This paper was presented at the 2023 ISPIM Innovation Conference, held in Ljubljana, Slovenia on 04 June to 07 June 2023. ISBN 978-952-65069-3-7.

Early Validation of High-Tech Start-ups by Using Big Data

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Abstract: Majority of the start-ups fail in the early stage of the development due to lack of validation. This paper focuses on high-tech start-ups and investigates the use of data and/or big data at this stage. The study found that early-stage start-ups fail because they create products or services not needed in the market. Early validation through an agile approach can help these young companies to manoeuver through a turbulent external environment. The results show that big data or data can act as a support at this stage. However, there are various barriers that need to be addressed for successful data adoption. The paper proposes an early validation user guide (EVU) to overcome these barriers and make data adoption easier. The EVU can provide start-ups the tools to use big data or data as a support for early validation based on the market context of the start-ups.

Keywords: Innovation; Entrepreneurship; Startups; Stakeholder management; Big data; Early-validation; Market research; Lean methodology; Systems

1 Introduction

Startups are young companies that produce unique products or services, fill a market gap or solve a problem (Baldridge, 2021). The entrepreneurs running these young companies often do not understand the importance of doing validation in the early stages. They have a vague idea about the market they want to enter but their research is usually scarce.

Previous studies show that there is a need for startups to validate their ideas in the early stage for success through lean and agile methodology (Bosch et al., 2013; Enkler and Sporleder, 2019; Silva et al., 2021). However, reliance on assumptions and biases corrode their judgment, resulting in a failure to consider market demand to make their ideas more sustainable. This lack of validation leads to developing ideas that the market does not need, and the whole exercise results in the loss of time and resources (Giardino et al., 2014). This loss is also incurred by other stakeholders involved in the startup's development, such as incubators, investors, and in some cases Universities.

This study is part of a Norwegian innovation project called 'Harvesting Value from Big data and Digitalization through a Human Systems Engineering Innovation Framework (HSEIF) ("HSEIF 2," 2020). It is a research collaboration project with two academic partners and ten industry partners funded by the Research Council of Norway. The H-SEIF project's main goal is to explore the usage of big data with the purpose of early validation to support engineers and designers in creating innovative systems. This paper's focus is on high-tech startups and the study is done in collaboration with one of the H-SEIF partners, an innovation incubator named Kongsberg innovation (KI). This research has a particular interest in the Norwegian context because of the rapidly emerging startup ecosystem, and the interest in the development of industry 4.0. The main partner KI enrolls startups in their incubator program that focus on the high-tech sector with a global potential. The incubator aims to provide startups with networks, mentors, technological development, and financial funding opportunities.

This study aims to understand if and how big data can be used in the early validation of startups, and whether this could benefit early-stage startups. It aims to mitigate risks for all stakeholders within the innovation ecosystem, including but not limited to incubators and investors. The primary purpose is to facilitate high-tech startups in leveraging data to their advantage in the early stage, making it possible for them to validate their ideas. Although there is no consensus on the definition of big data, this research differentiates between «big data» and «data». Big data is a large set of variable data collected from different sources which is constantly updated (Davenport et al., 2012; Kaminskiy, 2017) and often includes the 6 Vs, namely Value, Volume, Velocity, Veracity, and Variability. Data can be any amount of information collected to generate insights, and is only beneficial if it can provide value. For this paper, the word '(Big) data' will be used to consider both data and big data.

The research questions of the study are divided into a primary research question and three sub-questions. Four start-ups in KI's ecosystem were selected as case studies to answer the research questions.

PRQ. How can startups validate their business ideas in the early stage by using (big) data?

SRQ1. How do startups validate their business ideas in the early stage currently?

SRQ2. How do startups use (big) data in the development of their business idea?

SRQ3. How to assist startups in validating their ideas in the early stage?

