup networks, and direct company contacts. The questionnaire consisted of four parts: an introduction, screening questions, the main section with measurement items, and demographic questions. Collected data were then exported, cleaned, and analyzed using the "IBM SPSS" software package to test the proposed hypotheses and examine the relationships defined in the conceptual model.

Introduction. In this section, potential respondents were informed about the purpose of the survey, the confidentiality of their responses, and the intended use of the research results. The introduction also specified the type of questions included in the questionnaire and the estimated time required to complete it.

Main Section. The main part of the questionnaire was developed using constructs identified in previous scientific research. To evaluate respondents' answers, a five-point Likert scale was applied, where respondents expressed their level of agreement with each statement. The scale ranged from 1 to 5, with 1 representing "strongly agree," 2 – "agree," 3 – "neutral," 4 – "disagree," and 5 – "strongly disagree." The survey included five construct scales in total:

Market Timing (timing perception). To evaluate respondents' perception of the company's market entry timing, a three-item scale was developed based on the principles of Contingency Theory. The construct measures how employees assess whether the firm's timing decisions align with market conditions and contribute to the company's opportunity for success. Respondents were asked to indicate their level of agreement with statements such as "I believe that our startup has entered the market at the right time," "Our timing strategy fits current market conditions," and "I think our timing gives us a fair chance to succeed."

Internal alignment. To understand respondents' perception of internal alignment between teams in startup, a four-item scale was created. This construct measures how well teams agree on timing decisions and how well technical and business teams cooperate. Respondents were asked to indicate their level of agreement with statements such as "Different teams agree on the company's timing plans", "There is good cooperation between technical and business teams," "Teams adjust plans when needed without major issues," "We have enough resources to follow the planned timeline."

Adaptation and responsiveness. To assess respondents' perceptions of the company's ability to adapt and respond to changes in its environment, a three-item scale was developed. This construct captures how quickly and effectively the firm adjusts its actions and plans in response to changes in customer needs, regulatory conditions, and signals from external stakeholders. Respondents were asked to indicate their level of agreement with statements such as: “The company reacts quickly to changes in customer needs,” “The company reacts quickly to regulatory changes,” and “The company consistently tracks signals from partners or investors.”

Market Fit perception. To assess respondents’ views of the market’s fit for the company’s product, a three-item scale was created. This construct measures how employees perceive the alignment between the product’s technological maturity and the current market environment, as well as customers’ understanding of its value. Respondents were asked to indicate their level of agreement with statements such as “Our product’s technological maturity matches our planned market entry moment,” “The market is ready for our product,” and “Customers understand the value of our product.”

Startup Success. To evaluate respondents’ perceptions of the company’s overall performance and progress, a three-item scale was developed. This construct measures how employees assess the success of the startup in terms of growth, strategic achievement, and general satisfaction with results. Respondents were asked to indicate their level of agreement with statements such as “Our startup has achieved consistent growth since entering the market,” “Our company has reached most of its strategic objectives,” and “We are satisfied with our startup’s overall performance.”

Demographic Questions. The final part of the survey consisted of three demographic questions. These questions aimed to gather background information about respondents to better interpret the research results. With these questions, participants' age group, education level and gender were determined.

Data Collection and Procedures. The research was conducted using a questionnaire survey method through an online format. Quantitative data were collected from December 2 to December 16, 2025, using the survey design and administration platform “Google Forms”. This tool allowed for the convenient preparation of survey questions and the efficient export of collected responses for further analysis.

Selection of Respondents (Cases). Respondents for the study were selected using a non-probability convenience sampling method, as this approach is the most practical and requires fewer resources for data collection.

Research Sample. A small-population sample size formula (1) was used to calculate the needed number of respondents. The estimated proportion in the population was set at 50 percent (p = 0.5), with a 90 percent confidence level (Z = 1.645) and a sample error of 5 percent. After calculation, the target sample size is 92,59 ≈ 93 respondents, which is suitable for general patterns within the startup employee population.

A small-population sample size equation:

$$1)\quad n = \frac{p(1-p)}{\frac{e^2}{z} + \frac{p(1-p)}{N}}$$

Where:

n – sample size, p – proportion in the population, e – sample error, z - confidence level, N – population size.

A confidence level of 90 percent was selected for this study due to the characteristics of the target population and the exploratory nature of the research. According to (Fraenkel et al., 2019a), the recommended number of individuals for a descriptive study is less than 100. Deep-tech startup employees represent a narrow and hard-to-reach group, which limits the feasible sample size. Increasing the confidence level to 95 percent would require a substantially larger sample that is not realistic for a master's thesis in this context. Because the survey aims to identify patterns in how employees perceive market timing rather than to produce population-level estimates, a 90 percent confidence level provides a reasonable balance between statistical rigor and practical accessibility. This choice is further supported by the mixed-method design, where quantitative findings are complemented by qualitative interviews, strengthening the overall validity of the research.

External validity is limited because the sampling method is not random. The target group is narrow, which makes purposive sampling suitable.

Quantitative Data Analysis Plan

Data analysis in SPSS includes:

1. Coding of Likert-scale responses based on constructs.
2. Descriptive statistics to show distributions and central tendencies.
3. Correlation tests examine relationships between market timing, internal alignment, adaptation/responsiveness and market fit. Later will analyze the relationship with startup success.
4. Reliability testing (Cronbach's alpha)
5. Regression analysis to test hypotheses on how readiness and signal sensitivity relate to timing understanding.
6. Group comparisons using t-tests or ANOVA to examine differences across roles or team types.

Hypotheses are evaluated by significance levels, effect sizes, and direction of relationships.

2.2 Justification of the Research Method (Qualitative Interview)

A second method, the qualitative interview, is used to collect detailed insights from founders or high-role decision makers. This method helps reveal how strategic timing decisions are made at the top of science-based startups. "The qualitative research interview seeks to describe the meanings of central themes in the life world of the subjects. The main task in interviewing is to understand the meaning of what the interviewees say" (Kvale, 1996).

This method is needed because timing decisions involve context, experience, and interpretation. These topics cannot be captured with survey items. Interviews allow founders to explain why they choose early or late entry, how they read signals, and how they adjust plans.

Qualitative interviews also give space to talk about setbacks, delays, pivots, and lessons learned. For this thesis, self-selection was used when finding participants. "Self-selection is more appropriate than randomness, because the participants must give permission to be interviewed. In other words, there is no pure random approach" (Alsaawi, 2014).

Sampling Strategy for Interviews

Participants must be founders or senior leaders of deep-tech or science-based startups. Purposive sampling is used because the role criteria are strict. Self-selection is required because founders must agree to share experience. Five participants provide enough variation for thematic narrative analysis.

Qualitative Data Analysis Plan

Interviews are transcribed. The analysis follows a thematic narrative approach. The process includes:

1. Reading each transcript.
2. Summarize and code each answer into the table.
3. Comparing stories to identify common patterns and unique cases.
4. Identifying the main themes.
5. Grouping answers into subthemes.
6. Interpret the coded data.

The qualitative results explain the mechanisms behind the quantitative patterns.

2.3 Methodological Quality and Research Integrity

Integration of Mixed Methods

The study uses sequential integration. Survey patterns come first. Interview insights then explain or extend these patterns. The integration creates a combined interpretation that links operational results with strategic decision processes.

Validity, Reliability, and Limitations

Construct validity:

Each measurement item was directly derived from the research model and linked to a clearly defined construct. Market timing, internal alignment, adaptation and responsiveness, market fit, and startup success were operationalized based on prior scientific literature and Contingency Theory. This ensured conceptual consistency between theory and empirical measurement.

Content validity:

The questionnaire items were reviewed and refined to ensure clarity, relevance, and alignment with the theoretical definitions of each construct. This process reduced ambiguity and strengthened theoretical coherence.

Internal reliability:

Internal consistency of each construct will be assessed using Cronbach's alpha. This supports the stability of the quantitative measurements.

External validity:

The study applied purposive and convenience sampling due to the narrow and hard-to-reach population of deep-tech startup employees and founders. As a result, findings do not represent all startups or industries. The sample remains appropriate for the research aim, which focuses on identifying patterns within deep-tech environments rather than producing population-level generalizations.

Conceptual limitations:

The research model is grounded in Contingency Theory and focuses on alignment between internal and external factors. This theoretical focus narrows the scope of interpretation and frames results through an alignment-based lens. Startup success is measured through perceived performance rather than objective financial indicators, which limits comparison across firms.

Methodological limitations:

Quantitative data relies on self-reported perceptions of employees. Such data reflects subjective assessments rather than verified organizational outcomes. Social desirability bias and individual interpretation may influence responses. Qualitative interviews depend on retrospective accounts provided by founders and senior managers, which may reflect personal narratives or selective recall. “The researcher should not agree, disagree or suggest an answer” (Stuckey, 2013), this guideline is followed to reduce interviewer influence.

Sampling limitations:

The quantitative sample size is constrained by access to deep-tech startup employees. The qualitative sample includes a limited number of founders due to self-selection and availability constraints. These factors restrict cross-sector comparison and limit variation across national and regulatory contexts.

Mitigation through triangulation:

A mixed-method design was applied to reduce the impact of individual method weaknesses. Quantitative patterns were interpreted alongside qualitative insights, allowing cross-validation of findings. Triangulation strengthened the credibility of results by combining operational perceptions with strategic decision-making perspectives.

Overall methodological justification:

Despite these limitations, the research design remains appropriate for the exploratory and explanatory goals of the thesis. The combination of theoretical grounding, structured measurement, and triangulated empirical evidence supports the reliability and relevance of the findings within the defined research scope.

Ethical and GDPR Considerations

Participation is voluntary. Respondents receive information on the purpose of the research, data use, and storage procedures. No personal identifiers are collected. Survey answers are anonymous. Interview recordings and transcripts are stored on secure university servers and deleted after the thesis is completed. All data use complies with GDPR. Participants can withdraw at any time.

3. RESULTS OF THE RESEARCH

3.1 Quantitative research analysis

3.1.1 Distribution of respondents according to their demographics

To gain insights into the deep tech startup success factors, a comprehensive research study was conducted. The study involved a sample of 157 participants, however, based on the screening questions results, 22 participants were dismissed from the survey analysis as they did not have any experience in deep-tech startups. Additionally, 2 more participants were excluded from the survey analysis as they have answered “strongly agree” to all questions. After applying the elimination criteria, the final sample consisted of 133 participants' responses used for analysis.

The study included three demographic questions - gender, age group, and education level - to provide a comprehensive overview of the social profile of startup respondents. Among the 133 participants, 47 (35.3%) were female, and 86 (64.7%) were male. As illustrated in Figure 3.1.1.1, male participants were nearly twice as numerous as female participants, indicating higher survey participation among males.

