Final Dissertation

Human success factors for French-speaking AI-oriented startups

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DECLARATION OF AUTHENTICITY

I declare that the material contained in this project is the end result of my own work and that due acknowledgement has been given in the bibliography and references to **ALL** sources be they printed, electronic or personal.

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Date: April 22nd, 2025

ABSTRACT

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TITLE	Human success factors for French-speaking AI-oriented startups
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KEYWORDS	Human factors, AI startups, startup success, investor-founder perceptions, emotional intelligence, quantitative research

Background: This study investigates critical human factors influencing the success of French-speaking AI-oriented startups, addressing a gap in existing research that predominantly focuses on technical, economic, and organizational success factors.

Purpose: While prior studies highlight the role of founder experience and cognitive biases like attribution theory (Ross, 1977) and individual elements of emotional intelligence (Côté and Miners, 2006), the holistic impact of attitudes, fears, and behavioural traits remains somewhat underexplored.

Methodology: Using a quantitative deductive approach, surveys were conducted with 24 founders and 35 investors across France, Switzerland, Belgium, and Luxembourg, employing Likert-scale assessments of 14 human factors. Spearman correlations, Jackknife stability tests and Cox survival models (concordance=80.4%) validated findings.

Finding: Results revealed four key findings for startups in general, and three specifically for AI startups: For startups in general, (1) Founder's fears increase startup failure by 18% and stress by 11%, while accountability reduces failure risk by 21%. (2) Serial founders value 12 human factors out of 14 higher than first-time founders. (3) There is no clear "learning by failure" for high-failure startups. (4) There is a pivotal moment at two failures or successes where human indicators require specific attention. Concerning AI startups specifically, (1) AI startups have 12.56% lower failure risk but systematically score as more sensitive to human factors than non-AI startups. (2) AI startups show a high risk of misalignment with investors, compared to non-AI startups which only show an average risk. (3) For AI startups, all human factors correlate more to success than academic knowledge in AI, communication or leadership and management.

Discussion: A self-reported 46% success rate indicates potential social desirability bias. Practical recommendations include emotional intelligence training for founders and investors, structured investor assessment frameworks to mitigate attribution biases, and collaborative governance models for AI startups. This research underscores the need for human-centric strategies in high-stakes AI environments.

ACKNOWLEDGEMENT

I wish to extend my deepest gratitude to several individuals whose support has been invaluable throughout my MBA journey in Artificial Intelligence at Robert Kennedy College (RKC) and the University of Cumbria (UoC).

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Lastly, I would like to thank my children, whose love and presence have motivated me to persevere and complete this significant milestone. Their smiles and enthusiasm have been a constant source of inspiration and joy.

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LIST OF ABBREVIATIONS

AGI	Artificial General Intelligence
AI	Artificial Intelligence
BA	Business Angel
CI	Cognitive Intelligence
EI	Emotional Intelligence
FAE	Fundamental Attribution Error
FO	Family Office
GDPR	General Data Protection Regulation
L&M	Leadership and Management
ML	Machine Learning
SPB	Selective Perception Bias
SSB	Self-Serving Bias
VC	Venture Capitalist

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GLOSSARY

This section reports the definition of commonly used words and acronyms throughout this dissertation.

AI Startup	A startup whose business model is centred on Artificial Intelligence-based solutions, offering services or products to clients that involve regular, systematic, or automated use of AI tools.
Attribution Theory	A psychological theory developed by Fritz Heider (1958) that defines the way people give interpretations to events and how their thinking and behaviours adjust to their interpretations.
Cognitive Dissonance	A state of psychological discomfort that occurs when a person has contradictory ideas or beliefs, or when new pieces of information conflict with other beliefs the person already holds.
Cox Proportional Hazards Regression Model	A statistical method used to investigate the effect of several variables on the time a specified event takes to happen, often applied in survival analysis.
Emotional Intelligence	The capacity to recognize, to make sense, and to be able to act upon the emotions of self as well as of others.
Fundamental Attribution Error	The tendency one may have to attribute someone's failure to internal human factors while underestimating the effect of environmental reasons.
Jackknife Resampling	A statistical technique used to estimate the bias and standard error in a statistic by systematically recalculating that statistic, leaving out one or more observations at a time.
Kruskal-Wallis Test	A non-parametric statistical procedure employed to assess whether multiple independent samples, potentially of unequal size, derive from a common distribution.
Likert Scale	A scale with generally 5 to 7 options, often used in surveys to measure attitudes or opinions.
Non-AI Startup	A startup that does not primarily focus on Artificial Intelligence in their services or products offered to clients.

Self-Serving Bias	A cognitive inclination to attribute personal successes to one's own internal traits, while shifting the blame for negative outcomes or failures onto external circumstances.
Selective Perception Bias	The tendency to perceive what we want to perceive, often ignoring contradictory information.
Spearman Correlation	A nonparametric statistical method used to evaluate the degree to which two variables maintain a monotonic relationship, based on their ranked observations.
Startup Success	Defined in this study as a startup that is profitable and still operating after 5 years of activity.

1. INTRODUCTION

1.1. THE SELECTION OF THE TOPIC

Startup failure is one of the most significant challenges in the entrepreneurial ecosystem. With a fair estimate of about 90 to 95% (Allen, 2022), it is not surprising that numerous studies have attempted to dissect the technical, organizational and economic reasons behind these outcomes. However, little has been written about the human aspects like attitudes, beliefs, behaviours, fears, stress, leading to startup failure or success (Duong, 2022). It may possibly be connected to the level of subjectivity of those factors and the amounts of biases that can get in the way of clear mathematical models.

This gap is particularly intriguing when opposed to some successful startup founders whom we approached, like Taïg Khris (OnOff professional telephony solution), Eric Larchevêque (Ledger crypto security), Mounir Lagoun (Finary finances) and Anthony Bourbon (Feed). They led AI (Artificial Intelligence) startups as well as non-AI startups. When asked about success, they agreed with the necessity of knowing themselves well, being fully "aligned" and overcoming their fears, even more than technical or financial aspects. According to Anthony Bourbon, even with an almost unlimited capital and all the required technical expertise, a founder who would not be personally "aligned" would fail their startup. He defined this notion of alignment as being connected to what is commonly known as "emotional intelligence" (EI).

This dissertation emerged from the desire to explore these personal testimonials through a rigorous research lens. The aim is to confirm or challenge these perspectives by surveying both startup founders and investors and provide possible insights into how human factors may or may not influence startup success, differentiating AI and non-AI ventures.

1.2. HISTORY AND EVOLUTION OF THE SUBJECT

Historically, especially before Covid, startup outcomes were often observed through the lens of technical aspects like finances, technical skills, leadership strategies, or external environment specificities. These concrete aspects are very well adapted to statistical analysis due to their rationality. On the other hand, human aspects like stress, fear, beliefs or stress-related behaviours, have often been treated as secondary, probably due to their intangible and subjective nature.

However, the influence of human factors cannot be neglected. In 2022, according to the American Psychology Association, 27% of American adults experience daily so much stress that they feel unable to “function” properly (*Stress in America 2022: Concerned for the future, beset by inflation*, 2022). In 2024, Gallup (2024) discovered in a worldwide survey that 37% of people in the world consistently experience high levels of stress. It is reasonable to consider that founders are part of these statistics, possibly being even at higher risk, considering the high pressure they may encounter, facing uncertain environments and high financial stakes.

The fast evolution of AI in recent years even complicated this landscape. For instance, Mistral, a French AI company, has received a 6 billion dollars valuation only one year after its creation (Kharpal, 2024). This exemplifies the growing complexity, pressures and stakes that arise in the realm of startups, and it underlines the necessity of considering human aspects when evaluating the success or failure of startups.

1.3. THE IMPORTANCE TO CURRENT ECONOMIC AND SOCIAL LANDSCAPES

Startups bring valuable innovations to the society. Every startup that fails generates substantial losses, both on the side of the founders, as well as on the side of the investors. A vicious circle may arise out of those failure, which might push investors to become more reluctant to invest. This in turn may become a problem in the startup ecosystem where, by definition, risks may be high, with high valuations opposed to little or even no profit at the time of a fund raising. Therefore, any factor that could improve a venture’s success rate deserves serious consideration, even if it requires taking subjective evaluation risks.

AI is a raising and rather recent trend compared to the history of startups, with an estimate of 5% of AI-oriented startups out of 305 million startups created worldwide every year (Wise, 2023). However, their impact seems disproportionately large when compared to the high valuations they may receive, within very narrow periods of time.

If human factors like self-awareness, stress management or resilience are proven to have a measurable impact on startup outcomes, then both founders and investors may benefit. It seems surprising to observe the apparent low level of interest manifested by scholars about the impact of human factors in startup success or failure.

1.4. BRIEF OVERVIEW OF THE TOPIC

The core problem this dissertation addresses is the seemingly low representation of human factors in research on startup success and failure.

This research intends to bridge that gap by focusing on a comparative analysis between AI and non-AI startups, investigating whether and how human factors manifest differently in these contexts. Additionally, by incorporating perspectives from both startup founders and investors, this work seeks to provide a comprehensive understanding of how human aspects may influence outcomes.

Taking those human factors into consideration in this dissertation represents a challenge, and the reader must be warned of the risk of biases connected to the high levels of subjectivity.

This dissertation is not aimed at reflecting a unique truth, but rather a different angle on a subject somewhat neglected by academics, which may lead to further research work.

1.5. THE RESEARCH QUESTION AND AIM OF THIS DISSERTATION

The question revolving around this research is:

> *"To what extent human factors like attitude, beliefs, behaviours, fears or stress may affect the overall success of an AI or non-AI-oriented startup?"*

Therefore, the aim of this dissertation is to explore the influence of human factors on the success or failure of startups, with particular attention to the distinctions between AI-driven and non-AI-driven startup companies.

1.6. THE OBJECTIVES TO ACHIEVE THE AIM

To achieve the aim of this dissertation, the following objectives are proposed.

The first objective (O1) will be to conduct a critical review of academic literature relating to the role of human factors (such as beliefs, attitudes, stress, or behaviours) in the success or failure of startups.

The second objective (O2) is to define and differentiate AI-oriented startups from non-AI-oriented startups.

Then, we will explore how success and failure are conceptualised and measured within startup contexts, from both entrepreneurial and investor perspectives (O3).

Concerning human factors, we will develop a research methodology appropriate for investigating the impact of human factors on startup outcomes, including the selection of suitable data collection and tools for analysis (O4).

We will collect and analyse empirical data from startup founders and investors to identify perceived influences of human factors on startup performance (O5).

We will finally interpret and critically analyse the findings in the context of the literature, drawing conclusions about the relative impact of human elements on startup success, and discussing any distinctions between AI and non-AI contexts (O6).

1.7. BRIEF REVIEW OF THE PROPOSED RESEARCH METHODOLOGY

The approach of this dissertation is quantitative research. Two distinct surveys will be developed and sent. One will be for startup founders and one for investors. The results may show differences between their perceptions, and lead to useful learnings from each protagonist's "map of the world", or vision of the world, in order to discover possible areas of improvement to promote startup success.

Both surveys will use Likert-scale questions addressing specific human factors like stress, fears, alignment and belief systems.

The surveys will also include discriminating questions to identify for instance whether respondents belong to AI or non-AI sectors, allowing comparative analysis. The collected data will be statistically analysed to discover trends, correlations, and possible discrepancies in perception between founders and investors. Given the subjective nature of the factors studied, particular attention will be paid to the limitations of self-reporting and the inherent biases in human responses.

The focus will be set on success as well as on failure, since it is possible that a given human factor like stubbornness might in some cases lead to success, and in other cases, it might lead to failure.

1.8. BRIEF INTRODUCTION TO THE RESEARCH ENVIRONMENT

The geographical scope of this research is intentionally narrowed to French-speaking startups and investors. This decision balances the need for cultural and linguistic consistency with the practical requirement of obtaining a sufficiently large and relevant sample size. While this may limit the global generalisability of the findings, it enables deeper insight into a well-defined startup ecosystem.

AI and non-AI startups from various sectors (including high-tech and low-tech industries) are included, ensuring diversity in business models, challenges, and investor expectations. This approach allows for benchmarking across sectors and technologies, shedding light on whether AI entrepreneurs face unique psychological or emotional demands.

1.9. INTRODUCTION TO THE FOLLOWING CHAPTERS

The structure of this dissertation is designed to guide the reader through a logical and comprehensive journey from theory to practice.

Chapter 2 will present a critical review of existing studies on startup success factors, with a focus on the human dimension and distinctions between AI and non-AI sectors, so that the reader knows what the literature already presents about the subject.

Then, chapter 3 will discuss the research methods, including the development of the surveys, the selection of the sample, and the methods used for data analysis, therefore presenting the "how".

Once the data is collected with the methods above, a detailed presentation of the empirical findings, including statistical analysis, group comparisons, and interpretation of human factors will be provided in chapter 4. The same chapter will also integrate those findings with the existing literature, examining convergences and discrepancies.

Finally, chapter 5 and 6 will provide a summary of key insights, as well as recommendations for founders and investors, and suggestions for future research. It will be followed by an evaluation of the present research in chapter 7.

The next chapter will provide the reader with a detailed literature review about the subject.

2. LITERATURE REVIEW

This chapter will present a detailed literature review. The first part will be the choice of the academic theories which will be the starting point of this research. After connecting them with other academic literature, we will develop the necessary bridges with our subject matter.

2.1. INTRODUCTORY ELEMENTS

This dissertation will focus on internal human factors affecting the success or the failure of startups. Since we will not cover the external factors which are already widely discussed by science literature, we will identify one academic theory dealing with internal human factors, as well as one academic theory bridging internal and external factors, in order to be exhaustive and stay focused. Those will be the basis on which we will construct this work. All the referenced studies are stored in a Zotero database.

2.2. THEORY BRIDGING INTERNAL AND EXTERNAL FACTORS

Among all the academic theories studied in the MBA, one specifically attracted our attention as a basis for our work, because it bridges internal and external factors, while providing patterns matching with investors, with founders as well as with both. It is Heider's (1958) **attribution theory**. Since academics have covered this theory very widely, even recently, it will be the basis of our work.

Several academics have built upon the attribution theory which examines the interpretations people give to the causes of given events, separating them between internal causes (or dispositional attributions) and external causes (situational attributions). As Weiner considers it as a field of study and suggests that it cannot be considered as a unified theory (2008), he focuses on outcomes and perceptions, which relates well to the very notion of success or failure for startups.

Figure 2.1 – The attribution theory (created with Napkin)

The attribution theory has been recently used to analyse human behaviours. For instance, a meta-analysis synthetised 38 studies to explore and explain Covid-19 behaviours (Sharma *et al.*, 2022). Another meta-analysis of 22 studies about founder's communication style analysed the attribution patterns adopted by employees (Safira *et al.*, 2023), and showed that the style of communication employed by a given person has a significant impact on teams as well as on its global efficiency.

Three attribution patterns stem from the attribution theory. These patterns are of a specific interest in this research, as they cover specifically the founder, the investor and also both of them.

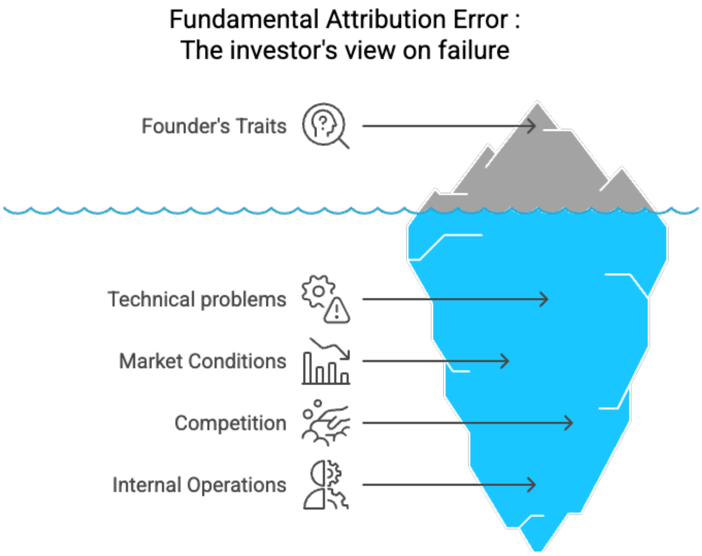


Figure 2.2 – The Fundamental Attribution Error (created with Napkin)

The first one is the **fundamental attribution error**, which may alter the evaluation made by the investor when a startup fails, attributing the failure more to emotional or personal traits of the founder rather than external factors (Ross, 1977) like resources, economy, competition, market conditions or technical limitations. Seven years later, Miller establishes that this attribution bias is actually subjected to cultural differences (Miller, 1984) which could imply that those biases could be at least partially learnt, which opens the possibility of change by limiting the impact of this cognitive bias. The proportion to which this cognitive bias would be "engraved" in the person or learnt is not covered by the study. This is also why culturally restricting the targeting for the survey will be important, so that cultural differences may influence as little as possible, while keeping enough potential answers for efficient statistics. Much more recently, it has been shown that in project management, a failure was generally considered to be caused by the project manager's personal traits (Christopher Paul, 2021) instead of the external contextual elements. Walker (2025) challenges the traditional idea that the fundamental attribution error is indeed a cognitive bias, by suggesting that it may rather be the result of a probability, or a heuristic, making it more mathematically predictable. His idea somehow correlates to Miller's (1984) observation about the fact that the fundamental attribution error is culturally influenced, therefore it could be more or something else that a pure cognitive bias. However, even if it were a heuristic, it would not intrinsically disprove the fact that it is a cognitive bias, which is confirmed by a 2022 study showing that people also manifest the fundamental attribution error with robots (Edwards and Edwards, 2022) and not only with humans, which seems to confirm the traditional academic concept. Therefore, during this research, we will stay with the academic idea that the fundamental attribution error is indeed a cognitive bias.

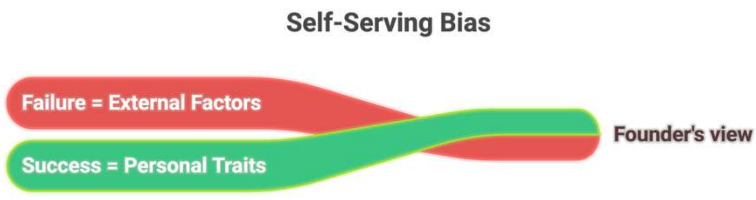


Figure 2.3 – The Self-Serving Bias (created with Napkin)

The second one is the **self-serving bias** which will especially concern the founder, who may attribute the success of the startup to himself and to his personal traits and attitudes, while having the tendency to attribute the failure of the startup to external factors like technological problems, economic problems or event political problems. A meta-analysis has been conducted to prove the reality of this bias (Mezulis *et al.*, 2004). It shows significant cultural differences even among Europeans. The reality of the self-serving bias confirms the necessity of surveying not only the founders, but also the investors who have an external point of view, although they are themselves subjected to the previous attribution bias. This combined complexity increases the subjectivity of this research. Rogoff et al. (2004) point to the fact that entrepreneurs are significantly more negatively subjected to this bias than experts, arguing that entrepreneurs are actors in the company, whereas experts are more in a position of an external observer. This again confirms the importance of including investors as external observers in order to confirm or not the attribution bias and possibly find ways to counterbalance it.

We might argue that this self-serving cognitive bias could either prevent learning from failures, or on the other hand it could also increase resilience, especially if we connect it with the notion of cultural differences pointed to by Mezulis et al (2004). However, it is to be noted that this self-serving bias is recognized to be variable in its intensity. For instance, gaming “addicts” show a lowered self-serving bias (Wang *et al.*, 2024), as well as depressed people who surprisingly show a better self-perception ability (Benz and Reinhard, 2023). The study however does not tell whether depression is only correlated to better self-perception, or whether it is a cause, which would certainly be an important piece of information for the purpose of this study oriented towards internal human factors and self-perception.

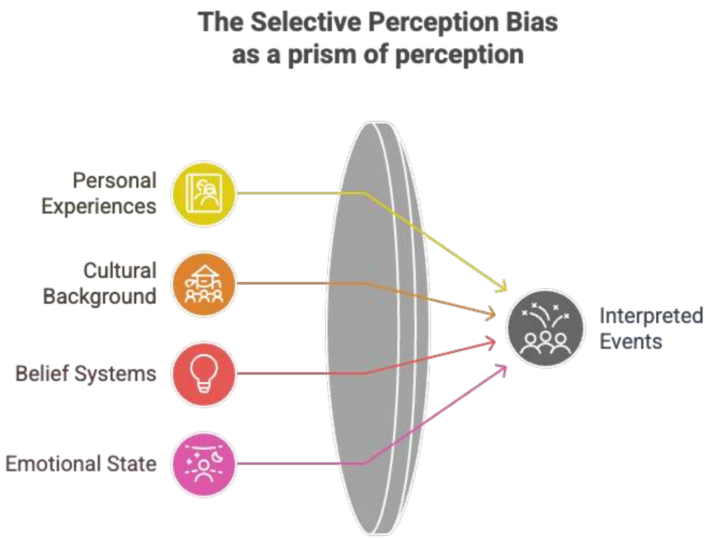


Figure 2.4 – The Selective Perception Bias (created with Napkin)

The third attribution pattern we observe is the **selective perception bias**. Hastorf (1954) showed how individual perceptions often have a strong impact over how one interprets events. Dearborn and Simon (1958) add that the interpretations may differ according to the person's "functional background". While Dearborn and Simon (1958) focused precisely on executives, some might consider that investors and founders may not necessarily fit to what was considered to be an executive, back in 1958. However, we will take it into consideration and be careful that even among investors, there may be differences of perceptions between those who are only investors and those who are or have been both investors and founders. Another more recent study shows that a cognitive bias is much easier to recognize in others than within self, calling it a "blind spot" (Pronin, Lin and Ross, 2002). This view (1) confirms again the necessity to integrate investors as external observers, and it (2) confirms the necessity to go further than just the attribution bias, and search also on the concept of emotional intelligence, since having a blind spot may require at least a better knowledge of self. Moreover, a 2024 study confirmed that this bias can potentially be controlled, as it is directly connected to how the person stores the initial information (Park *et al.*, 2024), which means that heuristics can be built to avoid or at least limit the negative effects of this bias.

2.3. THEORY ABOUT INTERNAL FACTORS

Although popularized by Daniel Goleman, Emotional Intelligence (EI) was initially based on John Mayer and Peter Salovey's work (Salovey and Mayer, 1990) who defined EI as the capacity to discern and have an impact on one's own emotions as well as others'. It is essential to underline that EI is not only about assessing emotions but is also about the capacity to act upon them, implying therefore a notion of tools or techniques. For the purpose of our study, it is also very significant to keep in mind that emotional intelligence has, according to Salovey and Mayer (1990), a systemic impact, as it may impact personal emotions as well as other people's emotions, which implies a notion of influence over self as well as over others.

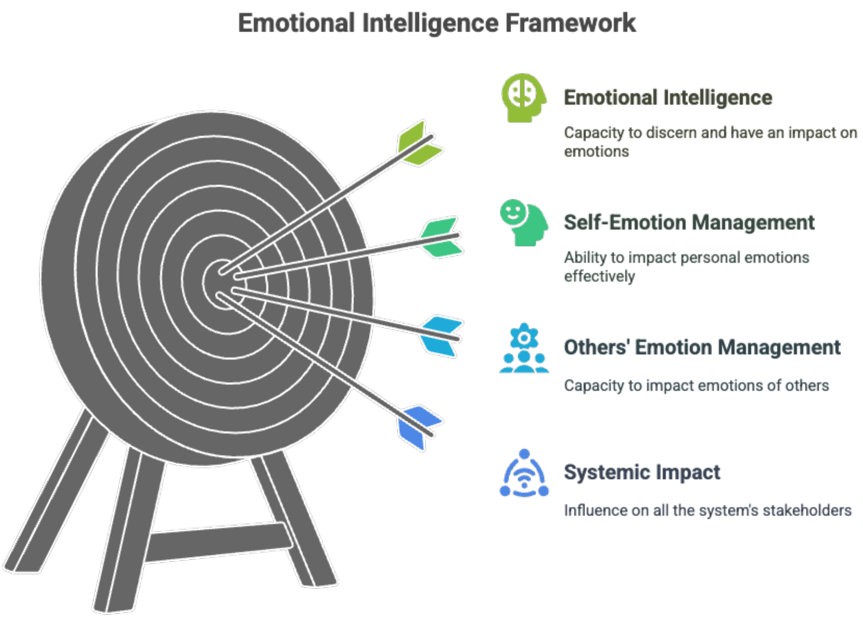


Figure 2.5 – Emotional Intelligence (created with Napkin)

Emotional intelligence has been a vast subject of study since the earliest publications. Historically, Walter et al. (2011) identified and explored the discrepancies between academics and practitioners who had a different perspective on EI. Indeed, academics were questioning the importance of EI in leadership, whereas practitioners were viewing EI as a necessity.

However, the academic position kept evolving through the years, especially after the Covid-19 pandemic. For instance, a 2023 meta-analysis of 104 peer-reviewed studies showed that Emotional Intelligence helps founders improve the company's outcome as well as overall performance (Coronado-Maldonado and Benítez-Márquez, 2023). Another study even shows that the quality of the decision-making process can be improved when there is an alignment between self-assessed and actual Emotional Intelligence (Gillioz *et al.*, 2023), which goes along the ancient maxim "Know thyself" in the temple of Apollo.

The interest for the subject has been growing steadily and significantly as on the "Science Direct" database for example, 354 review articles were published in 2019 on emotional intelligence. Five years later, post-Covid, in 2024, 1205 review articles were published, which is 3.4 times more (see Appendix A01).

This increased interest will possibly also generate in the next few years a growing interest for the impact of Emotional Intelligence on startup success and failure. Although the field of social psychology has covered a very large spectrum of theories about the impacts of human factors like fears, beliefs, attitudes, behaviours or stress, nevertheless very few of those theories have been applied to analysing startup failure or success (Duong, 2022) especially before the Covid-19 pandemic.

However rational the world can be, the pandemic seems to have stimulated researchers to focus more on the impacts of human-related aspects, cognitive biases and “psychological baselines” within the professional environments (Scalabrini *et al.*, 2023). Such an interest combined with an improvement of startup success could have a significant impact on the world economy, considering the fair estimate of the startup failure rate of 90 to 95% (Allen, 2022) applied to the 305 million startups created every year worldwide (Wise, 2023), which makes between 275 and 290 millions of failed startups every year. The impact is not only economical, but it also represents a significant social impact.

One example of such a psychological baseline mentioned earlier is the role of anxiety. The impact of stress on risk taking appears to be inversely proportional to the person’s anxiety level (Hengen and Alpers, 2021). Therefore, anxious people will tend to reduce their capacity to take risks as their stress level grows, whereas non-anxious people will tend to increase their capacity to take risks as their stress level goes up. This is a major insight for founders and investors whose work is significantly based on risk taking. This once more emphasizes the possible importance of Emotional Intelligence and human factors in startup success, which we will study in more details in this research.

EI has also been recently a major subject of interest for AI research, in order to better model and reproduce human-like systems (Narimisaei *et al.*, 2024), therefore computer engineering is helping us better understand human beings. The combination of AI and EI also supports understanding further the complexity and the subjectivity of human emotional intelligence (Filippis and Foysal, 2024). This is understandable considering how much AI has been inspired by the actual human brain, with neurons and synaptic connections.

2.4. EMOTIONAL INTELLIGENCE (EI) AND COGNITIVE INTELLIGENCE (CI)

The previous section defined what EI is. However, it is important to distinguish between Emotional Intelligence (EI) and Cognitive Intelligence (CI) which have a different theoretical base. We will therefore complete our former definition of EI with a definition of CI, which is a very wide topic. We will only “scratch the surface” as we do not want to confuse the mind of the reader but rather stay focus on EI.

Cognitive intelligence is commonly considered as being the capacity to think concretely as well as abstractly, to organize, to understand complex concepts, to learn and to solve problems (Colom, 2020). A significant number of academic theories have been elaborated around cognitive intelligence (Chen *et al.*, 2019) which we will not cover here. However, the concept of General Intelligence (Detterman, 2000) which was initially exclusively reserved to human beings has been lately taken into consideration dealing with AI, using the term AGI, which stands for Artificial General Intelligence, as a kind of ultimate goal for AI systems tending to copy or reproduce the human general intelligence (Fei *et al.*, 2022).

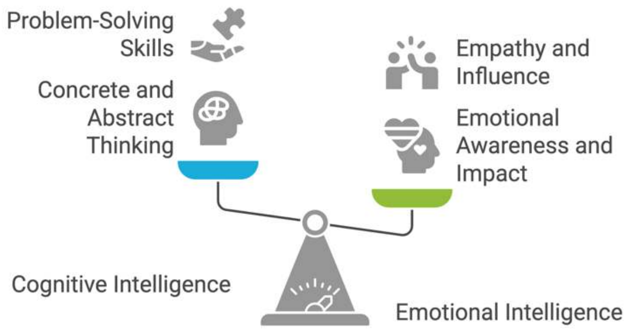


Figure 2.6 – Balancing CI and EI (created with Napkin)

Although Jung et al. (2019) discovered that EI and cognitive intelligence are intrinsically linked because of their shared physical neurological foundations (they share the same brain) and interdependent brain functions, which means that improving one may have a positive impact on the other, and vice-versa, however, Agnoli et al. (2019) underline that the overlapping between EI and CI is not clearly established by science. Therefore, there is no consensus on their actual connection or disconnection.

Research has also shown that EI has an established impact on CI (Fernández-Berrocal and Checa, 2016) which emphasizes one more time the importance of taking both into account; as we do while examining the human factors impacting startup success or failure.

Jung et al.'s (2019) discovery about the intrinsic connections between EI and CI may at least partially explain Gillioz et al.'s (2023) discovery that the alignment between self-assessed and actual Emotional Intelligence can indeed improve the quality of decisions, as cognitive intelligence and emotional intelligence share the same neurological foundations.

2.5. CONNECTING THE DOTS

Now that we developed the attribution theory as well as the emotional intelligence theory, we may start to "connect the dots" to clarify the mind of the reader about the connections between those theories.

While we saw the problems induced by attribution biases, a study suggests that EI may reduce those biases, when the person develops a more thorough perception of themselves and others (Petrides and Furnham, 2003). This suggestion opens the possibility of improving startup success through the development of human factors.

Côté and Miners (2006) explicitly separate cognitive and emotional intelligence, and show that both can improve work performance. With the evolution of Artificial Intelligence, as cognitive tasks are being taken over by computers, Côté and Miners (2006) elaborated almost 20 years ago that a higher emotional intelligence may compensate lower use of cognitive intelligence. Therefore, emotional intelligence may take more and more importance in the next decade as AI evolves, which reinforces the need of this research.

2.6. DEEPER INTO THE HUMAN INVESTOR AND FOUNDER

Almeida et Devedzic (2022) highlight the fact that emotional intelligence is the most relevant soft skill for entrepreneurs. Although their quantitative study focused only on Serbia and Portugal, the nuances that may appear on other territories will probably not offer opposite or radically different results.

Furthermore, Szerb and Vörös (2021) also confirm that the founder's cognition builds up and overconfidence evolves to become more nuanced through experience, and it has a clear impact on performance and success.

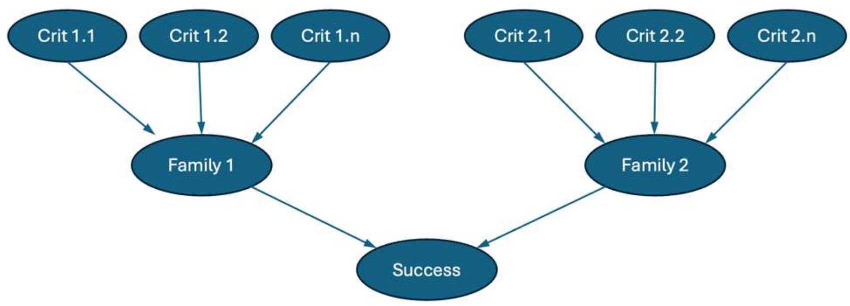


Figure 2.7 - Example of a Bayesian decision-making system (Created with PowerPoint)

One model has been developed to evaluate and anticipate startup success, combining different internal, external and activity indicators in a Bayesian system (Kofanov and Zozul`ov, 2018), which is a decision-making or inference model to determine the probability of a hypothesis as more evidence or data becomes available. Although we were very optimistic to see the notion of internal indicators, hoping to see human qualities taken into consideration, however, we discovered that the only human-like indicators selected by the authors were leadership style and educational level, which we argue are possibly not enough to define an internal environment. Therefore, we would rather question their conclusion that the external environment is the most important element for startup success, since the initial data about internal indicators seems somewhat incomplete. Still, we do agree with their observation that startup success may only happen when all components (internal and external) are present, which confirms the need to consider the human internal indicators.