2 Literature

2.1 Early Validation:

Early validation is a vital step to determine whether the startup would be sustainable. This requires a lot of research, data collection, and a somewhat standardized framework that could define the success factors of the startup in question (Antunes et al., 2021; Mäkilä et al., 2013). In recent years, startups have started using Business model canvas (BMC) (Osterwalder and Pigneur, 2010) as a management tool to test their ideas. The canvas organizes ideas into a structured format and gives space to test the hypothesis. This typically implies the lean startup methodology that focuses on continuous iterations (Reis, 2011). Applying a lean and agile approach throughout the development and using BMC in the early phase can help improve the chances of success (Ghezzi, 2019; Ladd, 2018). (Big) data can help startups look at market structures in a systemic way, which can provide better insights into the market potential. This could be valuable for early validation of the ideas. However, it is necessary to have the tools and skills available to use this data (Bosch, 2016).

2.2 Market Research:

The first step of a startup venture is typically determining the market of the product or service they are creating. It involves researching the market size, the competitors, the uniqueness of the product, and the market share they are aiming to capture. By doing this research, startups can find out the potential of their business idea and justify its launch. Market research also helps the startups to know their target market, and narrow down the scope of their potential customers, allowing them to create their products or service according to the market demand (Cote, 2020). However, sometimes this research can also become overwhelming, and startups can lose time to market entry, losing their position as a potential first entrant. Often startups fail to validate their business venture in the concept phase. The entrepreneurs are biased towards their ideas that they fail to see that their business ideas are not needed in the market (Levitt, 2002). This bias is especially common in technology startups, where the need of the business is vague. These mistakes lead to future financial and time losses for all the stakeholders involved in the process. The entrepreneurs can also lose the trust of the investors and the customers during this process (Konya-Baumbach et al., 2019). It is thus necessary to validate the business ideas in the early stage (Colomina Climent and Yáñez Muñoz, 2014).

2.3 The Norwegian Market:

In recent years, there has been a considerable growth in the number of startups in Norway. However, According to SSB, only 27.6% of the startups survive ("Nyetablerte foretaks overlevelse og vekst," 2019). Startup failures may not directly involve a lack of market research, and therefore other factors must also be considered. For example, Norwegian investors tend to move towards growth-stage startups and make capital less accessible to early-stage startups (Tobiassen, 2015). The investors may lack interest in these startups due to the possibility of the absence of return on investment (ROI).

External factors such as tax laws and policies may also contribute to the failure rate of the startups in the early stage (Keuschnigg and Nielsen, 2003).

2.4 Management Team:

One of the critical reasons startups fail is that their teams do not have the expertise, networks, capacities, and resources to realize the idea to make it marketable. The inconsistency of the strategy executions and the behavioral factors of the management team plays a significant role in the failure of a startup (Giardino et al., 2014). These factors are crucial in the early stages of a startup as a strong vision, clear strategic goals, and the right managerial practices set up the basis for the organization to perform well. A good management team can thus lift the startup to success (Binowo and Hidayanto, 2023; Victor, 2021).

2.5 Big Data:

Big data does not have one clear definition, but in the context of this research study, it could be defined as a large set of data accumulated from various sources. It consists of 6 Vs; Volume, velocity, value, variety, variability, and veracity (Gani et al., 2016; Kaminskiy, 2017). Big data can provide essential insights into the market and help organizations perform better (Sagiroglu and Sinanc, 2013). The sources of big data are dynamic, have widely differing qualities, and are continuously updating (Dong and Srivastava, 2013). However, finding relevant information from big data comes with its challenges and barriers (Berg et al., 2018; Ronkainen and Abrahamsson, 2003). Startups often cannot employ capable people who are efficient in data analysis, nor do they have the financial or time resources to bring the required results. Using analytics tools is often not part of the short-term strategic goal of the startups and it becomes difficult to integrate it into their plan. Moreover, these startups wait for investments to apply these tools (Al-Sharhan et al., 2018) while some startups target a niche that does not have much data availability (Fosso Wamba et al., 2015).