Table 3.1.1.1

Table of respondents' gender distribution

		Frequency	Percent
Gender	Female	47	35,3%
	Male	86	64,7%
	Total	**133**	**100%**

Source: Made by authors, based on performed analysis in SPSS

Next, the age distribution of the respondents was analyzed. As shown in Figure 3.1.1.2, the largest age group among participants who are or have been involved in deep-tech startups is 25 - 34 years, comprising 77 respondents (57.9%). The second largest group is 18 - 24 years, with 33 participants (24.8%). The smallest group is 35 - 44 years, which includes 23 respondents (17.3%). Overall, the sample is predominantly composed of young adults, reflecting the typical age profile of individuals engaged in deep-tech startup activities.

Table 3.1.1.2

Table of respondents' age group distribution

		Frequency	**Percent**
Age Group	18-24	33	24,8%
	25-34	77	57,9%
	35-44	23	17,3%
	Total	**133**	**100%**

Source: Made by authors, based on performed analysis in SPSS

Moving on table 3.1.1.3 presents the educational background of the respondents. The majority of participants hold a graduate degree, representing 48 individuals (36.1%). This is followed by undergraduate students, who account for 37 respondents (27.8%), and postgraduate participants, totaling 30 individuals (22.6%). Respondents with upper secondary education comprise 12 participants (9%), while both the vocational secondary and basic (lower secondary) education groups are the smallest, with 3 respondents each (2.3%). Overall, the sample reflects a relatively high level of educational attainment, with the majority of participants holding tertiary-level qualifications.

Table 3.1.1.3

Table of respondents' educational level distribution

		Frequency	Percent
Education	Basic (lower secondary) education	3	2,3%
	Upper secondary education	12	9%
	Vocational secondary	3	2,3%
	Undergraduate	37	27,8%
	Graduate	48	36,1%
	Postgraduate	30	22,6%
	Total	**133**	**100%**

Source: Made by authors, based on performed analysis in SPSS

3.1.2 Construct means, normality and reliability tests

Construct means. In this study, mean scores were calculated for each construct. A total of five constructs were identified and measured using a five-point Likert scale ranging from “Strongly agree” to “Strongly disagree”. This scaling approach allows for straightforward calculation of mean values and facilitates meaningful comparison across constructs, providing an overall representation of respondents’ attitudes and perceptions for each measured dimension.

Table 3.1.2.1

Table of Construct Means

Construct	Mean
Market Timing	2,29
Internal alignment	2,28
Adaptation and responsiveness	2,08
Market Fit	2,23
Startup Success	2,26

Source: Made by authors, based on performed analysis in SPSS

The results (see table 3.1.2.1) indicate that the mean values of the constructs range from 2.08 to 2.29. Given that responses were measured on a five-point Likert scale, where values below 2.5 are interpreted as positive evaluations, the findings suggest that respondents generally hold favorable perceptions across all examined constructs. The overall average mean of all constructs is 2.23, further supporting this positive assessment.

Among the constructs, Market Timing shows the highest mean score ($\bar{x} = 2.29$), indicating that employees of deep-tech startups generally perceive their firms' timing decisions as well aligned with prevailing market conditions. This suggests that respondents believe their organizations are relatively effective in identifying appropriate moments to introduce technologies, products, or strategic initiatives, thereby enhancing the firm's opportunities for success in dynamic markets.

Likewise, Adaptation and Responsiveness record the lowest mean score ($\bar{x} = 2.08$). Although this value still reflects a positive evaluation, it indicates a comparatively stronger agreement among respondents regarding the firm's ability to adapt and respond to environmental changes. This finding implies that employees perceive their organizations as particularly capable of adjusting actions and plans in response to evolving customer needs, regulatory shifts, and signals from external stakeholders. Overall, while all constructs are evaluated positively, the results suggest that adaptability and responsiveness are perceived as a relative strength, whereas market timing, although still favorable, represents an area with slightly more varied or cautious evaluations.

To assess the distribution of the data and its conformity to normality, the Kolmogorov–Smirnov test was conducted (see Table 3.1.2.2). This test was selected due to the sample size of the study, which consisted of 133 respondents. The Kolmogorov–Smirnov test is appropriate for larger samples, as it effectively evaluates whether the data follows a normal distribution by comparing the empirical distribution with the theoretical one.

Table 3.1.2.2

Table of Kolmogorov-Smirnov results

	Kolmogorov-Smirnov		
Construct	**Statistic**	**df**	**Significance**
Market Timing	0,201	133	<0.001
Internal alignment	0,321	133	<0.001
Adaptation and responsiveness	0,148	133	<0.001
Market Fit	0,178	133	<0.001
Startup Success	0,313	133	<0.001

Source: Made by authors, based on performed analysis in SPSS

Based on the obtained results (see Table 3.1.2.2), the significance of the constructs is less than 0.001 ($p < 0.001$). This result indicates that the data distribution does not meet the assumption of normality; however, the analysis can be continued, as such results are common in social research that uses Likert scales and larger samples (McDonald, 2014).

Next, a reliability analysis was conducted for all constructs and their corresponding measurement items (see Table 3.1.2.3). The Market Timing construct, measured using three statements, achieved a Cronbach's alpha coefficient of $\alpha = 0.929$, indicating very high internal consistency. The Internal Alignment construct consisted of four statements and yielded a Cronbach's alpha of $\alpha = 0.791$. Although lower than that of Market Timing, this value exceeds the commonly accepted threshold of α = 0.70 and is therefore considered reliable. The Adaptability and Responsiveness construct, measured with three statements, produced a Cronbach's alpha of α = 0.823, demonstrating strong reliability and higher internal consistency than Internal Alignment. Similarly, the Market Fit construct, also measured with three statements, resulted in a Cronbach's alpha of α = 0.785, which remains within the acceptable range for reliability. Finally, the Startup Success construct, comprising three statements, achieved a Cronbach's alpha coefficient of α = 0.827, indicating good internal consistency. Overall, all constructs exceeded the minimum reliability threshold, confirming that the measurement scales are internally consistent and suitable for further statistical analysis.

Table 3.1.2.3

Table of Reliability test

Construct	No of Statements	Cronbach's Alpha coefficient
Market Timing	3	0.929
Internal Alignment	4	0.791
Adaptability and Responsiveness	3	0.823
Market Fit	3	0.785
Startup Success	3	0.827

Source: Made by authors, based on performed analysis in SPSS

3.1.3 Hypothesis testing

For the purposes of research analysis and hypothesis testing, simple and multiple linear regression analyses were employed to examine the influence of one or more independent variables on a dependent variable.

When conducting linear regression analysis using the "IBM SPSS" software, the first step is to evaluate the p-value presented in the ANOVA table, as it indicates the overall statistical significance of the regression model. A p-value below 0.05 suggests that the independent variable has a statistically significant effect on the dependent variable. Conversely, if the p-value exceeds 0.05, the regression model is considered statistically insignificant and is therefore excluded from further analysis.

Once model significance has been established, attention is directed to the coefficient of determination (R^2), which indicates the proportion of variance in the dependent variable explained by one or more independent variables. It is generally recommended that the R^2 value exceed 0.20 to ensure sufficient explanatory power.

Finally, the coefficients table is examined to assess both the statistical significance and the strength of the relationships between variables. This evaluation is based on the p-values and the standardized beta (β) coefficients, which reflect the magnitude of the independent variables' influence on the dependent variable. According to commonly accepted guidelines, β values between 0 and 0.2 indicate a very weak effect; values between 0.2 and 0.4 suggest a weak effect; values between 0.4 and 0.6 indicate a moderate effect; and values between 0.6 and 0.8 represent a strong effect.

H1: **Market timing has a positive impact on Market fit.**

H2: Internal alignment has a positive impact on Market fit.

H3: Adaptation and responsiveness have a positive impact on Market fit.

First, hypotheses H1, H2, and H3 were tested using multiple linear regression analysis, as Market Fit is influenced by three independent variables: market timing, internal alignment, adaptation and responsiveness. The results indicate (see Table 3.1.3.1) that the regression model is statistically significant, as evidenced by the ANOVA p-value being below 0.05 ($F(3) = 62.276$, $p < 0.001$). This finding suggests that at least one of the independent variables has a significant effect on the dependent variable.

Table 3.1.3.1

Table of ANOVA test (H1, H2 and H3)

Model		Sum of Square	df	Mean Square	F	Sig.
1	Regression	90,094	3	30,031	62,276	0,000
	Residual	57,584	129	0,446		
	Total	147,678	132			

Source: Made by authors, based on performed analysis in SPSS

The coefficient of determination (R^2) is equal to 0.610, indicating that 61% of the variance in the dependent variable (Market Fit) is explained by the independent variables: market timing, internal alignment, and adaptation and responsiveness (see Table 3.1.3.2).

Table 3.1.3.2

Table of Model Summary (H1, H2 and H3)

Model	R	R Square	Adjusted R square	Std. Error of the Estimate
1	0,781	0,610	0,601	0,66812

Source: Made by authors, based on performed analysis in SPSS

An analysis of the coefficients table indicates that internal alignment has the strongest effect on the dependent variable ($\beta = 0.512$, $p < 0.001$). This finding may be attributed to respondents placing greater importance on strong alignment among startup teams and effective coordination between technical and business functions. The results also confirm the absence of autocorrelation, as the tolerance value is within acceptable limits ($0.458 > 0.25$). Furthermore, no multicollinearity issues were detected, with a VIF value of 2.182, which is below the recommended threshold of 4, suggesting that the predictors are sufficiently independent.

Following that, Adaptation and responsiveness also demonstrate a statistically significant effect on the dependent variable; however, the strength of this relationship is weaker ($\beta = 0.224$, $p = 0.017$). No evidence of multicollinearity or autocorrelation was found for this variable (VIF = $2.860 < 4$; tolerance = $0.350 > 0.25$), indicating that it is a significant predictor with a weak effect.

In contrast, market timing was found to be statistically insignificant, as its p-value exceeds the 0.05 threshold ($\beta = 0.124$, $p = 0.122$). Consequently, this variable was excluded from further analysis.

Based on the results of the regression analysis, hypotheses H2 and H3 are accepted, while hypothesis H1 is rejected (see Table 3.1.3.3).

Table 3.1.3.3

Market timing, Internal alignment, Adaptation and responsiveness has a positive impact on Market fit

	Unstandardized	Coefficients	Standardized Coefficients	t	Sig.	Collinearity statistics	
	B	Std. Error	Beta			Tolerance	Vif
(Constant)	0,059	0,165		0,360	0,720		
Market Timing	0,112	0,072	0,124	1,558	0,122	0,481	2,079
Internal alignment	0,618	0,098	0,512	6,309	0,000	0,458	2,182
Adaptation and responsiveness	0,241	0,100	0,224	2,413	0,017	0,350	2,860

Source: Made by authors, based on performed analysis in SPSS

H4: Market fit has a positive impact on Start-up Success.

To test the fourth hypothesis, linear regression analysis was conducted to examine the relationship between market fit and start-up success. The ANOVA results (see Table 3.1.3.4) indicate that the regression model is statistically significant, demonstrating that market fit positively influences start-up success ($F(1) = 5989.067$, $p < 0.001$). This confirms that variations in market fit are closely associated with changes in start-up performance outcomes.