Pierrakis and Owen (2023) focused on how different kinds of investors value human capital. Again, the main human capital indicator they used was prior experience, which may not seem enough to be thorough. Miloud et al. (2012) also limited human capital to prior experience. Nigam et al. (2021) added the notion of relational capital to the equation, but we argue it is probably still not enough. Moreover, their study was specific to India, which may also raise cultural biases. It is interesting to observe how the human factors have been the poor cousins of research until very recently, as we indicated earlier.

Prior experience is controversial when dealing with success, since Gottschalk and Müller (2022) suggest in their comparative study that failure makes the second startup experience worse than the first one. Their view is supported by Pretorius and Roux (2011) whose longitudinal study identified similar patterns in successive failures, which shows according to them that the founder did not learn the lesson from their past experiences. Pretorius and Roux (2011) give us however a precious insight, which is that to extract lessons from the past, one needs conscious reflexion about what happened.

In order to limit self-serving biases, Freiberg and Matz (2023) conducted a large study on founders' personality traits using what is called "digital footprints", observing how founders interact with technological resources. This however appears to reflect only a part of human traits, presupposing also that human traits can be precisely extracted from human outer interactions, which we doubt until proven to be true.

Roundy (2022) raises concern on the possible detrimental impacts of AI for team members in the startup ecosystem and shows that AI startups are somehow outliers in the startup world and require special interest and consideration. It is important to keep in mind that this was written in 2022, and the situation now in 2025 is probably already very different already, considering the fast improvements in the field of AI. Moreover, this study tends to consider the use of AI within internal processes, but as we will see in chapter 2.8, it is not the approach we will follow regarding AI startups.

Therefore, the gaps we notice in the literature confirm the necessity of our study.

2.7. CHOOSING THE INDICATORS

Almeida and Devedzic (2022) analysed 38 soft skills for startups in Portugal and Serbia and concluded that taking emotional intelligence into account is important in startup activity.

In order to limit the number of items in the surveys, we will select indicators (prefixed with letter I) that have already been studied individually by academics, to have concrete reference points.

2.7.1. COMMUNICATION

Communication skills (I01) on behalf of the leaders (Men, Qin and Mitson, 2021) have been shown to improve team engagement within 1027 Chinese startups. Although China is culturally distant from Europe, it will be interesting to check whether the capacity to communicate efficiently has also a positive effect on the startup within our study, should it be on the side of the investor, or on the side of founders, or both.

The **capacity to resolve conflicts** (I02) has also shown its efficiency for startup success (Liu *et al.*, 2023). This study emphasizes the importance of moderate conflicts within startups, as they stir up creativity and improve agility, when handled properly with resilience. One key insight from this study is that surprisingly, conflicts are a predictor of startup success, again, when handled properly. Adham (2023) however indicates that the style of conflict resolution is crucial to determine the outcome, which can be positive (using constructive dialogue for instance) or negative (using open confrontation). Therefore, the capacity to resolve conflicts is multifaceted, implying not only attitudes, but also specific communication skills.

Because of the surprising and counterintuitive effects of conflicts observed above, we will also check whether, to a lesser extent, **negative interactions** (I03) also impact startup success or failure, without necessarily getting to situations of conflicts. We will consider negative interactions on the side of founders, as well as on the side of investors.

2.7.2. INTERNAL PERCEPTIONS

Prior experience (I04) appears to have a positive impact on startup success (Chen *et al.*, 2024). However, the systematic positive outcome caused by past experience may be subjected to controversies due to human cognitive biases. For instance, negative past experience may generate emotional stigma limiting future startup success (Pan *et al.*, 2022). It is also important in our case to distinguish between the founder's past experience, and the investor's past experience, as the investor probably faced different startup fails with different founders in their career, which will provide an interesting observer perspective.

Beliefs (I05) are commonly recognized by academics to have an impact on professional efficiency (Murphy and Reeves, 2019) through the concept of "growth mindset", as opposed to the concept of "fixed mindset". Nevertheless, the authors solely insist on the development of confidence through beliefs, forgetting to address the possible impacts of overconfidence which may negatively alter the success outcomes. Indeed, the impact of beliefs can be negative, like in the case of incorrect beliefs about the market which could have detrimental effects on startup success (Qiu and Jiang, 2021). This research will cover for instance the founder's beliefs about their ability to succeed or not, but also the investor's beliefs about the founder's capacity to lead the startup to success.

2.7.3. INTERNAL COPING SKILLS

Fears (I06) have also been widely covered by research, noting their negative impacts on startup success (Dutta and Sobel, 2021), although the authors observe that having better finances may mitigate the negative effects of fear because of the freedom money brings. Fears may also blur the ability to assess new business opportunities (Grichnik, Smeja and Welpe, 2010). Gao et al. (2024) confirm the overall negative effects of fear of failure among almost 1000 college students with intentions to create a venture. However, it is not possible to generalize about the universal negative impact of fear, or even the popular idea that "quantity is the poison", as in the case of the possible life-threatening fear of Covid-19, positive effects have been observed on the propension of fear to seek new challenges (Zampetakis, 2022). This shows that high-intensity fears may have negative, as well as positive effects on humans, which could possibly also be the case for moderate or low fears until proven false.

Similarly to fears, **stress** (I07) is commonly recognized as a negative influence for startup success (Drnovšek and Slavec Gomezel, 2022) but according to the authors of this 2022 research, its effects can be strongly reduced through positive affects, which points to the possible importance of the other human factors. Kiefl et al. (2024) warn us about the fact that excessive stress may lead to mental health disorders, with a propensity for entrepreneurs to put themselves in danger. However, stress is also considered by academics as a possible source of positive stimulation, since when it is controlled, it may stimulate efficiency and the capacity to innovate (Paresashvili and Avsajanishvili, 2023). It may develop resilience and it may also become itself a coping skill (Ahmed *et al.*, 2022). Positive stress is frequently referred to as “eustress” (Pluut, Curşeu and Fodor, 2022), which is a word borrowed to Hans Selye, in opposition to “distress”. However, it is important to note that the academic literature does not draw a clear and systematic line between “good” and “bad” stress, which means that no generalization can be drawn. Every situation needs to be assessed independently.

2.7.4. INTERNAL TIME-ORIENTED STRATEGIES

The conscious **management of time** (I08) is shown to lower startup failure (Lichtinger, Engelen and Teubner, 2023). In fact, time management is not only about reducing and optimising time, it is also about taking enough time for conscious planning (Duchesneau and Gartner, 1990). Time management is therefore context dependent and, following the selective perception bias (chapter 2.2), its meaning may be significantly different individually for every founder, just as for every investor. This again highlights the subjectivity associated with this research.

Visualisation (I09) or guided imagery is already well-implanted within sport for performance improvement through mindfulness practices (Fadare *et al.*, 2022) and a meta-analysis (Si, Yang and Feng, 2024) confirms its overall efficiency in order to improve performance and success. Visualisation has also been tested by the militaries in the context of space missions, and showed positive outcomes in mission efficiency (Le Roy, Martin-Krumm and Trousselard, 2023). Therefore, although academics still show limited interest in visualisation in the context of startup success, we will test this indicator to check whether further study could be beneficial in the field.

2.7.5. INTERNAL ACCOUNTABILITY

Accountability (I10), or taking responsibility for past failures and successes, is shown to improve the future chances of success (Pan *et al.*, 2022). However, the Self-Serving bias related to Heider’s (1958) attribution theory may limit the capacity to take accountability for failures. Therefore, this indicator will be valuable for our research, in order to find correlations with success or failure.

2.7.6. INTERNAL OPINIONS

Similarly to the capacity to resolve conflicts and negative interactions, we will also provide an indicator for the founder's general **point of view on things** (I11), in order to not only focus on "negative" aspects of opinions and communication, but also stay on a more neutral vision, as suggested by a study showing how much personal points of view leading to openness and self-expression may impact startup success (McCarthy *et al.*, 2023). We want to have polarised but also non-polarised indicators.

2.7.7. ATTITUDE

Negative attitudes (I12) may be prejudicial to founders success (Pan *et al.*, 2022). Moreover, negative experiences also tend to increase negativity (Shore, Pittaway and Bortolotti, 2024). This shows a potential vicious circle connected to negativity. Therefore, we will keep this indicator.

Inflexible attitudes, commonly referred to as **stubbornness** (I13), are also correlated with startup failure (Szathmári *et al.*, 2024). On the other hand, stubbornness can also be manifested through perseverance or persistence, which is showed to potentially increase startup success (Pan *et al.*, 2022). Here again, the selective perception bias will impact this indicator as it can be seen from two opposite angles, which can be positive or even negative.

2.7.8. BALANCE

Academic literature has interestingly covered the significant role of **work/life balance** (I14) for performance and success in startups (Sun, 2024). Although the study was lead within Shanghai startups, the observation has been confirmed by a literature review made about younger generations between 2018 and 2022 (Waworuntu, Kainde and Mandagi, 2022) whose performance increases when work/life balance is optimal. Another meta-analysis on a larger time-scale, from 1994 to 2023, confirmed the significant increase in performance when properly balancing work and life (Ariasari and Tjahjono, 2024). It is important to note the apparent subjectivity of this indicator, as every individual may assess differently what a work/life balance is, and most of all, what a balanced work/life balance is.

2.8. WHAT AN AI STARTUP IS

Bessen et al. (2023) define AI startups as a venture that develops and sells AI products. Their vision is product centred, not considering service driven companies. With a different approach, Jorzik et al. (2024) suggest another vision and consider an AI startup to be one having an AI-driven business model for innovation. Di Bernardo et al. somewhat combine the first two visions and consider an AI-oriented startup to be one that has a business model based on "Artificial Intelligence-centred solutions" (Di Bernardo *et al.*, 2021).

There is no academic unanimity on this definition. However, the first definition proposed by Bessen et al. (2023) ignores service-oriented companies. Therefore, we will not take it as is. The second definition is interesting but is very vague about how AI is indeed being used. If a founder uses ChatGPT to query about innovative concepts and uses the answers to improve his business model, would it then be an AI startup? Such a definition would not be clear in our survey.

Therefore, to clarify the concept for the respondent, we will develop Di Bernardo et al.'s (2021) definition combined with Bessen et al.'s (2023) definition, and define an AI-oriented startup as being a startup whose services or products offered to the clients involve a regular or systematic or automated use of AI tools. We could also focus on AI within internal processes of the startup but since now a vast majority of tools are based on AI (Accounting tools, Microsoft CoPilot, ChatGPT, …), such a definition would probably bias the qualification. Therefore, we will keep the definition based on the service or product offered to the client.

2.9. WHAT STARTUP SUCCESS AND FAILURE ARE

The literature offers very different approaches of what startup success or failure is. While Keogh and Johnson (2021) define it in terms of revenue and employment without giving a precise definition, Kee and Rahman (2020) agreed in a systematic literature review that startup success is multifaceted and is primarily based on "financial and non-financial indicators". However, in agreement with Zahra and Kirchhoff (2005), they decided to define a successful startup as being a venture with a survival period of at least 5 years. Keogh and Johnson (2021) also quote various other definitions of a successful startup from several authors and agree that there is no precise definition of what it is or is not. Several academic research papers discuss startup failure, but rare are the academics who suggest a concrete definition, which is curious in terms of academic precision. How is it possible to qualify and study something that cannot even be defined?

Pollman (2023) precises that startup failure is very poorly covered by academic literature, and insists on the psychological aspects of non-profitable ventures who are looking for what they call a “soft landing” to absolutely avoid the term “failure”. This offers a reasonable explanation for the reason why it is complicated to have unanimity on one single definition.

However, we need to be able to make it clear for the respondent so that the survey responses remain homogenous throughout this research. Therefore, since scholars have no clear and unanimous definition of it, we will take the same path as Kee and Rahman (2020) and Zahra and Kirchhoff (2005), and consider that a successful startup is one which is profitable and alive after 5 years of activity.

This definition is clear enough for respondents to be able to qualify their venture without any doubt.

In this chapter, we have covered a detailed literature review about the academic theories used as a basis for this research. We critically analysed what other academic authors had to say on the subject, and we defined a clear pathway for this dissertation’s journey. Then we detailed academically the different indicators or human factors that we will retain, and which will be part of the survey sent to investors as well as to founders.

We showed that this whole work may be subjected to biases due to the very subjective nature of the indicators.

In the next chapter, we will present the methodology that we are going to use in order to achieve this research’s aim and answer the research question.

3. METHODOLOGY

3.1. INTRODUCTION TO RESEARCH METHODS.

This chapter will present the methodology followed through this research.

3.2. RESEARCH PHILOSOPHY, APPROACHES AND STRATEGIES

Philosophically, this research tends to oscillate between the participants' interpretations in a form of Relativism, and a desire to structure and get insights about a possible rationale in a form of Realism.

Since we want to try to converge the subjectivity of the topic towards possible concrete deductions, we will follow a deductive approach.

Our strategy will be based on a survey sent to investors and founders.

The survey will be quantitative, as we want to gather as much information as possible, to counterbalance the subjectivity of this work (Lim, 2024).

Because we want to collect specific data and have a limited time, the research will be cross-sectional, as we will collect data at one moment in time, slightly extended because of email deliverability constraints.

Therefore, we decided to have an exploratory deductive quantitative approach, because of the low coverage of the topic by the literature (Saka, Osademe and Ononokpono, 2023), using a survey as our core strategy. Although a qualitative non-positivist approach would seem to be more fitted to the situation, as we are dealing with intangible human concepts within intangible environments, however, the important piece for us is not to understand what in the person's environment makes them think one way or the other, but rather we are interested in how this impacts the person's reality and what conclusions can be drawn out of it. So, we willingly take a different point of view on the situation.

The data collection and data analysis strategy will be covered in the next chapter.

3.3. DATA COLLECTION METHODS

We focused on the Likert rating scale to reduce biases of interpretation, and allow statistical consistent analysis (Rokeman, 2024). We therefore avoid adding up subjectivity through any kind of opened questions.

We used the Likert probability rating scale: 1 (Not probable), 2 (Somewhat improbable), 3 (Neutral), 4 (Somewhat probable) and 5 (Very probable). We decided not to add the "I do not know" option since the questions are all perception-oriented, therefore we consider that the answers need to be subjective with no "emergency exit".

Below is the list of indicators defined in chapter 2.7. Please see Appendix D01 for a connection between the indicators and the academic theories seen in chapter 2.

Table 3.1 – The list of selected indicators

Family	Indicator – What is according to you the impact of…
Communication	The ability to communicate
	The ability to disengage disputes
	Negative interactions
Internal perceptions	Possible past similar experiences
	Positive/negative beliefs or personal convictions
Internal coping skills	Fears
	Stress
Internal time-oriented strategies	The management of time
	The ability to visualise the future of the startup
Internal accountability	The ability to take responsibility for successes and failures
Internal opinions	The point of view on things
Attitude	Negativity
	Stubbornness
Balance	The ability to have a work/life balance

These indicators will later be prefixed with "Scale" to indicate that those are the Likert-scale indicators. They will be referred to as "the scales", or "human factors" or the 14 indicators, in the rest of this document.

3.3.1. THE FORM ITSELF

The whole form can be found in Appendix F01.

Basic information is collected, like the first name, last name, email address, phone number (for deliverability), country, their age range, their level of knowledge in AI, in communication and in leadership and management.

Then the 14 Likert scales indicators are surveyed for investors and founders, for AI and non-AI ventures. The survey is proposed twice each time, one for success factors, and one for failure factors.

Complementary questions are asked, like the number of members in the board, the number of startups failed and succeeded by the founder, the type of investor (VC, BA, FO or other).

The respondent must check the legal consent check box and sign the form.

3.4. SAMPLE SIZE

We targeted 2438 investors, with 1537 valid email addresses through a cold email sequence (Appendix E01). 58% of them opened the email, and a total of 35 responded (2.27%).

We also targeted 2519 founders, with 1694 valid email addresses through a cold email sequence (Appendix E02). 48% opened the email, with a total of 24 responded (1.42%).

The response rate is somewhat low, but reasonable due to the length of the survey and the probably busy profile of the respondents, with 7 to 9 minutes to fill it.

However, since the sample size raises questions about the reliability of the results, we will cross-check with different statistical methods.

3.5. TYPES OF ANALYSIS ON THE DATASET

This section will present the types of analysis we will implement on the data due to their very nature, as well as the reason for the choice of the given analysis methods.

3.5.1. PEARSON OR SPEARMAN CORRELATIONS

Most data in our dataset are the values based on the Likert scale. Likert scales are generally considered ordinal data, which means that the interval between one value and the next one is not necessarily equal. Although this assumption is subjected to controversy concerning Likert-scales, research seems to favour the use of Spearman Correlations instead of Pearson Correlations, when dealing with those scales (Winter, Gosling and Potter, 2016). The controversy is about whether the Likert scale is indeed ordinal or not. In our case, since the questions are dealing with pure perceptions, with words that do not express clear intervals (VERY probable, SOMEWHAT probable, NEUTRAL), we will follow the recommendations of Winter, Gosling and Potter and use Spearman correlations.

3.5.2. ANOVA OR KRUSKAL-WALLIS FOR SIGNIFICANT DIFFERENCE

The same question appears in the evaluation of significant differences. Likert scales being non-ordinal for our purpose, the use of Kruskal-Wallis appears to be preferred to Anova, according to Koo and Yang (2025). For the same reason we mentioned in the previous subchapter, we will follow Koo and Yang's recommendation and use Kruskal-Wallis.

We need to define a threshold, to decide whether a Kruskal-Wallis result is statistically significant or not. Although subjected to debate in science literature, we will refer to a study providing a scientific basis to use the value 0.05 as a threshold (Andrade, 2019).

In the case there are only two non-ordinal groups, the Mann-Whitney test is commonly preferred, but Kruskal-Wallis with two groups is equivalent to Mann-Whitney, and offers the advantage of allowing to increase the amount of groups (Lachin, 2011). Therefore, we will use the Kruskal-Wallis test even with two groups.

3.5.3. MACHINE LEARNING ANALYSIS

With a dataset of 144 entries, the question arose whether to do machine learning or deep learning analysis of the data.

Small-size datasets may promote overfitting and therefore make false generalizations based on random variations (Charilaou and Battat, 2022). Therefore, we will use exclusively traditional statistical methods (Spearman correlations and Kruskal-Wallis tests) on this dataset, which provide robust and proven results. With a larger dataset, we would have used machine learning to find patterns and correlations in the data and possibly create a predictive model of success for startups. This could be a very interesting further study.

3.5.4. JACKKNIFE RESAMPLING TO CHECK STABILITY

Because of the small dataset, it is useful to check the stability of the most statistically significant results through Jackknife resampling, which (1) reduces biases by recalculating iteratively the p-values or slopes on the complete dataset minus each individual data, (2) and helps detect outliers or unstable results.

3.5.5. COX PROPORTIONAL HAZARDS REGRESSION MODEL

To crosscheck the results, we apply the Cox proportional hazards regression model to confirm or contest the findings. The Cox model is not considered as a Machine Learning model, but is often used as a benchmark in the case of survival analysis involving ML, with similar results (Wang *et al.*, 2022). Therefore, although we will not directly use Machine Learning on our dataset, we will have similar results.

The Cox model is a survival model, especially used in clinical research to evaluate the chances of survival of patients. We will apply it to the survival of the startup, as it will give us precious insights about the factors that could accelerate startup "death" or "survival".

This chapter showed the methodology employed to answer this dissertation's question. The next chapter will discuss the results, and the findings extracted from the answers.

3.6. STEPS TO WORK ON THE RAW DATA

The raw data is accessible exclusively to RKC and UoC for verifications purposes.

The data has been anonymized, streamlined and void cells have been filled (see Appendix F02) within a CSV file.

The curated data has been integrated to Google Colab for analysis, with Python language, to control how data is being. The link to the Colab space can be found in Appendix F03.

3.7. ETHICS

Both surveys were oriented towards professionals (with Linkedin Sales Navigator and Lemlist). Therefore, we had the possibility to contact them directly on their professional email addresses while respecting GDPR rules.

Appendix E03 shows the approved ethics form which details how ethics have been managed throughout the research.

The end of the survey shows the consent form that the participant had to digitally sign (Appendix E04, or Appendix F01 to see the full survey).

Given the length of the survey, a complementary informed consent message has been sent by email to summarize and detail even more the context to the participant, so that they might be fully informed of their rights, as well as the use of their data. Since email deliverability is an issue, the participants has been informed in the survey's consent that they will receive a complementary email.

All the identifiable information has been totally anonymized. The only personal information is the age, and to assure the anonymity, the age has been asked in 10-year increments. The other critical pieces of information are the Likert scale evaluations which are only based on personal perceptions. Therefore, the data used for this research is "safe" regarding personal rights.

3.8. VALIDITY OF THE RESEARCH AND DATA

To ensure the validity of the data, especially dealing with the number of startup success and failure, it was necessary to give a precise definition of startup success and failure (Chapter 2.9) as well as a precise definition of what an AI startup is (Chapter 2.8). This precaution at least prevented false rational evaluations. However, the cognitive biases we mentioned, including the Selective Perception Bias (SPB) may have induced the respondents to wrongly qualify their successes and failures (possibly for example by "hiding" some of their failures). One possibility to limit this risk would have been to do post-survey personal interviews, challenging the answers to help the respondent clarify the reality. However, due to the important length of the survey, this second step would have even further limited the number of respondents. Therefore, we decided to accept the risks connected to human biases, as the most important answers are in the field of individual perception, through the Liker scales.

Moreover, one other constraint we anticipated was the lack of motivation on behalf of founders and investors to answer our survey. We needed to find how to give them enough motivation to invest their time in this research, while maintaining the reliability of the answers. Therefore, the counterparty needed to have a reasonable value to avoid random "self-serving" answers.

We decided to offer to the respondents, whose answers would be valid for the study, an online training which provides value to both investors and founders, which is a "Speed Reading" training. Even though there could have been a risk of complaisant response to get the training, we considered that the profile of the respondents (investors and founders) as opposed to the "low value" of the training, mitigated that risk, while possibly increasing the response rate.

3.9. RELIABILITY OF THE RESEARCH AND DATA

Because of the limited number of responses (144), to validate the reliability of the research, we decided to check the consistency of the Spearman / Kruskal-Wallis results with a Jackknife resampling. For instance, Chapter 4.1.4 shows a stability ratio of 100%.

The worst stability observed was in Chapter 4.4.1 where the impact of failure and success showed a moderate instability.

Therefore, to "double-check" the consistency of the results, we wanted to oppose the previous results with a Cox proportional hazards model which showed overall a 0.8038 concordance index, indicating that the model is able to rank failure risk properly slightly more than 80% of the time.

Therefore, those checks confirm the reliability of the research analysis.

Furthermore, to prevent researcher's biases, which could have led to an "oriented" piece of research, we decided to explore seven different angles related to the data, which are (1) AI versus non-AI startups (Chapter 4.1), founders versus investors (Chapter 4.2), the impacts of age (Chapter 4.3), the impacts of failures and successes (Chapter 4.4), the experience from failed startups (Chapter 4.5), first time founders versus serial founders (Chapter 4.6) and the insights from the Cox proportional hazards regression model (Chapter 4.7).

4. RESULTS, FINDINGS AND ANALYSIS

In this chapter, we will explore the findings stemming from this research and analyse the data collected within the previous chapter.

4.1. AI VERSUS NON-AI STARTUPS

A Spearman Correlation matrix applied individually on AI startups and non-AI startups will be the basis for this section (see Appendix G01).

4.1.1. AI STARTUPS

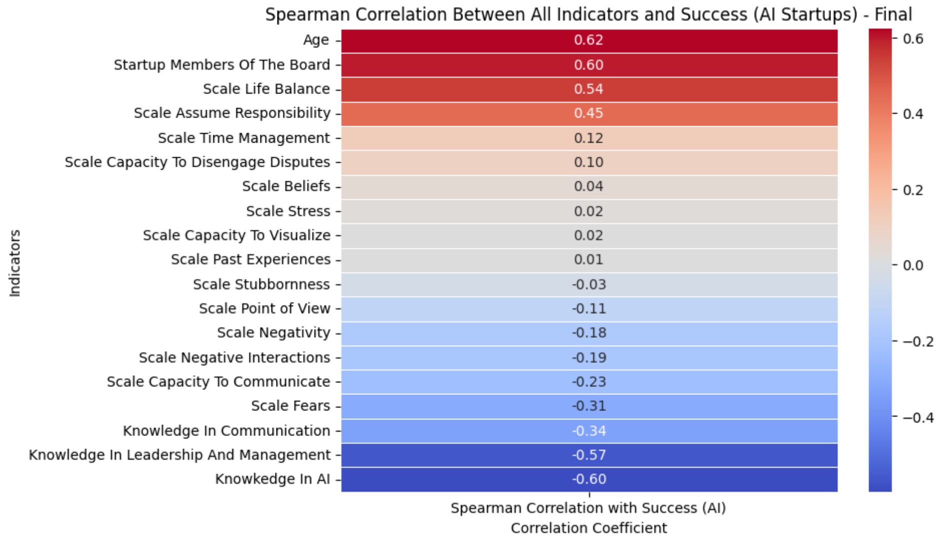


Figure 4.1 – Success for AI startups

We observe that the two most important factors to AI startup success are the age of the founder (0.62) as well as the number of members in the board (0.60). Human factors like the perception of the impact of work/life balance (0.54), assuming responsibility (0.45) and time management (0.12) rank only next.

The importance of the number of members in the board (regardless their quality) for AI startups may be connected to the high stakes leading to the need of securing the startup with more experts.

4.1.2. NON-AI STARTUPS

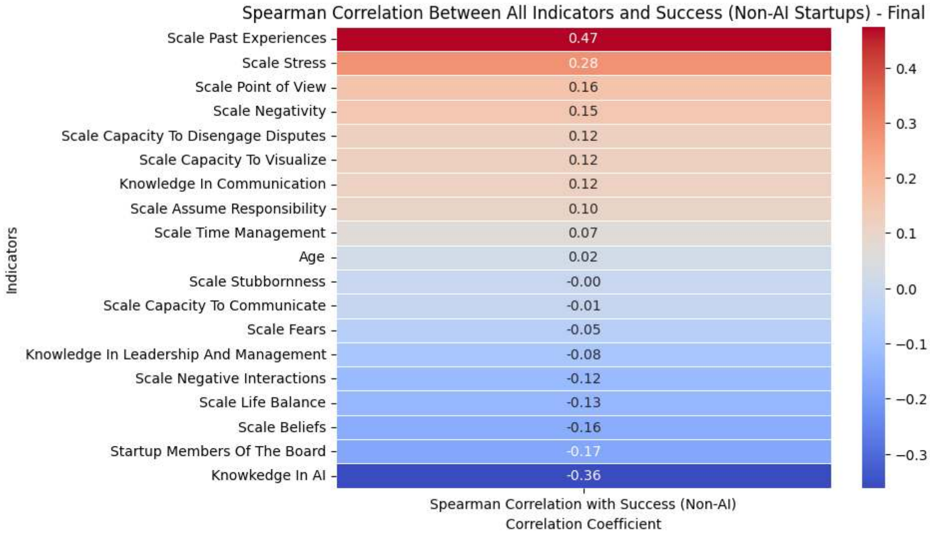


Figure 4.2 – Success for non-AI startups

For non-AI startups, the most prominent influencers are all human factors, like how much the founder values the perception of the impact of past experiences (0.47), then stress (0.28), then the point of view on things (0.16), followed by negativity (0.15) and the capacity to disengage disputes (0.12). This correlates with Pierrakis and Owen (2023) and Miloud et al. (2012) who used past experience to qualify human capital.

4.1.3. ACADEMIC KNOWLEDGE

It is intriguing to notice that for AI startups, the three least important elements for success (with even negative correlations) are the founder's level of knowledge in AI (-0.60), then their knowledge in leadership and management (-0.57) and then their level of knowledge in communication (-0.34).

For non-AI startups, the founder's level of knowledge in AI is also last (-0.36), which is understandable, but there is a positive correlation between success and knowledge in communication (0.12) and almost no correlation with the level of knowledge in leadership and management (-0.08).

Within AI startups, it is plausible that the board has one or more AI experts. We hypothesise that the need for the founder to be well-educated in AI could therefore be reduced.

Concerning the level of knowledge in Leadership and Management or L&M (-0.57 for AI startups and -0.08 for non-AI startups), we are facing an obvious bias as we did not clarify what L&M includes, since it is not only a set of techniques, but also an attitude (mindset). The negative correlation could reflect the fact that the best techniques could be insufficient to counterbalance wrong leadership attitudes.

Knowledge in communication (academic degree, self-learned of none) is also very intriguing, because within AI startups, the correlation to success is negative (-0.34), whereas it is low but positive for non-AI startups (0.12). It seems to indicate that education in communication does not clearly correlate with startup success. Further study could clarify this aspect which may be subjected to biases.

4.1.4. KRUSKAL-WALLIS TEST AND JACKKNIFE RESAMPLING

The Kruskal-Wallis test (Appendix G01) reveals that the only statistically significant difference between AI and non-AI startups to qualify success, with a p-value lower than 0.05, is the number of members in the board (p-value=0.04).

At the first sight, it is complex to draw conclusions about this data because the survey only covers the number of members, not their quality, and this triggers the logical question about quantity versus quality.

We validated the stability of this result by applying a Jackknife resampling, which perfectly fits small datasets. The result offers p-values ranging from 0.0002 to 0.0154, with a 100% stability ratio, which shows that this observation is indeed supported across the whole dataset.

4.2. FOUNDERS VERSUS INVESTORS

In this section, we will focus on the most important perception differences between founders and investors (See Appendix R01).

4.2.1. STARTUP SUCCESS FOR FOUNDERS AND INVESTORS

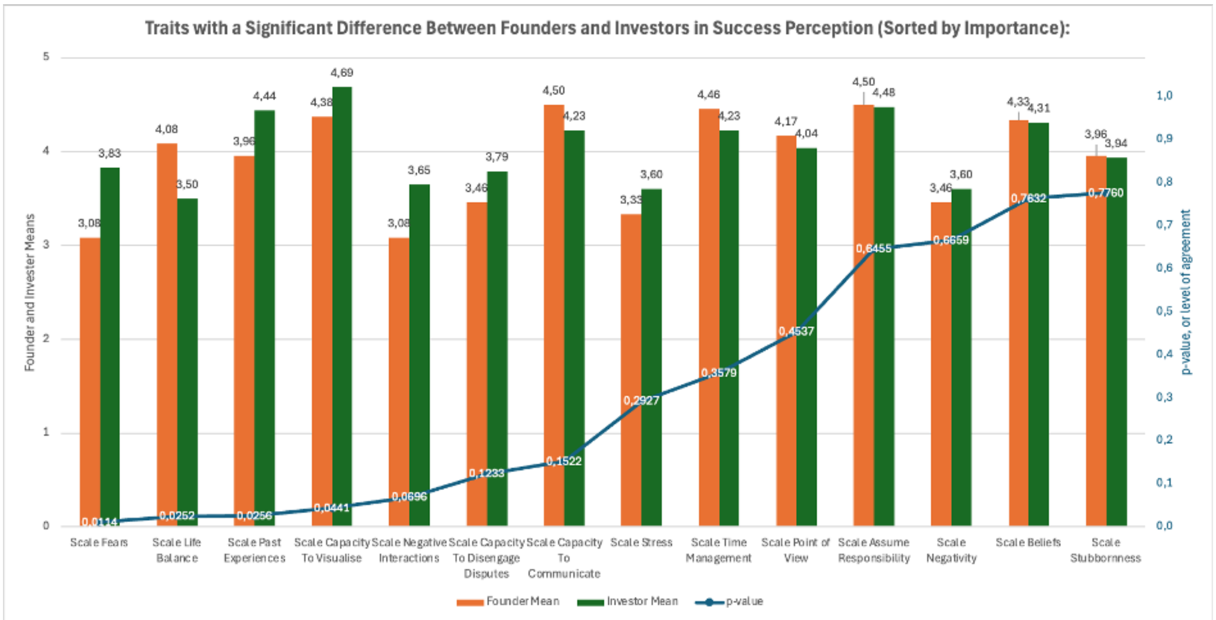


Figure 4.3 – Investors and founders regarding startup success

The Kruskal-Wallis test reveals that investors consider the impact of fear to influence the success of startups significantly more (p-value=0.0114) than founders do.