2.6 Big data tools:

Data analytics tools are an essential part of conducting market research. Through these tools, one can realize the power of (big) data and artificial intelligence which can help in filtering the relevant data during market research (Verma et al., 2021). There are various analytics tools available in the market that startups can use. These technologies include but are not limited to Hadoop, Map reduce, API programming, No SQL, and Microsoft Excel to work with big data. Big data cannot be analyzed without having the skills to run these software programs (Blayney and Sun, 2019; Singh and Singla, 2015).

2.7 Agile and Lean Approach:

New technologies for data analysis enable businesses to use (big) data as a driver for accurate and lean decision-making according to the rapidly changing external variables.

This agile or lean approach allows businesses to make decentralized decisions (Unhelkar, 2017). The integration of lean methodology in the business models of the startups can help them leverage their resources (Bocken and Snihur, 2020; Seggie et al., 2017). This approach is essential for early-stage startups to work efficiently (Nguyen-Duc et al., 2018).

3 Research Methodology

This study adopts the multi-case study research method (Yin, 2018). The methodology helps in understanding the problem in depth by selecting multiple cases (startups), and gives an opportunity to derive comparisons between them (Jiao and Evans, 2016). This helps in generating more robust results while creating an iterative approach to doing the research. This is important as it allows going back and forth to understand the problem better, formulate the research questions more efficiently, and build a realistic solution. The research design is illustrated in figure 1.

The data for this study was collected from semi-structured interviews with the selected startups, and literature review, which included peer-reviewed journal articles, conference papers, and to some extent grey literature such as press release, news articles etc. Three startups in the early stage and one in growth stage were selected as case studies based on their pre-incubation affiliation with the main research partner KI, and their high-tech business (table 1).

Table 1: Startup Profiles

Participant	***Company***	***Application***	***Role***	***Experience***
1	Alpha	Remote Inspection toolkit	Managing Director	14+ Years
2	Gamma	Aquaculture: Farming microalgae and capturing CO2	Managing Director	2 Years
3	Delta	Sub-sea wells data collection through submersive buoy	CEO	2 Years
4	Sigma	Autonomous solution (SaaS)	Ex-CEO	30 Years

Semi-structured interviews allowed for a more open discussion where the interviewees shared their ideas and vision freely. The purpose of the interviews was to seek answers to the research questions which helped in creating the user guide.

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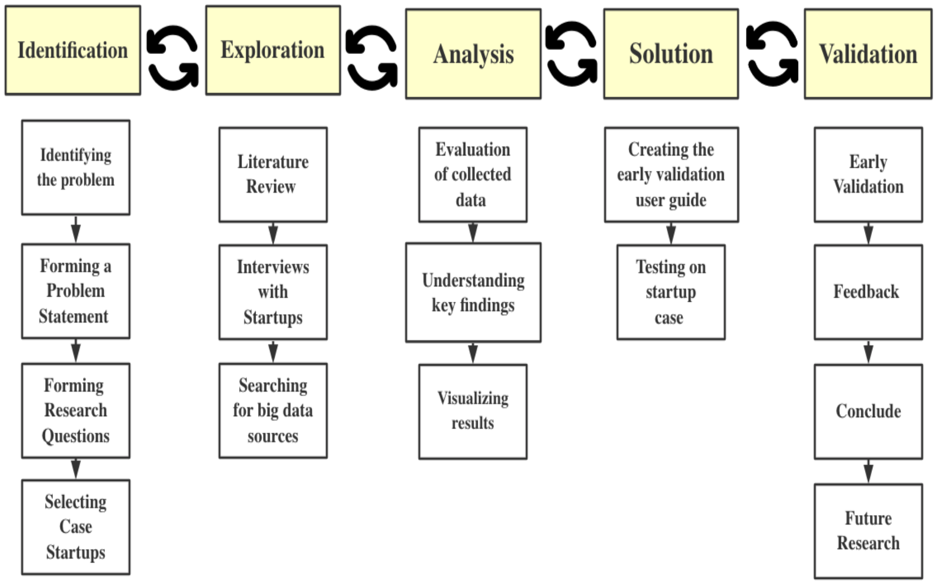