Table 3.1.3.4

Table of ANOVA test (H4)

Model		Sum of Square	df	Mean Square	F	Sig.
1	Regression	136,109	1	136,109	5989,067	0,000
	Residual	2,977	131	0,023		
	Total	139,086	132			

Source: Made by authors, based on performed analysis in SPSS

The coefficient of determination (R^2) for the model is 0.979, which indicates that 97.9% of the variance in start-up success is explained by market fit alone (see Table 3.1.3.5). This exceptionally high R^2 value suggests that market fit is a critical predictor and plays a dominant role in determining the success of start-ups.

Table 3.1.3.5

Table of Model Summary (H4)

Model	R	R Square	Adjusted R square	Std. Error of the Estimate
1	0,989	0,979	0,978	0,15075

Source: Made by authors, based on performed analysis in SPSS

Further examination of the regression coefficients (see Table 3.1.3.6) shows that the standardized beta value is 0.989, indicating a very strong effect of market fit on start-up success ($\beta = 0.989$, $p < 0.001$). This strong positive relationship highlights the importance of achieving a good alignment between a start-up's offerings and the market's needs, emphasizing that start-ups with better market fit are far more likely to succeed.

Overall, the results of the linear regression analysis provide strong empirical support for hypothesis H4. They underscore the central role of market fit in driving start-up performance and suggest that entrepreneurs should prioritize understanding and responding to market demands to maximize their chances of success.

Table 3.1.3.6

Market fit has a positive impact on Startup Success

	Unstandardized	**Coefficients**	**Standardized Coefficients**	**t**	**Sig.**	**Collinearity statistics**	
	B	**Std. Error**	**Beta**			**Tolerance**	**Vif**
(Constant)	0,119	0,031		3,896	0,000		
Market fit	0,960	0,012	0,989	77,389	0,000	1,000	1,000

Source: Made by authors, based on performed analysis in SPSS

In summary, the empirical analysis tested four hypotheses, of which three were accepted, and one was rejected (see Table 3.1.3.7). The findings indicate that internal alignment and adaptation and responsiveness significantly contribute to achieving market fit, which in turn strongly influences start-up success. Although market timing did not demonstrate a significant effect in this study, the overall results largely confirm the theoretical assumptions derived from Contingency Theory and prior research, highlighting the importance of aligning internal capabilities with market conditions to enhance deep-tech startup performance.

Table 3.1.3.7

Results of hypothesis testing

Hypothesis	Result
H1: Market Timing has a positive impact on Market Fit	REJECTED
H2: Internal alignment has a positive impact on Market Fit	ACCEPTED
H3: Adaptation and responsiveness has a positive impact on Market Fit	ACCEPTED
H4: Market Fit has a positive impact on Start-up success	ACCEPTED

Source: Made by authors, based on performed analysis in SPSS

The regression analysis confirmed that internal alignment and adaptation and responsiveness significantly contribute to achieving market fit. Internal alignment alone explains a substantial portion of the variance in market fit, highlighting the importance of coordinated efforts across departments and clear communication of strategic goals. As noted by Schuh (2022) and Capatina (2024), when teams are aligned, startups can effectively integrate market knowledge, coordinate technological development, and align commercialization strategies, enabling offerings to better meet emerging market needs. Adaptation and responsiveness, while slightly weaker in effect, also play a meaningful role, reflecting the importance of dynamic capabilities that allow startups to sense opportunities, respond quickly to market signals, and reconfigure resources as necessary.

Market timing, in contrast, did not demonstrate a statistically significant impact in this study. While theory suggests that entering the market when customer demand and technological readiness coincide can enhance market fit, in this research context, internal capabilities and adaptability proved to be more critical determinants.

Market fit itself was found to have a very strong positive effect on start-up success. This aligns with prior theoretical and empirical work (Andreesen, 2007), emphasizing that ventures achieve sustainable growth, attract investment, and improve long-term survival only when their products meet market needs effectively. The coefficient of determination indicates that the majority of variance in start-up success can be explained by market fit, underlining its central role in deep-tech startup performance.

Overall, the study tested four hypotheses, of which three were accepted and one was rejected. The results empirically validate the theoretical framework derived from Contingency Theory, confirming that internal alignment and adaptation are key drivers of market fit, which in turn is a critical determinant of startup success. The rejection of the market timing hypothesis suggests that, within this context, the synchronization of internal readiness and market conditions is less influential than organizational capabilities and responsiveness in achieving product - market fit and startup performance.

3.2 Qualitative Research Analysis

3.2.1 Thematic Narrative Analysis

In our research, we have interviewed 3 founders, 1 CEO, and 1 VP of growth of deep tech startups. After analyzing all five interviews, a system of common themes was developed, revealing the key factors influencing startup market entry and success (Figure 3.2.1). Through the analysis and grouping of codes, several recurring subthemes were identified, appearing in at least half (3/5) of the interview narratives. By combining these subthemes, five main themes were distinguished: Keys to Success, Timing and Market Entry, Regulatory Influence, Challenges and Barriers, and Strategic Advice. These themes collectively describe how startup founders and high-level management interpret market conditions, adapt to regulatory and timing pressures, and make strategic decisions that influence their overall success.

Table 3.2.1

Thematic analysis results: main themes and subthemes.

Keys to success	**Timing and market entry**	**Regulatory Influence**	**Challenges and Barriers**	**Strategic Advice**
Recognizing market signals	Early mover advantages	Need for full compliance before launch	Markets are difficult to penetrate	Align entry timing with regulatory readiness
Identifying what helped make the first move	Late mover adjustments	Regulatory complexity with limited impact on timing	Product line or segment launched prematurely	Identify product demand before launch
Understanding the key factors that enabled success				Launch Now

Source: Made by authors, based on thematic analysis.

Keys To Success

The first theme, "Keys to Success", discusses the main factors that contributed to startup growth and achievement. Founders or other key leaders recognition of critical factors (i.e., identifying and capitalizing on early market signals; understanding what facilitated the first mover advantage) and their application of those factors in order to achieve a successful outcome is represented by this theme. Many respondents also stated that learning from early challenges, making decisions based upon data, and adapting strategies quickly, were all important for achieving success and being able to develop their companies successfully over time. Timing of decision-making, coordination among the team and responsiveness to customer needs are crucial for long-term success and sustainability of the business.

Recognizing Market Signals

Three out of five participants emphasized that market demand plays a central role in determining startup success. They explained that the clearest signal for entering a market is visible traction and demonstrated consumer need. According to them, startups must carefully observe market behavior to identify where demand already exists or where gaps are evident. All five participants agreed that noticing what is missing or underdeveloped in the market creates a natural opportunity to introduce a product that adds value and simplifies the launch process.

As one participant explained: *"In the early days, we noticed something very clear: most HR teams were still using spreadsheets or disconnected tools to do employee evaluations - which was time-consuming and often not very useful for decisions. There was also strong interest from companies that wanted modern, digital tools based on psychology research rather than checklist forms. That demand from HR practitioners - saying "we need something better that's easy to use and actually actionable" - strongly influenced our roadmap."* (Participant 4)

This reflection shows how identifying concrete market needs can guide product development and ensure stronger market alignment. For these participants, success was not about launching early but about recognizing the right opportunity and responding to it effectively.

Identifying what helped make the first move

This subsection highlights the key signals that influenced participants decisions to launch or expand into new markets. Across the interviews, several common factors emerged as indicators of the right time to act. The most frequently mentioned elements were customer demand, pilot project success, and clear feedback from early users confirming market interest. Some participants also pointed to paid marketing results as a practical way to test traction and measure real engagement before committing to a full launch. In industries with stricter oversight, regulatory clarity was another important factor that provided confidence to proceed.

As one participant explained: *"The key signals were increasing customer demand, successful pilot projects, and positive feedback from early users. Clearer regulatory guidance and stable technical performance also indicated that it was the right moment to move forward."* (Participant, 2)

These shared insights show that startups rely on a combination of verified demand, early validation, and measurable signals from the market to make informed and timely decisions about when to take their first move.

Understanding the key factors that enabled success

When discussing the process of launching their startups or entering new markets, all participants shared valuable insights based on their experiences. They agreed that pilot testing and early user feedback were crucial steps in preparing for market entry. Feedback from initial clients allowed them to identify weaknesses, improve product functionality, and gain confidence before a full launch. For participants developing deep-tech physical products such as drones, regulatory readiness was another critical factor. Compliance with technical and safety standards often determined when a launch could occur.

As one participant explained: *"We decided to enter the market once we had validated demand through client feedback and small pilot projects. After testing prototypes and confirming technical feasibility and regulatory compliance, we moved forward with a phased market entry."* (Participant 2)

The responses suggest that the decision to launch was influenced not only by external market signals but also by the internal state of readiness. Participants highlighted that once the product was validated and technically mature, delaying entry could risk losing momentum or market relevance. Launching at the right time, when both the product and the market were ready, was described as a key factor in achieving initial traction and long-term success.

Timing and Market Entry

The second theme, "Timing and Market Entry" explores how founders made decisions about when to introduce their products or technologies to the market. The interviews revealed both early-mover and late-mover experiences. Some startups benefited from entering the market early, gaining visibility and customer interest before competitors. Others deliberately delayed entry to ensure product readiness and better alignment with market conditions. Several respondents described timing as a strategic balance between opportunity and risk, noting that premature launches often led to slower adoption. The ability to adapt entry strategies based on market readiness and feedback was viewed as a defining element of successful commercialization.

Early mover advantage

None of the respondents believed that being the very first in the market guarantees success. Instead, most agreed that entering as the second or third mover often provides a better position, as the market has already been partially educated by early entrants. In such cases, startups can focus on refining existing solutions and capturing customers through small but meaningful improvements to the product. Several participants also noted that early entry can be advantageous only when the market is already prepared for the product, and adoption barriers are low.

As one interviewee explained: *"A very good example is the case of Uber versus Bolt, where Uber was the first mover, and then Bolt came in and captured many of those markets."* (Participant 1)

This perspective suggests that market readiness, rather than pure speed, determines whether early or later entry leads to success.

Late mover adjustments

The majority of participants described taking a late-mover stance, entering the market only after it had reached a certain level of maturity. This approach allowed them to observe existing competitors, learn from their mistakes, and adapt their own strategies accordingly. By entering later, startups were able to tailor their products to current market needs, refine their value propositions, and avoid the risks commonly faced by first movers. Respondents viewed this strategy as an opportunity to deliver improved solutions that are better aligned with user expectations and technological trends.

As one participant explained: *"Honestly, in the HR tech space we didn't aim to be a first-mover in assessments, there were existing tools and tests already. But we wanted to be a better-mover with a more integrated, research-driven system that was easier for teams to adopt. There was strategic value in not being the absolute first, because we could learn from what others had done and provide something that avoided common pitfalls. But we also didn't want to wait too long, we wanted to be among the solutions shaping the future of HR assessment."* (Participant 4)

Another respondent reinforced this idea by noting: *"Yes, as a late mover we were thinking from the perspective of a disruptor, what is needed to challenge the status quo, what inefficiencies could be solved by us in order to eat into the pie."* (Participant 5)

Together, these reflections highlight that being a late mover can offer strategic advantages. Entering an established market enables startups to refine product-market fit, capitalize on existing awareness, and position themselves as improved alternatives rather than untested innovators.