The next elements that show a statistically significant difference are work/life balance (p-value=0.0252) higher for founders, past experiences (p-value=0.0256) higher for investors, and the capacity to visualise (p-value=0.0441) also higher for investors.

At the opposite of the spectrum, the elements on which investors and founders agree most are the impact of stubbornness (p-value=0.7760) followed by the impact of beliefs (p-value=0.7632) and the impact of negativity (p-value=0.6659).

4.2.2. STARTUP FAILURE FOR FOUNDERS AND INVESTORS

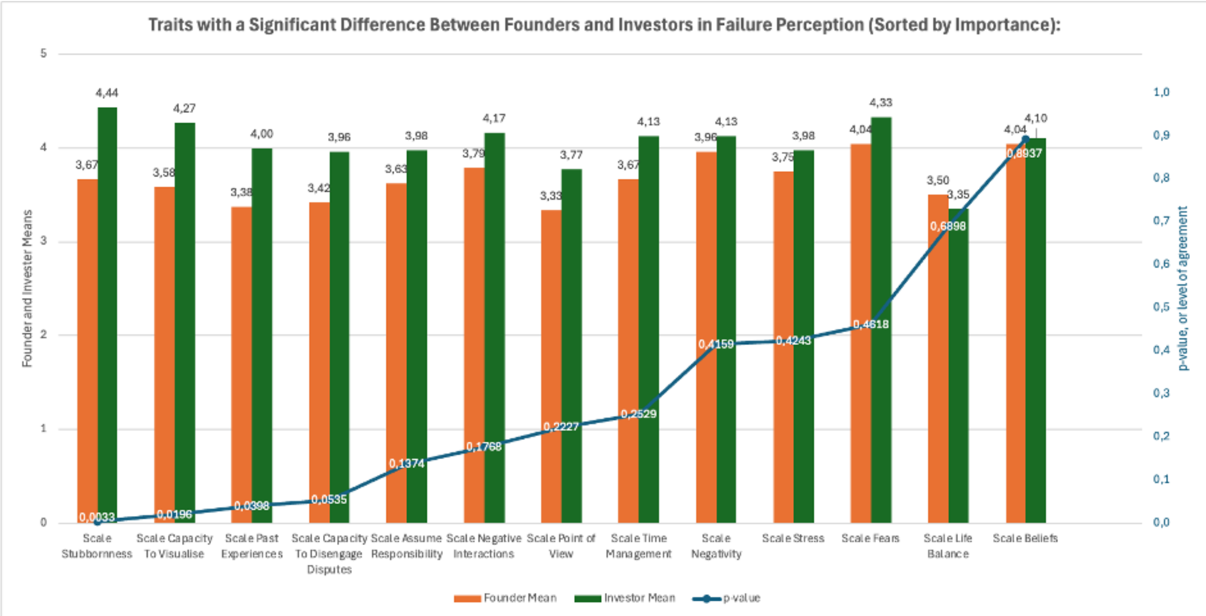


Figure 4.4 – Investors and founders regarding startup failure

Regarding startup failure, investors consider the impact of stubbornness to influence the failure of startups significantly more (p-value=0.0033) than founders do. Then, we find the impact of the capacity to visualise (p-value=0.0196), followed by past experiences (p-value=0.0398).

The elements on which investors and founders agree most are the impact of beliefs (p-value=0.8937), then work/life balance (p-value=0.6898) followed by fears (p-value=0.4618) and stress (p-value=0.4243).

According to Heider's attribution theory, focusing on the fundamental attribution error (chapter 2.2), investors should theoretically attribute the failures to founder's human traits. Therefore, we should expect to see higher evaluations for investors on the indicators. Indeed, in the ranking, the 11 top human indicators are higher on the investor's side, which means that this dataset seems to confirm the fundamental attribution error in the attribution theory.

Similarly, according to the self-serving bias (chapter 2.2), we should see founders attribute their failure to external factors rather than human factors. Therefore, we should see lower evaluations for founders on the indicators, which is exactly the case in this dataset for the 11 top human indicators.

It is also interesting to note that in startup success, investors and founders **most agree** on the perception of stubbornness (maximum p-value of 0.7760): "The founder succeeded because of their persistence". But in the case of a failure, they **most disagree** on the perception of stubbornness (minimum p-value of 0.0033) where the investor considers that the startup failed due to the founder's stubbornness (recalling again the fundamental attribution error), and the founder disagrees about the impact of this personality trait (recalling the self-serving bias).

4.2.3. CORRELATION WITH SUCCESS AND FAILURE

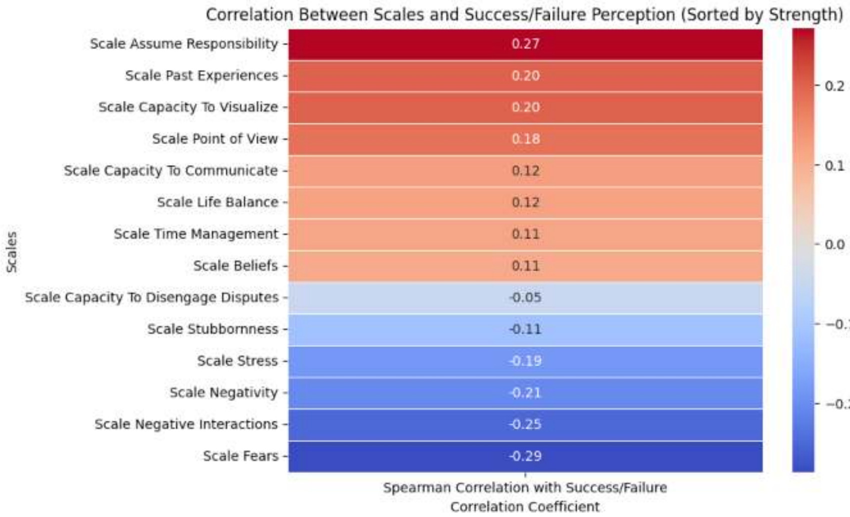


Figure 4.5 – Correlation between scales and success/failure perception

The Spearman correlation shows that among all the indicators, regardless of the nature of the startup and of the profile of the respondent, the four ones which are most correlated to success or failure are the perception of the impact of (1) accountability (0.27 coefficient), (2) past experiences (0.20 coefficient), (3) the capacity to visualise (0.20 coefficient), (4) the point of view on things (0.18 coefficient).

In chapter 2.6, we saw that Pierrakis and Owen (2023) as well as Miloud et al. (2012) used prior experience as the main qualifier of human capital. We suggest that adding accountability to prior experience could lead to better results within the mix of AI and non-AI startups, according to this dataset analysis.

(See the calculation in Appendix R03)

4.2.4. SPLITTING BETWEEN AI AND NON-AI STARTUPS

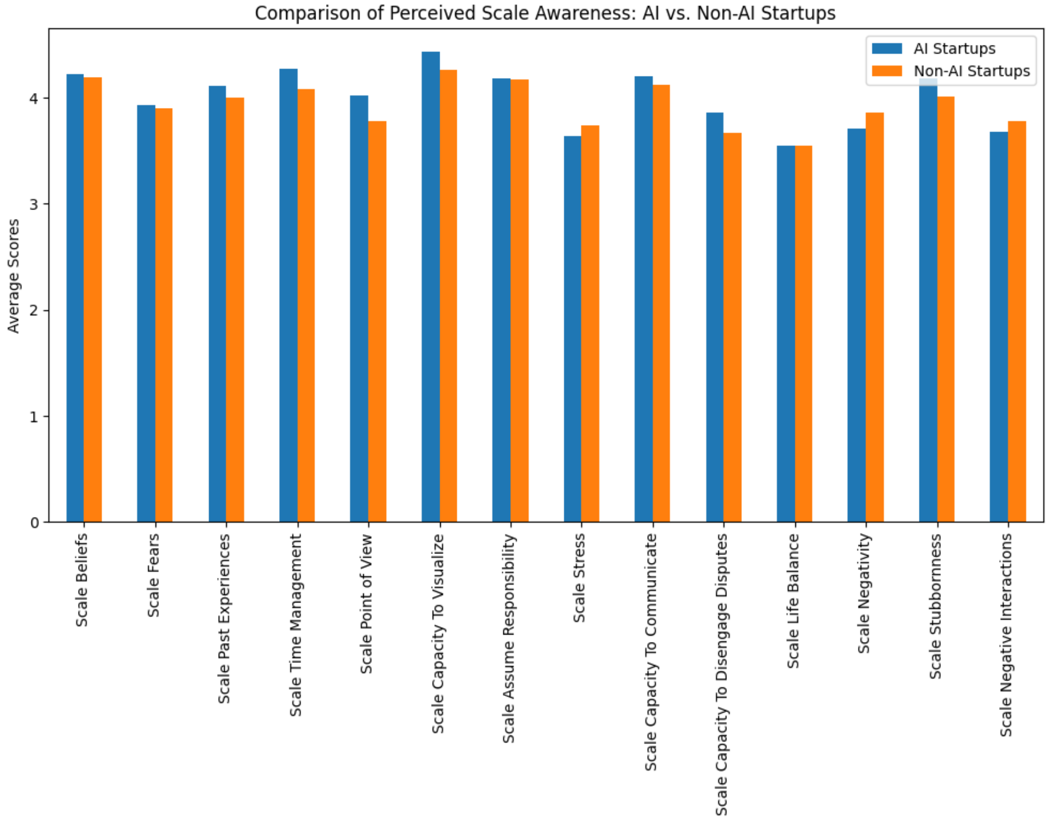


Figure 4.6 – Perceived scale awareness between AI and non-AI startups

When making a distinction between AI and non-AI startups, regardless of success or failure, we can observe that the AI founder is more aware than the non-AI founder on 10 indicators, except for the impact of Stress, negativity, negative interactions and work/life balance.

In the Kruskal-Wallis test (shown in Appendix R07), we find no statistically significant difference between AI and non-AI startups. One criterion is however "on the edge" of being statistically significant, which is the impact of the capacity to visualise (p-value=0.054).

4.3. THE IMPACTS OF AGE

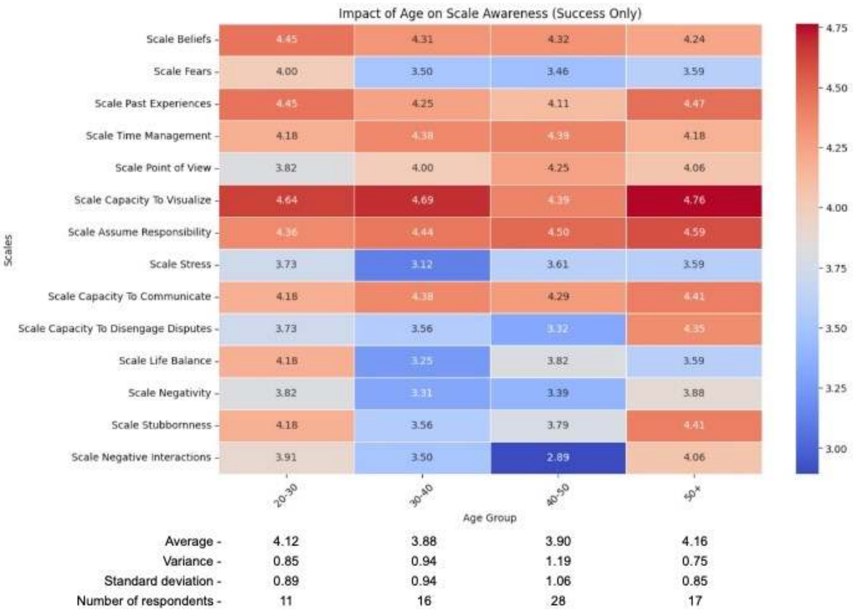


Figure 4.7 – Impacts of age on indicators' awareness for success

Figure 4.7 shows that the average perception of the 14 indicators is highest for the oldest age group (average 4.16 with the lowest standard deviation), followed closely by the youngest age group (average 4.12), however, the standard deviation keeps growing through the age ranges and finally drops to its minimum for the older group. We may conclude that age and experience could contribute to developing a more unanimous opinion about human factors being important.

The lowest average perception is for the 30-40 age group (average 3.88), and then it gradually increases. This may seem contradictory to the common idea that awareness increases with age and experience, as the average curve is U-shaped.

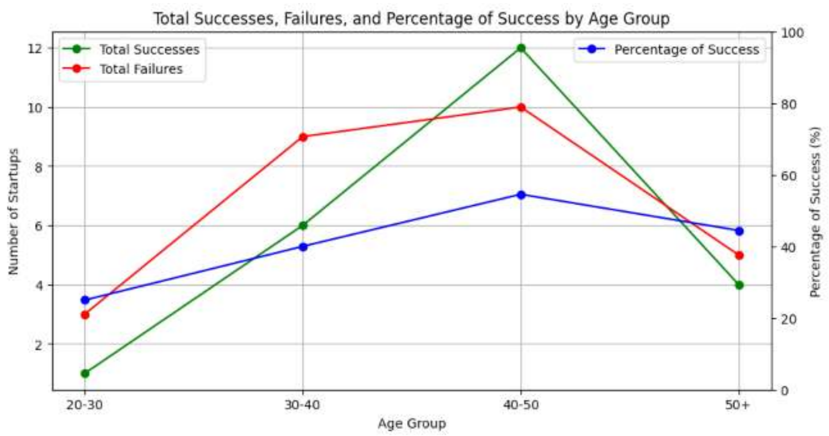


Figure 4.8 – Total successes and failures by age group

The figure above shows that the highest percentage of success (in blue) is reached after the awareness slope we just mentioned (which means at 40-50 years old), when the perception starts to raise again right after having reached its minimum.

The drop of the percentage of success for age group 50+ may be multifactorial. Some reasons may be (1) the Lemlist algorithm that possibly pushes younger people's profiles above older ones, or (2) the fact that older people probably have less opportunities to be funded for their projects, with therefore less successes for non-bootstrapped startups, or (3) the small amount of data points for 50+ years old with only 2 startups, or (4) the paradox that although older people realize more than others the importance of the human factors, still, they are faced with a possible decline in their ability to implement those attitudes and behaviours the right way (Plys *et al.*, 2023) which could in turn explain this paradox.

Please refer to Appendix R04 for detailed calculation.

4.3.1. AI VERSUS NON-AI STARTUPS

Table 4.1 – Age Group Summary Statistics (Success Only)

Age	AI average	Non-AI average
20-30	4.30	4.01
30-40	3.89	3.87
40-50	3.92	3.88
50+	4.29	4.12

It is worth noting, when looking at the differences between AI and non-AI startups (see above or Appendices R08 and R09 for details), that in each age group, AI startups score more in the average perception awareness of our indicators.

Appendix R10 shows that the Kruskal-Wallis test shows no statistically significant difference between AI and non-AI startups.

4.4. IMPACTS OF FAILURES AND SUCCESSES

This section will focus on the impacts of failures and successes over the perception of the 14 indicators. Please refer to Appendix R02 for detailed data.

4.4.1. FAILURES

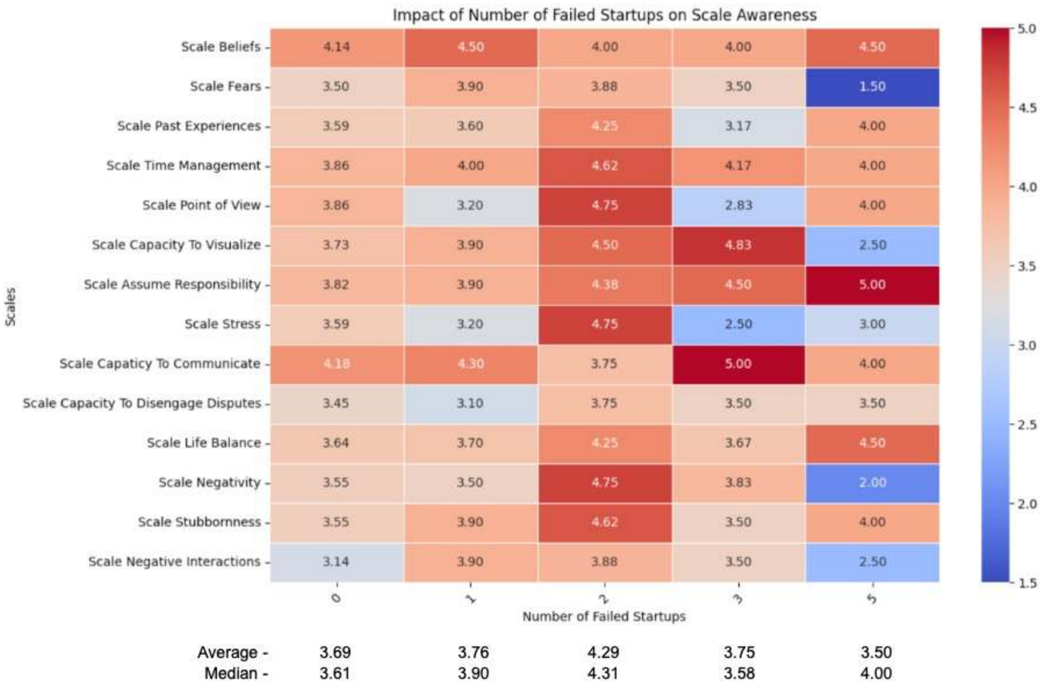


Figure 4.9 – Impact of the number of failed startups on the indicators

Concerning the influence of failures, a paradox appears. On the one hand, we observe that the more they fail, the more they realize the importance of the impact of assuming their own responsibility (this criterion is steadily increasing at each new failure, from 3.82 to 5.00). But on the other hand, the average perception of the 14 indicators increases up to 2 failures (from 3.69 to 4.29) and then decreases systematically with each new failure.

We may formulate three hypotheses to explain this phenomenon.

The first hypothesis is that considering the observation (chapter 4.2.1) that investors diverge most with founders about their stubbornness, this could indicate that after about 2 failures, founders begin to be less congruent or perhaps even “lie to themselves” more.

The second hypothesis is the cognitive dissonance bias, which might be stimulated after a 2 failures and which might entrench the overconfidence bias, as suggested by Szerb and Vörös (2021). This hypothesis would support Gottschalk and Müller (2022) as well as Pretorius and Roux (2011) in their idea that failed experiences do not improve future results.

We conducted a Jackknife resampling test to check the stability of the observation that the third failure decreases the awareness of the indicators. The results confirm that the threshold is at 3 failures. The slope variance on the Jackknife resampling is equal to 0.0366, based on a post-threshold slope of -0.833, which shows moderate instability. The differentiation between AI and non-AI startups provides similar instability (see Appendix R12). Therefore, the third hypothesis is a bias due to the limited quantity of data, because of the moderate instability of the Jackknife test.

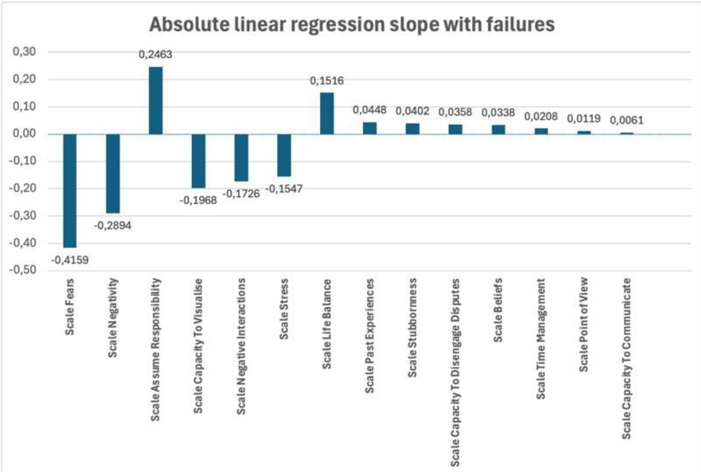


Figure 4.10 – Absolute linear regression slope with failures

As we observe the absolute value of the linear regression slope with increasing failures, we observe that the criteria which evolve most in the case of failures are the perception of the impact of fear (-0.4159 slope), negativity (-0.2894 slope), then assuming responsibility (+0.2463 slope).

4.4.2. SUCCESSES

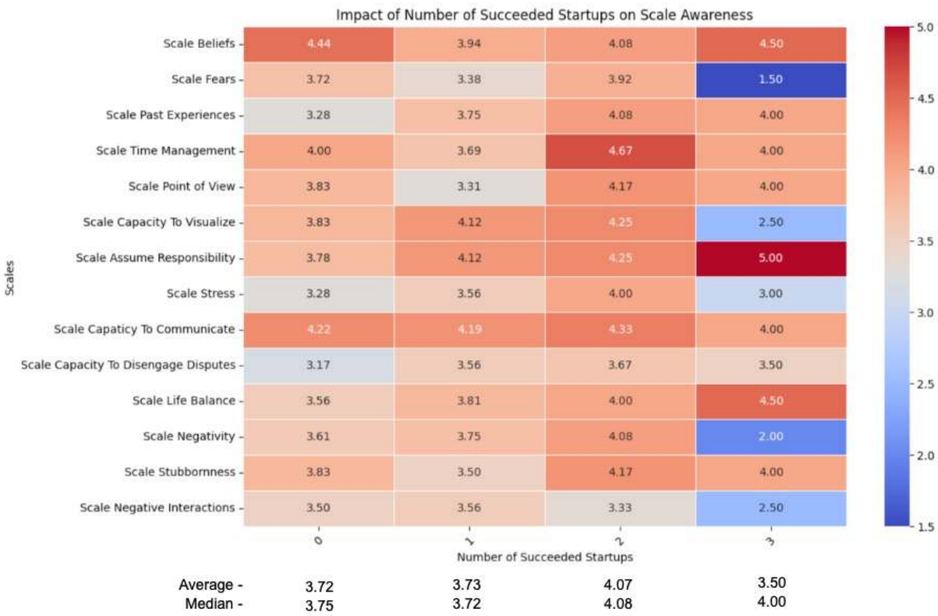


Figure 4.11 – Impact of the number of failed startups on the indicators

Concerning the impact of successes, the same phenomenon appears. Up to 2 successes, the average perception increases, and then, it starts decreasing, while the impact of assuming responsibility grows constantly with every success.

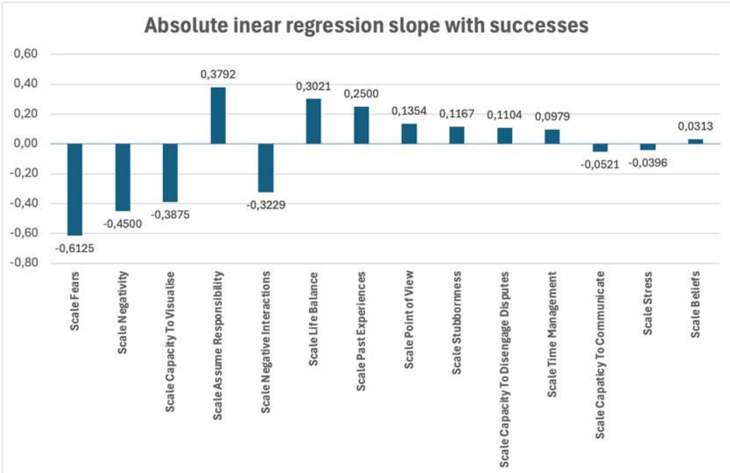


Figure 4.12 – Absolute linear regression slope with successes

In the case of successes, the most impacted indicators are the perception of the impact of fears (-0.6125 slope), then negativity (-0.4500), then the capacity to visualise (-0.3875), and assuming responsibility (+0.3792 slope).

It is interesting to observe that there is a strong similarity between the slopes of the top 5 human factors in the context of successes (Figure 4.12) as well as in the context of failures (Figure 4.10). The same tendencies appear, but with systematically a steeper slope in case of a success.

4.4.3. THE NEGATIVE SLOPE PARADOXES

It may be surprising that the impact of the perception of fear decreases both in failure (-0.4159) as well as in success (-0.6125), but a meta-analysis on fear (Tannenbaum *et al.*, 2015) shows that it is usual to have it decrease even after a negatively-perceived event. Indeed, fear is often connected to unknown situations, and by habituation, a failure becomes less unknown after it happens, therefore fear decreases.

Three other indicators decrease both in success and failure, namely the perception of the impact of negativity, the capacity to visualise and negative interactions. The decrease in case of failure could be understood through the prism of the self-serving bias (chapter 2.2). Since the founder will tend to attribute failures to the external environment, it is understandable that the perception of the impact of those internal factors would decrease through reinforcement, but only up to a point in time when a certain maturity appears (Plys *et al.*, 2023), which is exactly what we observe for the 50+ group, where the perceptions of the impacts of the human factors suddenly increase to their maximum, in agreement with Plys et al (2023).

4.4.4. THE POSITIVE SLOPES

The perception of the impact of assuming responsibility has a positive slope for failure (0.2463) as well as for success (0.3792). This in turn does not comply with Plys et al.'s (2023) observation. We suggest the reason might be directly connected to the self-serving bias (chapter 2.2). By attributing failures to the outside and successes to the inside, the self-serving bias may also be subjected to reinforcement by repetition. A bias, per se, tricks the mind of the person who experiences it. Therefore, it is possible that the more the person attributes the responsibility of their failure to the outside, the more their mind is tricked into believing they are accountable and can safely be even more accountable, since the bias makes them not guilty.

4.4.5. AI VERSUS NON-AI STARTUPS

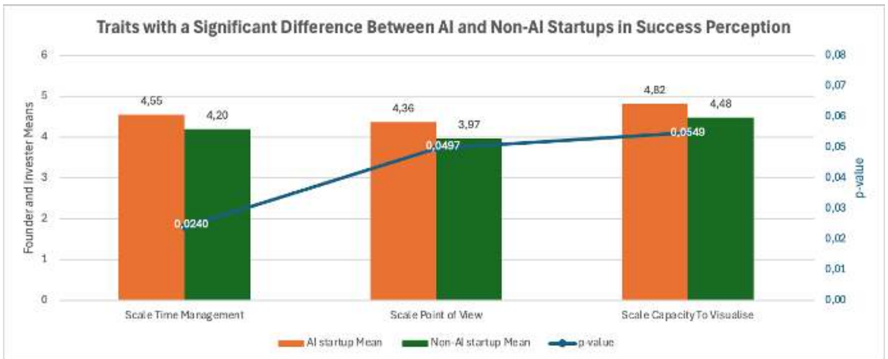


Figure 4.13 – Traits with a Significant Difference Between AI and Non-AI Startups in Success Perception

The Kruskal-Wallis test above (see Appendix R10) shows that in the case of successful startups, the statistically significant difference between AI and non-AI startups are the perception of the impact of time management (p-value=0.0240), then the point of view on things (p-value=0.0497), followed closely by the capacity to visualise (p-value=0.0549). In all those cases, AI startup founders are more sensitive to human factors than non-AI startup founders, as already observed in chapter 4.3.1.

There is no statistically significant difference between AI and non-AI failed startups.

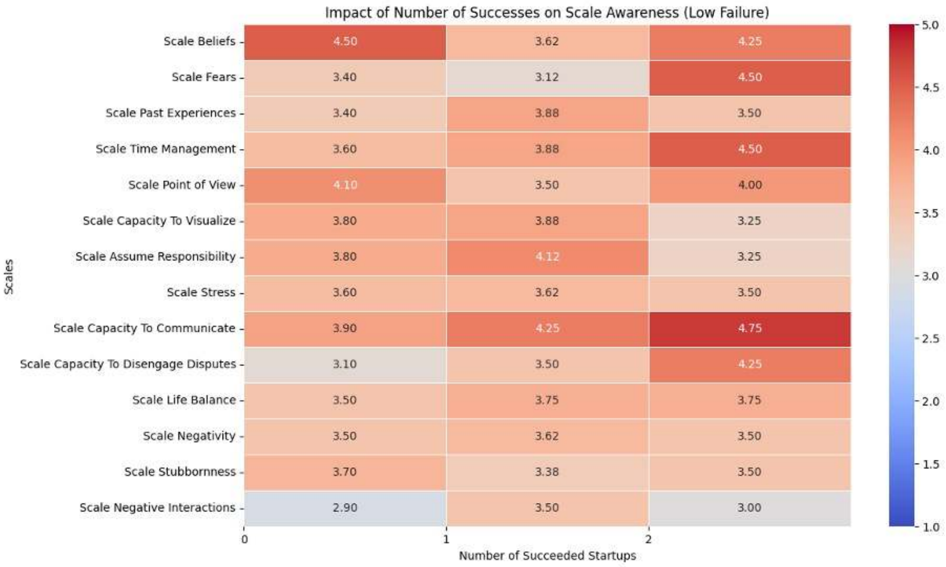
4.5. EXPERIENCE FROM FAILED STARTUPS

It is commonly heard that people learn from their failures. Therefore, we will compare the difference in perceptions for founders who experienced few failures versus more failures. With a smaller granularity, to limit biases, we will dismiss datasets with only 1 or 2 items.

We will split the low and the high-failure groups using the median, to have equivalently sized datasets.

4.5.1. FOUNDERS WITH LOW VERSUS HIGH FAILURE RATES

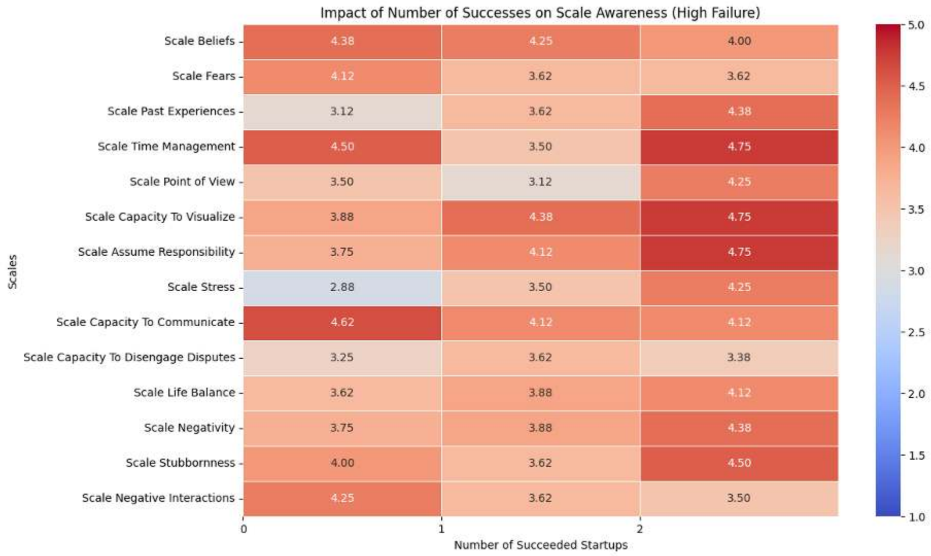
See Appendix R05.



Average -	3.63	3.69	3.82
Median -	4.00	4.00	3.75
Variance -	1.60	1.56	1.44
Standard deviation -	1.24	1.23	1.15
Data points used -	10	8	4

Figure 4.14 – Impact of the number of successes on scale awareness (low failure)

For the low-failure group, each new success systematically increases the average perception of the human factors, while systematically reducing the variance, which shows a converging perspective globally on all the indicators. This seems to confirm that there might be a correlation between successes and the awareness of human factors.



Average -	3.83	3.78	4.20
Median -	4.00	4.00	4.50
Variance -	0.87	1.66	0.89
Standard deviation -	0.91	1.26	0.88
Data points used -	8	8	8

Figure 4.15 – Impact of the number of successes on scale awareness (high failure)

In the case of the high-failure startup group, the pattern changes and may seem paradoxical. Indeed, the first success after several failures reveals a decrease in the perception of the indicators, and a doubling of the variance, which shows a much more mitigated perception about each individual indicator. It is only after the second success that the perception of the impact of the indicators increases, while the variance decreases.