Figure 1 Research Design Used for the Study

4 Results

The results from the interviews suggest that early stage high-tech startups tend to spend less time on market research in the early stage as their main focus is to create the product and get to the market as quickly as they can. This provides them the opportunity to get more investment in the future and helps them continue to function. Moreover, they consider (big) data can hold good potential for early validation but are skeptic about its adoption because of numerous barriers related to its implementation. Table 2 shows the summarized interview results:

Table 2: Summarized results from the interviews

Interview Questions	*Startups*	*Answers*
What channels were used for primary market research?	Alpha	Calls, interviews, and Industry Visits
	Gamma	
	Delta	
	Sigma	
What channels were used for secondary research?	Alpha	Google Search and Statista
	Gamma	Google Search, Scholar, Proff.no, and SSB
	Delta	Google search, Fact pages NPD, Proff.no
	Sigma	Not clear
How was the market	Alpha	Primary data research

gap determined?	Gamma	Primary and Secondary Data Research
	Delta	
	Sigma	Primary data research
How much time was spent on this research?	Alpha	3 weeks
	Gamma	8 weeks
	Delta	Continuous
	Sigma	
What are the challenges of using (big) data in research?	Alpha	Less time, Skills, and difficult to filter
	Gamma	Non-availability of data
	Delta	Non-availability of data and Less time
	Sigma	Less time, Lack of skills, and Opportunity cost
How can startups overcome these challenges?	Alpha	Skilled Workforce and More time
	Gamma	Difficult to overcome
	Delta	By having more resources and time
	Sigma	By creating a magic algorithm
How can startups adopt (big) data strategies early on?	Alpha	It has to be made easier
	Gamma	Better accessibility to (big) data
	Delta	Understanding of (big) data
	Sigma	Strategic intent
Do you think a user guide or a toolbox that integrates (big) data may be helpful?	Alpha	Yes. If it tells me when, what, and how to use
	Gamma	Maybe
	Delta	Yes. But it should apply a lean approach
	Sigma	User guide yes. Toolbox, not sure
What tools were used for early validation?	Alpha	Calls, Interviews, and testing
	Gamma	Not validated
	Delta	Business model canvas, and business plan
	Sigma	Business model canvas, Interviews, and testing

4.1 Key Impact Factors that affect the adoption of big data:

Four key impact factors were identified that affect the use and adoption of (big) data, These factors directly contribute to the perception of startups about (big) data adoption:

Reluctance: Early-stage startups are reluctant to adopt (big) data for early validation. They realize the benefits and value it brings but they also recognize the challenges related to data availability and limited resources etc.

Lack of Structured Process*:* Startups usually do not follow a structured approach in the early phase. Their approach depends on the industry and customers. This is mostly true for High-tech startups that have a limited number of potential customers.

Team Experience*:* The professional experience of the management team defines how the startup deals with customers and approaches the market. The team with more experience is more open to adopting (big) data while the less experienced team seems more reluctant.

Time spent on Research: This is varied and depends on the industry context. The startups that spent less time on research are more driven by one individual (entrepreneur). This shows that there might be some bias involved concerning the product or service.

4.2 Early Validation User Guide (EVU)

The EVU is created for startups that follow the market pull strategy, i.e. the startups that identify a problem or gap and then enter the market. It provides steps startups can take in the early stage and integrates the use of (big) data in specific phases. It has four phases and ten steps, where iterations can be made at any phase or step depending on the need of the startup. This allows startups to understand when to use (big) data and when to consider not using it. Figure 2 illustrates the EVU:

Phase 1: The first phase identifies the problem where the value proposition is presented, and the target market is selected through segmentation. There are three steps in this phase. Utilization of multiple tools is possible at each step (some examples are provided in the guide). We can link the steps with multiple data sources to use in the initial market research. A separate box shows these data types and sources.