Regulatory Influence

The third theme, "Regulatory Influence" addresses how legal and compliance factors affected startup timing and operations. Respondents noted that regulations played a major role, especially in industries with strict safety or technological standards. For some, full compliance was a prerequisite to entering the market, while others experienced regulatory complexity that slowed progress but did not directly determine success. Many participants mentioned that understanding and meeting compliance requirements early reduced uncertainty and improved credibility with investors and customers. Startups that integrated regulatory readiness into their strategy were better positioned to launch efficiently and gain trust in competitive markets.

Need for full compliance before launch

The interviews revealed that several startups prioritized full regulatory compliance prior to launching their operations, particularly in areas involving sensitive data and industry-specific standards. Compliance requirements shaped the development of products and processes, ensuring that offerings met legal and ethical standards.

One participant emphasized, *"Yes, regulations had a strong influence on our startup launch. Aviation and data security regulations affected when and how we could enter the market, and we had to ensure full compliance before scaling our operations."* (Participant 2)

Another stated, *"We didn't want to rush into the market without being compliant. Making sure data handling, consent, and storage were aligned with regulations took time and slightly slowed down the launch, but it was necessary for credibility and trust."* (Participant 4)

These responses highlight that adherence to regulatory frameworks, particularly GDPR, aviation, and data security regulations, was considered essential for establishing credibility, safeguarding user trust, and avoiding potential legal issues before market entry

Regulatory complexity with limited impact on timing

Conversely, some startups reported that, while regulations added complexity to operations, they had a limited or negligible effect on the timing of the launch. Startups engaging in cross-border activities, for example, faced challenges in understanding and implementing VAT compliance and other regional rules, yet these did not significantly delay market entry.

As one respondent noted: *"It made it more complicated but it has not influenced the launch date."* (Participant 3)

Another explained: *"Regulations, regulatory compliance had very little influence on the timing decisions."* (Participant 5)

These insights suggest that although regulatory requirements introduced operational complexity, startups were generally able to integrate compliance measures without major disruptions to their planned launch schedules. The findings indicate that regulatory complexity is a manageable aspect of startup operations rather than a prohibitive factor for market entry.

Challenges and Barriers

The fourth theme, “Challenges and Barriers” focuses on the obstacles startups encountered when entering and competing in the market. Participants reported problems entering already-established markets; some reported a lack of knowledge by customers about the products they were offering. Some respondents also reported that they introduced their product too early in the marketplace and that they had many other resource limitations including a lack of money for marketing and a very small team of people. Because of these types of limitations, many of the respondents were forced to go back and re-look at how they positioned their product or company and how well they communicated its value. The ability to identify and overcome those obstacles, respondents said, represented a major part of what it meant to be resilient in the long term and to understand their target markets.

Markets are difficult to penetrate

Respondents highlighted that entering new markets often presented unexpected challenges, particularly when customer demand or organizational readiness was lower than anticipated. Some startups experienced difficulties in aligning their offerings with market conditions, which complicated the entry process and extended timelines.

One participant reflected on the challenge, noting: *“In some cases, we entered certain conversations or segments a bit too early, before companies were fully ready to change their existing HR processes. That meant longer sales cycles than expected.”* (Participant 4)

Another mentioned regional difficulties, stating: *“We had some regional difficulties, probably in Poland”* (Participant 1) indicating that market-specific conditions could hinder smooth entry. These responses suggest that startups must carefully evaluate market readiness and anticipate potential barriers, as even well-prepared strategies can face practical obstacles when attempting to penetrate complex or nascent markets.

Product Line or Segment launched prematurely

Several respondents indicated that launching products or entering segments before adequate preparation led to suboptimal results. Premature launches were often linked to insufficient market validation, incomplete operational readiness, or lack of internal experience in scaling.

One interviewee explained: *“One timing decision that did not work as planned was entering the drone racing market too early, before sufficient customer demand existed. That experience showed us the importance of stronger market validation before committing resources.”* (Participant 2)

Another noted: *“You could say we launched certain markets pre-maturely. E.g., we launched a few cities in Germany right after launching Berlin while we still haven't really figured out how to grow in any of the German cities. However, we believe any sort of action is better than no action because action produces information and with that information we improved our subsequent launches.”* (Participant 3)

A further example was shared regarding product categories: *“Opening new food categories without thorough think-through.”* (Participant 5)

These insights demonstrate that premature entry, whether by segment or product line, can create operational inefficiencies and longer adjustment periods, highlighting the importance of staged validation and careful planning before scaling.

Strategic Advice

The fifth theme, “Strategic Advice” captures the lessons and recommendations that founders shared based on their experiences. Many respondents advised aligning market entry with regulatory and customer readiness to avoid premature launches. Others emphasized the importance of identifying clear demand and testing assumptions before scaling. Several participants encouraged new startups to act decisively and launch as soon as feasible, provided there is sufficient market validation. Overall, the advice reflected a balance between preparation and agility - planning carefully but responding quickly when opportunities arise.

Align entry timing with regulatory readiness

Several respondents emphasized the importance of considering regulatory requirements when deciding on market entry. Startups need to ensure that they can operate legally and comply with relevant standards before launching, as this can influence both operational efficiency and credibility.

One participant advised: *"...It's important to align entry timing with regulatory readiness, test through pilots, and stay flexible so you can adjust quickly as new information appears."* (Participant 2)

This perspective highlights that regulatory preparedness is a key factor in mitigating risk and ensuring that market entry does not encounter unnecessary delays or legal complications.

Identify Product Demand Before Launch

Another common recommendation focused on validating real customer demand prior to entering a market. Several founders stressed that assumptions about user needs or market size are often unreliable, and that early testing and market research are essential.

As one respondent noted: *"My advice would be to validate real customer demand early and not rely only on assumptions."* (Participant 2)

Similarly, another highlighted the need to critically evaluate competition and resources: *"Assess the competition carefully and realistically, considering how much you can compete, the financial resources required, and factors like AI hype or well-funded competitors - even the best idea can be pushed out by players with deep pockets."* (Participant 1)

These insights underline that understanding market demand is crucial for determining the optimal timing and approach for launching a startup.

Launch Now

A third perspective emphasized taking action and entering the market without waiting for perfect conditions. Founders suggested that delaying a launch in pursuit of an ideal product or perfect timing can result in missed opportunities.

One participant advised simply to *"Launch now,"* (Participant 3) while another stated, *"Don't wait for perfect timing or a perfect product, it usually doesn't exist. Enter the market when you can deliver real value, listen closely to users, and be ready to adapt quickly based on what you learn."* (Participant 4)

Another added: *"Launch asap, focus on insights and user feedback, and iterate quickly. If you're in a push market you will have a much harder time growing; if it's a pull market — that's where the magic happens."* (Participant 5)

These responses suggest that proactive market entry, combined with iterative learning, is often more effective than waiting for ideal conditions.

3.2.2 Triangulation of The Research

This section integrates quantitative and qualitative findings through methodological triangulation. The aim is to compare statistical results with interview insights and assess convergence, complementarity, or divergence across methods. This approach strengthens result credibility and improves interpretation depth.

Internal Alignment and Market Fit

Quantitative analysis shows internal alignment as the strongest predictor of market fit. The regression model reports a standardized beta of 0.512 with high statistical significance. This result indicates a strong relationship between coordinated internal processes and perceived market fit.

Qualitative findings support these results as well. Team coordination, a shared understanding of the product by all departments, (both business and technical) and a clear strategic direction were expressed repeatedly as key to founding success. Launches that were successful, and early traction achieved through both product development and market understanding, were attributed to alignment across product development, market understanding and execution. Quotes from founders about pilot testing, a clear roadmap for future growth, and coordinating efforts with other teams all describe aspects of what is referred to here as internal alignment, which was one of the constructs measured in the survey.

Both methods converge clearly. Strong internal alignment appears central for achieving market fit in deep tech startups. From a Contingency Theory and market fit perspective, the finding that internal alignment strongly predicts market fit confirms that deep-tech startup success depends on how well a firm's internal structures, capabilities, and coordination are matched to external market demands.

Adaptation and Responsiveness and Market Fit

Quantitative results show adaptation and responsiveness as a significant but weaker predictor of market fit. The standardized beta equals 0.224. This suggests a meaningful yet secondary role compared to internal alignment.

Qualitative evidence reinforces this finding. Interviewees stressed fast learning cycles, feedback driven iteration, and responsiveness to market signals. Several founders described premature launches followed by rapid adjustments. Others emphasized learning through action and improving subsequent entries. These insights align with the adaptation construct yet also show varied intensity across cases.

The triangulation shows complementarity. Quantitative data confirms statistical relevance. Qualitative data explains how adaptation operates in practice through iteration, learning, and correction rather than structured planning. The finding that adaptation and responsiveness predict market fit reflects how deep-tech startups improve alignment with market readiness by continuously learning from signals, iterating their roadmaps, and adjusting their pace between agility and patience.

Market Timing and Market Fit

The quantitative evidence is that there are no statistically significant differences between market timers and non-market timers in the regression model.

The qualitative evidence is also consistent with this finding. The interviewees repeatedly dismissed timing as a source of competitive advantage; none reported that being the first to enter was an important source of advantage. Rather, most interviewees preferred late mover (or second, third mover) strategies. In particular, the founders decisions were based on validating demand, being ready, having a functioning product and understanding what their competitors did rather than simply entering the market quickly. Additionally, several interviewees specifically identified that entering the market early increases the level of risk for a firm unless it has the necessary internal capacity to respond appropriately.

As such, the qualitative evidence supports the quantitative evidence through providing an additional explanation for why timing does not appear to be a primary determinant of success. It seems that timing can only provide a competitive advantage when it is combined with sufficient internal readiness and adaptability. Consistent with market-timing theory, the lack of performance differences between market timers and non-timers shows that timing alone does not create advantage in deep-tech; rather, outcomes depend on how well entry decisions are coordinated with internal readiness, demand validation, and the ability to respond to external conditions.

Market Fit and Startup Success

Statistical data indicates that there is an incredibly high correlation between market fit and the success of a start-up. Beta was .989 with the model explaining almost all the variation in success of the start-ups.

Interviewee responses showed an equally strong qualitative confirmation of the statistical results. Every interviewee indicated their successful companies were based on solving real problems, existing customer demand and user pull. They identified traction (i.e., customers using products), customer validation and product relevance as key drivers of their company's growth and investment as well as its survival.

The advice sections from all interviews also emphasized the importance of validating demand before increasing scale.

Therefore, the two methods converge in identifying market fit as the primary driver of startup success, supporting both Andreesen's view and Contingency Theory that sustainable performance arises when a venture's product and capabilities are aligned with genuine market demand.