This paradox could be linked to the cognitive dissonance bias, as well as to the "stigma" generated by successive failures which may create a phenomenon of distrust on the first experience. One dissertation clearly shows this precise pattern, but it is only a partial fulfilment of a PhD dissertation (Lee, 2017). Therefore, until academically proven true, we will consider this hypothesis as a supposition.

The high-failure group is, in this dataset, systematically higher than the low-failure group in the perception of human indicators. Each indicator could be the object of a study by itself.

The general Kruskal-Wallis test (see Appendix R06) however reveals that there is no specific indicator that would show a statistically significant difference between low-failure startups and high-failure startups regarding their average perception of human indicators. The increase in the perception is globally homogenous.

4.5.2. AI VERSUS NON-AI STARTUPS

Please refer to Appendix R06 for detailed results.

In the case of AI startups, there is no statistically significant difference between low and high failure startups groups.

However, in the case of non-AI startups, three human indicators stand out, which are the perception of the impact of [1] time management (p-value=0.024), [2] stubbornness (p-value=0.029) and [3] negative interactions (p-value=0.034).

4.6. FIRST TIME FOUNDERS VERSUS SERIAL FOUNDERS

Regardless of the number of failures, we will dive into the difference between first time founders and serial founders. See Appendix R15 for the detailed results.

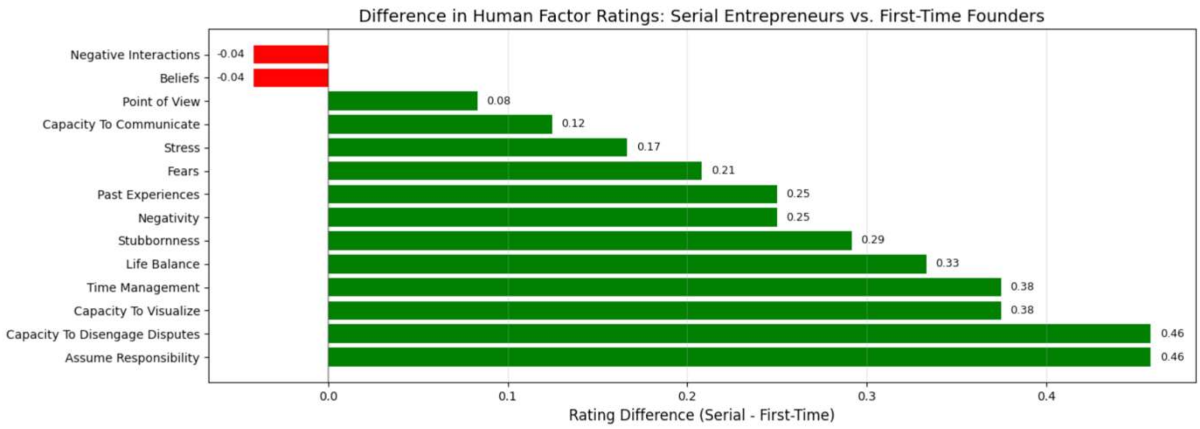


Figure 4.16 – First-time versus serial founders

Figure 4.16 shows in red the human factors rated higher by first-time founders, and in green, the human factors rated higher by serial founders. The graph is based on raw mean differences:

(Difference = $\text{Mean}^{\text{SerialFounder}} - \text{Mean}^{\text{FirstTimeFounder}}$)

We observe a significant shift of perspective as the founder succeeds in their first startup.

First-time founders attach more importance to the impact of negative interactions and beliefs, while serial founders attach more importance to all the other factors, especially assuming responsibility and the capacity to disengage disputes.

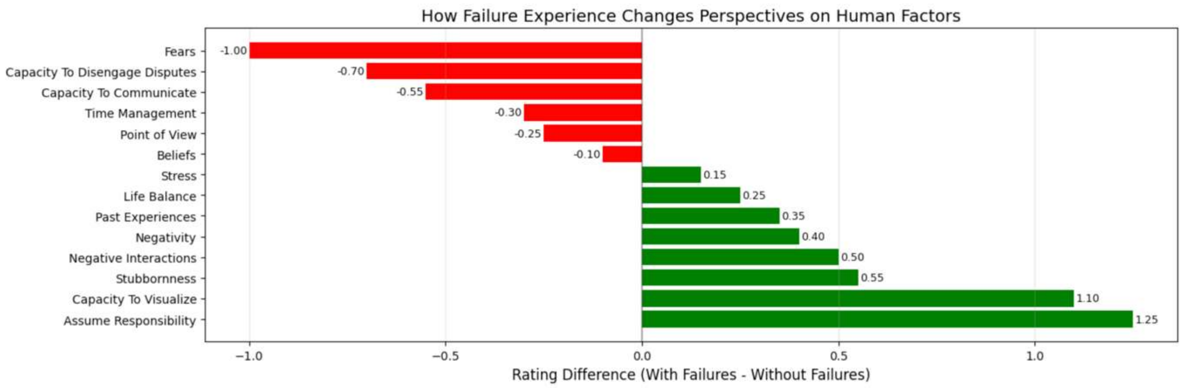


Figure 4.17 – The impact of failure on human factors

Figure 4.17 shows how the perception of the human factors changes after failures occur. Green bars mean founders with failures rated the indicator higher than those without. Red bars mean founders without failures rated the indicator higher than those with failures. (Difference = $\text{Mean}^{\text{HasFailure}} - \text{Mean}^{\text{NoFailure}}$)

We observe that the most impacted human factors when a failure occurs are the perception of the impact of [1] assuming responsibility (+1.25 points), [2] the capacity to visualise (+1.10 points) and [3] fears (-1.00 points).

The difference between AI and non-AI startups could not be calculated due to insufficient data.

4.6.1. HOMOGENEITY AND HETEROGENEITY

Looking closer at Figure 4.16 and Figure 4.17, one can observe two different situations.

One homogeneous example is the impact of assuming responsibility. Serial founders value it much higher than first-time founders (0.46 points). Similarly, failed experiences strongly increase (1.25 points) this indicator, which makes sense.

On the other hand, one heterogenous example is the impact of the capacity to disengage disputes. In Figure 4.16, we can observe that serial founders value it much more than first-time founders (0.46 points), which rationally makes sense. But Figure 4.17 shows that a failure drastically decreases this perception (-0.70 points), which may seem illogical. However, one possible interpretation could be that serial founders learn that avoiding unnecessary disputes may save time and energy, thus increasing the valuation. But those who experience failure might specifically learn that sometimes, confronting problems more directly can be necessary, instead of just disengaging them.

4.6.2. SERIAL FOUNDERS' EMOTIONAL INTELLIGENCE

Serial founders have a higher perception of the impact of accountability (taking responsibility, 0.46 points), visualization (interiorization, 0.38 points) and conflict resolution (0.46 points) for instance, compared to first-time founders, which may create a bridge between success and emotional intelligence. This seems to align with Côté and Miners' (2006) who argue that emotional intelligence can compensate technical gaps in high-stakes environments.

4.7. COX PROPORTIONAL HAZARDS REGRESSION MODEL

See Appendix R13 for details.

The Cox proportional hazards regression model appears to be trustworthy, with a concordance index of 0.8038, which means that it ranks failure risk correctly between startup pairs approximately 80% of the time.

The Cox model focuses on startup survival and confirms the observations made in the previous chapters (see Appendix C01 for the detailed Cox confirmation table).

4.7.1. IMPACT OF HUMAN FACTORS ON STARTUP FAILURE RISK

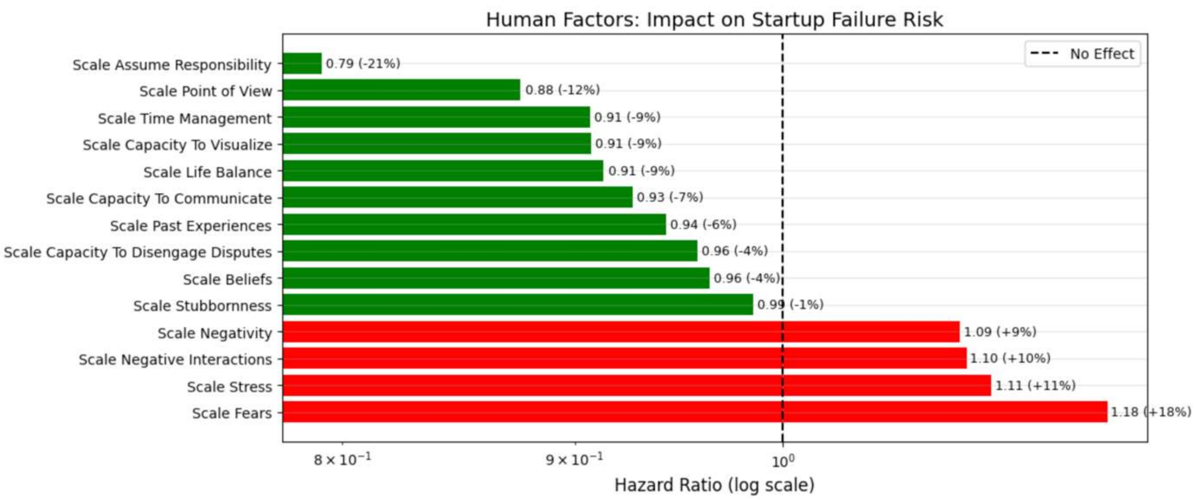


Figure 4.18 – Cox proportional hazards model for startup failure risk

Figure 4.18 offers a clear distinction between what the model considers to be protective factors (lowest green values), as well as risk factors (highest red values) for survival.

It shows that fear represents a 18% higher failure risk factor for startups, stress 11%, and negativity 9 to 10%. On the other hand, assuming responsibility reduces by 21% the risk of failure.

4.7.2. IMPACT OF CONTROL VARIABLES ON STARTUP FAILURE RISK

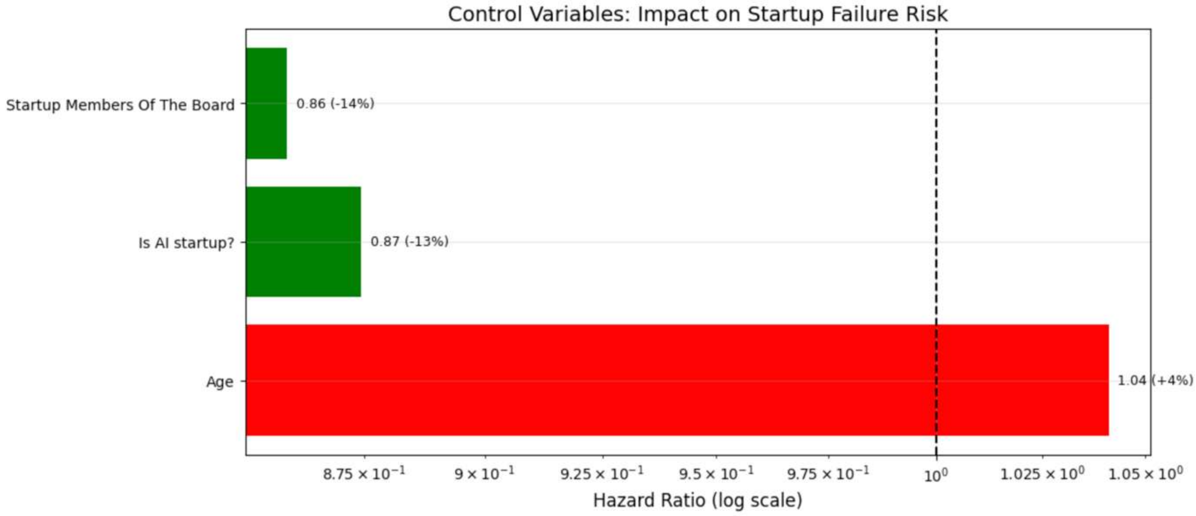


Figure 4.19 – Control variables – Proportional hazards model for startup failure risk

The figure above shows that age is a concrete risk factor for startup survival, whereas the number of members in the board as well as whether the startup is AI oriented are protective.

4.7.3. FAILURE RISK FACTORS FOR AI AND NON-AI STARTUPS

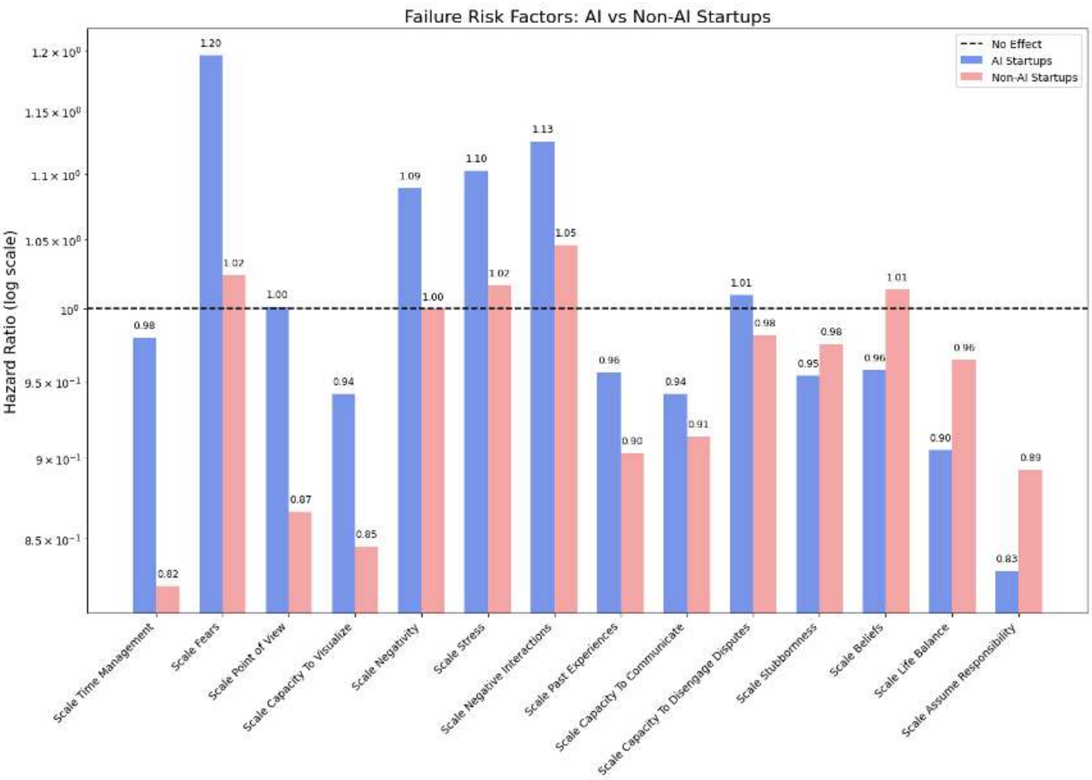


Figure 4.20 – Cox failure risk factors for AI and non-AI startups

Figure 4.20 shows the difference between AI and non-AI startup failure risk factors, ordered by decreasing risk delta. It shows that AI startups are generally more sensitive to human factors for their survival, confirming chapter 4.3.1's observation. On 10 indicators, AI startups show a higher or significantly higher risk factor for failure. Only 4 indicators show a higher risk factor for non-AI startups, namely the impact of assuming responsibility, the impact of work/life balance, the impact of beliefs and the impact of stubbornness.

4.7.4. RELATIVE IMPACT FOR AI VERSUS NON-AI RISK FACTORS

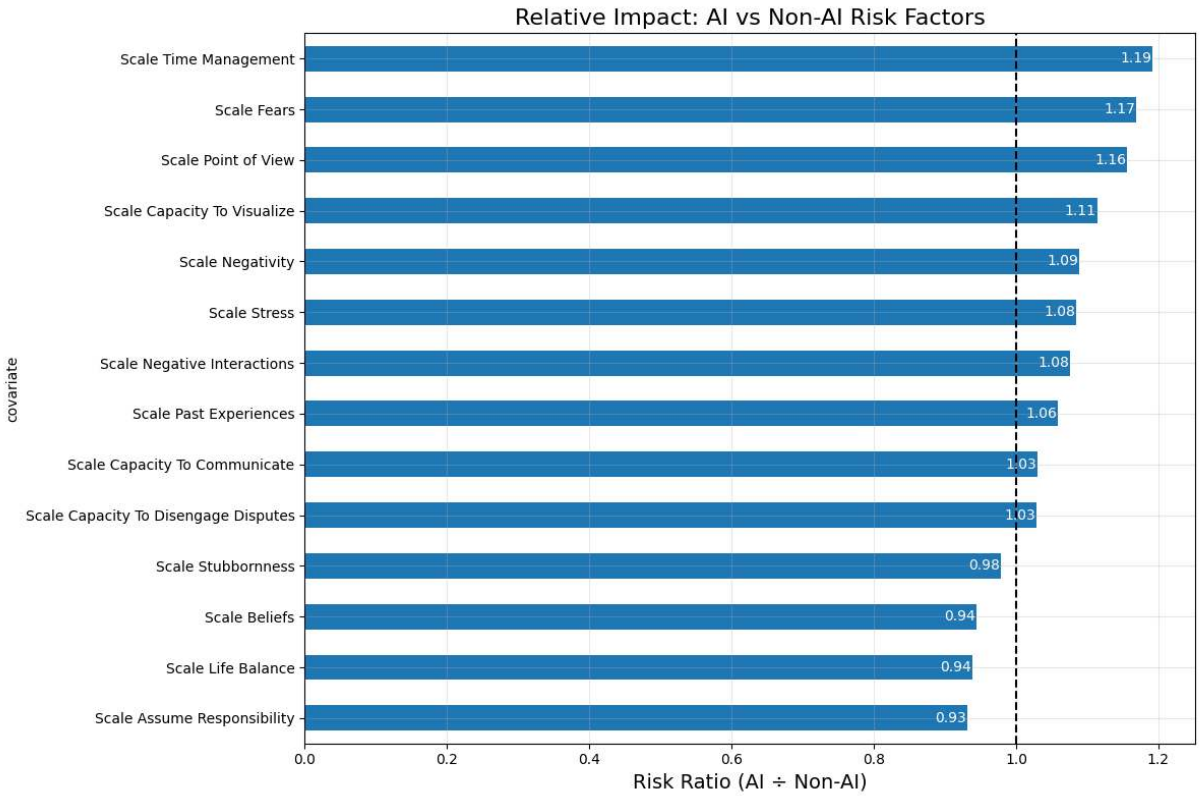


Figure 4.21 – Cox relative impact of AI versus non-AI risk factors

Figure 4.21 presents the relative impact, which is: Hazard ratio for AI startups divided by Hazard ratio for non-AI startups.

Therefore, ratios above 1 represent factors with a stronger impact on AI startup failure risk, and rations below 1 represent factors with a stronger impact on non-AI startup failure risk.

We see that most of the human factors impact AI startups much more than non-AI startups, as confirmed in chapter 4.3.1.

4.7.5. MISALIGNMENT RISK MODEL

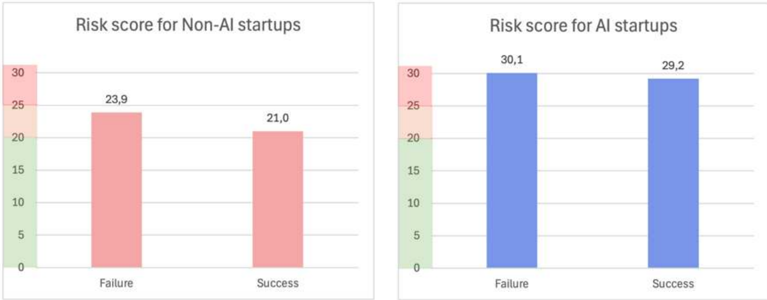


Figure 4.22 – Misalignment risk model

Based on the Cox model, an investment risk model has been calculated (see Appendix R14 for details). The misalignment risk scores can be low (<20), moderate (20-25), or high (>25).

AI startups show a higher perception misalignment risk both for success (29.2>21.0) and failure (30.1>23.9), which indicates a greater potential for conflicts between investors and founders in AI startups, in case of a failure, but also in case of success. This can be understood through the high stakes and valuations, and possibly the human desire to control the outcome which may lead to conflicts.

This could also explain in some ways why AI startups are much more sensitive to human factors for their survival (chapter 4.4.5), and this emphasizes why this dissertation recommends founders to invest in developing their own personal human factors.

4.7.6. AI STARTUPS SPECIFICITY

Table 4.2 – Risk reduction for AI startups

Indicator	p-value	Hazard Ratio exp(coef)	Risk reduction (1 – hazard ratio)
Is AI startup?	0.686095	0.874423	0.125577 (12,56%)

AI startups show 12,56% lower failure risk than non-AI startups (see details in Appendix R13). Although it is not statistically significant (p-value=0.686), this result shows that overall, AI startups have more chances to succeed, despite higher valuations and stakes.

This lower failure risk combined with the higher reliance on human factors for AI startups (Chapter 4.7.3) seems to contradict Kofanov and Zozul`ov's (Kofanov and Zozul`ov, 2018) emphasis on external factors, but it aligns with Roundy's (Roundy, 2022) idea that AI startups are outliers who necessitate more unique human-centric strategies.

5. CONCLUSION

This research addresses a notable gap in understanding how human factors (like fears, beliefs, negativity, etc.) can influence AI and by extension non-AI startup success within the French-speaking ecosystem.

This chapter will recapitulate the proposed research question, aim and objectives. It will then develop the various notable findings that this research produced, and it will present the conclusions stemming from this research.

5.1. RESEARCH QUESTION, AIM AND OBJECTIVES

As startup failure shows a fair estimate of about 90 to 95% (Allen, 2022), academics seem to have shown very little interest about the human aspects that may have influenced those statistics (Duong, 2022). Therefore, the research question stated at the origin of this work was: “To what extent human factors like attitude, beliefs, behaviours, fears or stress may affect the overall success of an AI or non-AI-oriented startup?”

This question led to the aim of exploring the influence of human factors on the success or failure of AI and non-AI startups, by focusing on French speaking founders and investors (who are external observers). The idea was to confront not only the vision on factors leading to success, but also to oppose it with the factors leading to failure and see whether the different perceptions can bring insights to better understand the connection between human factors and success.

Chapter 2 proposes a complete critical literature review to satisfy the first objective (O1). Then, chapter 2.8 defines the difference between an AI and a non-AI startup to satisfy the second objective (O2), while chapter 2.9 clarifies what success and failure are in the context of a startup according to objective O3.

To satisfy the fourth objective (O4), chapter 3 develops a thorough research methodology to study the impact of human factors on startup failure and success in AI and non-AI oriented startups. Then, chapter 3.6 and the following ones describe the collection of the data necessary for objective O5, and finally, chapter 4 consists in critically analysing and proposing interpretations of the data collected, in order to satisfy the final objective (O6).

In order to achieve this research, we targeted 2438 investors, with 1537 valid email addresses through a cold email sequence (Appendix E01). 58% of them opened the email, and a total of 35 responded (2.27%).

We also targeted 2519 founders, with 1694 valid email addresses through a cold email sequence (Appendix E02). 48% opened the email, with a total of 24 responded (1.42%).

The response rate is somewhat low, but sufficient regarding to the length of the survey which takes between 7 and 9 minutes to fill.

5.2. KEY INSIGHTS FROM THE DATA

In line with the original aim, the quantitative analysis of 35 investors and 24 founders revealed several key findings, namely four concerning startups in general, and three concerning specifically AI startups.

5.2.1. INSIGHTS FOR STARTUPS IN GENERAL

The first finding for startups in general (chapter 4.7.1) concerns risk factors and protective factors. Founder's fears increase the risk of startup failure by 18%, agreeing with Dutta and Sobel (2021) as well as Gao et al.'s (2024). Then, stress increases the risk of failure by 11%, just as Drnovšek and Slavec Gomezel's (2022) observed in their research. Furthermore, negativity (negative interactions and negative attitude) increases by 9-10% the risk factor for startup failure, while on the other hand, the most protective human factor for startup success is the founder's accountability (assuming responsibility), which reduces failure risk by 21%. Both of these observations are in agreement with Pan et al. (2022) concerning negativity and accountability.

Should it be an AI startup or a non-AI startup, founders may lower those risks by learning stress management methods, as well as techniques to cope with their own fears and their own negativity, in agreement with the 2023 meta-analysis of 104 peer-reviewed studies which proved that EI is significantly efficient to bring the company better results and improve performance (Coronado-Maldonado and Benítez-Márquez, 2023), as well as improve decision-making processes (Gillioz *et al.*, 2023).

Focusing on the difference between first-time founders and serial-founders, the second finding for startups in general (chapter 4.6) is that serial founders value 12 human indicators out of 14 higher than first-time founders, which emphasizes the importance of considering those human factors as soon as possible within the startup experience through emotional intelligence and resilience.

The third finding (chapter 4.5.1) is that between low-failure and high-failure startups, there is no statistically significant difference in the perception of human factors, which shows in this dataset no particular “learning by negative experience”, in agreement with Pretorius and Roux (2011) who observed similar patterns in their longitudinal study. However, no significant detrimental effect was observed, unlike Gottschalk and Müller (2022).

In this case, Pretorius and Roux (2011) suggested that in order to optimise this process and indeed learn from the past experience, one should give the situation a structured conscious thought and rationally think about what happened. As suggested by their research, this might possibly have a positive impact on startup success.

Finally, the fourth finding for startups in general (chapters 4.4.1 and 4.4.2) shows an apparent pivotal moment after two successes or two failures, where the global perception of the human indicators drops (by 0.54 Likert points in case of failure, and 0.57 Likert points in case of success). This pivotal moment is however questionable as the Jackknife stability test showed only moderate stability. Even though those results are subject to doubt, it seems rational to suggest the founder to pay a little more attention to this specific step when reaching 2 to 3 successes or failures.

5.2.2. INSIGHTS FOR AI STARTUPS SPECIFICALLY

Focusing specifically on AI startups, the first finding is that although AI startups show a 12.56% lower failure risk than non-AI startups (chapter 4.7.6), the data shows that AI startups systematically score higher on the evaluation of the human indicators compared to non-AI startups (chapters 4.2.4, 4.3.1, 4.4.5, 4.7.3 and 4.7.5). This observation is confirmed by the insight that out of 14 human criteria, 10 criteria represent a higher failure risk for AI startups (chapter 4.7.4),

It appears that founders and investors should prioritize emotional intelligence training, especially within AI startups.

The second AI-specific finding (chapter 4.7.5) points to a higher risk of misalignment between founders and investors regarding the perception of the human factors for AI startups (with a high risk of 30.1 points in case of failure and 29.2 points in case of success) compared to non-AI startups (with an average risk of 23.9 points in case of failure and 21.0 points in case of success), which points a particular need of efficient communication in case of AI startups.

Therefore, this research encourages founders to promote collaborative governance, which may lower the risks in high-stakes AI complex environments.

The risk of misalignment also encourages founders to learn and work on a transparent strategic communication strategy with investors, as well as to experience visualizing the future of the startup, according to what even academics call "self-fulfilling prophecies" (Madon *et al.*, 2018) which effects can be detrimental when the protagonist visualises bad stereotypes about the future. As in the case of Mistral valuated at 6 billion dollars one year after its creation (Kharpal, 2024), such valuations may easily trigger conflicts and emotional reactions. Even in the case of successes, some strategies like cleaning the cap table may generate severe conflicts, especially when the personal interests of the founders are at stake.

The third AI-specific finding (chapter 4.1.3) reveals that all human factors correlate to success more (with p-values ranging from -0.31 to +0.62) than the level of academic knowledge in AI (-0.60), in leadership and management (-0.57) or in communication (-0.34).

This also points to the importance of developing emotional intelligence and resilience for founders and investors, since as we observed, its importance has been under-evaluated by research for the benefit of technical and economic aspects.

5.2.3. BRIDGES WITH THE MAIN THEORETICAL MODELS

Chapter 4.2.2 shows that the theoretical patterns hypothesised by Heider's (1958) attribution theory are indeed observed in the dataset of this research, which emphasizes the importance for founders as well as investors to take into account their own cognitive biases. As mentioned in the results, investors tend to prioritize founder attitudes (like stubbornness, or bad management of fear) as failure predictors, while founders consider personal choices like work-life balance as the main failure predictor. Therefore, investors would possibly gain efficiency by using structured frameworks in founder assessment to counter the fundamental attribution bias which clearly appears in this study.

According to research, cognitive biases are apparently not completely avoidable (Berthet, 2022), however, by acknowledging them, it becomes easier to develop shortcuts or heuristics to limit their impact (Martín and Valiña, 2023) and possibly alleviate their negative consequences.

Therefore again, like Pretorius and Roux (2011) suggested, this research recommends each "failing founder" to take a moment to consciously reflect on all the aspects that led them to failure, in order to maximize their learning by experience. Investors are also encouraged to take more into consideration the external factors that led the founders to failure.

5.1. CONCLUSION OF THE RESEARCH

The previous insights lead us to answer positively to the research question, namely that there is a concrete impact of human factors like beliefs, fears, attitudes, stress or behaviours on the overall success of a startup. This research also confirms that there are clear differences between AI and non-AI startups, according to the key insights above.

6. RECOMMENDATION

This research gives rise to several recommendations, which we will classify and order per stake holder.

6.1. RECOMMENDATIONS TO FOUNDERS

The first and foremost recommendation to founders, especially for AI-oriented startups, is to invest in their own emotional intelligence and resilience by learning stress management techniques (possibly reducing by up to 11% the risk of failure), by learning also how to reduce fears (possibly lowering by 18% the risk of failure) and negativity (9 to 10% possible risk reduction), thereby developing behavioural flexibility and limiting the excesses of stubbornness which appeared to be significantly important in this study. This could also help limiting their selective perception bias by changing their internal representations.

The second recommendation to founders is, after every experience (failed or succeeded), to take some time to think about the situation, collect feedback from external sources (to mitigate personal cognitive biases), and assess rationally what internal and what external elements led to the present situation, to compensate for the self-serving bias which is confirmed by this research. A particular attention can be attached to the moment around the second or the third failure which seems to be a specific turning point regarding human factors, according to this research's data.

The third recommendation to founders is to develop strategic communication skills, in order to lower as much as possible the risks of misalignment with investors, should it be in failures, or even in successes.

The fourth recommendation to founders is to promote collaborative governance, which may lower the risks in high-stakes AI complex environments, taking advantage of all the members of the board who have a special importance, especially within AI startups.

6.2. RECOMMENDATIONS TO INVESTORS

The first recommendation to investors is to also train and invest in their emotional resilience and intelligence, to improve their perception of the human indicators and limit the impact of their own cognitive biases, including the over-judgment bias and the selective perception bias, by evolving their own internal perceptions.

The second recommendation to investors is to invest in their own strategic communication skills, to limit the misalignments with founders and alleviate the unnecessary stress levels which contribute to startup failure.

The third recommendation to investors is, after every failure, to take more into consideration the external factors that led the founders to fail. Investors would benefit to make sure they evaluate founders not only through their past experience, but they may also assess to what degree the founder takes responsibility for the situation, as well as the founder's ability to visualise better outcomes, to improve the chances of success. This would allow them to limit the effect of the fundamental attribution error bias.

6.3. FINAL OBSERVATIONS

We can observe that the dataset of this research leads to somewhat similar recommendations to investors and founders. This is why investing in a more efficient collaborative governance will probably be efficient to help improve the startup success levels.

Further research on more specific aspects of human factors would certainly benefit startups as well as investors.

7. EVALUATION OF RESEARCH

7.1. SKILLS DEVELOPMENT

The research process has been extremely valuable for me under several aspects.

First, it helped me develop an academic rigor which is especially necessary in the present era where fake news is omnipresent. In a C-level professional context, fake news is no option, and academic rigor is the last bastion against misinformation.

Second, this process made me realize that there are still a lot of fields where academics have not yet put their attention, which means that there is still a lot of work to do, which is a good thing.

Third, I could clearly understand that even though AI may be a help in many respects, however, it can be a trap in others. Although AI systems have seriously improved, there is still a lot of hallucinations, which showed me that in academic research, even to find relevant papers, it is not mature yet and may lead to errors and false information. As I tried to use it to find information, it took me more time to check and correct what AI was proposing rather than leading the research process personally.

I needed to develop the skill of understanding when AI use is proper and useful, and where it is not. It took a lot of trial and error.