Phase 2: In the second phase, startups determine the total addressable market (TAM) and define the high-level product specification. It determines the market the startup can capture and generate revenue from, while the high-level product specification outlines the key features of the product determining how it would function, and what will be its outputs. In this phase, using (big) data is recommended. It connects the last two steps in the phase and can help startups optimize and continuously improve their product to address the market gap. A separate box shows the sources, and each step indicates the tools. The user has the option to adopt (big) data as per their needs, and it is not a requirement as it is designed to provide flexibility.

Phase 3: The results from the previous two phases help create a minimum viable product (MVP) using tools such as illustrative CONOPS and prototyping. MVP is one of the core attributes of the lean methodology that helps startups determine the usage of the product and to validate the technology (Alonso et al., 2023). While illustrative CONOPS is a systems engineering tool that shows a step-by-step graphical representation of a product working in a system, and communicates its characteristics to the relevant stakeholders (Cloutier et al., 2009). The type of prototyping used depends on the Startup. For example, it could either be a digital prototype or a basic product. Afterward, the MVP undergoes market tests and focus groups to check the product-market fit and the product's performance in the field. After the market testing, the startup must decide whether to move ahead with the product or pivot.

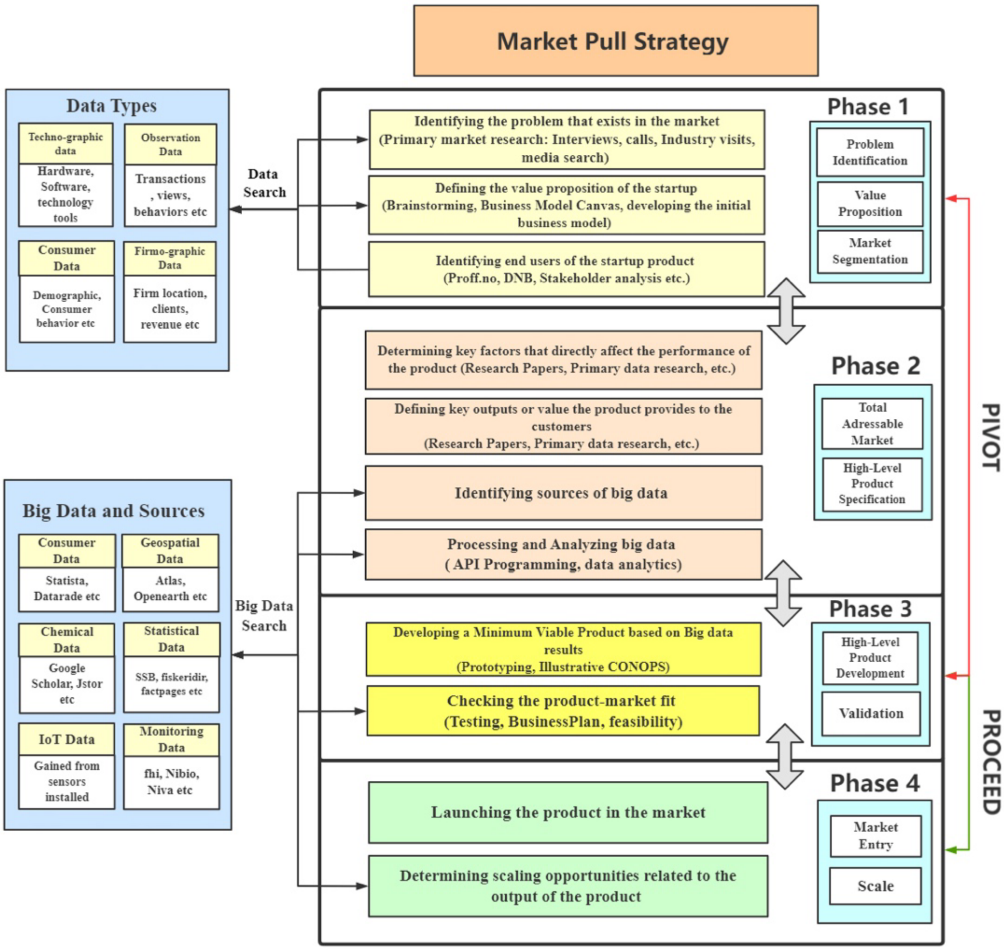

Figure 2 Early Validation User-Guide (EVU)