Regulatory Influence as a Contextual Factor

Regulatory readiness is referenced only within the qualitative phase of this research. The interview participants indicated that regulatory readiness was viewed as an absolute prerequisite to adoption, and/or an absolute constraint to adoption based upon the type of industry they were in. Regulatory readiness was not included as an independent variable in any of the quantitative models.

The results from the triangulation indicate that the qualitative data expand the scope of the quantitative data rather than contradict it. The qualitative results build on the quantitative model through the identification of regulation as one of many contextual conditions that impact both the timing and readiness for the adoption of a technology. Thus, these results align with the theoretical framework by showing regulatory readiness functions as a contextual condition shaping market timing and adoption decisions, consistent with the contingency perspective outlined in the regulatory and institutional theory section.

Overall Triangulation Outcome

The analysis shows a high degree of agreement in terms of internal alignment, adaptation to the market, and how well each firm fits into their respective markets. There was only one area that showed disagreement, which is with respect to market timing; however, the qualitative results provide an explanation as to why the quantitative results did not support the qualitative results. The addition of the qualitative information added additional insight to the model, specifically to the role of regulation in this market, and the use of judgment by the management teams.

Overall, both the results from the quantitative (triangulation) and qualitative analysis confirm the contingency-based framework. In other words, the firms' internal capabilities and ability to adapt to their respective markets have a direct impact on the level at which each firm fits into its respective markets. The better that each firm fits into its respective market, the greater the likelihood that the firm will be successful. Therefore, while timing of entering the market may be important, it has little value if the firm does not possess the necessary internal capabilities to become ready to enter the market, align itself with the market and/or learn about the market.

Conclusions and Recommendations

This study aimed to examine market timing in deep tech startups and assess how internal alignment, adaptation and responsiveness, and market timing influence market fit and startup success. Based on the theoretical analysis, quantitative survey results, qualitative interviews, and triangulation of findings, several conclusions can be drawn:

1. Theoretical analysis confirms market timing as an alignment problem rather than a single-entry decision. Deep tech start-up timing for market entry has been shown to depend upon interdependent coordination of all four of these areas. In previous studies each element was treated independently. This paper develops them into a contingency model where the success of the organization's timing will depend upon the degree of fit between internal organizational factors and the external conditions. Market timing is seen as a continuous process of coordination which takes place under the influence of long development cycles and large amounts of uncertainty.

2. Quantitative results show internal alignment and adaptation strengthen perceived market fit. Survey analysis indicates strong positive relationships between internal alignment and market fit, and between adaptation and responsiveness and market fit. Employees perceive better fit when teams share timing goals, coordinate across functions, and react to external signals. Market timing alone shows weaker effects without internal coordination. This supports contingency theory, where external conditions only translate into performance when internal processes align.

3. Market fit mediates the relationship between timing-related factors and startup success. Quantitative findings show market fit links market timing, internal alignment, and adaptation with startup success. Startups perceived as well aligned with market needs report stronger growth, goal achievement, and performance satisfaction. Timing without fit does not lead to success. This confirms market fit as a central mechanism connecting alignment and performance in deep-tech contexts.

4. Qualitative findings show founders treat timing as staged and reversible. Interviews reveal founders rarely describe timing as early or late in absolute terms. Founders describe timing

as a sequence of validation steps. These steps include pilot customers, regulatory signals, investor feedback, and partner readiness. Founders delay or accelerate entry based on signal strength rather than fixed schedules. This explains why internal adaptation appears critical in quantitative results.

5. Triangulation confirms alignment as the core driver of success in deep-tech startups. Integration of methods shows strong consistency. Quantitative patterns match founder narratives. Internal misalignment weakens timing decisions even under favorable market conditions. Strong alignment allows startups to adjust pacing and avoid premature or delayed entry. This confirms contingency theory as an appropriate lens for explaining performance differences among deep-tech startups.

The conducted research contributes to existing scientific literature by systematizing market timing in deep-tech startups as an alignment problem rather than a single market entry decision. The results demonstrate how internal alignment and adaptation shape market fit and how market fit mediates the relationship between timing-related factors and startup success. The integration of quantitative and qualitative findings confirms the central role of alignment in explaining performance differences among deep-tech startups. Based on these conclusions, the following recommendations are formulated for future research and for practical application in deep-tech startup management.

Theoretical recommendations:

1. Future research may further develop the contingency-based model by incorporating additional internal factors, such as leadership coordination and decision clarity. Examining these dimensions would contribute to a deeper understanding of how alignment emerges and is maintained within deep-tech startups.

2. The application of longitudinal research designs would enable scholars to observe how market timing, internal alignment, and adaptation evolve across different stages of startup development. Such approaches would provide richer insights into timing as an ongoing process rather than a static decision, overcoming the limitations of cross-sectional data.

3. Combining perceptual measures with objective performance indicators—such as funding rounds, revenue growth, or commercialization milestones—would strengthen construct validity and enhance the robustness of empirical findings.

4. Comparative studies across industries and geographic regions could further illuminate how variations in regulatory environments and ecosystem maturity influence the relationship between timing and market fit. This would support the generalizability of contingency-based insights.

5. Finally, expanding qualitative research with larger and more diverse founder samples would allow for a deeper exploration of differences in timing logic across various deep-tech domains, capturing a broader range of strategic approaches and contextual conditions.

Practical recommendations:

1. Market timing should be managed as a continuous coordination process rather than as a single launch decision. Founders should treat timing as a sequence of validation steps rather than a fixed schedule. Regular assessments of technological readiness, market signals, and feedback from partners can support more informed pacing and entry decisions.

2. Internal alignment between technical and commercial teams plays a critical role in achieving market fit. The establishment of shared timing objectives and cross-functional planning processes enhances coordination and improves the startup's ability to respond effectively to market conditions. For founders, misalignment between technical development and commercial planning increases the risk of entering the market either prematurely or too late, even when external conditions appear favorable.

3. The development of structured adaptation mechanisms is also recommended. The use of pilot projects, staged validation, and systematic feedback loops enables startups to adjust timing decisions based on the strength and clarity of external signals.

4. Delays in market entry should be approached as strategic instruments rather than indicators of failure. Controlled postponement can serve as a risk-mitigation strategy, particularly

when regulatory requirements or market readiness remain uncertain. This finding suggests that postponement decisions should be evaluated as strategic alignment choices rather than as negative performance signals.

5. Active engagement with ecosystem partners, including investors, accelerators, and research institutions, is essential. These stakeholders provide valuable external validation signals that can inform and support more accurate timing decisions. For policymakers, this highlights the importance of ecosystem structures that enable early interaction between startups, regulators, and public institutions, supporting better aligned timing decisions.

6. Finally, investors and advisors are encouraged to align their expectations with the maturity of technology and the level of market readiness. Excessive pressure for premature scaling may weaken market fit and increase the likelihood of startup failure.

References

Baker, M., & Wurgler, J. (2002). Market timing and capital structure. *The Journal of Finance*, *57*(1), 1–32.

Donaldson, L. (2001). Organic theory and research. In Organic theory and research (pp. 35-60). SAGE Publications, Inc.,

Andreesen, M. 2007. Product/Market Fit. Stanford University.

Thomas, R. J. (1985). TIMING—THE KEY TO MARKET ENTRY. *Journal of Consumer Marketing*, *2*(3), 77–87.

McDonald, R. M., & Eisenhardt, K. M. (2019). Parallel play: startups, nascent markets, and effective business-model design. *Administrative Science Quarterly*, *65*(2), 483–523.

Argaw, Y. M., & Liu, Y. (2024). The Pathway to Startup Success: A Comprehensive Systematic Review of Critical Factors and the Future Research Agenda in Developed and Emerging Markets. *Systems*, *12*(12), 541.

Nfx. (2022, May 3). *Why Startup Timing is Everything*. NFX.

Gbadegeshin, S. A. (2022). Overcoming the valley of death: A new model for high-tech innovation ventures. *Technological Forecasting & Social Change.*

Springer. Nguyen, N. T. H. (2024). Sustainable entrepreneurial process in the deep-tech industry. Sustainability, 16(19), 8714.

Dionisio, E. A., Inacio, E., Junior, Morini, C., & De Quadros Carvalho, R. (2023). Identifying necessary conditions to deep-tech entrepreneurship. *RAUSP Management Journal*, *58*(2), 162–185.

de Apodaca, O. B. R., Murray, F., & Frolund, L. (2023). *What is "deep tech" and what are deep tech ventures*. Tech. rep.). MIT Regional Entrepreneurship Acceleration Program.

Urbinati, A., Chiaroni, D., Chiesa, V., & Frattini, F. (2018). The role of business model design in the diffusion of innovations: An analysis of a sample of Unicorn-Tech companies. *International Journal of Innovation and Technology Management*, *16*(01).

Bobier, J.F., A.D. Coulin, M. Portincaso and A. Legris (2022). Can Europe create its own Deep-Tech giants?, Boston Consulting Group.

Aaltonen, P., & Kurvinen, E. (2025). Contemporary Issues in Industry 5.0. In Technology, work and globalization.

Kames, D., Mamasioulas, A., Schlund, S., & Chryssolouris, G. (2023). Hardware start-ups and manufacturing innovation. Production & Manufacturing Research.

Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies 'Engines of growth'? *Journal of Econometrics*, *65*(1), 83–108.

Hsu, H. C. S. (2013). Technology timing of IPOs and venture capital incubation. *Journal of Corporate Finance*, *19*, 36-55.

K Singh. (2022). *Growth of reusable space technology: Commercial opportunities and military implications*. Journal of Strategic Studies.

U.S. International Trade Commission. (2023). *U.S. private space launch industry is out of this world*. Executive Briefing on Trade.

Vance, A. (2015). *Elon Musk: Tesla, SpaceX, and the quest for a fantastic future*. HarperCollins.

Terzi, A., Nicoli, F., & Directorate-General for Economic and Financial Affairs. (2024). *Space Possibilities for our Grandchildren: Current and Future Economic Uses of space*. Economy and Finance.

VentureBeat. (2023, February 23). How Nvidia dominated AI — and plans to keep it that way as generative AI explodes. Retrieved from

Gompers, P. A., & Lerner, J. (2004). *The venture capital cycle*. MIT press.

Noel, L., & Sovacool, B. K. (2016). Why Did Better Place Fail?: Range anxiety, interpretive flexibility, and electric vehicle promotion in Denmark and Israel. *Energy Policy*, *94*, 377–386.

The Guardian. (2013, March 5). Better Place: what went wrong for the electric car startup?

Corvello, V. (2023). A dynamic capability framework for collaboration with start-ups. Technological Forecasting and Social Change, 187, 123456.

Murray, F., Basilio Ruiz de Apodaca, O., & Frolund, L. (2022). What is "Deep Tech" and what are Deep Tech Ventures? MIT REAP.

Murray, F., & Frolund, L. (2023). *What is "Deep Tech" and what are Deep Tech Ventures?* MIT REAP.

Adner, R. (2017). Ecosystem as structure: An actionable construct for strategy. *Journal of Management, 43*(1), 39–58.

Schuh, G. (2022). *Development of a life cycle model for deep-tech startups.* Fraunhofer IPT.