This is an important metaphor to professional fields where one could have the illusion that "AI can do everything" and therefore be led into errors that could be detrimental to the company. As an MBA, I believe this kind of maturity is an absolute advantage.

Fourth, the extremely time-consuming process showed me that time management is indeed a choice. This is a strong lesson in efficiency.

Therefore, I would like again to give my thanks to Robert Kennedy College and the University of Cumbria for having granted me this MBA opportunity.

7.2. LIMITATIONS OF THIS WORK

During this whole work, we observed several limitations that we will describe in this section.

7.2.1. RESEARCH METHOD

Using the survey was interesting since there was little academic history about our subject.

However, surveys provide self-reported perceptions, which may induce biases compared to objective behavioural indicators.

This approach may be faced with the social desirability cognitive bias, which induces that people often talk easier about successes. That is why on everything that was declared in the surveys, there are 23 successes and 27 failures, with a total of success rate of 46% average per founder, as opposed to the 5 to 10% success rate commonly accepted (Allen, 2022).

The gap between our 46% success rate and the commonly accepted 5-10% shows that the results we generated may be biased, due to the complexity of human psychology. We accept however this bias as human psychology is complex.

The training offered to respondents as a compensation for answering the survey might also have attracted participants just interested in the training and not about the content. However, the niche we are addressing (startups and investors) has personal financial interest in the subject of our dissertation. Therefore, we decided to take that risk and assume the maturity of the respondents.

7.2.2. DURATION OF THE STUDY

Initially, we planned one month to let the participants properly answer the survey. However, we did not consider the necessity to send daily reduced batches of emails to ensure email deliverability. Therefore, we distributed the sending of all the emails on a period of one month, plus one month to answer, in the case some possible respondents would be absent or on holidays while receiving the communication. The time period being large, there might have been environmental biases like political changes or social changes that would create different contexts for different respondents. January 2025 was specifically marked by the election of President Donald Trump, with a lot of political changes and possibly fears generated worldwide, which may have generated biases throughout the two months of the surveying.

7.2.3. GEOGRAPHICAL CONSTRAINTS

We initially wanted to search only the French/Swiss startups. Indeed, we noticed that the number of respondents was significatively different, as France was much more represented that Switzerland, and the overall results were too low. Therefore, we decided to extend the scope to French-speaking countries and add Belgium and Luxemburg. We would have saved precious time, had we done this earlier, even though ultimately France represents 68% of respondents, Switzerland 22% and the other countries 10%.

7.2.4. SAMPLE SIZE, SELECTION

If we had to do the work again, instead of targeting about 2500 investors and 2500 founders, we would have doubled the targeting also because of the important number of invalid emails. With a response rate of 2.27% for investors and 1.42% for founders, we would have had sufficient data to conduct all the statistical analysis we wanted and have all the differentiations between AI and non-AI startups.

To conduct machine learning models (others than decision trees), we would have needed either to increase the response rate by limiting the number of questions (which would have limited the scope of our analysis), or to increase the targeting even more.

We did not want to rely on already existing public startup surveys, as we had very specific questions in mind.

The other possible bias was the Lemlist algorithm. We suppose that Lemlist search results are subjected to an algorithm of theirs, which does not give us control over the randomness of the results. This might possibly explain the 46% success rate (chapter 7.2.1) if the algorithm favours successful businesses. However, we contacted Lemlist support who told us that there was no such explicit sorting on top of the criteria the user specifies. We cannot confirm this information as we cannot be sure that the level of information the support has is accurate.

7.3. IMPROVEMENTS

7.3.1. METHODOLOGY IMPROVEMENTS

“Cold surveys” may not give sufficient trust for respondents to reveal their failures. Therefore, a mixed approach with a light survey and an interview may help to build up a trust relationship and learn more about the failures.

Partnering with incubators could help in the trust relationship leading to quality responses. However, another conformity bias may be introduced by this choice, since the incubated startups would already have been pre-filtered by the incubator's internal criteria, on which we would have no control.

Nevertheless, such a partnership could result in broader diffusion of the results of the dissertation, and it could generate more positive changes in the realm of startups.

7.3.2. TARGETING IMPROVEMENTS

Further studies may benefit from a long-term targeting with a longitudinal study. A 5 years tracking of 500-1000 startups and investors would allow the use of complementary machine learning algorithms to possibly improve the predictions even more.

Apart from the targeting, split testing the emails sent to the founders and the investors would allow maximizing the response rates.

7.3.3. RECOMMENDATIONS

We covered specific recommendations stemming from this dissertation in chapter 6 throughout the various subchapters.

However, because of the low success rates of startups, and because of the impact of human factors discovered in this piece of work, we suggest researchers to continue to explore this direction because one startup with the right idea could change the world. Every failing startup is not only a loss for a founder and for an investor, but it may be a loss for the community. It is a shame to imagine that a revolutionary idea could fail not because of technical feasibility, but because of human factors not seen due to cognitive bias blindness. The results of this study, although imperfect due to the many possible biases we identified, give a hope about new research findings on startup success.

Contrary to the studies we quoted which sometimes covered individual human factors separately, we recommend a holistic study based on machine learning to not only gauge the individual impact of human factors, but their systemic interactions.

We also recommend introducing a notion of chronology in further studies. Knowing that one founder failed 3 times and succeeded 4 times is interesting, but very important insights could result from the chronology of those events. Very different conclusions could be drawn from 3 failures followed by 4 successes, and on the other hand 4 successes followed by 3 failures, or any different combination. Such a chronology could really answer to the questions about learning from experience, debated in this dissertation.

7.4. THE POTENTIAL PRACTICAL VALUE OF THE DISSERTATION

The impact of human factors emerging from this dissertation may lead to new areas of research, combining existing academic literature for instance on practical tools which might be used to balance and work on human factors like fears, limiting beliefs, self-confidence, stress, and so on.

This insight may bring positive changes for the founders, as they would put more emphasis on making sure their team and themselves would be more careful about their internal state management.

It could also bring significant changes for the investors who, becoming more sensitive to those aspects within the founding team, could possibly make better decisions based on validated key human elements which may increase the possible success rate.

This research gap deserves to be addressed, while taking fully into account the subjectivity implied by this work.

7.5. FUTURE PERSONAL DEVELOPMENT

Being myself an investor in startups (through equity), this work completely changed my way of handling possible deals. When a startup wants me in their board, I am much more careful to the founding team's human indicators. My relationship with investors has also changed, since after a failure, I tend to challenge them to extract the real causes of the failure, and I do not let them stay with their fundamental attribution error bias concerning the founding team.

I now understand much better what startups, founders and investors need and I can now accompany them much better through emotional intelligence development tools, which I will continue to do, but with much more efficiency after this piece of work.

REFERENCES

Adham, T.K.I. (2023) 'Conflict Resolution in Team: Analyzing the of Conflicts and Best Skills for Resolution', *Scholars Journal of Engineering and Technology*, 11(08), pp. 152–162. Available at: https://doi.org/10.36347/sjet.2023.v11i08.001.

Agnoli, S. *et al.* (2019) 'The Relationship Between Trait Emotional Intelligence, Cognition, and Emotional Awareness: An Interpretative Model', *Frontiers in Psychology*, 10, p. 1711. Available at: https://doi.org/10.3389/fpsyg.2019.01711.

Ahmed, A.E. *et al.* (2022) 'Integrating Psychological Resilience, Stress, and Coping in Entrepreneurship: A Critical Review and Research Agenda', *Entrepreneurship Theory and Practice*, 46(3), pp. 497–538. Available at: https://doi.org/10.1177/10422587211046542.

Allen, G.J. (2022) 'ConceptureallizeTM: a new contribution to generate real-needs-focussed, user-centred, lean business models', *Journal of innovation and entrepreneurship*, 11(1), pp. 6–6. Available at: https://doi.org/10.1186/s13731-022-00198-4.

Almeida, F. and Devedzic, V. (2022) 'The Relevance of Soft Skills for Entrepreneurs', *Journal for East European management studies*, 27(1), pp. 157–172. Available at: https://doi.org/10.5771/0949-6181-2022-1-157.

Andrade, C. (2019) 'The P Value and Statistical Significance: Misunderstandings, Explanations, Challenges, and Alternatives', *Indian Journal of Psychological Medicine*, 41(3), pp. 210–215. Available at: https://doi.org/10.4103/IJPSYM.IJPSYM_193_19.

Ariasari, A.N. and Tjahjono, H.K. (2024) 'Trends and Relationships Between Work-Life Balance and Employee Performance: A Scientometric Analysis', *Society*, 12(2), pp. 294–318. Available at: https://doi.org/10.33019/society.v12i2.703.

Benz, D. and Reinhard, M.-A. (2023) 'Depression, Race-Based Bias, and Judgments of Veracity', *European Journal of Psychology Open* [Preprint]. Available at: https://econtent.hogrefe.com/doi/10.1024/2673-8627/a000040 (Accessed: 5 April 2025).

Berthet, V. (2022) 'The Impact of Cognitive Biases on Professionals' Decision-Making: A Review of Four Occupational Areas', *Frontiers in Psychology*, 12. Available at: https://doi.org/10.3389/fpsyg.2021.802439.

Bessen, J.E. *et al.* (2023) 'The Business of AI Startups'. Rochester, NY: Social Science Research Network. Available at: https://doi.org/10.2139/ssrn.3293275.

Charilaou, P. and Battat, R. (2022) 'Machine learning models and over-fitting considerations', *World Journal of Gastroenterology*, 28(5), pp. 605–607. Available at: https://doi.org/10.3748/wjg.v28.i5.605.

Chen, S. *et al.* (2024) 'Impact of entrepreneurs' prior experience on their new ventures' early-stage performance: the mediation effect of entrepreneurial mindset level', *Frontiers in Organizational Psychology*, 2, p. 1435134. Available at: https://doi.org/10.3389/forgp.2024.1435134.

Chen, Y. *et al.* (2019) 'Testing a Cognitive Control Model of Human Intelligence', *Scientific Reports*, 9, p. 2898. Available at: https://doi.org/10.1038/s41598-019-39685-2.

Christopher Paul (2021) 'The Role of the Fundamental Attribution Error in the Context of

Human Resource Management', *Journal of Psychology Research*, 11(1). Available at: https://doi.org/10.17265/2159-5542/2021.01.002.

Colom, R. (2020) 'Intellectual abilities', *Handbook of Clinical Neurology*, 173, pp. 109–120. Available at: https://doi.org/10.1016/B978-0-444-64150-2.00012-5.

Coronado-Maldonado, I. and Benítez-Márquez, M.-D. (2023) 'Emotional intelligence, leadership, and work teams: A hybrid literature review', *Heliyon*, 9(10), p. e20356. Available at: https://doi.org/10.1016/j.heliyon.2023.e20356.

Côté, S. and Miners, C.T.H. (2006) 'Emotional Intelligence, Cognitive Intelligence, and Job Performance', *Administrative Science Quarterly*, 51(1), pp. 1–28. Available at: https://doi.org/10.2189/asqu.51.1.1.

Dearborn, D.C. and Simon, H.A. (1958) 'Selective Perception: A Note on the Departmental Identifications of Executives', in *Sociometry*, p. 140. Available at: https://doi.org/10.2307/2785898.

Detterman, D.K. (2000) 'General intelligence and the definition of phenotypes', *Novartis Foundation Symposium*, 233, pp. 136–144; discussion 144-148. Available at: https://doi.org/10.1002/0470870850.ch9.

Di Bernardo, I. *et al.* (2021) 'Advances in global services and retail management: Volume 2', *University of South Florida (USF) M3 Publishing*, 5(2021). Available at: https://www.doi.org/10.5038/9781955833035.

Drnovšek, M. and Slavec Gomezel, A. (2022) 'Keep it positive: Exploring the relationship between stress, positive affect, wellbeing, and success of entrepreneurs', *Frontiers in Psychology*, 13, p. 970797. Available at: https://doi.org/10.3389/fpsyg.2022.970797.

Duchesneau, D.A. and Gartner, W.B. (1990) 'A profile of new venture success and failure in an emerging industry', *Journal of Business Venturing*, 5(5), pp. 297–312. Available at: https://doi.org/10.1016/0883-9026(90)90007-G.

Duong, C.D. (2022) 'Entrepreneurial fear of failure and the attitude-intention-behavior gap in entrepreneurship: A moderated mediation model', *The international journal of management education*, 20(3), pp. 100707-. Available at: https://doi.org/10.1016/j.ijme.2022.100707.

Dutta, N. and Sobel, R.S. (2021) 'Entrepreneurship, fear of failure, and economic policy', *European Journal of Political Economy*, 66, pp. 101954-. Available at: https://doi.org/10.1016/j.ejpoleco.2020.101954.

Edwards, A. and Edwards, C. (2022) 'Does the Correspondence Bias Apply to Social Robots?: Dispositional and Situational Attributions of Human Versus Robot Behavior', *Frontiers in Robotics and AI*, 8, p. 788242. Available at: https://doi.org/10.3389/frobt.2021.788242.

Fadare, S.A. *et al.* (2022) 'A Voyage into the Visualization of Athletic Performances: A Review | American Journal of Multidisciplinary Research and Innovation'. Available at: https://journals.e-palli.com/home/index.php/ajmri/article/view/479 (Accessed: 6 April 2025).

Fei, N. *et al.* (2022) 'Towards artificial general intelligence via a multimodal foundation model', *Nature Communications*, 13(1), p. 3094. Available at: https://doi.org/10.1038/s41467-022-30761-2.

Fernández-Berrocal, P. and Checa, P. (2016) ‘Editorial: Emotional Intelligence and Cognitive Abilities’, *Frontiers in Psychology*, 7, p. 955. Available at: https://doi.org/10.3389/fpsyg.2016.00955.

Filippis, R. de and Foysal, A.A. (2024) ‘Decoding Emotions: How AI and Machine Learning Unravel the Human Psyche’, *Voice of the Publisher*, 10(4), pp. 382–399. Available at: https://doi.org/10.4236/vp.2024.104030.

Freiberg, B. and Matz, S.C. (2023) ‘Founder personality and entrepreneurial outcomes: A large-scale field study of technology startups’, *Proceedings of the National Academy of Sciences*, 120(19), p. e2215829120. Available at: https://doi.org/10.1073/pnas.2215829120.

Gallup, Inc. (2024) *Global Emotions Report*, *Global Emotions Report*. Available at: https://www.gallup.com/analytics/349280/gallup-global-emotions-report.aspx (Accessed: 6 July 2024).

Gao, Y. *et al.* (2024) ‘Entrepreneurial fear of failure among college students: A scoping review of literature from 2010 to 2023’, *Heliyon*, 10, p. e31072. Available at: https://doi.org/10.1016/j.heliyon.2024.e31072.

Gillioz, C. *et al.* (2023) ‘Emotional intelligence and emotion information processing: Proof of concept of a test measuring accuracy in discriminating emotions’, *Frontiers in Psychology*, 14. Available at: https://doi.org/10.3389/fpsyg.2023.1085971.

Gottschalk, S. and Müller, B. (2022) ‘A second chance for failed entrepreneurs: a good idea?’, *Small Business Economics*, 59(2), pp. 745–767. Available at: https://doi.org/10.1007/s11187-021-00584-4.

Grichnik, D., Smeja, A. and Welpe, I. (2010) ‘The importance of being emotional: How do emotions affect entrepreneurial opportunity evaluation and exploitation?’, *Journal of economic behavior & organization*, 76(1), pp. 15–29. Available at: https://doi.org/10.1016/j.jebo.2010.02.010.

Hastorf, A.H. and Cantril, H. (1954) ‘They saw a game: a case study’, *Journal of Abnormal Psychology*, 49(1), pp. 129–134. Available at: https://doi.org/10.1037/h0057880.

Heider, F. (1958) *The Psychology of Interpersonal Relations*. Psychology Press.

Hengen, K.M. and Alpers, G.W. (2021) ‘Stress Makes the Difference: Social Stress and Social Anxiety in Decision-Making Under Uncertainty’, *Frontiers in Psychology*, 12. Available at: https://doi.org/10.3389/fpsyg.2021.578293.

Jorzik, P. *et al.* (2024) ‘AI-driven business model innovation: A systematic review and research agenda’, *Journal of Business Research*, 182, p. 114764. Available at: https://doi.org/10.1016/j.jbusres.2024.114764.

Jung, Y.-H. *et al.* (2019) ‘Relationships among stress, emotional intelligence, cognitive intelligence, and cytokines’, *Medicine (Baltimore)*, 98(18), pp. e15345–e15345. Available at: https://doi.org/10.1097/MD.0000000000015345.

Kee, D.M.H. and Rahman, N.A. (2020) ‘How to Measure Start-Up Success? A Systematic Review from a Multidimensional Perspective’. Rochester, NY: Social Science Research Network. Available at: https://doi.org/10.2139/ssrn.3638863.

Keogh, D., K.N. Johnson, D., and Ph.D., Professor of Economics, Colorado College, Department of Economics and Business, 14 E Cache la Poudre Street, Colorado Springs, CO 80903, USA, e-mail: djohnson@coloradocollege.edu (2021) 'Survival of the funded: Econometric analysis of startup longevity and success', *Journal of Entrepreneurship, Management and Innovation*, 17(4), pp. 29–49. Available at: https://doi.org/10.7341/20211742.

Kharpal, A. (2024) *Microsoft-backed Mistral AI raises $645 million at a $6 billion valuation, CNBC*. Available at: https://www.cnbc.com/2024/06/12/mistral-ai-raises-645-million-at-a-6-billion-valuation.html (Accessed: 20 September 2024).

Kiefl, S., Fischer, S. and Schmitt, J. (2024) 'Self-employed and stressed out? The impact of stress and stress management on entrepreneurs' mental health and performance', *Frontiers in Psychology*, 15. Available at: https://doi.org/10.3389/fpsyg.2024.1365489.

Kofanov, O. and Zozul`ov, O. (2018) 'Successful development of startups as a global trend of innovative socio-economic transformations', *International and Multidisciplinary Journal of Social Sciences*, 7(2), pp. 191–217. Available at: https://doi.org/10.17583/rimcis.2018.3576.

Koo, M. and Yang, S.-W. (2025) 'Likert-Type Scale', *Encyclopedia*, 5(1), p. 18. Available at: https://doi.org/10.3390/encyclopedia5010018.

Lachin, J.M. (2011) 'Power and sample size evaluation for the Cochran-Mantel-Haenszel mean score (Wilcoxon rank sum) test and the Cochran-Armitage test for trend', *Statistics in Medicine*, 30(25), pp. 3057–3066. Available at: https://doi.org/10.1002/sim.4330.

Le Roy, B., Martin-Krumm, C. and Trousselard, M. (2023) 'Mindfulness for adaptation to analog and new technologies emergence for long-term space missions', *Frontiers in Space Technologies*, 4. Available at: https://doi.org/10.3389/frspt.2023.1109556.

Lee, C.K. (2017) 'BUSINESS FAILURE AND ENTREPRENEURSHIP: THREE ESSAYS ON THE EFFECTS OF THE COST OF FAILURE'.

Lichtinger, Y., Engelen, A. and Teubner, T. (2023) 'Time and timing in entrepreneurship research: insights from a systematic literature review', *International Journal of Innovation Management*, 27(01n02), p. 2330001. Available at: https://doi.org/10.1142/S1363919623300015.

Lim, W.M. (2024) 'What Is Quantitative Research? An Overview and Guidelines', *Australasian Marketing Journal*, p. 14413582241264622. Available at: https://doi.org/10.1177/14413582241264622.

Liu, X. *et al.* (2023) 'Influence of entrepreneurial team knowledge conflict on ambidextrous entrepreneurial learning— a dual-path perspective of entrepreneurial resilience and fear of failure', *Journal of Innovation & Knowledge*, 8(3). Available at: https://doi.org/10.1016/j.jik.2023.100389.

Madon, S. *et al.* (2018) 'The accumulation of stereotype-based self-fulfilling prophecies.', *Journal of Personality and Social Psychology*, 115(5), pp. 825–844. Available at: https://doi.org/10.1037/pspi0000142.

Martín, M. and Valiña, M.D. (2023) 'Heuristics, Biases and the Psychology of Reasoning: State of the Art', *Psychology*, 14(2), pp. 264–294. Available at: https://doi.org/10.4236/psych.2023.142016.

McCarthy, P.X. *et al.* (2023) 'The impact of founder personalities on startup success', *Scientific Reports*, 13, p. 17200. Available at: https://doi.org/10.1038/s41598-023-41980-y.

Men, L.R., Qin, Y.S. and Mitson, R. (2021) 'Engaging Startup Employees via Charismatic Leadership Communication: The Importance of Communicating "Vision, Passion, and Care"', *International journal of business communication (Thousand Oaks, Calif.)*, pp. 232948842110204-. Available at: https://doi.org/10.1177/23294884211020488.

Mezulis, A.H. *et al.* (2004) 'Is there a universal positivity bias in attributions? A meta-analytic review of individual, developmental, and cultural differences in the self-serving attributional bias', *Psychological Bulletin*, 130(5), pp. 711–747. Available at: https://doi.org/10.1037/0033-2909.130.5.711.

Miller, J.G. (1984) 'Culture and the Development of Everyday Social Explanation', *Journal of Personality and Social Psychology*, 46(5), pp. 961–978.

Miloud, T., Aspelund, A. and Cabrol, M. (2012) 'Startup valuation by venture capitalists: an empirical study', *Venture capital (London)*, 14(2–3), pp. 151–174. Available at: https://doi.org/10.1080/13691066.2012.667907.

Murphy, M.C. and Reeves, S.L. (2019) 'Personal and organizational mindsets at work', *Research in Organizational Behavior*, 39, p. 100121. Available at: https://doi.org/10.1016/j.riob.2020.100121.

Narimisaei, J. *et al.* (2024) 'Exploring emotional intelligence in artificial intelligence systems: a comprehensive analysis of emotion recognition and response mechanisms', *Annals of Medicine and Surgery*, 86(8), pp. 4657–4663. Available at: https://doi.org/10.1097/MS9.0000000000002315.

Nigam, N., Mbarek, S. and Boughanmi, A. (2021) 'Impact of intellectual capital on the financing of startups with new business models', *Journal of knowledge management*, 25(1), pp. 227–250. Available at: https://doi.org/10.1108/JKM-11-2019-0657.

Pan, L.-Y. *et al.* (2022) 'Entrepreneurial business start-ups and entrepreneurial failure: How to stand up after a fall?', *Frontiers in Psychology*, 13, p. 943328. Available at: https://doi.org/10.3389/fpsyg.2022.943328.

Paresashvili, N. and Avsajanishvili, E. (2023) 'Stress as a Method of Increasing Performance and Stimulating Innovation: A Synthesis of Literature', *Economics and Business*, 37, pp. 236–246. Available at: https://doi.org/10.2478/eb-2023-0015.

Park, H. *et al.* (2024) 'Confirmation Bias through Selective Use of Evidence in Human Cortex', *bioRxiv*, p. 2024.06.21.600060. Available at: https://doi.org/10.1101/2024.06.21.600060.

Petrides, K.V. and Furnham, A. (2003) 'Trait emotional intelligence: Behavioural validation in two studies of emotion recognition and reactivity to mood induction', *European Journal of Personality*, 17(1), pp. 39–57. Available at: https://doi.org/10.1002/per.466.

Pierrakis, Y. and Owen, R. (2023) 'Startup ventures and equity finance: How do Business Accelerators and Business Angels' assess the human capital of socio-environmental mission led entrepreneurs?', *Innovation (North Sydney)*, 25(4), pp. 371–395. Available at: https://doi.org/10.1080/14479338.2022.2029706.

Pluut, H., Curşeu, P.L. and Fodor, O.C. (2022) 'Development and Validation of a Short Measure of Emotional, Physical, and Behavioral Markers of Eustress and Distress (MEDS)', *Healthcare*, 10(2), p. 339. Available at: https://doi.org/10.3390/healthcare10020339.

Plys, E. *et al.* (2023) 'Psychological flexibility in older adulthood: a scoping review', *Aging & Mental Health*, 27(3), pp. 453–465. Available at: https://doi.org/10.1080/13607863.2022.2036948.

Pollman, E. (2023) 'Startup Failure'. Rochester, NY: Social Science Research Network. Available at: https://papers.ssrn.com/abstract=4535089 (Accessed: 9 April 2025).

Pretorius, M. and Roux, I. le (2011) 'Successive failure, repeat entrepreneurship and no learning: A case study', *SA Journal of Human Resource Management*, 9(1), pp. e1–e13. Available at: https://doi.org/10.4102/sajhrm.v9i1.236.

Pronin, E., Lin, D.Y. and Ross, L. (2002) 'The Bias Blind Spot: Perceptions of Bias in Self Versus Others', *Personality and Social Psychology Bulletin*, 28(3), pp. 369–381. Available at: https://doi.org/10.1177/0146167202286008.

Qiu, Q. and Jiang, L. (2021) 'Firms can benefit from inaccurate market beliefs', *Operations research letters*, 49(1), pp. 150–156. Available at: https://doi.org/10.1016/j.orl.2020.12.006.

Rogoff, E.G., Lee, M.-S. and Suh, D.-C. (2004) '"Who Done It?" Attributions by Entrepreneurs and Experts of the Factors that Cause and Impede Small Business Success', *Journal of Small Business Management*, 42(4), pp. 364–376.

Rokeman, N.R.M. (2024) 'Likert Measurement Scale in Education and Social Sciences: Explored and Explained', *EDUCATUM Journal of Social Sciences*, 10(1), pp. 77–88. Available at: https://doi.org/10.37134/ejoss.vol10.1.7.2024.

Ross, L. (1977) 'The Intuitive Psychologist And His Shortcomings: Distortions in the Attribution Process1', in L. Berkowitz (ed.) *Advances in Experimental Social Psychology*. Academic Press, pp. 173–220. Available at: https://doi.org/10.1016/S0065-2601(08)60357-3.

Roundy, P.T. (2022) 'Artificial intelligence and entrepreneurial ecosystems: understanding the implications of algorithmic decision-making for startup communities', *Journal of Ethics in Entrepreneurship and Technology*, 2(1), pp. 23–38. Available at: https://doi.org/10.1108/JEET-07-2022-0011.

Safira, M. *et al.* (2023) 'The implementation of attribution theory in leadership: a systematical literature review', *Brazilian Journal of Development*, 9(12), pp. 31872–31885. Available at: https://doi.org/10.34117/bjdv9n12-088.

Saka, R.O., Osademe, G.C. and Ononokpono, N.J. (2023) 'Exploratory Research Design in Management Science: A Review of Literature on Conduct and Application', *International Journal of Research and Innovation in Social Science* [Preprint]. Available at: https://doi.org/10.47772/IJRISS.2023.7515.

Salovey, P. and Mayer, J. (1990) 'Emotional intelligence', *Imagination, Cognition, and Personality* [Preprint]. Available at: https://doi.org/https://dx.doi.org/10.2190/DUGG-P24E-52WK-6CDG.

Scalabrini, A. *et al.* (2023) 'In Between the Psychological and Physiological Self – The

Impact of Covid-19 Pandemic on the Neuro-Socio-Ecological and Inflammatory Mind-Body-Brain System', *Clinical Neuropsychiatry*, 20(4), pp. 342–350. Available at: https://doi.org/10.36131/cnfioritieditore20230414.

Sharma, M.K. *et al.* (2022) 'COVID-19 Pandemic, Risk, and Blame Attributions: A Scoping Review', *Indian Journal of Psychological Medicine*, 44(3), pp. 227–233. Available at: https://doi.org/10.1177/02537176221091675.

Shore, A., Pittaway, L. and Bortolotti, T. (2024) 'From Negative Emotions to Personal Growth: Failure and Re-entry into Entrepreneurship', *British Journal of Management*, 35(4), pp. 1781–1797. Available at: https://doi.org/10.1111/1467-8551.12785.

Si, X.W., Yang, Z.K. and Feng, X. (2024) 'A meta-analysis of the intervention effect of mindfulness training on athletes' performance', *Frontiers in Psychology*, 15. Available at: https://doi.org/10.3389/fpsyg.2024.1375608.

Stress in America 2022: Concerned for the future, beset by inflation (2022) *https://www.apa.org*. Available at: https://www.apa.org/news/press/releases/stress/2022/concerned-future-inflation (Accessed: 6 July 2024).

Sun, X. (2024) 'The Influence of Work-Life Balance on Employee Performance with the Mediating Role of Employee Well-Being and Employee Engagement in Start-Ups of Shanghai City, China', *Uniglobal Journal of Social Sciences and Humanities*, 3(2), pp. 131–141. Available at: https://doi.org/10.53797/ujssh.v3i2.13.2024.

Szathmári, E. *et al.* (2024) 'Why do startups fail? A core competency deficit model', *Frontiers in psychology*, 15, pp. 1299135-. Available at: https://doi.org/10.3389/fpsyg.2024.1299135.

Szerb, L. and Vörös, Z. (2021) 'The changing form of overconfidence and its effect on growth expectations at the early stages of startups', *Small business economics*, 57(1), pp. 151–165. Available at: https://doi.org/10.1007/s11187-019-00297-9.

Tannenbaum, M.B. *et al.* (2015) 'Appealing to fear: A Meta-Analysis of Fear Appeal Effectiveness and Theories', *Psychological bulletin*, 141(6), pp. 1178–1204. Available at: https://doi.org/10.1037/a0039729.

Walker, D.E. (2025) 'The "Fundamental Attribution Error" is rational in an uncertain world.'

Walter, F., Cole, M.S. and Humphrey, R.H. (2011) 'Emotional intelligence: sine qua non of leadership or folderol?', *Academy of Management perspectives*, 25(1), pp. 45–59. Available at: https://doi.org/10.5465/AMP.2011.59198449.

Wang, M. *et al.* (2022) 'Dementia risk prediction in individuals with mild cognitive impairment: a comparison of Cox regression and machine learning models', *BMC Medical Research Methodology*, 22(1), p. 284. Available at: https://doi.org/10.1186/s12874-022-01754-y.

Wang, Y. *et al.* (2024) 'An Empirical Investigation of the Relationships Among Self-Esteem, Depression and Self-Serving Bias in People with Internet Gaming Disorder', *Psychology Research and Behavior Management*, 17, pp. 2557–2571. Available at: https://doi.org/10.2147/PRBM.S462184.

Waworuntu, E.C., Kainde, S.J.R. and Mandagi, D.W. (2022) 'Work-Life Balance, Job Satisfaction and Performance Among Millennial and Gen Z Employees: A Systematic Review', *Society*, 10(2), pp. 384–398. Available at: https://doi.org/10.33019/society.v10i2.464.

Weiner, B. (2008) 'Reflections on the History of Attribution Theory and Research', *Social Psychology*, 39(3), pp. 151–156. Available at: https://doi.org/10.1027/1864-9335.39.3.151.

Winter, J.C.F. de, Gosling, S.D. and Potter, J. (2016) 'Comparing the Pearson and Spearman Correlation Coefficients Across Distributions and Sample Sizes: A Tutorial Using Simulations and Empirical Data', *Psychological Methods*, 21(3), pp. 273–290. Available at: https://doi.org/10.1037/met0000079.