Phase 4: If the startup proceeds with the product based on the results from the market test, it can start entry to market. This is a crucial phase in which the product is launched. If the previous phases and steps have been followed correctly and validation is done, then the startup would possibly get good results in the phase. However, if the result is negative, the EVU helps startups to pivot and understand the problem that could have affected their performance in the market. Once the startup has captured the market and spent considerable time on it, it can consider further scaling opportunities. The outputs of the startup are beneficial to many other industries or arenas, and the startups can decide to capture another market.

Iterations: High-tech startups face immense complexity and hence need to adapt constantly to changes. Such an iterative approach provides startups the flexibility required to maneuver through the challenges. For example, a startup defining the high-level product specification of their product in Phase 2, might realize they need to define the value proposition again in Phase 1.

4.3 Testing and Early Validation of EVU

Gamma was selected as a research vehicle to test the EVU. The purpose of this test was to check the value of (big) data in particular phases of the EVU. The information needed for phase 1 and phase 3 was obtained from interviews, while phase 2 and phase 4 were tested through secondary market research. Norway is selected as the target market. This study only uses phases 2 and 4 for the purpose of the test.

4.3.1 Phase 2

Factors that affect the performance of the product: Secondary research was used to determine the optimal environment for microalgae growth. This is: Temp: 15-30 C, pH: 6.3-10, Water depth: 15-20 cm, and light intensity: 6–400 µmol photons m^{-2} s^{-1} (Hinga, 2002; Metsoviti et al., 2019). From May to October, the conditions are good for microalgae growth in the Norwegian waters. However, it can be grown all year round.

Outputs: Fish feed, Omega-3, and CO2 capture

TAM: Gamma's main product as of now is the fish feed. Thus fish farms' production determines the market size. In the future, they also aim to get revenue from CO2 capture.

High-Level Product Specification: Outputs and TAM determine the high-level specification of the product. In this case, it establishes the technology used for harvesting microalgae.

Data: The data is taken from the Norwegian Directorate of Fisheries (NDF) and EY reports (Moe et al., 2021). Some of the numbers in the data in calculation from the CO2 capture income have been assumed. This has helped in understanding the potential revenue opportunity for Gamma. Over the last four years, the number of algae sites approved by the NDF has continuously increased across all the counties of Norway. This is shown in figure 3.

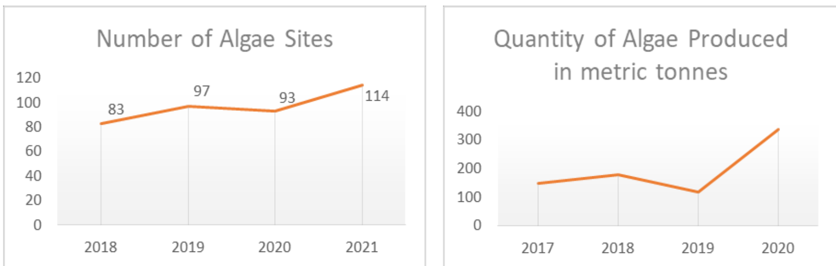

Figure 3 Number of algae sites and quantity produced in metric tonnes in Norway

Fish feed is the primary value provided by harvesting microalgae. The increased sale of fish shows that more fish are being bred and thus require more fish feed. The dip from

2019 to 2020 in the value is because of Covid-19 and supply chain factors (Figure 6: Sale of Fish). This indicates that fish farms in Norway will require diverse and efficient feeding options in the future.