Capatina, A., Bleoju, G., & Kalisz, D. (2024). Falling in love with strategic foresight, not only with technology: European deep-tech startups' roadmap to success. Journal of Innovation & Knowledge, 9(3), 100515.

Adner, R., & Levinthal, D. (2001). Demand Heterogeneity and Technology Evolution: Implications for product and process innovation. *Management Science*, *47*(5), 611–628.

Cohen, S., & Hochberg, Y. V. (2014). Accelerating startups: The seed accelerator phenomenon. Harvard Business School Working Paper 13-070.

Gans, J., & Stern, S. (2003). The product market and the market for "ideas": Commercialization strategies for technology entrepreneurs. *Research Policy, 32*(2), 333–350.

Thiel, J., & Clarysse, B. (2021). Rethinking the design principles of support systems for deep tech ventures.

Lévesque, M. (2002). A new venture's optimal entry time. *Journal of Business Venturing, 17*(5), 467–494.

Lieberman, M. B., & Montgomery, D. B. (1998). First-mover (dis)advantages: Retrospective and link with resource-based view. *Strategic Management Journal, 19*(12), 1111-1125

Te Kič, Z. (2024). Market-first or technology-first? Exploring unicorns via strategic orientation. *Technological Forecasting and Social Change, 198*, 122029.

Ramos-Rodríguez, A. R., Medina-Garrido, J. A., & Ruiz-Navarro, J. (2023). Why not now? Intended timing in entrepreneurial intentions. arXiv preprint.

Romme, A. G. L., Bell, J., & Frericks, G. (2023). Designing a deep-tech venture builder to address grand challenges and overcome the valley of death. *Journal of Organization Design*, *12*(4), 217-237.

Frey, P., & Kanbach, D. K. (2023). Design dimensions of corporate venture capital programs—a systematic literature review. *Management Review Quarterly*, *74*(4), 2787–2822.

Li, X., & Zhao, Y. (2022). Research on the Impact of Venture Capital Strategy on Enterprise Innovation Performance: Based on evidence of investment timing and rounds. *Frontiers in Environmental Science*, *10*.

Kaplan, S. N., & Lerner, J. (2016). Venture capital data: Opportunities and challenges. *Measuring entrepreneurial businesses: Current knowledge and challenges*, 413-431.

Harris, R. S., Jenkinson, T., Kaplan, S. N., & Stucke, R. (2020). Has persistence persisted in private equity? Evidence from buyout and venture capital funds. *National Bureau of Economic Research Working Paper 26755.*

Gornall, W., & Strebulaev, I. A. (2020). Squaring venture capital valuations with reality. *Journal of Financial Economics*, *135*(1), 120-143.

Nedayvoda, A., Delavelle, F., So, H. Y., Graf, L., & Taupin, L. (2021). Financing deep tech. *World Bank Group*.

Harlé, N., Soussan, P., & de la Tour, A. (2017). What deep-tech startups want from corporate partners. *The Boston consulting group & Hello tomorrow*.

Lerner, J. (2009). *Boulevard of Broken Dreams: Why Public Efforts to Boost Entrepreneurship and Venture Capital Have Failed--and What to Do About It*. Princeton: Princeton University Press.

De Wit-De Vries, E., Dolfsma, W. A., Van Der Windt, H. J., & Gerkema, M. P. (2018b). Knowledge transfer in university–industry research partnerships: a review. *The Journal of Technology Transfer*, *44*(4), 1236–1255.

Mankins, J. C. (2009). Technology readiness assessments: A retrospective. *Acta Astronautica, 65*(9–10), 1216–1223.

Engel-Cox, J. A., Merrill, W. G., Mapes, M. K., McKenney, B. C., Bouza, A. M., DeMeo, E., Hubbard, M., Miller, E. L., Tusing, R., & Walker, B. J. (2022). Clean energy technology pathways from research to commercialization: Policy and practice case studies. *Frontiers in Energy Research*, *10*.

Masuda, K., & Haruyama, S. (2021). Forecasting technology trends based on separation of product inventions and process inventions: The technology S-curve. *IOP Conference Series Materials Science and Engineering*, *1034*(1), 012123.

Teece, D. J. (2018). Business models and dynamic capabilities. *Long Range Planning, 51*(1), 40–49.

Mitchell, W., (1991). Dual clocks: Entry order influences on incumbent and newcomer market share and survival when specialized assets retain their value.

Dedehayir, O., Steinert, M. (2016). The hype cycle model. Technological Forecasting and Social Change. Link:

Leiponen, A., Thomas L. (2019). Small teams and the emergence of new industries. Strategic Management Journal. Link:

Chukhray, N., Mrykhina, O., & Izonin, I. (2022). Holistic Approach to R&D Products' Evaluation for Commercialization under Open Innovations. *Journal of Open Innovation Technology Market and Complexity*, *8*(1), 9.

Bafera, J., & Kleinert, S. (2022). Signaling Theory in Entrepreneurship Research: A Systematic Review and Research Agenda. *Entrepreneurship Theory and Practice*, *47*(6), 2419-2464.

Steigenberger, N., Garz, M., & Cyron, T. (2024). Signaling theory in entrepreneurial fundraising and crowdfunding research. *Journal of Small Business Management*, *63*(4), 1830–1855.

Meoli, M., & Vismara, S. (2020). Information manipulation in equity crowdfunding markets. *Journal of Corporate Finance*, *67*, 101866.

Colombo, O. (2020). The Use of Signals in New-Venture Financing: A review and research agenda. *Journal of Management*, *47*(1), 237–259.

Colombo, M. G., Cumming, D. J., & Vismara, S. (2016). Governmental venture capital for innovative young firms. *The Journal of Technology Transfer*, *41*(1), 10–24.

Burbridge, M., & Morrison, G. M. (2021). A Systematic literature review of partnership development at the University–Industry–Government Nexus. *Sustainability*, *13*(24), 13780.

Nagel, H., Huber, L. R., Van Praag, M., & Goslinga, S. (2018). The effect of a tax training program on tax compliance and business outcomes of starting entrepreneurs: Evidence from a field experiment. *Journal of Business Venturing*, *34*(2), 261–283.

Huang, L., & Knight, A. P. (2017). Resources and Relationships in Entrepreneurship: An exchange theory of the development and effects of the Entrepreneur-Investor relationship. *Academy of Management Review*, *42*(1), 80–102.

Arora, A., Fosfuri, A., & Rønde, T. (2024). The missing middle: Value capture in the market for startups. *Research Policy*, *53*(3), 104958.

Mohammadi, A., & Shafi, K. (2017). Gender differences in the contribution patterns of equity-crowdfunding investors. *Small Business Economics*, *50*(2), 275–287.

Borrás, S., & Edler, J. (2020). The roles of the state in the governance of socio-technical systems' transformation. *Research Policy, 49*(5), 103971.

Cave, S., Coughlan, K., & Dihal, K. (2019, January). " Scary Robots" Examining Public Responses to AI. In *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society* (pp. 331-337).

Pender, A., Kelleher, L., & O'Neill, E. (2023). Regulation of the bioeconomy: Barriers, drivers and potential for innovation in the case of Ireland. *Cleaner and Circular Bioeconomy*, *7*, 100070.

Cihon, P., Maas, M. M., & Kemp, L. (2020). Should Artificial Intelligence Governance be Centralised? *Proceedings of the AAAI/ACM Conference on AI Ethics and Society*, 228–234.

Gans, J. S., Stern, S., & Wu, J. (2019). Foundations of entrepreneurial strategy. *Strategic Management Journal*, *40*(5), 736–756.

Eyert, F., Irgmaier, F., & Ulbricht, L. (2020). Extending the framework of algorithmic regulation. The Uber case. *Regulation & Governance*, *16*(1), 23–44.

Cihon, P., Schuett, J., & Baum, S. D. (2021). Corporate governance of artificial intelligence in the public interest. *Information*, *12*(7), 275.

Downing, N. S., Aminawung, J. A., Shah, N. D., Braunstein, J. B., Krumholz, H. M., & Ross, J. S. (2012). Regulatory Review of novel therapeutics — Comparison of three regulatory agencies. *New England Journal of Medicine*, *366*(24), 2284–2293.

Sharma, S. (2023). Trustworthy Artificial intelligence: Design of AI Governance Framework. *Strategic Analysis*, *47*(5), 443–464.

Blind, K., Petersen, S. S., & Riillo, C. A. (2016). The impact of standards and regulation on innovation in uncertain markets. *Research Policy*, *46*(1), 249–264.

Gillham, B. (2008). Developing a questionnaire. A&C Black.

Boynton, P. M., & Greenhalgh, T. (2004). Selecting, designing, and developing your questionnaire. BMJ (Clinical research ed.), 328(7451), 1312–1315. https://doi.org/10.1136/bmj.328.7451.1312

Kvale, Steinar. (1996) Interviews An Introduction to Qualitative Research Interviewing, Sage Publications

Alsaawi, A. (2014). A critical review of qualitative interviews. European Journal of Business and Social Sciences, 3(4).

Stuckey, H. L. (2013). Three types of interviews: Qualitative research methods in social health. Journal of Social Health and Diabetes, 1(2), 56-59.

Ghanad, A. (2023). An overview of quantitative research methods. *INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH AND ANALYSIS*, *06*(08).

Denzin, N. K. (1978). The Research Act: A Theoretical Introduction to Sociological Methods Second edition. McGraw-Hill, New York NY.

Sharif, F., & Armitage, P. (2004). The effect of psychological and educational counselling in reducing anxiety' in nursing students. Journal of Psychiatric and Mental Health Nursing. 11(4), 386-392

Bans-Akutey, A., & Tiimub, B. M. (2021). Triangulation in research. *Academia Letters*, *2*(3392), 1-7.

Okrah, J., Nepp, A., & Agbozo, E. (2018). Exploring the factors of startup success and growth. The business & management review, 9(3), 229-237.

Borm, G. F., Fransen, J., & Lemmens, W. A. (2007). A simple sample size formula for analysis of covariance in randomized clinical trials. *Journal of Clinical Epidemiology*, *60*(12), 1234–1238.

Lawrence, P. R., & Lorsch, J. W. (1967). Differentiation and integration in complex organizations. *Administrative Science Quarterly*, *12*(1), 1.

Okrah, J., Nepp, A., & Agbozo, E. (2018). Exploring the factors of startup success and growth. *The business & management review*, *9*(3), 229-237.

Ries, E. (2011). *The Lean Startup: The Million Copy Bestseller Driving Entrepreneurs to Success*. Penguin UK.

Danneels, E., & Kleinschmidtb, E. J. (2001). Product innovativeness from the firm's perspective: Its dimensions and their relation with project selection and performance. *Journal of Product Innovation Management: An International Publication of the Product Development & Management Association*, *18*(6), 357-373.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic management journal*, *18*(7), 509-533.

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: The evolution of resources in dynamic markets. *Strategic Management Journal, 21*(10–11), 1105–1121.