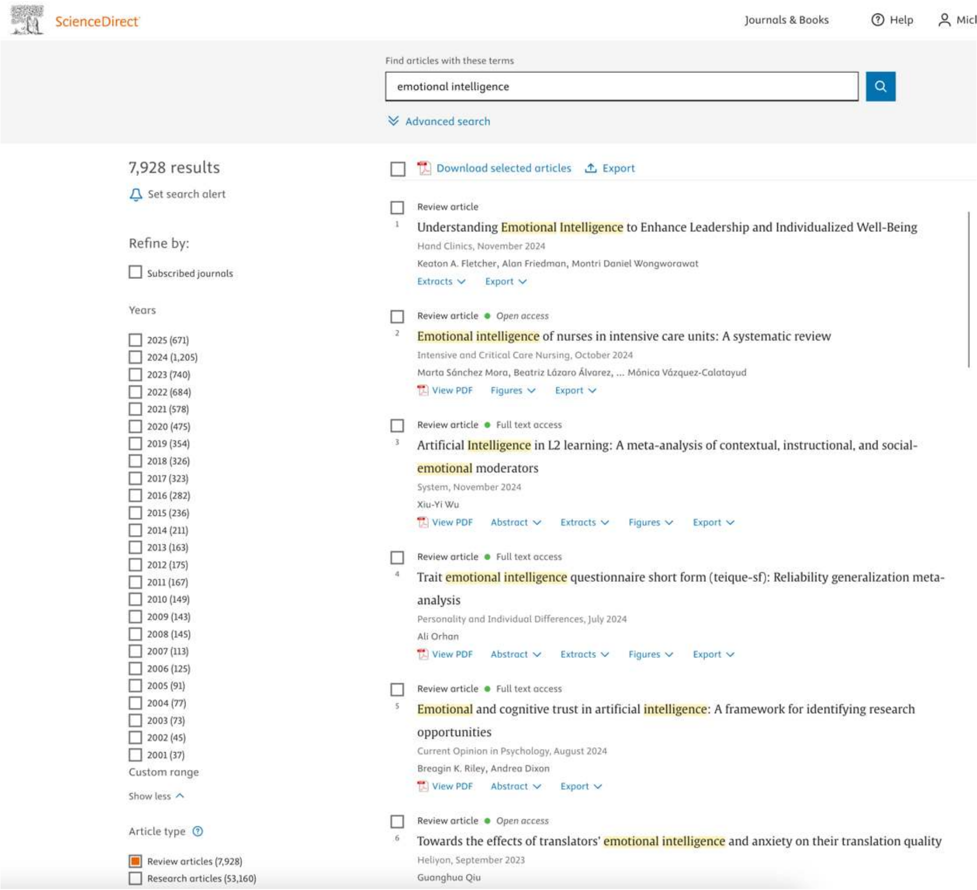
Wise, J. (2023) 'How Many Startups are Created Each Year? (Worldwide Stats) - EarthWeb', 10 August. Available at: https://earthweb.com/how-many-startups-are-created-each-year/ (Accessed: 6 July 2024).

Zahra, S.A. and Kirchhoff, B.A. (2005) 'Technological Resources and New Firm Growth: A Comparison of Start-up and Adolescent Ventures', in L. A. Keister (ed.) *Entrepreneurship*. Emerald Group Publishing Limited (Research in the Sociology of Work), pp. 101–122. Available at: https://doi.org/10.1016/S0277-2833(05)15005-5.

Zampetakis, L.A. (2022) 'Employees' fear at work, job crafting, and work engagement on a daily basis: The case for fear of COVID-19', *Applied Psychology = Psychologie Appliquee*, p. 10.1111/apps.12388. Available at: https://doi.org/10.1111/apps.12388.

APPENDICES

APPENDIX A01 – SCIENCE DIRECT AND EMOTIONAL INTELLIGENCE



APPENDIX C01 – CONFIRMATIONS BY THE COX MODEL

Elements confirmed by the Cox proportional hazards regression model:

Observation	Confirmed by Cox proportional hazards regression model
	Confirmations by Figure 4.18
Chapter 4.4.1	The most significant indicator is the perception of the impact of assuming responsibility. The perception of the impact of life balance, past experiences and stubbornness are also protective factors.
Chapter 4.2.3	The impact of assuming responsibility, the impact of past experiences, the impact of the capacity to visualise and the point of view on things are all protective indicators, although the hierarchy does not precisely match, except for the first one. This is not a surprise, considering the low amount of data points.
Chapter 4.2.2 Chapter 4.4.5	The impact of the capacity to visualise is statistically significant, which is confirmed here, as a protective factor for startup survival.
Chapter 4.2.1	In the realm of startup success, the impact of fear was the one dividing most investors (who value it) and founders (who undervalue it), which is clearly confirmed here with the fact that fear is the most important risk factor for startup survival.
	Confirmations by Figure 4.19
Chapter 4.1.4	The number of members in the board is the best predictor of startup success. Being an AI startup is also protective against failure.
Chapter 4.3	The age group of 20-30 years old have very good success rates, which then drops. The survival model indicates that age is not a good predictor of startup success.

APPENDIX D01 – THE INDICATORS AND THE ACADEMIC THEORIES

Below are listed the connections we anticipate finding between each indicator and the academic theories seen in chapter 2.

	Attribution Theory (AT)			
Indicator – What is according to you the impact of…	**FAE (Fundamental Attribution Bias)**	**SSB (Self-Serving Bias)**	**SPB (Selective Perception Bias)**	**EI (Emotional Intelligence)**
The ability to communicate	Yes	Yes		Yes
The ability to disengage disputes	Yes	Yes		Yes
Negative interactions	Yes	Yes	Possibly	Yes
Possible past similar experiences		Yes	Yes	Possibly
Positive/negative beliefs or personal convictions	Yes		Yes	
Fears	Yes	Yes	Yes	Yes
Stress	Yes		Yes	Yes
The management of time	Possibly	Yes	Yes	
The ability to visualise the future of the startup		Yes	Yes	
The ability to take responsibility for successes and failures	Yes		Yes	Yes
The point of view on things	Yes		Yes	
Negativity	Yes	Yes	Yes	Yes
Stubbornness	Yes	Yes	Yes	Yes
The ability to have a work/life balance	Yes	Possibly		Yes

APPENDIX E01 – EMAILS TO THE INVESTORS

The search on Lemlist was based on the keywords "Investor" and related words (Venture Capitalist, Business Angel, Family Office), within Switzerland, France, Belgium and Luxembourg.

Both campaigns were led over a period of 2 months (January and February 2025), for a total of about 10,000 emails sent (about 3000 emails on a sequence of 3 messages).

Email 1, day 0:

> Dear {{firstName}},
>
> I am Michel Wozniak and I am currently completing an MBA in Artificial Intelligence at Robert Kennedy College (Zurich) and the University of Cumbria (United Kingdom).
>
> As part of my final dissertation, I am conducting an in-depth study on the human factors that influence the success or failure of startups - whether they specialize in AI or not, based on the observation that 90-95% of startups fail (Allen, 2022), despite having started out with impactful ideas full of potential.
>
> As an investor, your expertise is valuable in understanding how to better target and support high-potential companies. By taking 6 to 9 minutes to complete a brief survey, you will be able to:
>
> * Discover how other investors refine their selection strategies,
>
> * Highlight good practices to minimize risk and maximize returns,
>
> * Access concrete data and recommendations based on rigorous analysis.
>
> To participate, please click on the following link: https://zfrmz.eu/1iN1NLXrUtXGKIjvBlkT
>
> Please answer conscientiously. To thank you for your participation, if your answers are admissible, we will offer you within 15 days the training most acclaimed by founders and investors, in Fast and Efficient Reading worth 97 euros (https://optimistra.com/e-sle), a capital subject for broadening one's field of competence.

I thank you in advance for the time you will devote to this study. Please do not hesitate to contact me if you have any questions.

Best regards,

Michel Wozniak (see my Linkedin profile)

Completion of the MBA in Artificial Intelligence at Robert Kennedy College (Zurich) / University of Cumbria (UK)

Click here if you no longer wish to receive communications from us.

Email 2, day 4:

Dear {{firstName}},

A few days ago, I invited you to participate in my study on the human factors that influence the success or failure of startups, whether or not they are focused on artificial intelligence.

This research, conducted as part of my MBA in Artificial Intelligence (Robert Kennedy College, Zurich University and the University of Cumbria in the UK), greatly benefits from the feedback of experienced investors such as yourself.

By taking part in this project, you will be able to:

* Obtain relevant information on the practices of other investors.

* Highlight concepts and methods to minimize risk and maximize returns.

* Improve your own selection criteria thanks to data and recommendations based on a rigorous analysis.

If you have not yet had the opportunity to take the survey, I invite you to do so now by clicking on the link below: https://zfrmz.eu/1iN1NLXrUtXGKIjvBlkT

Please answer conscientiously. To thank you for your participation, if your answers are admissible, within 15 days we will offer you the training most acclaimed by founders and investors, in Fast and Efficient Reading, worth 97 euros (https://optimistra.com/e-sle), a crucial subject for broadening your field of competence.

I sincerely thank you for your interest in this study and remain at your disposal for any further information.

Best regards,

Michel Wozniak (see my Linkedin profile)

Completion of the MBA in Artificial Intelligence at Robert Kennedy College (Zurich) / University of Cumbria (UK)

Click here if you no longer wish to receive communications from us.

Email 3, day 7:

Dear {{firstName}},

You only have a few days left to complete the survey on the human factors of startup success or failure, whether they are focused on artificial intelligence or not.

This study, carried out as part of my MBA in Artificial Intelligence (Robert Kennedy College, Zurich, and the University of Cumbria, UK), draws invaluable value from your contributions as an investor.

Your participation will allow you to:

* Discover how other investors refine their selection criteria,

* Highlight good practices to optimize your decision-making,

* Get an overview of the best strategies to reduce risk and maximize returns.

To contribute to this research before it is too late, please click on the link below: https://zfrmz.eu/1iN1NLXrUtXGKIjvBlkT

Answer conscientiously. If your answers are acceptable, within 15 days we will offer you the training course most acclaimed by founders and investors, in Fast and Efficient Reading, worth 97 euros (https://optimistra.com/e-sle), a crucial subject for broadening your field of competence in the world of startups and investments.

I thank you very much for the time you will devote to this process. Please do not hesitate to contact me if you have any questions.

Best regards,

Michel Wozniak (see my Linkedin profile)

Completion of the MBA in Artificial Intelligence at Robert Kennedy College (Zurich) / University of Cumbria (UK)

Click here if you no longer wish to receive communications from us.

APPENDIX E02 – EMAILS TO THE FOUNDERS

The keywords used for the founders' search were "Startup" and ("Owner" or "CEO"), within the same territories as the investors.

Email 1, day 0 :

Dear {{firstName}},

My name is Michel Wozniak, and I am currently completing an MBA in Artificial Intelligence at Robert Kennedy College in Zurich (Switzerland) and the University of Cumbria (United Kingdom).

As part of my final dissertation, I am conducting an in-depth study on the human factors that influence the success or failure of startups - whether they specialize in AI or not, based on the observation that 90-95% of startups fail (Allen, 2022), despite having started out with impactful ideas full of potential.

If you are a startup founder, your participation in this research is valuable. By taking 6 to 9 minutes to complete our survey, you will contribute to a better understanding of the key points of entrepreneurial success. The results of this study will be shared with you to help you:

* Quickly identify the areas where you should focus your improvement efforts,

* Better understand the human factors that promote healthy growth,

* Benefit from recommendations based on concrete and validated experiences.

Click here to take the survey: https://zfrmz.eu/1iN1NLXrUtXGKIjvBlkT

Please answer conscientiously. To thank you for your participation, if your answers are admissible, we will offer you within 15 days the training most acclaimed by founders and investors, in Fast and Efficient Reading worth 97 euros (https://optimistra.com/e-sle), a capital subject for broadening one's field of competence.

This study can have a significant impact in the world of startups, we are counting on you.

I thank you in advance for your participation and remain at your disposal for any questions.

Best regards,

Michel Wozniak (see my Linkedin profile)

Completion of the MBA in Artificial Intelligence at Robert Kennedy College (Zurich) / University of Cumbria (UK)

Click here if you no longer wish to receive communications from us.

Email 2, day 4:

Dear {{firstName}},

A few days ago, I invited you to participate in our study on the human factors of startup success or failure, as part of my MBA in Artificial Intelligence at Robert Kennedy College (Zurich) and the University of Cumbria (UK).

If you are a startup founder, I wanted to remind you that your contribution is essential to obtain relevant data and enrich this research.

By participating, you will be able to:

* Discover exclusive insights into the factors that influence the growth and stability of young companies,

* Compare your challenges and strategies with those of other startups,

* Optimize your chances of success through concrete recommendations.

Take a few minutes to answer the survey now:
https://zfrmz.eu/1iN1NLXrUtXGKIjvBlkT

Also, because this study is very important to us, to thank you for your participation, if your answers are admissible, we will offer you within 15 days the training most acclaimed by founders and investors, in Fast and Efficient Reading worth 97 euros (https://optimistra.com/e-sle), a capital subject for broadening one's field of competence.

This study can have a significant impact in the world of startups, we are counting on you.

Many thanks for your time and support. If you have any questions, please do not hesitate to contact me.

Best regards,

Michel Wozniak (see my Linkedin profile)

Completion of the MBA in Artificial Intelligence at Robert Kennedy College (Zurich) / University of Cumbria (UK)

Click here if you no longer wish to receive communications from us.

Email 3, day 7:

Hello {{firstName}},

Time is running out! You only have a few days left to complete the survey on the human factors of startup success or failure. If you are a startup founder, your participation is crucial to enable an in-depth analysis and strengthen the reliability of this study carried out as part of my MBA in Artificial Intelligence (Robert Kennedy College, Zurich University and University of Cumbria, UK).

Why is this important?

You will benefit from priority access to the conclusions and recommendations resulting from the research.

You will have the opportunity to compare your approach with other startups and thus adjust your strategy.

You will directly contribute to advancing knowledge on the keys to entrepreneurial success.

Act now by responding to this survey: https://zfrmz.eu/1iN1NLXrUtXGKIjvBlkT

Answer conscientiously. If your answers are admissible, within 15 days we will offer you the training most acclaimed by founders and investors, in Fast and Efficient Reading, worth 97 euros (https://optimistra.com/e-sle), a crucial subject for broadening your field of competence in the world of startups and investments.

This study can have a significant impact in the world of startups, we are counting on you.

I thank you very much for your time and your support. Please do not hesitate to contact me if you have any questions.

Best regards,

Michel Wozniak (see my Linkedin profile)

Completion of MBA in Artificial Intelligence at Robert Kennedy College (Zurich) / University of Cumbria (UK)

Click here if you no longer wish to receive communications from us.

University of Cumbria

Research Ethics Application for Taught Degree (Bachelors & Masters) students

Application for study involving Human Participants

NB: This form should be submitted to your research project module leader once reviewed, discussed and signed by your research supervisor. The form is designed as a discussion document as well as a record of ethical approval. Please ensure you have carried out a Privacy Impact Assessment if your project involves collection of personal data.

All fields will expand as required.

1. Title of Project: Human success factors for French-speaking AI-oriented startups
2. As this a student project, please indicate type of course you are on by ticking/ highlighting the relevant box: □ BSc □ BA □ MSc □ MA X MBA □ PgC □ PgD □ LLM
3. Type of study: please indicate type of study you are on by ticking/ highlighting the relevant box: X Involves direct involvement by human subjects □ Involves existing documents/anonymised data only.

4. Name of applicant (the student): Michel Wozniak
5. Your project supervisor(s) Name(s): Pr. Richard Adlam E-mail(s): richard.adlam@rkc.edu

6. Provide a concise **summary of your research project in lay terms** (maximum length 150 words). What are you planning to do?

I am planning to survey investors as well as founders in order to evaluate to what extent they perceive that human factors like stress, beliefs, fears, etc. may impact startup success or startup failure.
7. Describe the **sample of participants** (including for example, number, age, gender). We want to target founders as well as investors regardless their age and gender, so that we can extract at least a hundred data points, which will be reasonable considering their levels of occupation.
8. Explain concisely how you will **recruit the participants** (be specific). We will use Lemlist (a tool using Linkedin professional databases) and contact them by email, considering possible email deliverability challenges like the fact that not all have an up-to-date email address. The search will be based on keywords like “investor”, “investment”, or “startup”, “founder”.
9. Explain concisely how you **obtain informed consent from participants**. You need to ensure it is easy for people to withdraw consent and tell them how. The survey form ends with an informed consent that is being digitally signed by the respondent. A separate email is also sent to the respondent to have further record of the consent. The respondent is informed that they can withdraw with a simple email addressed to Michel Wozniak.
10. Explain how you will **maintain data protection**. State what personal and/ or sensitive data you may collect and how this will be stored (see guidance UK General Data Protection Regulations (GDPR)). All the personal data is removed from the dataset (first name, last name, email, phone, company name). The remaining data is the age range (10 years ranges) as well as the evaluations made by the respondent. The personal data is kept until the validation of the dissertation, in order to send the results of the research to them. Then the personal data will be destroyed.
11. Explain concisely how you will offer **review opportunities**, a debrief or, follow up for participants (as appropriate). When the research is validated by RKC/UoC, the research document will be sent to the participants. There is no other specific form of debrief or follow-up for participants.

12. Briefly describe each of your **data collection and analysis methods** (you may just have one method)	
Method 1	Survey using Likert scale for the evaluation of the impact of human factors.
Method 2	Spearman correlations to extract insights from the data

Method 3	Kruskal-Wallis tests to extract significant differences within groups of data
Method 4	Jackknife resampling to check the stability of the results across all the dataset
Method 5	Cox proportional hazards regression model to confirm (or not) the validity of methods 2 to 4 and get possible complementary insights.

13. Risks	Explain any risks that your research participants might face because of the research project (this might include psychological and reputational risks)	Describe how you will control the risks you have identified
1	No risk has been identified for the participant since no personal or sensitive data is being exposed. The data is self-assessed.	The anonymization of the data allows the mitigation of any risk in our case.
2		
3		
4		

14. Other ethical considerations
Explain any risks that you may face as a researcher, and what steps you will take to control them. In our case, there is no identified risk as a researcher. It is exploratory research aimed at evaluating startup success or failure.
Explain briefly any benefits that your research participants may gain from participation. The insights from the research may bring possible keys to improve their likelihood of success (for founders), as well as the likelihood of success of the startups investors invest in.
Explain briefly how you will collect each type of data– such as hard copy paper / digital / audio / video.

The data will be collected through a digital Zoho Form.
State a date when you will destroy by shredding, burning or deletion your data files. Note: this should be after the award of a confirmed grade for your degree. Within a week (7 days) after the confirmed grade, the digital files and the form will be destroyed.

15. Check you have considered each issue below and fully explained it in your application, then put x in the box	
I have identified and taken steps to control any physical, emotional or psychological risk to participants	X
I have identified and taken steps to control any cultural offence that might be caused	X
I have identified any vulnerable groups involved and taken steps to control the risks	X
I have explained how I will get permission from managers to recruit participants on their premises	N/A
I have made clear that no deception is involved in the study	X
I have explained the level of anonymity for participants and how it will be maintained	X
I have explained how participants will be informed and have the chance to ask questions beforehand	X
I have explained how participants may make follow up enquiries after their part in the study	X
I have explained how data will be kept secure and destroyed after the study	X

16. Role	**Name**	**e-Signature**	**Date**
You (Student)	Michel Wozniak		
Your Supervisor	Pr. Richard Adlam	Richard Adlam	27-04-25

Module leader or lecturer responsible for the research ethics within your programme/ module			

Supportive Materials Checklist

Please attach all necessary supportive materials and indicate in the checklist below.

Supportive Material	**Version and Date**
Research protocol or research proposal	File ID 358435 in Thesis Repository (07/07/2024)
Participant Information Sheet	Consigned in the final version of the research
Debriefing Sheet	
Consent Form	Consigned in the final version of the research
Letter of invitation	
Other (such as interview schedule, questionnaires, measures: please state, and explain)	

APPENDIX E04 – CONSENT FORM AFTER THE SURVEY

At the end of the survey, a consent form containing the most important confidentiality and rights data is given to the participant, and the participant needs to digitally sign the consent and the survey. Due to the length of the survey, a complementary informed consent is sent by email (Appendix E05).

Here is the extract of the last page of the survey (Appendix F01) with the consent:

J'accèpte que ces information soient utilisées strictement dans le cadre d'une étude académique et qu'aucune information indiquée ci-dessus permettant de m'identifier ne sera utilisée ou publiée. Une notice de consentement plus détaillée me sera envoyée par mail. Je sais que je peux retirer ma participation à tout moment au cours de l'étude en informant Michel Wozniak. / I agree that this information will be used strictly for academic purposes and that none of the above identifying information will be used or published. A more detailed consent information will be sent to me by email. I understand that I can withdraw my participation at any time during the study by informing Michel Wozniak.

Je confirme accepter cela / I confirm that I accept this *

☐ J'accèpte / I accept

Signature

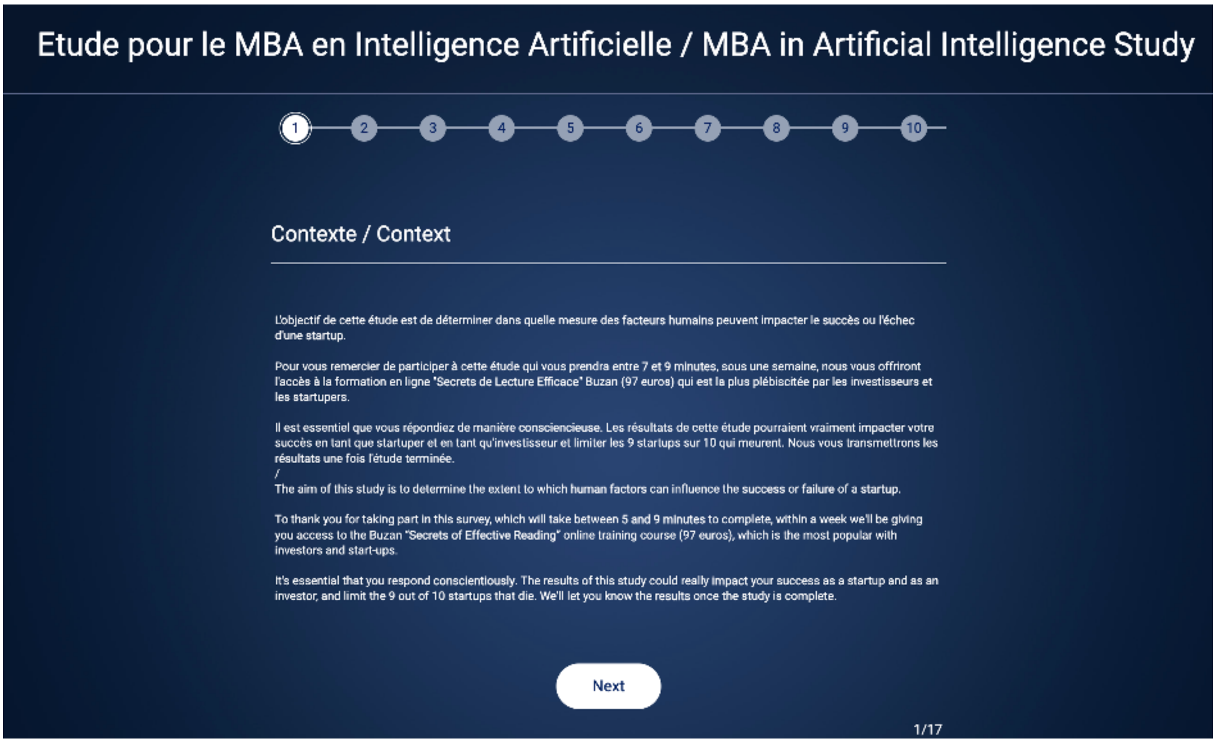
APPENDIX E05 – PARTICIPANT'S INFORMED CONSENT

This message has been sent to the participants with the detailed consent information. The survey informed the participants about the fact they would receive this message, to ensure deliverability.

> You are invited to participate in our quantitative study on human factors influencing startup success or failure. This study explores the perception of how much human aspects like stress, fears, beliefs, communication, … may have an impact on the success or the failure of a startup.
>
> You are invited because you are an investor and/or a founder and your experience may be valuable for the whole startup community. Therefore, we contacted you by email.
>
> The data collected will by quantitatively analysed to generate insights to contribute to a better understanding of human aspects leading to failure or success of a startup. The collection of the data was made on a period of 2 months, between January and February 2025. On your behalf, there is no risk in your participation and the time required is less than 10 minutes.
>
> Personal information about you (first name, last name, email, phone, company name) is totally anonymized. None of it is available to the public. The researcher is Michel Wozniak, student at Robert Kennedy College on the MBA in Artificial Intelligence. The research tutor is Pr. Richard Adlam.
>
> We are very thankful for your voluntary and valued participation. You may withdraw your participation any time during the process of the study by notifying the researcher by email.
>
> The signature of the survey form confirms that you deliberately decided to participate to this research. Thank you very much.

APPENDIX F01 – THE SURVEY FORM

It is worth noting that one person who is founder (2 Likert queries) as well as investor in AI (2 Likert queries) and non-AI (2 Likert queries) startups, could possibly be asked 6 times their perception on all the 14 indicators.


Etude pour le MBA en Intelligence Artificielle / MBA in Artificial Intelligence Study
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Contexte / Context
L'objectif de cette étude est de déterminer dans quelle mesure des facteurs humains peuvent impacter le succès ou l'échec d'une startup.
Pour vous remercier de participer à cette étude qui vous prendra entre 7 et 9 minutes, sous une semaine, nous vous offriront l'accès à la formation en ligne "Secrets de Lecture Efficace" Buzan (97 euros) qui est la plus plébiscitée par les investisseurs et les startupers.
Il est essentiel que vous répondiez de manière consciencieuse. Les résultats de cette étude pourraient vraiment impacter votre succès en tant que startuper et en tant qu'investisseur et limiter les 9 startups sur 10 qui meurent. Nous vous transmettrons les résultats une fois l'étude terminée.
/
The aim of this study is to determine the extent to which human factors can influence the success or failure of a startup.
To thank you for taking part in this survey, which will take between 5 and 9 minutes to complete, within a week we'll be giving you access to the Buzan "Secrets of Effective Reading" online training course (97 euros), which is the most popular with investors and start-ups.
It's essential that you respond conscientiously. The results of this study could really impact your success as a startup and as an investor, and limit the 9 out of 10 startups that die. We'll let you know the results once the study is complete.
Next
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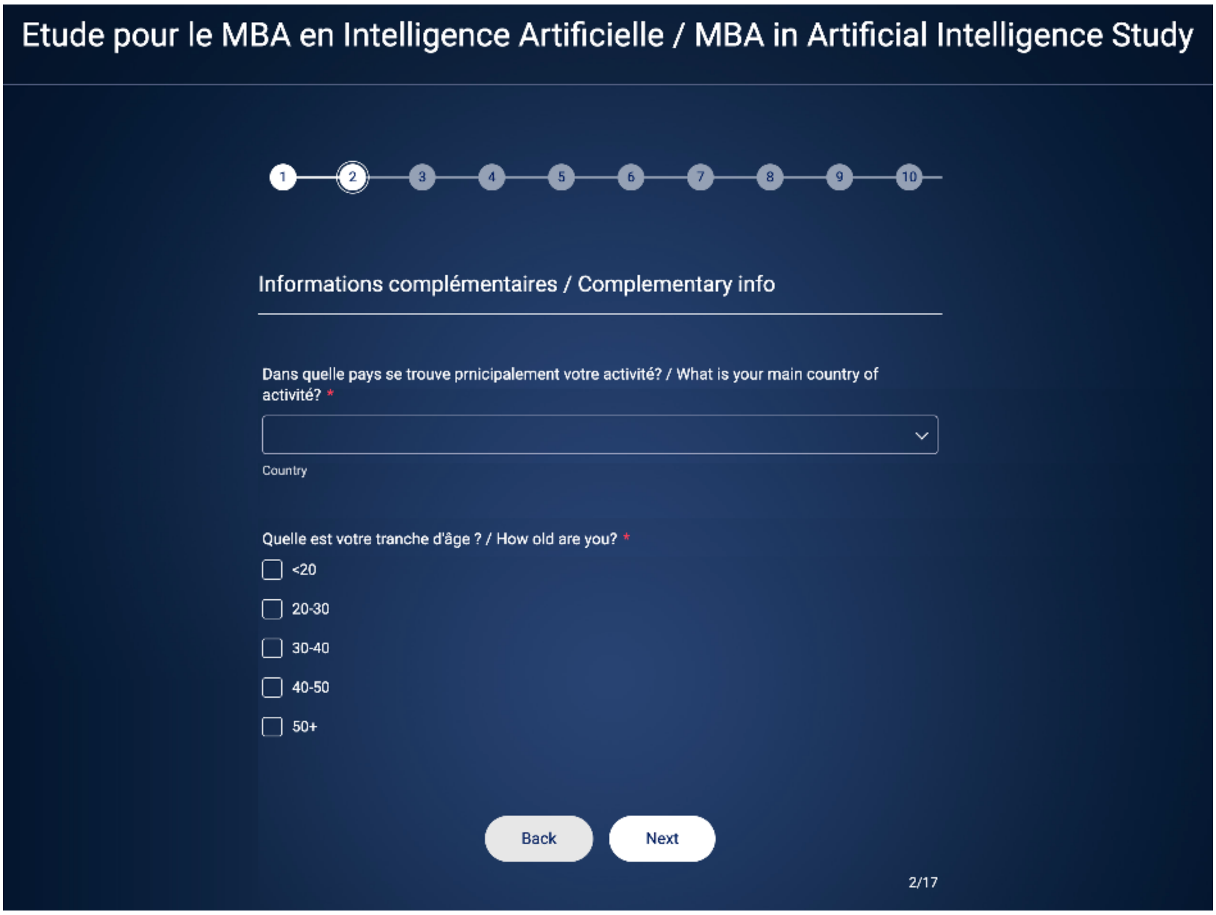
Etude pour le MBA en Intelligence Artificielle / MBA in Artificial Intelligence Study
1
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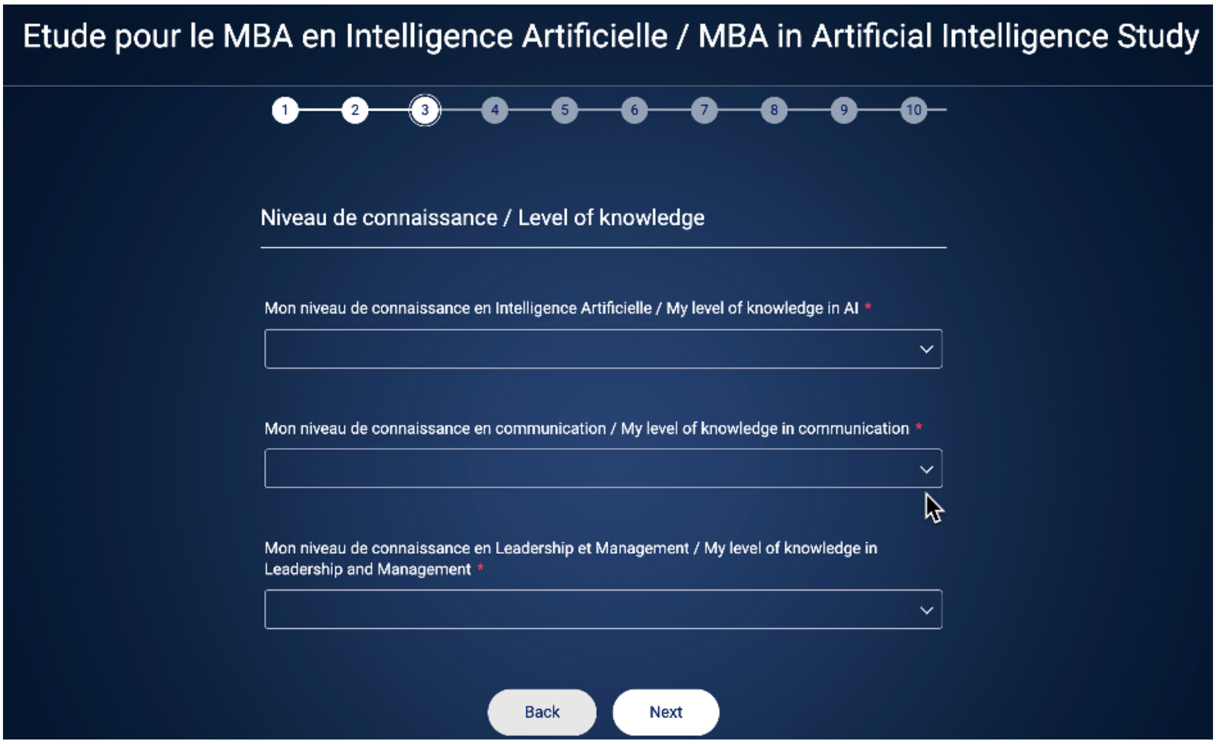
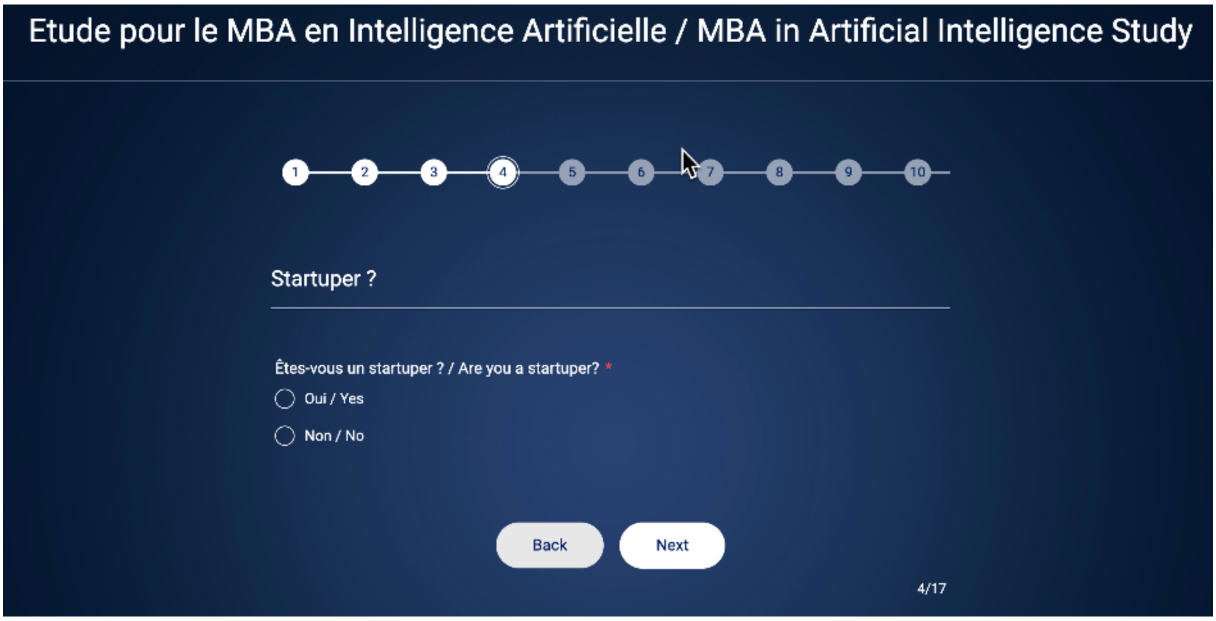
9
10
Informations complémentaires / Complementary info
Dans quelle pays se trouve pnricipalement votre activité? / What is your main country of activité? *
Country
Quelle est votre tranche d'âge ? / How old are you? *
<20
20-30
30-40
40-50
50+
Back
Next
2/17