Zahra, S. A., Sapienza, H. J., & Davidsson, P. (2006). Entrepreneurship and dynamic capabilities: A review, model and research agenda. *Journal of Management studies*, *43*(4), 917-955.

Fraenkel, J., Wallen, N., & Hyun, H. (2019a). How to design and evaluate research in education (10th ed.). McGraw Hill LLC.

John H. McDonald (2014) *Introduction - Handbook of Biological Statistics*.

Deep tech startups in Lithuania. (2025, October 22). tracxn.com.

Annexes

Annex 1

Quantitative questionnaire

Screening Question

1. Are you currently working, or have you worked, in a deep-tech or technology-focused startup?

   • Yes

   • No

If "No": Thank you for taking part in the survey.

MAIN QUESTIONS

Please choose the most applicable answer to you based on the Likert scale from 1 to 5 (Strongly Agree to Strongly Disagree).

Market Timing

2. I believe that our startup has entered the market at the right time.

   1) Strongly agree
   2) Agree
   3) Neutral
   4) Disagree
   5) Strongly disagree

3. Our timing strategy fits current market conditions.

    1) Strongly agree
    2) Agree
    3) Neutral
    4) Disagree
    5) Strongly disagree

4. I think our timing gives us a fair chance to succeed.

    1) Strongly agree
    2) Agree
    3) Neutral
    4) Disagree
    5) Strongly disagree

Market fit perception

5. Our product's technological maturity matches our planned market entry moment.

    1) Strongly agree
    2) Agree
    3) Neutral
    4) Disagree
    5) Strongly disagree

6. The market is ready for our product.

    1) Strongly agree
    2) Agree
    3) Neutral
    4) Disagree
    5) Strongly disagree

7. Customers understand the value of our product.

    1) Strongly agree
    2) Agree
    3) Neutral
    4) Disagree
    5) Strongly disagree

Internal alignment

8. Different teams agree on the company's timing plans.

1) Strongly agree
2) Agree
3) Neutral
4) Disagree
5) Strongly disagree

9. There is good cooperation between technical and business teams.

1) Strongly agree
2) Agree
3) Neutral
4) Disagree
5) Strongly disagree

10. Teams adjust plans when needed without major issues.

1) Strongly agree
2) Agree
3) Neutral
4) Disagree
5) Strongly disagree

11. We have enough resources to follow the planned timeline.

1) Strongly agree
2) Agree
3) Neutral
4) Disagree
5) Strongly disagree

Adaptation and responsiveness

12. The company reacts quickly to changes in customer needs.

1) Strongly agree
2) Agree

3) Neutral
4) Disagree
5) Strongly disagree

13. The company reacts quickly to regulatory changes.

1) Strongly agree
2) Agree
3) Neutral
4) Disagree
5) Strongly disagree

14. The company consistently tracks signals from partners or investors.

1) Strongly agree
2) Agree
3) Neutral
4) Disagree
5) Strongly disagree

Startup success

15. Our startup has achieved consistent growth since entering the market.

1) Strongly agree
2) Agree
3) Neutral
4) Disagree
5) Strongly disagree

16. Our company has reached most of its strategic objectives.

1) Strongly agree
2) Agree
3) Neutral
4) Disagree
5) Strongly disagree

17. We are satisfied with our startup's overall performance.

1) Strongly agree
2) Agree
3) Neutral
4) Disagree
5) Strongly disagree

DEMOGRAPHIC QUESTIONS

18. Please select your age group in years:

1) Under 18
2) 18 – 24
3) 25 – 34
4) 35 – 44
5) 45 – 54
6) 55+

19. Please select your gender:

1) Male
2) Female

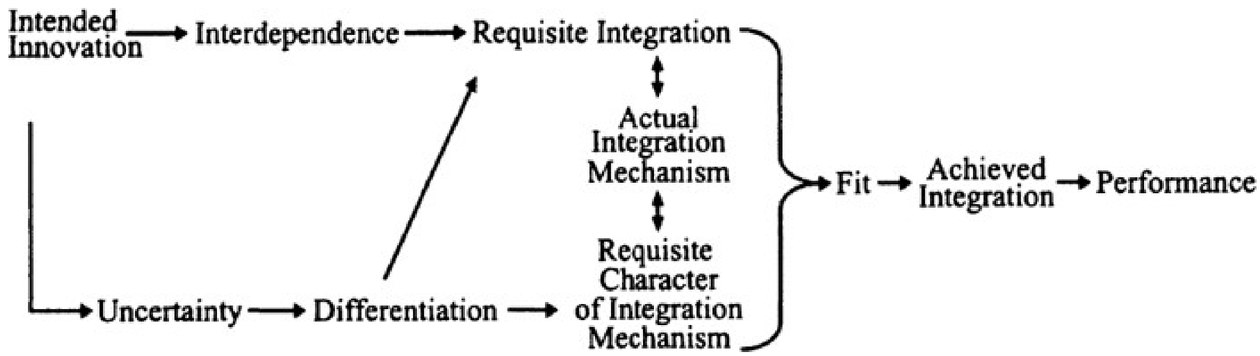
20. What is your education level:

1) Basic (lower secondary) education
2) Upper secondary education
3) Vocational secondary
4) Undergraduate
5) Graduate
6) Postgraduate

Thank you for your time and effort spent on this Survey! Have a Good Day/Night

Annex 2

Contingency Theory Model



Source: Lex Donaldson (2001)

Annex 3

Cronbach's Alpha test (Adaptation and responsiveness)

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,823	,829	3

Item Statistics

	Mean	Std. Deviation	N
AR1	2,08	1,181	133
AR2	1,99	1,041	133
AR3	2,16	1,205	133

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
AR1	4,15	4,038	,691	,570	,744
AR2	4,24	4,275	,779	,632	,668
AR3	4,08	4,328	,585	,365	,855

Annex 4

Cronbach's Alpha test (Internal Alignment)

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,791	,792	4

Item Statistics

	Mean	Std. Deviation	N
IA1	2,24	1,053	133
IA2	2,23	1,139	133
IA3	2,15	1,131	133
IA4	2,50	1,152	133

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
IA1	6,88	7,455	,653	,475	,714
IA2	6,89	7,731	,519	,282	,779
IA3	6,97	6,878	,701	,522	,686
IA4	6,62	7,587	,536	,295	,771

Annex 5

Cronbach's Alpha test (Market Fit)

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,785	,791	3

Item Statistics

	Mean	Std. Deviation	N
MF1	2,39	1,397	133
MF2	2,08	1,187	133
MF3	2,20	1,198	133

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
MF1	4,29	4,630	,580	,337	,771
MF2	4,59	5,182	,643	,436	,693
MF3	4,47	5,054	,664	,456	,670

Annex 6

Cronbach's Alpha test (Market Timing)

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,929	,932	3

Item Statistics

	Mean	Std. Deviation	N
MT1	2,26	1,329	133
MT2	2,23	1,100	133
MT3	2,39	1,296	133

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
MT1	4,62	5,282	,847	,724	,906
MT2	4,65	6,336	,845	,725	,912
MT3	4,49	5,267	,888	,789	,869

Annex 7

Cronbach's Alpha test (Startup Success)

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,827	,827	3

Item Statistics

	Mean	Std. Deviation	N
SS1	2,28	1,208	133
SS2	2,24	1,175	133
SS3	2,25	1,190	133

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
SS1	4,49	4,676	,641	,410	,804
SS2	4,53	4,554	,707	,509	,737
SS3	4,52	4,509	,704	,507	,740

Annex 8

Descriptive statistics results

Descriptives

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Mean_MT	133	1,00	5,00	2,2932	1,16561	1,359	,731	,210	-,591	,417
Mean_MF	133	1,00	4,67	2,2256	1,05772	1,119	1,015	,210	-,282	,417
Mean_IA	133	1,00	4,75	2,2801	,87745	,770	,720	,210	-,142	,417
Mean_AR	133	1,00	5,00	2,0777	,98378	,968	,993	,210	,418	,417
Mean_SS	133	1,33	4,67	2,2556	1,02649	1,054	1,094	,210	-,261	,417
Valid N (listwise)	133									

Annex 9

Collinearity Diagnostics table (H1, H2, H3)

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Mean_MT	Mean_IA	Mean_AR
1	1	3,780	1,000	,01	,01	,00	,00
	2	,118	5,653	,64	,23	,00	,06
	3	,064	7,655	,18	,68	,23	,20
	4	,037	10,063	,17	,09	,76	,73

a. Dependent Variable: Mean_MF

Annex 10

Model summary, Anova test and Coefficients (H1, H2, H3)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,781[a]	,610	,601	,66812

a. Predictors: (Constant), Mean_AR, Mean_MT, Mean_IA

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	90,094	3	30,031	67,276	,000[b]
	Residual	57,584	129	,446		
	Total	147,678	132			

a. Dependent Variable: Mean_MF

b. Predictors: (Constant), Mean_AR, Mean_MT, Mean_IA

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	,059	,165		,360	,720		
	Mean_MT	,112	,072	,124	1,558	,122	,481	2,079
	Mean_IA	,618	,098	,512	6,309	,000	,458	2,182
	Mean_AR	,241	,100	,224	2,413	,017	,350	2,860

a. Dependent Variable: Mean_MF

Annex 11

Model summary, Anova test, Coefficients and Collinearity Diagnostics (H1, H2, H3)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,989[a]	,979	,978	,15075

a. Predictors: (Constant), Mean_MF

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	136,109	1	136,109	5989,067	,000[b]
	Residual	2,977	131	,023		
	Total	139,086	132			

a. Dependent Variable: Mean_SS

b. Predictors: (Constant), Mean_MF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	,119	,031		3,896	,000		
	Mean_MF	,960	,012	,989	77,389	,000	1,000	1,000

a. Dependent Variable: Mean_SS

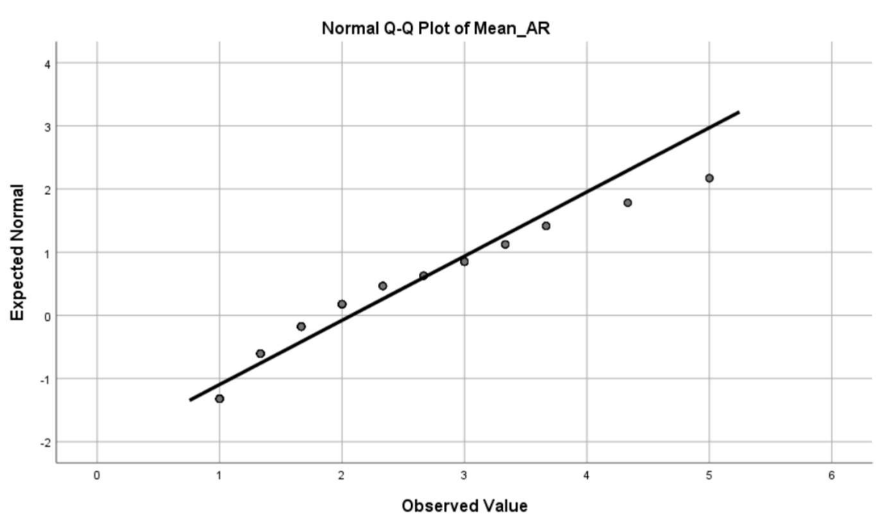
Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions	
				(Constant)	Mean_MF
1	1	1,904	1,000	,05	,05
	2	,096	4,449	,95	,95

a. Dependent Variable: Mean_SS

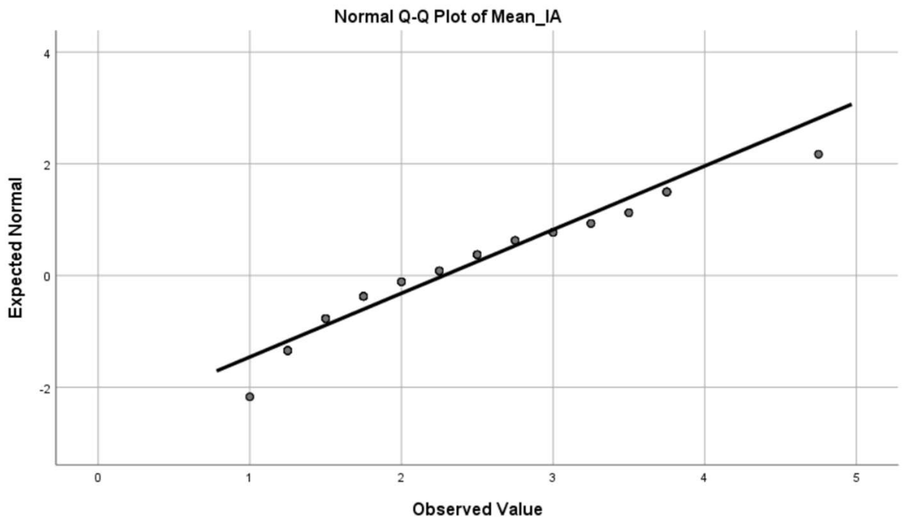
Annex 12

Normality graph (Adaptation and responsiveness)



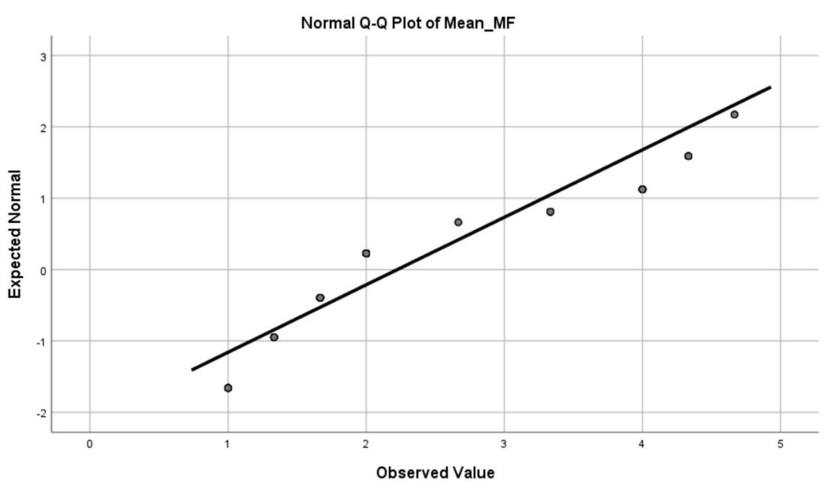
Annex 13

Normality graph (Internal Alignment)



Annex 14

Normality graph (Market Fit)

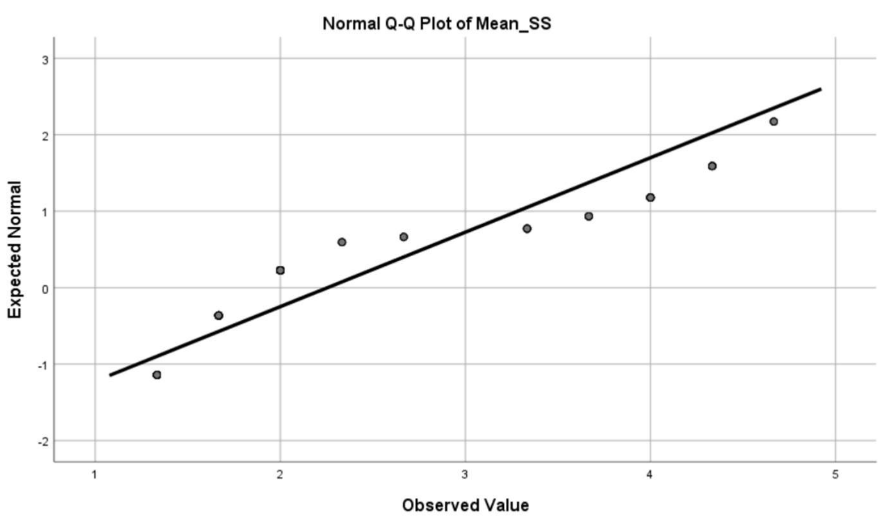


Annex 15

Normality graph (Market Timing)

Annex 16

Normality graph (Startup Success)



Annex 17

Tests of Normality

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Mean_MT	,201	133	,000	,890	133	,000
Mean_MF	,321	133	,000	,823	133	,000
Mean_IA	,148	133	,000	,927	133	,000
Mean_AR	,178	133	,000	,889	133	,000
Mean_SS	,313	133	,000	,785	133	,000

a. Lilliefors Significance Correction

Annex 18

Interview Coding table

	Question	Interview 1	Interview 2	Interview 3	Interview 4	Interview 5
1	Startup description	Ovoko, B2B Marketplace with AI integration .	Drone Industry Startup	B2B Marketplac e with AI Integration	Cloud-based HR assessment platform	B2B Market Place with AI implementatio n
2	Targeted market	Baltics, Poland, Western Europe	Internatinal markets through partners.	Primarily Germany, Poland, Baltics, Hungary.	Internationall y	Central Europe, Baltics.
3	Early signals	Consumer Demand, need for revenue growth.	Client needs, gaps in the market, growing demand, competitor analysis, Colaboration with university.	Long-term growth potential, strategic decisions of what would bring growth.	Consumer demand	1) Highly fragmented supply chain; 2) Sub-par end-customer experience; 3) Manual and time consuming nature of transactions;

						4) High degree of optimism
4	Decision to enter market	A lot of concentration and capital, when you have them you can enter,	Customer feedback, pilot projects so started sooner. Regulation as well.	Not timed, started as soon as was ready.	Started as soon as had good pilot users, did not wait for perfect time.	We ran through a discovery (how the market currently works) and MVP development (simple platform with the core e-commerce functionality).
5	Market entry position	Second-third	First-mover	Challenger, late-mover	First-mover with good technology	Late-mover
6	Factors to move early/late	Investors direction, need for growth	egulatory readiness, technology maturity, and access to funding	launching as soon as possible;	Trial usage, technology is validated, good market feedback	Entered very mature market
7	First mover/ Late mover	Better second third mover, first mover is not a good position.	Early mover in certain markets, late in uncertain.	No, market was very established.	Later mover as can adjust and do better than competitors.	Late mover position as it allowed to fix competitor mistakes.
8	Judging market readiness	Competition and product market fit.	Customer intrest, pilot projects, customer feedback. Regulation, technological readiness, customer willingness to pay.	Launched and observed quantitative and qualitative data.	Demand for target customers, frustration with existing technology, willingness to	N/A

					pay, market trends.	
9	Regulations, insights	Only fear of regulations, but it did not change it much.	Very much so, had to ensure full complience.	Made it complicated, but did not influence the launch.	Data protection and privacy regulation, GDPR. Did not stop but influenced.	PSD2, GDPR, VAT and other regulations.
10	Regulations influence timing	There was fear, but it did not influence the timing.	Clear role, hat to wait for clear regulations. Slowed down and created opportunities.	VAT Laws, complience, corporate structure.	Made sure that they were compliant first befor launching.	Very little influence on timing decisions.
11	Timing across different regions	Continens are united, unless launching in another continet	Partners and experts in every region.	Did not time launch because of rules.	GDPR created baseline, nothing changed much through different countries	N/A
12	Signals that help make a move	Consumer demand, pilot user revenue. Paid marketing.	Customer demand, pilot projects, clear regulatory guidance.	Paid marketing, customer demand, competitor companies, booming markets.	Customer demand, demo requests, clear feedback.	N/A
13	Foresight Tools	Google analytics, keyword splatter, competitor analysis, demographic data.	Market scanning, reports, conferences, insights,	Competitro analysis, Market analysis, Financial statements, market size calculations.	Market scanning through customers.	Yes
14	Signals Changed Plans	No	Yes signals showed a shift in demand and needed adjustment.	No	Need for fetures accelerated improvement.	N/A

15	Entry timing/New information	ROI, spend asks for adjustment. Negotiation and power in the markets is key.	Regulations, customer feedback, pilot users.	Workload and changes in terms with partners.	Customer feedback and pilot customers shifted demand,	Complience and regulations.
16	Helped stay Flexible	Many markets that you operate in, spread of the revenue and targets.	Customer feedback, and close collaboration with research partners and regulators.	Refocus on current market needs, start light.	Small team, close contact with customers.	Optimism
17	Investors, partners, customers influence	Logistics partners and investors influence.	Investors(funding,, customers(feedback), partners (more efective moves) helped.	Investors push for expansion, investors also push to show that you can work.	Customers influence.	No
18	Pilot Users help to start	Key group that help you see traction.	Direct impact on entry.	No pilot users.	Early users play a big role.	Pilot users are very usefull when building the product.
19	Importance of networks, accelerators, public programs	Investors have insights and networks make it easier.	Public programs very important, EU, funding, partnerships. Access to test environments.	Not important	Not important	Goof network and notabble people help market the product.
20	Timing Entry decisions help Grow	Seasonality is very important. Not to enter when buying power is low.	market readiness is very important, pilot projects, customer demand.	Starting in big markets is very important.	Entering market early but with stable product.	Start early i big market.
21	Timing/Entr y made Harder	Some markets are hard to penetrate.	Entering a market with another product line too early.	Launch some markets prematurely .	Enter segments too early.	Opening a product segment too early.

22	Exit strategy or Outcome	Works, no exit planned.	Growing and attracting investment.	Focused on building and scaling.	Build and grow the product.	growing and scaling.
23	Advice for Other Founders	Go to the markets with hype and do it fast.	validate entry, rely on feedback, align with regulations.	Launch now	Enter market when you can deliver.	Launch asap and focus on the feedback.

Annex 19 Use of AI tools

In the process of creating and writing this study, AI tools have been used to assist with searching and filtering the most relevant previous studies and choosing and getting familiar with the references.

1.Searching and filtering potential references

i. ChatGPT

1. OpenAI, ChatGPT model 5, was used to find and filter potential references according to the topics.

2. Choosing and getting familiar with the references

i. Notebook LM

1. Each relevant reference for our research was uploaded to Notebook LM in order to quickly find quotes related to studied subjects.