Etude pour le MBA en Intelligence Artificielle / MBA in Artificial Intelligence Study
1 2 3 4 5 6 7 8 9 10
Niveau de connaissance / Level of knowledge
Mon niveau de connaissance en Intelligence Artificielle / My level of knowledge in AI *
Mon niveau de connaissance en communication / My level of knowledge in communication *
Mon niveau de connaissance en Leadership et Management / My level of knowledge in Leadership and Management *
Back
Next


Etude pour le MBA en Intelligence Artificielle / MBA in Artificial Intelligence Study
1 2 3 4 5 6 7 8 9 10
Startuper ?
Êtes-vous un startuper ? / Are you a startuper? *
Oui / Yes
Non / No
Back
Next
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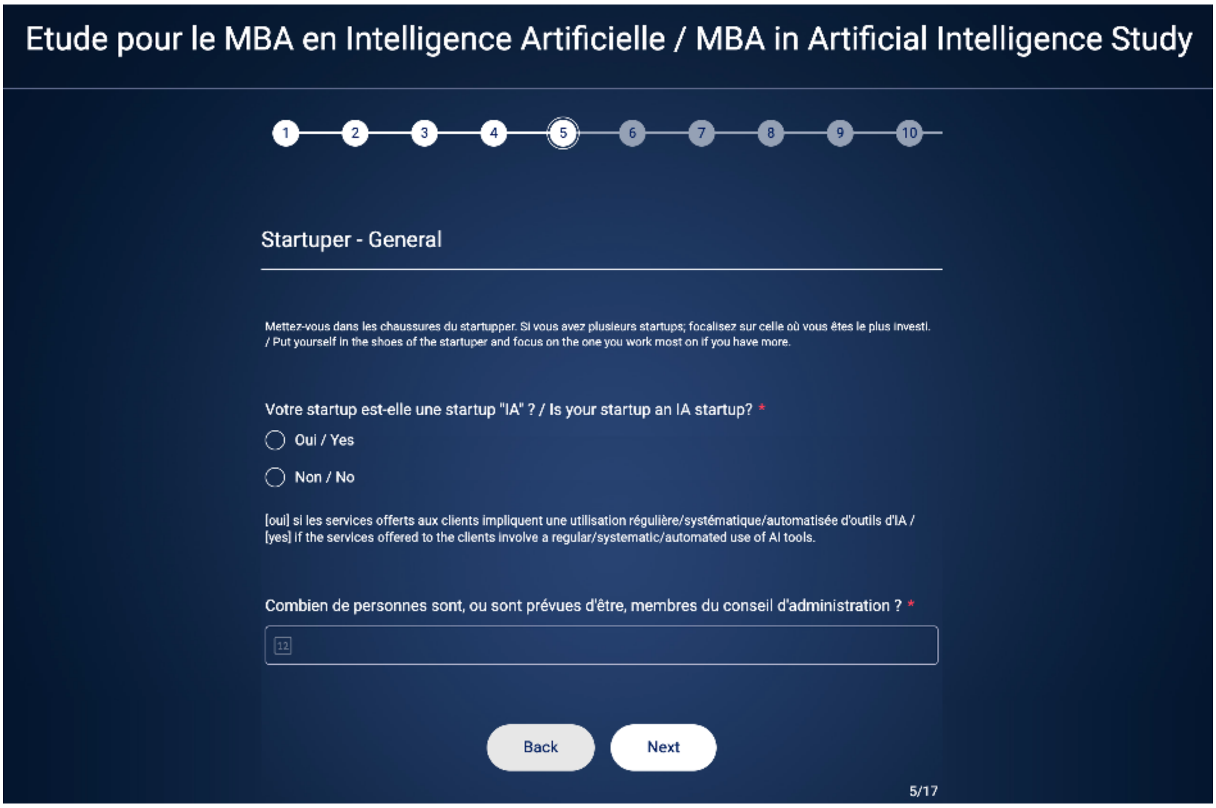

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1 2 3 4 5 6 7 8 9 10

Startuper - General

Mettez-vous dans les chaussures du startupper. Si vous avez plusieurs startups; focalisez sur celle où vous êtes le plus investi. / Put yourself in the shoes of the startuper and focus on the one you work most on if you have more.

Votre startup est-elle une startup "IA" ? / Is your startup an IA startup? *

- Oui / Yes
- Non / No

[oui] si les services offerts aux clients impliquent une utilisation régulière/systématique/automatisée d'outils d'IA / [yes] if the services offered to the clients involve a regular/systematic/automated use of AI tools.

Combien de personnes sont, ou sont prévues d'être, membres du conseil d'administration ? *

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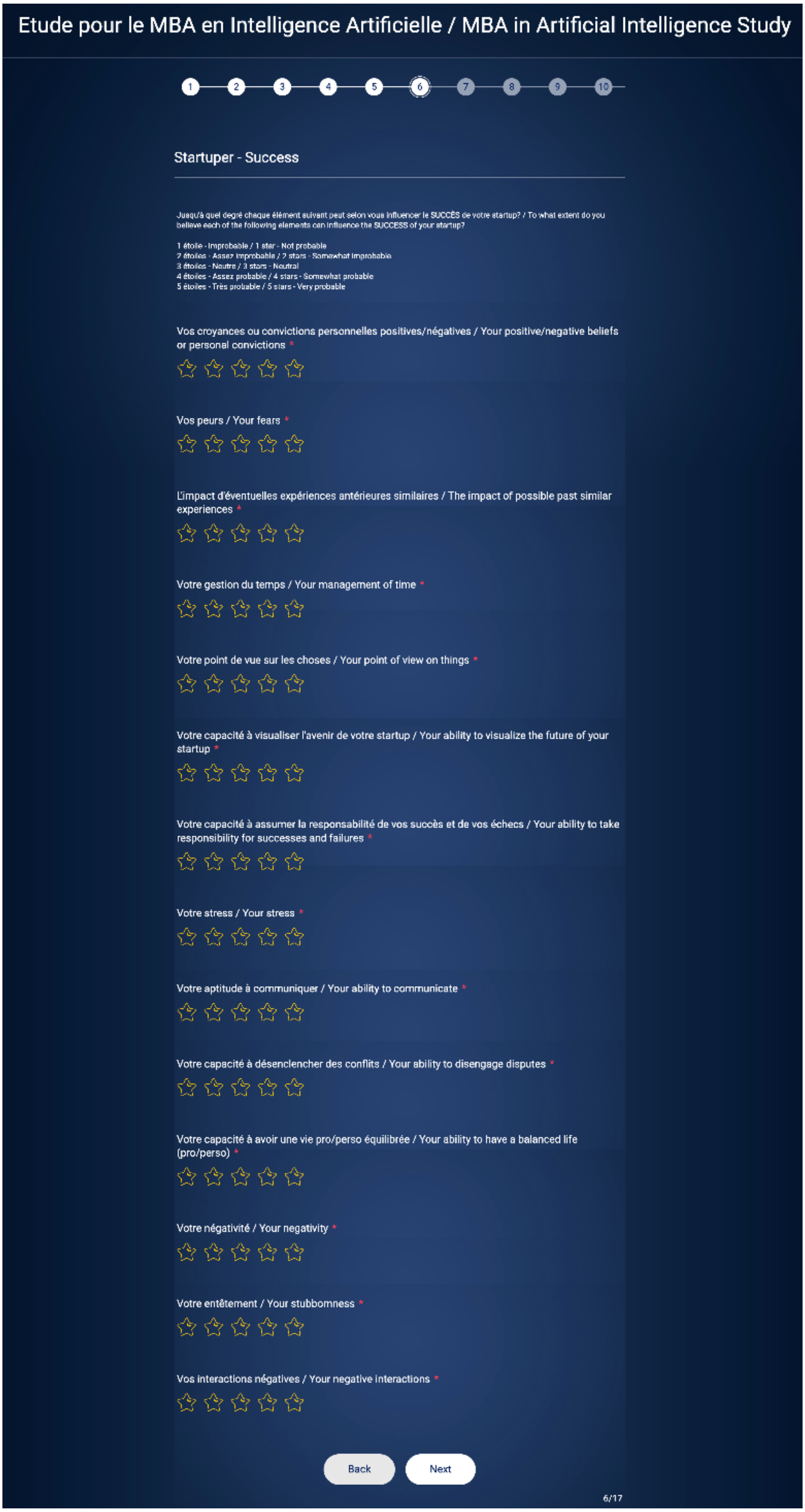
Etude pour le MBA en Intelligence Artificielle / MBA in Artificial Intelligence Study

1 2 3 4 5 6 7 8 9 10

Startuper - Success

Jusqu'à quel degré chaque élément suivant peut selon vous influencer le SUCCÈS de votre startup? / To what extent do you believe each of the following elements can influence the SUCCESS of your startup?

1 étoile - Improbable / 1 star - Not probable
2 étoiles - Assez improbable / 2 stars - Somewhat improbable
3 étoiles - Neutre / 3 stars - Neutral
4 étoiles - Assez probable / 4 stars - Somewhat probable
5 étoiles - Très probable / 5 stars - Very probable

Vos croyances ou convictions personnelles positives/négatives / Your positive/negative beliefs or personal convictions *

Vos peurs / Your fears *

L'impact d'éventuelles expériences antérieures similaires / The impact of possible past similar experiences *

Votre gestion du temps / Your management of time *

Votre point de vue sur les choses / Your point of view on things *

Votre capacité à visualiser l'avenir de votre startup / Your ability to visualize the future of your startup *

Votre capacité à assumer la responsabilité de vos succès et de vos échecs / Your ability to take responsibility for successes and failures *

Votre stress / Your stress *

Votre aptitude à communiquer / Your ability to communicate *

Votre capacité à désenclencher des conflits / Your ability to disengage disputes *

Votre capacité à avoir une vie pro/perso équilibrée / Your ability to have a balanced life (pro/perso) *

Votre négativité / Your negativity *

Votre entêtement / Your stubbornness *

Vos interactions négatives / Your negative interactions *

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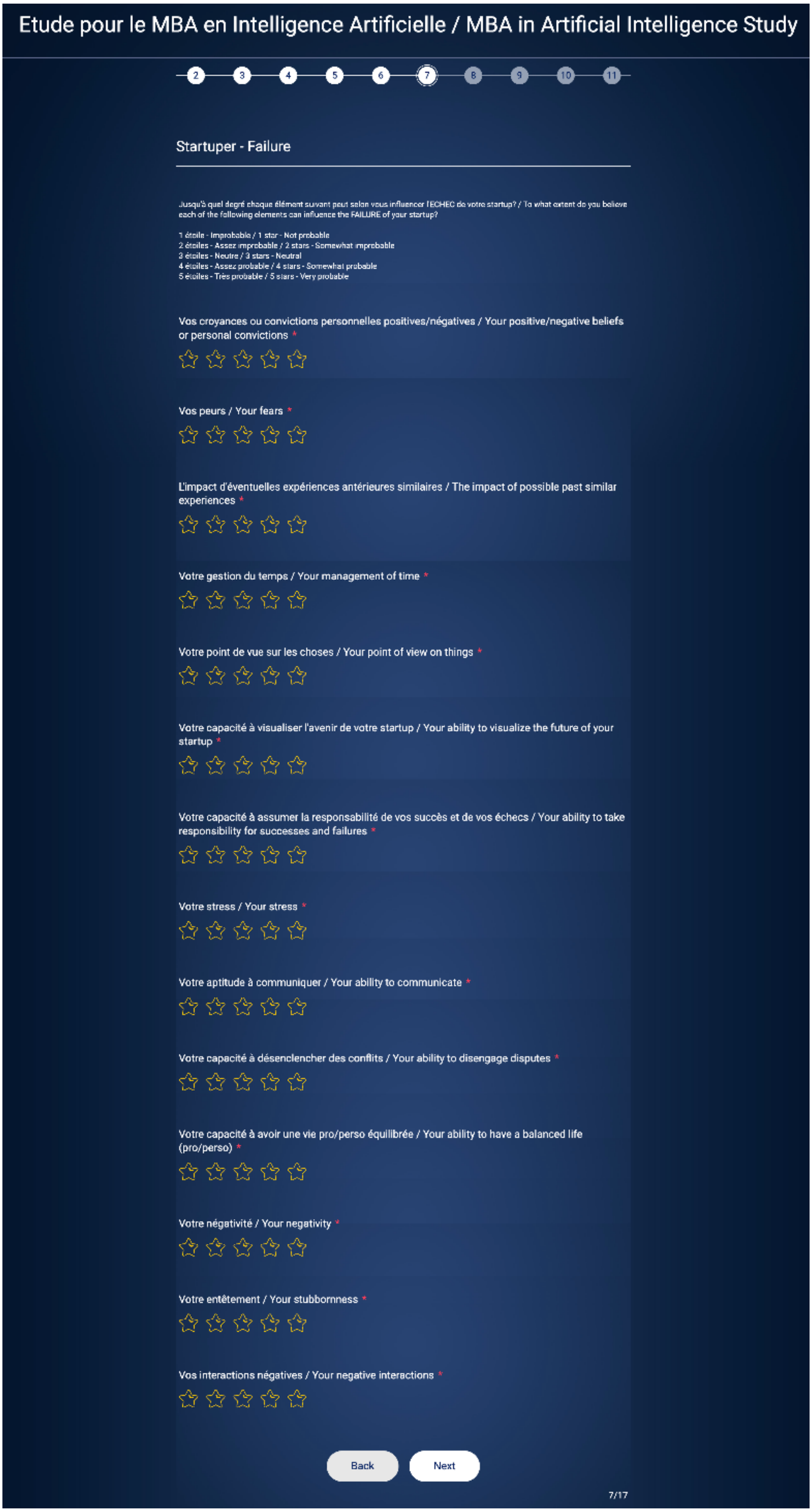
Etude pour le MBA en Intelligence Artificielle / MBA in Artificial Intelligence Study

2 3 4 5 6 7 8 9 10 11

Startuper - Failure

Jusqu'à quel degré chaque élément suivant peut selon vous influencer l'ECHEC de votre startup? / To what extent do you believe each of the following elements can influence the FAILURE of your startup?

1 étoile - Improbable / 1 star - Not probable
2 étoiles - Assez improbable / 2 stars - Somewhat improbable
3 étoiles - Neutre / 3 stars - Neutral
4 étoiles - Assez probable / 4 stars - Somewhat probable
5 étoiles - Très probable / 5 stars - Very probable

Vos croyances ou convictions personnelles positives/négatives / Your positive/negative beliefs or personal convictions *

Vos peurs / Your fears *

L'impact d'éventuelles expériences antérieures similaires / The impact of possible past similar experiences *

Votre gestion du temps / Your management of time *

Votre point de vue sur les choses / Your point of view on things *

Votre capacité à visualiser l'avenir de votre startup / Your ability to visualize the future of your startup *

Votre capacité à assumer la responsabilité de vos succès et de vos échecs / Your ability to take responsibility for successes and failures *

Votre stress / Your stress *

Votre aptitude à communiquer / Your ability to communicate *

Votre capacité à désenclencher des conflits / Your ability to disengage disputes *

Votre capacité à avoir une vie pro/perso équilibrée / Your ability to have a balanced life (pro/perso) *

Votre négativité / Your negativity *

Votre entêtement / Your stubbornness *

Vos interactions négatives / Your negative interactions *

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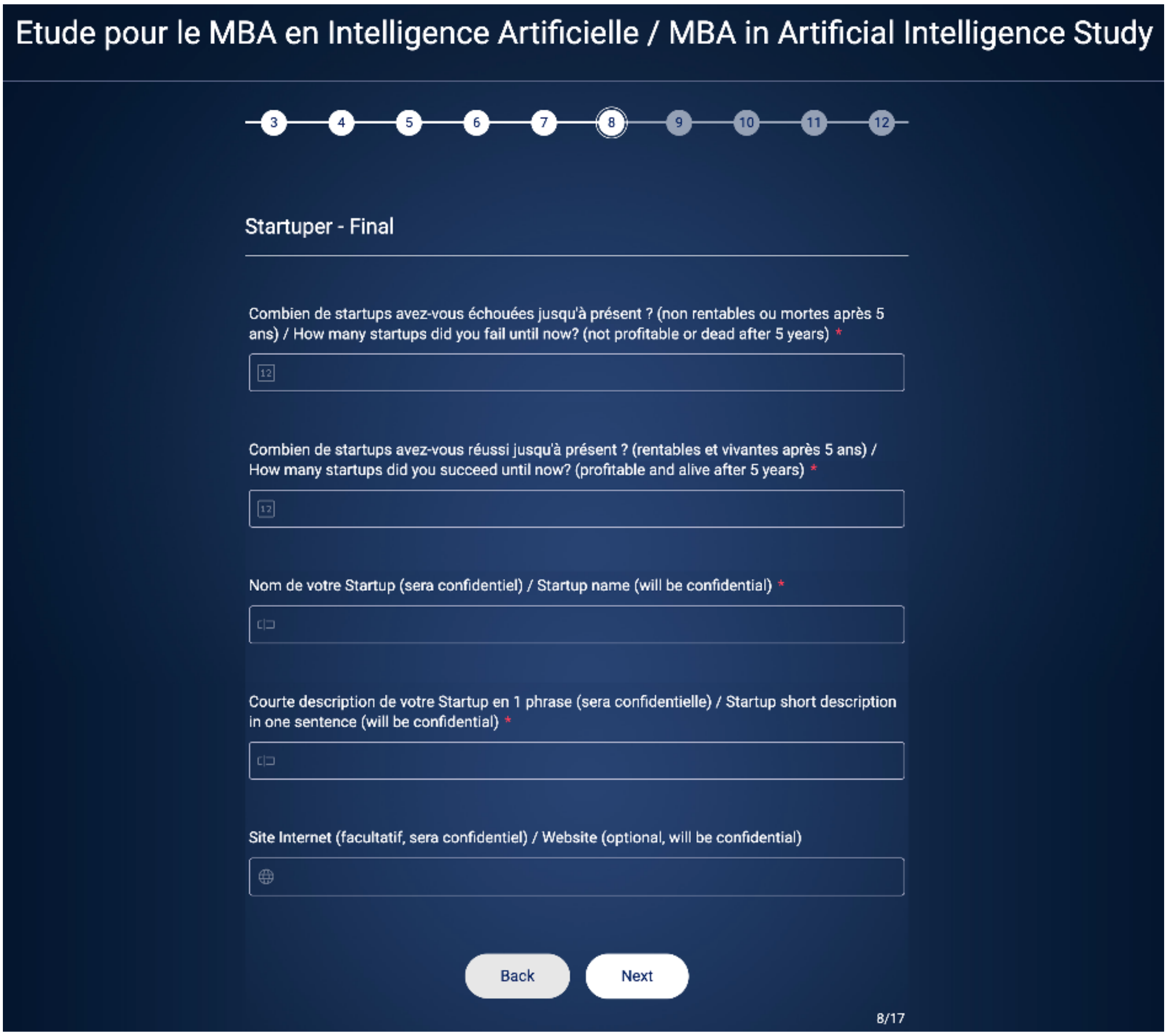
Etude pour le MBA en Intelligence Artificielle / MBA in Artificial Intelligence Study
3 4 5 6 7 8 9 10 11 12
Startuper - Final
Combien de startups avez-vous échouées jusqu'à présent ? (non rentables ou mortes après 5 ans) / How many startups did you fail until now? (not profitable or dead after 5 years) *
Combien de startups avez-vous réussi jusqu'à présent ? (rentables et vivantes après 5 ans) / How many startups did you succeed until now? (profitable and alive after 5 years) *
Nom de votre Startup (sera confidentiel) / Startup name (will be confidential) *
Courte description de votre Startup en 1 phrase (sera confidentielle) / Startup short description in one sentence (will be confidential) *
Site Internet (facultatif, sera confidentiel) / Website (optional, will be confidential)
Back
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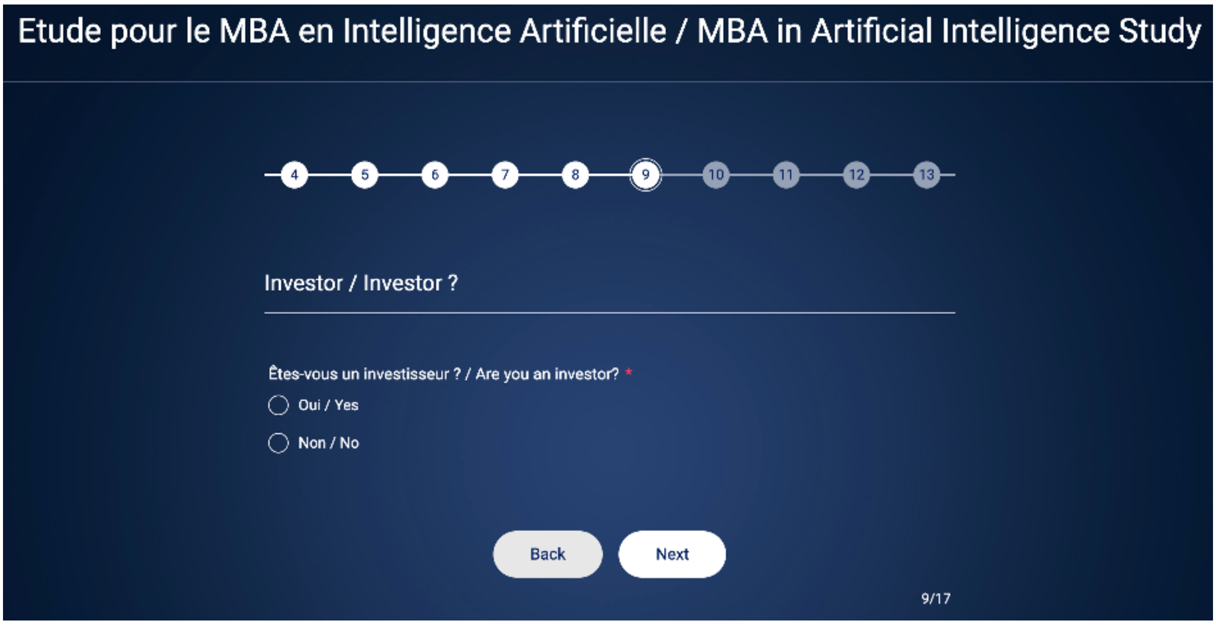
Etude pour le MBA en Intelligence Artificielle / MBA in Artificial Intelligence Study
4 5 6 7 8 9 10 11 12 13
Investor / Investor ?
Êtes-vous un investisseur ? / Are you an investor? *
Oui / Yes
Non / No
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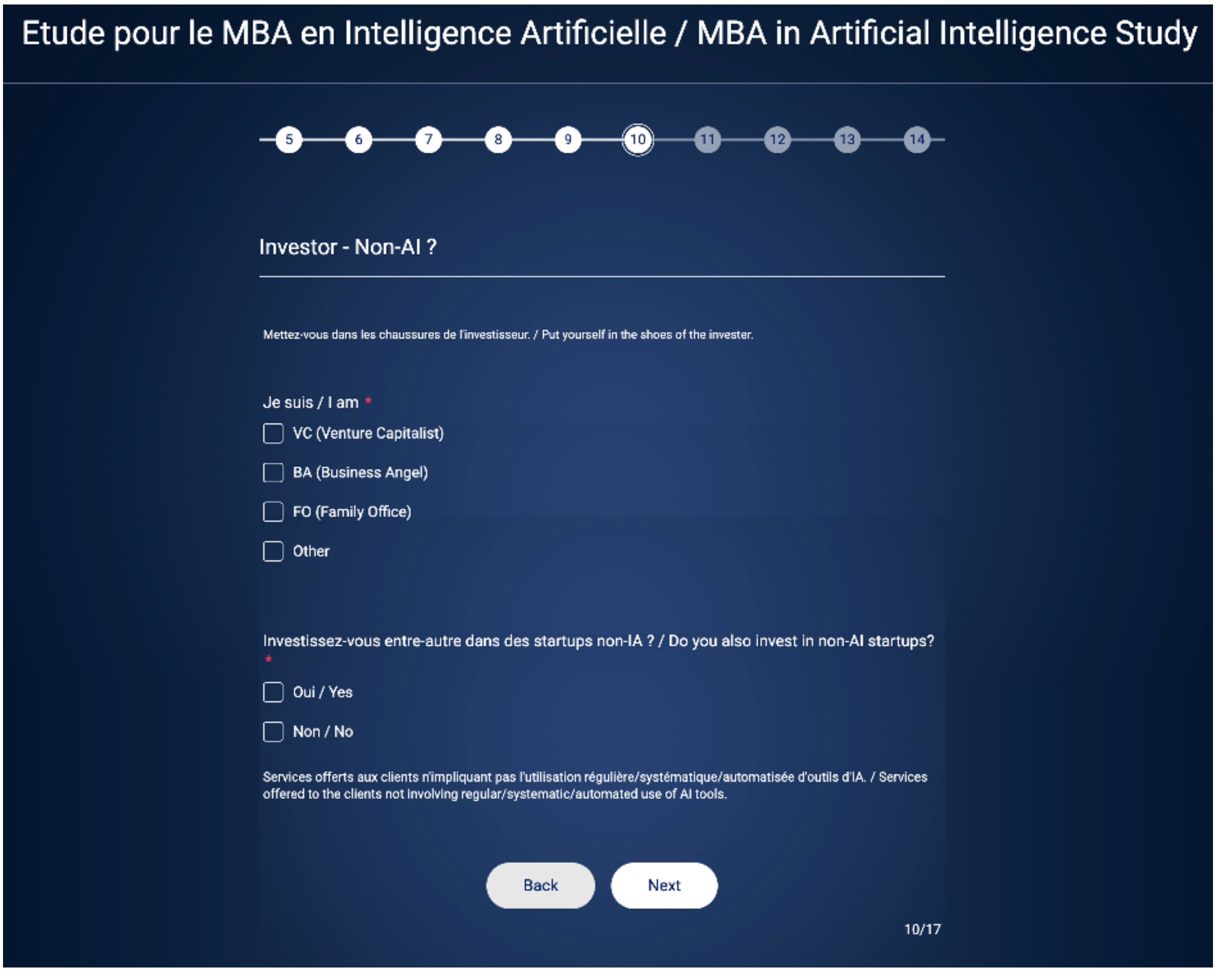

Etude pour le MBA en Intelligence Artificielle / MBA in Artificial Intelligence Study

5 6 7 8 9 10 11 12 13 14

Investor - Non-AI ?

Mettez-vous dans les chaussures de l'investisseur. / Put yourself in the shoes of the invester.

Je suis / I am *

- [ ] VC (Venture Capitalist)
- [ ] BA (Business Angel)
- [ ] FO (Family Office)
- [ ] Other

Investissez-vous entre-autre dans des startups non-IA ? / Do you also invest in non-AI startups? *

- [ ] Oui / Yes
- [ ] Non / No

Services offerts aux clients n'impliquant pas l'utilisation régulière/systématique/automatisée d'outils d'IA. / Services offered to the clients not involving regular/systematic/automated use of AI tools.

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6 7 8 9 10 11 12 13 14 15

Non-AI Investor - Success

Focalisez-vous sur vos investissements Startups NON-IA, et focalisez-vous plus particulièrement sur le fondateur et/ou l'équipe dirigeante. Jusqu'à quel degré chaque élément suivant peut selon vous influencer le SUCCÈS de ces startups? / Focus on your NON-AI startup investments, and in particular on the founder and/or management team. To what extent do you believe each of the following elements can influence the SUCCESS of these startups?

1 étoile - Improbable / 1 star - Not probable
2 étoiles - Assez improbable / 2 stars - Somewhat improbable
3 étoiles - Neutre / 3 stars - Neutral
4 étoiles - Assez probable / 4 stars - Somewhat probable
5 étoiles - Très probable / 5 stars - Very probable

Ses croyances ou convictions personnelles positives/négatives / Their positive/negative beliefs or personal convictions *

Ses peurs / Their fears *

L'impact d'éventuelles expériences antérieures similaires / The impact of possible past similar experiences *

Sa gestion du temps / Their management of time *

Son point de vue sur les choses / Their point of view on things *

Sa capacité à visualiser l'avenir de sa startup / Their ability to visualize the future of their startup *

Sa capacité à assumer la responsabilité de ses succès et de ses échecs / Their ability to take responsibility for successes and failures *

Son stress / Their stress *

Son aptitude à communiquer / Their ability to communicate *

Sa capacité à désenclencher des conflits / Their ability to disengage disputes *

Sa capacité à avoir une vie pro/perso équilibrée / Their ability to have a balanced life (pro/perso) *

Sa négativité / Their negativity *

Son entêtement / Their stubbornness *

Ses interactions négatives / Their negative interactions *

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7 8 9 10 11 12 13 14 15 16

Non-AI Investor - Failure

Focalisez-vous sur vos investissements Startups NON-IA, et focalisez-vous plus particulièrement sur le fondateur et/ou l'équipe dirigeante. Jusqu'à quel degré chaque élément suivant peut selon vous influencer l'ECHEC de ces startups? / Focus on your NON-AI startup investments, and in particular on the founder and/or management team. To what extent do you believe each of the following elements can influence the FAILURE of these startups?

1 étoile - Improbable / 1 star - Not probable
2 étoiles - Assez improbable / 2 stars - Somewhat improbable
3 étoiles - Neutre / 3 stars - Neutral
4 étoiles - Assez probable / 4 stars - Somewhat probable
5 étoiles - Très probable / 5 stars - Very probable

Ses croyances ou convictions personnelles positives/négatives / Their positive/negative beliefs or personal convictions *

Ses peurs / Their fears *

L'impact d'éventuelles expériences antérieures similaires / The impact of possible past similar experiences *

Sa gestion du temps / Their management of time *

Son point de vue sur les choses / Their point of view on things *

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Sa capacité à assumer la responsabilité de ses succès et de ses échecs / Their ability to take responsibility for successes and failures *

Son stress / Their stress *

Son aptitude à communiquer / Their ability to communicate *

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Sa négativité / Their negativity *

Son entêtement / Their stubbornness *

Ses interactions négatives / Their negative interactions *

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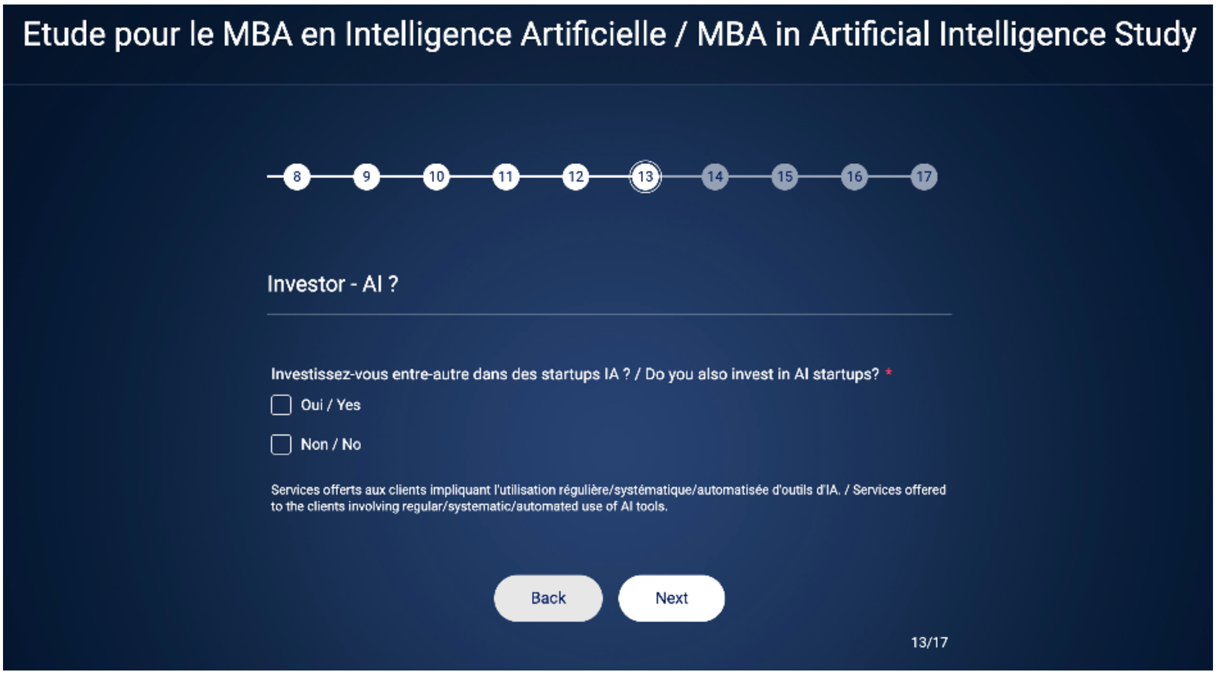
Etude pour le MBA en Intelligence Artificielle / MBA in Artificial Intelligence Study

8 9 10 11 12 13 14 15 16 17

Investor - AI ?

Investissez-vous entre-autre dans des startups IA ? / Do you also invest in AI startups? *

- [ ] Oui / Yes
- [ ] Non / No

Services offerts aux clients impliquant l'utilisation régulière/systématique/automatisée d'outils d'IA. / Services offered to the clients involving regular/systematic/automated use of AI tools.

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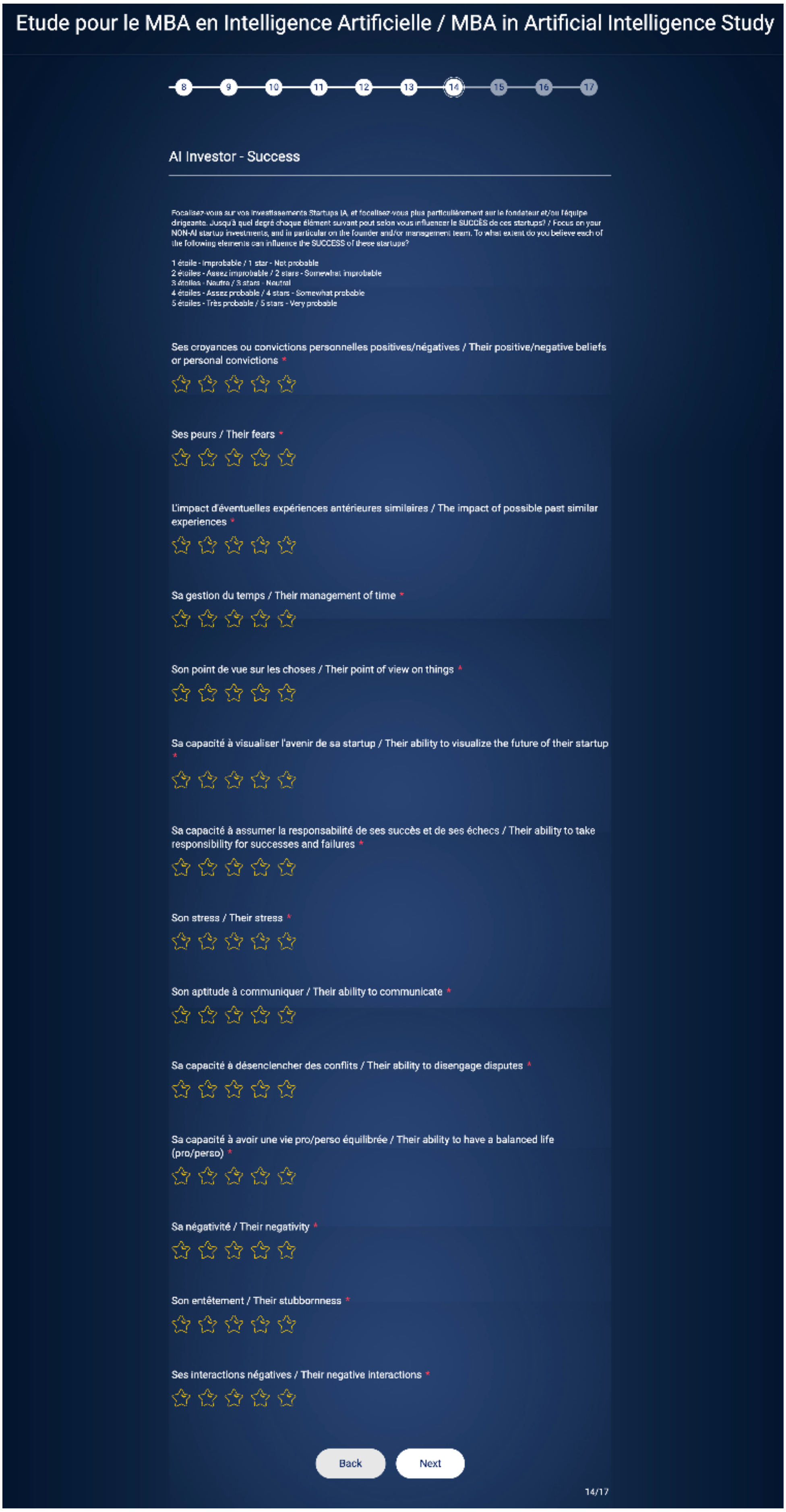

Etude pour le MBA en Intelligence Artificielle / MBA in Artificial Intelligence Study

8 9 10 11 12 13 14 15 16 17

AI Investor - Success

Focalisez-vous sur vos investissements Startups IA, et focalisez-vous plus particulièrement sur le fondateur et/ou l'équipe dirigeante. Jusqu'à quel degré chaque élément suivant peut selon vous influencer le SUCCÈS de ces startups? / Focus on your NON-AI startup investments, and in particular on the founder and/or management team. To what extent do you believe each of the following elements can influence the SUCCESS of these startups?

1 étoile - Improbable / 1 star - Not probable
2 étoiles - Assez improbable / 2 stars - Somewhat improbable
3 étoiles - Neutre / 3 stars - Neutral
4 étoiles - Assez probable / 4 stars - Somewhat probable
5 étoiles - Très probable / 5 stars - Very probable

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Ses peurs / Their fears *

L'impact d'éventuelles expériences antérieures similaires / The impact of possible past similar experiences *

Sa gestion du temps / Their management of time *

Son point de vue sur les choses / Their point of view on things *

Sa capacité à visualiser l'avenir de sa startup / Their ability to visualize the future of their startup *

Sa capacité à assumer la responsabilité de ses succès et de ses échecs / Their ability to take responsibility for successes and failures *

Son stress / Their stress *

Son aptitude à communiquer / Their ability to communicate *

Sa capacité à désenclencher des conflits / Their ability to disengage disputes *

Sa capacité à avoir une vie pro/perso équilibrée / Their ability to have a balanced life (pro/perso) *

Sa négativité / Their negativity *

Son entêtement / Their stubbornness *

Ses interactions négatives / Their negative interactions *

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AI Investor - Failure
Focalisez-vous sur vos investissements Startups IA, et focalisez-vous plus particulièrement sur le fondateur et/ou l'équipe dirigeante. Jusqu'à quel degré chaque élément suivant peut selon vous influencer l'ECHEC de ces startups? / Focus on your NON-AI startup investments, and in particular on the founder and/or management team. To what extent do you believe each of the following elements can influence the FAILURE of these startups?
1 étoile - Improbable / 1 star - Not probable
2 étoiles - Assez improbable / 2 stars - Somewhat improbable
3 étoiles - Neutre / 3 stars - Neutral
4 étoiles - Assez probable / 4 stars - Somewhat probable
5 étoiles - Très probable / 5 stars - Very probable
Ses croyances ou convictions personnelles positives/négatives / Their positive/negative beliefs or personal convictions *
Son point de vue sur les choses / Their point of view on things *
Sa capacité à visualiser l'avenir de sa startup / Their ability to visualize the future of their startup *
Sa capacité à assumer la responsabilité de ses succès et de ses échecs / Their ability to take responsibility for successes and failures *
Son stress / Their stress *
Son aptitude à communiquer / Their ability to communicate *
Sa capacité à désenclencher des conflits / Their ability to disengage disputes *
Sa capacité à avoir une vie pro/perso équilibrée / Their ability to have a balanced life (pro/perso) *
Sa négativité / Their negativity *
Son entêtement / Their stubbornness *
Ses interactions négatives / Their negative interactions *
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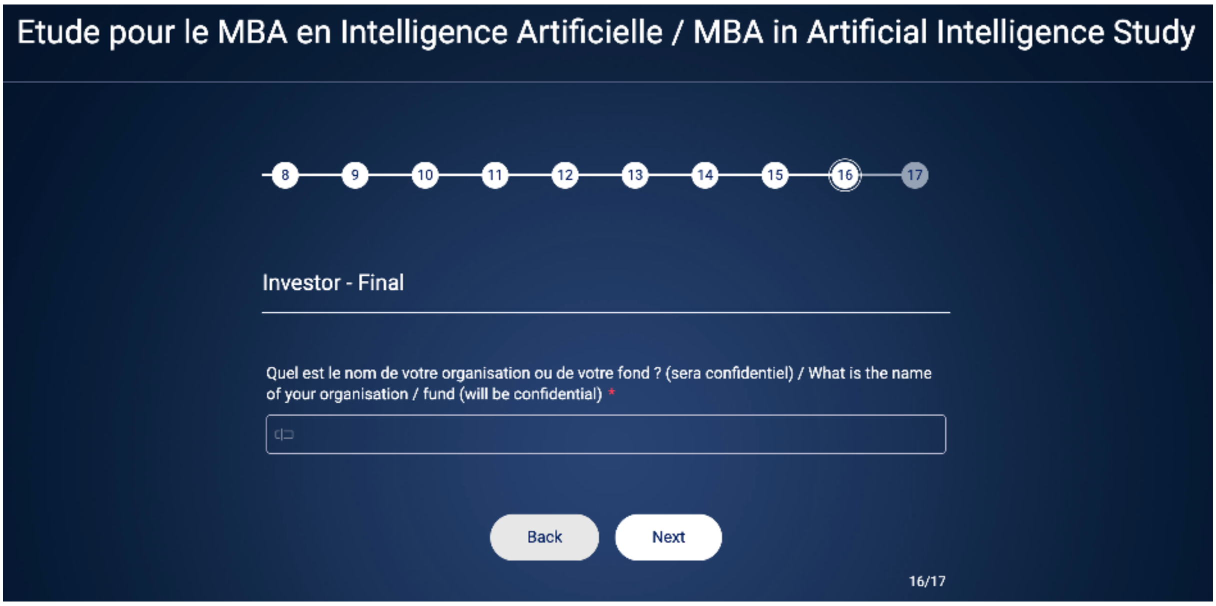
Etude pour le MBA en Intelligence Artificielle / MBA in Artificial Intelligence Study
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Investor - Final
Quel est le nom de votre organisation ou de votre fond ? (sera confidentiel) / What is the name of your organisation / fund (will be confidential) *
Back
Next
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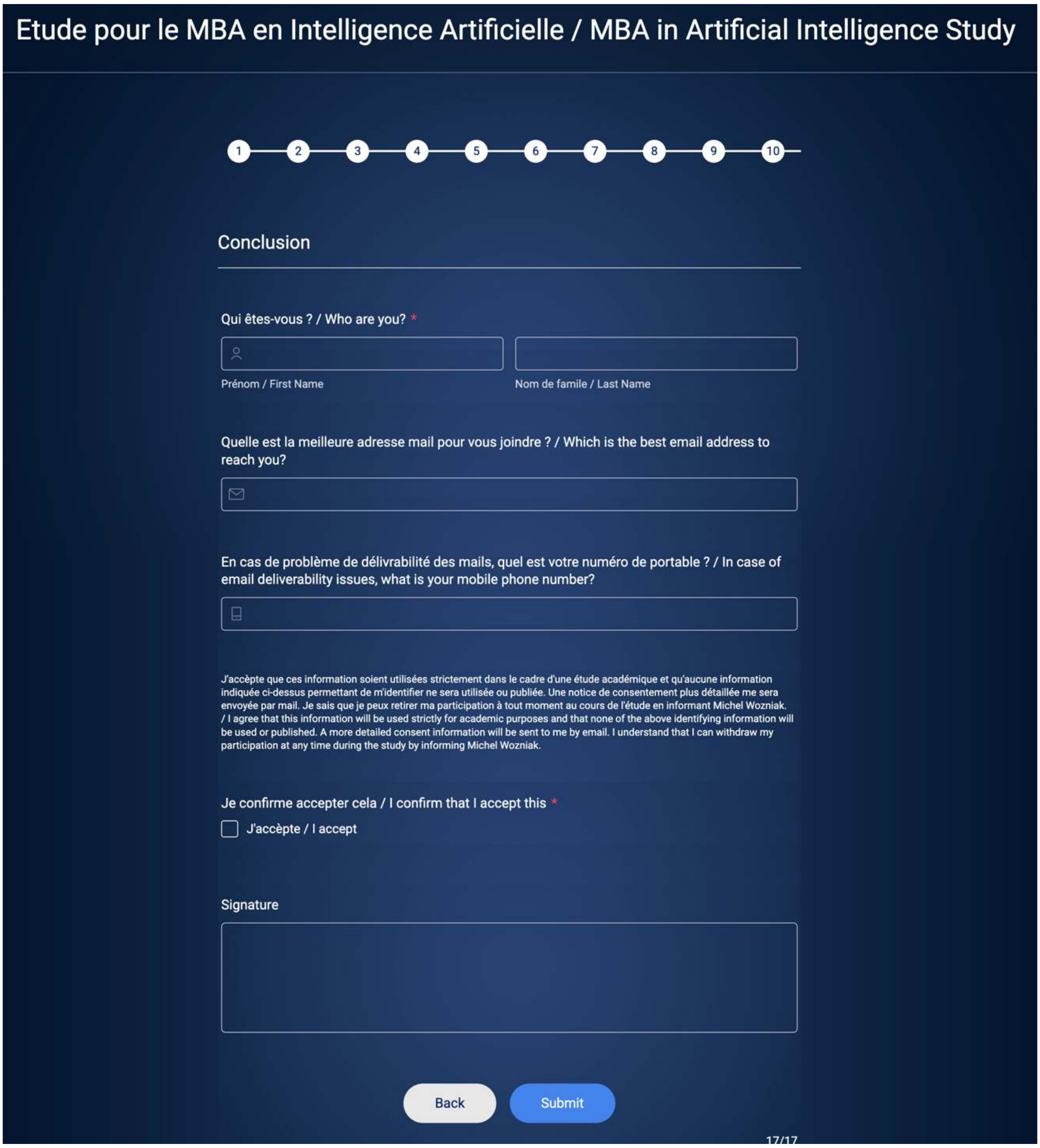

Etude pour le MBA en Intelligence Artificielle / MBA in Artificial Intelligence Study

1 2 3 4 5 6 7 8 9 10

Conclusion

Qui êtes-vous ? / Who are you? *

Prénom / First Name

Nom de famile / Last Name

Quelle est la meilleure adresse mail pour vous joindre ? / Which is the best email address to reach you?

En cas de problème de délivrabilité des mails, quel est votre numéro de portable ? / In case of email deliverability issues, what is your mobile phone number?

J'accèpte que ces information soient utilisées strictement dans le cadre d'une étude académique et qu'aucune information indiquée ci-dessus permettant de m'identifier ne sera utilisée ou publiée. Une notice de consentement plus détaillée me sera envoyée par mail. Je sais que je peux retirer ma participation à tout moment au cours de l'étude en informant Michel Wozniak. / I agree that this information will be used strictly for academic purposes and that none of the above identifying information will be used or published. A more detailed consent information will be sent to me by email. I understand that I can withdraw my participation at any time during the study by informing Michel Wozniak.

Je confirme accepter cela / I confirm that I accept this *

J'accèpte / I accept

Signature

Back

Submit

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APPENDIX F02 – THE RAW FILES

The raw files can be found here:

- The anonymized file from chapter 3.6: https://www.dropbox.com/scl/fi/hphsmmrcyuopj9vquu4ao/Sondage-v01-Anonymized.csv?rlkey=8bvbzwlt037t2fne0i24eis0k&dl=1
- The streamlined, cleaned and filled file from chapter 3.6: https://www.dropbox.com/scl/fi/3vhj0td56mmkordkbf580/Sondage-v04-Void-Cells-Filled.csv?rlkey=u9qptb63i3ao80omojhnrmp61&dl=1

- Some people had 6 sets of indicators filled. In this case, the one line from the original file was split into 6 lines, adding indicators to show whether the profile was investor or startup, whether the startup was AI or non-AI, and whether the indicators reflected success or failure. This gave a total of 148 lines.
- We then filtered the respondents who answered the same Likert evaluation in every response (like a 5). One respondent was matching this condition. The four sets filled by respondent 30 were therefore removed from the dataset, leaving 144 valid lines, or 144 sets of Likert-scale evaluations.
- Since three columns contain data only valid for founders, namely (1) the amount of people in the board, (2) the amount of failed startups, (3) and the amount of succeeded startups, we will fill the empty values with the word: "Irrelevant".

APPENDIX F03 – THE GOOGLE COLAB PAGE

Here is the link to the Google Colab page where all the code to generate the analysis is stored. You can make a copy of the environment and run it yourself to check the results. Every cell can be run separately:
https://colab.research.google.com/drive/1rhy91v01t8NFnZNECVpku9mD2ddRb58Y?usp=sharing

The language used is Python and the dataset is fully available from within each cell.

APPENDIX G01 – KRUSKAL-WALLIS TEST FOR SUCCESS

See Google Colab Cell 21. This shows the Kruskal-Wallis test for significant differences between AI and non-AI startups regarding success.

```
Traits with a Significant Difference Between AI and Non-AI Startups in Success Perception (Final Version - Sorted by
Importance <0.05):
                                        p-value
Startup Members Of The Board           0.044180
Knowledge In Communication             0.056197
Scale Point of View                    0.143021
Scale Capacity To Disengage Disputes   0.303214
Scale Negative Interactions            0.305933
Scale Stubbornness                     0.332099
Scale Life Balance                     0.397228
Scale Past Experiences                 0.455095
Age                                    0.457909
Knowkedge In AI                        0.508332
Scale Time Management                  0.641467
```

Scale Capacity To Visualise	0.676321
Scale Capacity To Communicate	0.721647
Scale Assume Responsibility	0.755295
Scale Beliefs	0.762417
Knowledge In Leadership And Management	0.831170

APPENDIX R01 – KRUSKAL-WALLIS ANALYSIS OF STARTUPS AND INVESTORS

The following calculations stem from Google Colab, cell number 3 (reproduced as is):

Traits with a Significant Difference Between Startupers and Investors (Sorted by Importance):

	p-value	Startuper Mean	Investor Mean
Scale Capacity To Visualise	0.002375	3.979167	4.479167
Scale Past Experiences	0.002995	3.666667	4.218750
Scale Capacity To Disengage Disputes	0.013391	3.437500	3.875000
Scale Fears	0.019350	3.562500	4.083333
Scale Stubbornness	0.024220	3.812500	4.187500
Scale Negative Interactions	0.034600	3.437500	3.906250
Scale Life Balance	0.083467	3.791667	3.427083
Scale Stress	0.220800	3.541667	3.791667
Scale Capacity To Communicate	0.292308	4.229167	4.104167
Scale Negativity	0.412965	3.708333	3.864583
Scale Assume Responsibility	0.414458	4.062500	4.229167
Scale Beliefs	0.750610	4.187500	4.208333
Scale Point of View	0.752887	3.750000	3.906250
Scale Time Management	0.837148	4.062500	4.177083

Traits with a Significant Difference Between Startupers and Investors in Success Perception (Sorted by Importance):

	p-value	Startuper Mean	Investor Mean
Scale Fears	0.011366	3.083333	3.833333
Scale Life Balance	0.025182	4.083333	3.500000
Scale Past Experiences	0.025585	3.958333	4.437500
Scale Capacity To Visualise	0.044116	4.375000	4.687500
Scale Negative Interactions	0.069612	3.083333	3.645833
Scale Capacity To Disengage Disputes	0.123287	3.458333	3.791667
Scale Capacity To Communicate	0.152194	4.500000	4.229167
Scale Stress	0.292675	3.333333	3.604167
Scale Time Management	0.357931	4.458333	4.229167
Scale Point of View	0.453680	4.166667	4.041667
Scale Assume Responsibility	0.645505	4.500000	4.479167
Scale Negativity	0.665850	3.458333	3.604167
Scale Beliefs	0.763161	4.333333	4.312500
Scale Stubbornness	0.776008	3.958333	3.937500

Traits with a Significant Difference Between Startupers and Investors in Failure Perception (Sorted by Importance):

	p-value	Startuper Mean	Investor Mean
Scale Stubbornness	0.003342	3.666667	4.437500
Scale Capacity To Visualise	0.019644	3.583333	4.270833
Scale Past Experiences	0.039807	3.375000	4.000000
Scale Capacity To Disengage Disputes	0.053529	3.416667	3.958333
Scale Assume Responsibility	0.137384	3.625000	3.979167
Scale Negative Interactions	0.176839	3.791667	4.166667
Scale Point of View	0.222721	3.333333	3.770833
Scale Time Management	0.252939	3.666667	4.125000
Scale Negativity	0.415866	3.958333	4.125000
Scale Stress	0.424348	3.750000	3.979167
Scale Fears	0.461829	4.041667	4.333333
Scale Life Balance	0.689751	3.500000	3.354167
Scale Beliefs	0.893710	4.041667	4.104167
Scale Capacity To Communicate	**0.898188**	**3.958333**	**3.979167**

APPENDIX R02 – IMPACTS OF FAILURES AND SUCCESSES

The impact of failures: (Google Colab Cell 4)

The impact of successes: (Google Colab Cell 5)

APPENDIX R03 – SPEARMAN CORRELATION WITH SUCCESS/FAILURE

See Google Colab Cell 1.

APPENDIX R04 – THE IMPACT OF AGE ON THE INDICATORS' AWARENESS

See Google Colab Cell 2.

APPENDIX R05 – FOUNDERS BY FAILURE RATE

See Google Colab Cell 22.

APPENDIX R06 – KRUSKAL-WALLIS TEST ON LOW VERSUS HIGH FAILURE RATE

See Google Colab Cell 23.

```
===== Global Kruskal-Wallis Test Results for low versus high failure rate =====

                                  p-value  Data Points Used
Scale Negative Interactions      0.094525                46
Scale Capacity To Visualise      0.099801                46
Scale Negativity                 0.133582                46
Scale Stubbornness               0.141756                46
Scale Time Management            0.211558                46
Scale Assume Responsibility      0.366724                46
Scale Fears                      0.446110                46
Scale Point of View              0.521520                46
Scale Life Balance               0.549204                46
Scale Stress                     0.853827                46
Scale Past Experiences           0.909081                46
Scale Beliefs                    0.933482                46
Scale Capacity To Communicate    0.960462                46
Scale Capacity To Disengage Disputes  0.981689           46


===== AI Startups Kruskal-Wallis Test Results for low versus high failure rate =====

                                  p-value  Data Points Used
Scale Capacity To Visualise      0.056407                14
Scale Negativity                 0.204841                14
Scale Life Balance               0.224061                14
Scale Assume Responsibility      0.322617                14
Scale Beliefs                    0.478574                14
Scale Capacity To Communicate    0.478592                14
```

Scale Point of View	0.529343	14
Scale Fears	0.602949	14
Scale Time Management	0.633384	14
Scale Stubbornness	0.637557	14
Scale Capacity To Disengage Disputes	0.658787	14
Scale Negative Interactions	0.770048	14
Scale Past Experiences	0.824012	14
Scale Stress	0.883527	14

===== Non-AI Startups Kruskal-Wallis Test Results for low versus high failure rate =====

	p-value	Data Points Used
Scale Time Management	**0.023902**	**32**
Scale Stubbornness	**0.028759**	**32**
Scale Negative Interactions	**0.034224**	**32**
Scale Fears	0.117558	32
Scale Negativity	0.174395	32
Scale Capacity To Visualise	0.187094	32
Scale Capacity To Communicate	0.493864	32
Scale Assume Responsibility	0.619071	32
Scale Capacity To Disengage Disputes	0.755686	32
Scale Point of View	0.759815	32
Scale Past Experiences	0.838497	32
Scale Beliefs	0.850466	32
Scale Stress	0.869127	32
Scale Life Balance	1.000000	32

APPENDIX R07 – KRUSKAL-WALLIS FOR AI AND NON-AI STARTUPS

See Google Colab Cell 11.

Traits with a Significant Difference Between AI and Non-AI Startups (Sorted by Importance):

	p-value	AI Startups Mean \
Scale Capacity To Visualise	0.054477	4.431818
Scale Point of View	0.060340	4.022727
Scale Time Management	0.101836	4.272727
Scale Stubbornness	0.108589	4.181818
Scale Capacity To Disengage Disputes	0.308762	3.863636
Scale Past Experiences	0.310548	4.113636
Scale Beliefs	0.458220	4.227273
Scale Capacity To Communicate	0.487498	4.204545
Scale Negative Interactions	0.551925	3.681818
Scale Assume Responsibility	0.552629	4.181818
Scale Fears	0.574159	3.931818
Scale Negativity	0.673630	3.704545
Scale Life Balance	0.724146	3.545455
Scale Stress	0.733486	3.636364

	Non-AI Startups Mean
Scale Capacity To Visualise	4.26
Scale Point of View	3.78
Scale Time Management	4.08
Scale Stubbornness	4.01
Scale Capacity To Disengage Disputes	3.67
Scale Past Experiences	4.00
Scale Beliefs	4.19
Scale Capacity To Communicate	4.12
Scale Negative Interactions	3.78

```
Scale Assume Responsibility                         4.17
Scale Fears                                         3.90
Scale Negativity                                    3.86
Scale Life Balance                                  3.55
Scale Stress                                        3.74
```

APPENDIX R08 – THE IMPACT OF AGE FOR AI STARTUPS

See Google Colab Cell 13

APPENDIX R09 – THE IMPACT OF AGE FOR NON-AI STARTUPS

See Google Colab Cell 14

```
Age Group Summary Statistics (Success Only, Non-AI Startups):
        Average  Variance  Standard Deviation
Age
20-30  4.010204  0.761905            0.836538
30-40  3.870130  0.874026            0.905685
40-50  3.883459  1.141604            1.032376
50+    4.115385  0.709707            0.825489
```

APPENDIX R10 – SUCCESSFUL AND FAILED STARTUP FOR AI AND NON-AI

See Google Colab Cells 19 and 20:

APPENDIX R11 – JACKKNIFE RESAMPLING ON THE IMPACT OF BOARD MEMBERS

Please refer to Google Colab, cell 24:

```
Original p-value: 0.0039
Jackknife p-value range: 0.0002 - 0.0154
Stability ratio (p < 0.05): 100.0%

Most influential respondents:
Respondent 59.0: p = 0.0102
Respondent 31.0: p = 0.0154
Respondent 5.0: p = 0.0154
```

APPENDIX R12 – JACKKNIFE RESAMPLING ON THE THIRD FAILURE

Please refer to Google Colab, cell 25:

```
Original Inflection Point: 3
Original Post-Threshold Slope: -0.833
Slope Variance: 0.0366
Unstable Respondents (>±0.1 variation): [21, 26, 29, 38, 39]
```

APPENDIX R13 – COX PREDICTIVE SURVIVAL MODEL

Please refer to Google Colab, cell 26:

```
Concordance Index: 0.8038
Note: A concordance index > 0.5 indicates better than random prediction

Cox Model Summary (All Startups):
                                      coef  exp(coef)  se(coef)  \
covariate
Scale Beliefs                    -0.036856   0.963814  0.146090
Scale Fears                       0.164423   1.178713  0.165238
Scale Past Experiences           -0.059310   0.942415  0.163973
Scale Time Management            -0.097517   0.907087  0.159766
Scale Point of View              -0.132789   0.875650  0.160932
Scale Capacity To Visualise      -0.096999   0.907557  0.152218
Scale Assume Responsibility      -0.233670   0.791623  0.167998
Scale Stress                      0.105641   1.111423  0.160528
Scale Capacity To Communicate    -0.076226   0.926606  0.162246
Scale Capacity To Disengage Disputes -0.043162   0.957756  0.154183
Scale Life Balance               -0.090707   0.913285  0.165691
Scale Negativity                  0.089628   1.093767  0.163955
Scale Stubbornness               -0.014917   0.985193  0.164259
Scale Negative Interactions       0.093064   1.097532  0.164035
Age_Numeric                       0.040253   1.041074  0.155283
Startup Members Of The Board     -0.151601   0.859331  0.154852
Is_AI                            -0.134191   0.874423  0.332024

coef: Coefficient, log hazard ratio
exp(coef): Hazard ratio. 1.xx is xx% higher risk, 0.xx is (100-xx)% of risk reduction.
se(conf): Standard error


                                         p  -log2(p)
covariate
Scale Beliefs                     0.800820  0.320450
Scale Fears                       0.319704  1.645193
Scale Past Experiences            0.717572  0.478805
Scale Time Management             0.541616  0.884658
Scale Point of View               0.409299  1.288773
Scale Capacity To Visualise       0.523970  0.932443
Scale Assume Responsibility       0.164253  2.606006
Scale Stress                      0.510481  0.970070
Scale Capacity To Communicate     0.638483  0.647280
Scale Capacity To Disengage Disputes  0.779521  0.359339
Scale Life Balance                0.584073  0.775780
Scale Negativity                  0.584610  0.774453
Scale Stubbornness                0.927638  0.108366
Scale Negative Interactions       0.570483  0.809744
Age_Numeric                       0.795463  0.330133
Startup Members Of The Board      0.327578  1.610089
Is_AI                             0.686095  0.543520
```

APPENDIX R14 – MISALIGNMENT RISK MODEL

See Google Colab Cell 27.

Based on the Cox predictive survival model, a misalignment risk model has been built based on:

- Calculating alignment scores for each human factor: (1/(1+absolute_difference))
- Aggregating these scores by scenario: (AI/non-AI × Success/Failure)
- Converting to risk scores per scenario 100*(1-alignment_score)

APPENDIX R15 – FIRST TIME FOUNDERS VERSUS SERIAL FOUNDERS

See Google Colab Cell 28.