The value of farmed algae indicates a positive trend in the production and the sale of its outputs. This entails a growing demand for algae in Norway, and it would continue to grow. Being in the market now might give a considerable return on investment opportunity for Gamma. Figure 4 shows the value of fish and farmed algae in Million Norwegian Kroner (MNOK) in Norway.

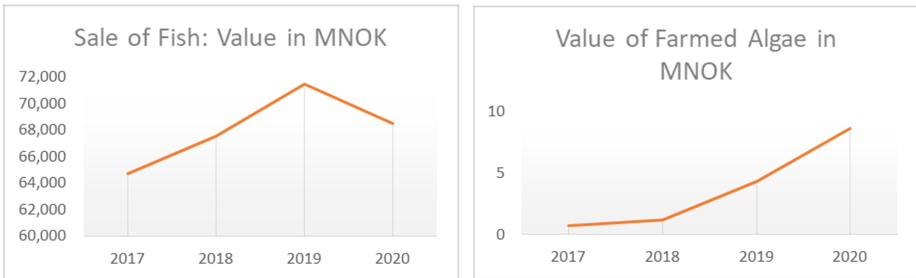

Figure 4 Value of fish and farmed algae

4.3.2 Phase 4

Entry to Market: Based on the data, Gamma could decide to launch the product in the market and see how it performs.

Scaling: After validation of the market, the business could determine whether there is an opportunity for scaling or if they should pivot. In the case of Gamma, there is a potential market in CO2 capture, Omega-3, and Pharmaceuticals. For this study, only the potential income from CO2 capture is analyzed. Table 3 and table 4 show the potential income from CO2 capture (Sayre, 2010) in Norway.

Table 3: Estimated income from CO2 capture per ton

Area of Algae	*CO2 Capture*	*Income*
0.004 Km2	2.7 tonnes/ day	52 Nok/tonne

Table 4: Estimated income from CO2 capture per year in Norway

Number of Sites in Norway	*Area of Algae Cultivation km2*	*CO2 Capture per Year in Mil Tonnes*	*Income per Year in Million NOK*
106	912	2.2	1152

Adopting (Big) data can thus support Gamma in comprehending the market potential their product has and using the EVU can provide them the framework to structurally use

(Big) data in specific stages of the development, which they currently lack. It can also give an idea of the scaling opportunities Gamma has in the future.

Early validation of the EVU was conducted through second round of interviews from KI and Sigma. Table 5 illustrates the benefits and concerns provided by the interviewees:

Table 5: Feedback from the Interviewees

Benefits	***Concerns***
• Shows when to use (big) data. • Defines phases and steps that can be easily followed. • Iterations	• The iterations need to be more clearly depicted. • Big data sources are numerous. This needs to be shown more clearly.
• Differentiation between Data and (big) data, and at which stage to use each. • Easy to read and understand. • Can be applied generally.	• IoT data is not easy to process and needs professional skills. This can be difficult in Phase 2. • The value proposition has to be made more clear.

5 Discussion

This study aims to contribute to the body of knowledge concerning innovation and entrepreneurship in the early stage startups, and addresses the paucity in literature on the role of (big) data in validating the innovative concepts that drive these types of organizations. The literature and the interviews provided insight into how startups conduct validation in the early stages.

The results showed that startups in the high-tech industry using the market pull strategy do not follow a set path in validating their business ideas. As these startups have initially identified the opportunity or gap in the market through initial market research, their focus is on developing the technology or the product to capture the market quickly. They are fighting for survival and are continuously seeking new funding, and hence need to show progress to investors fast. Almost all the interviewed startups rely on interviews and industry visits to check if their product is relevant to their potential customers. These startups target a Business-to-Business (B2B) niche market and do not need to run big marketing campaigns to capture customers. None of these startups used a structured approach for the early validation process. This lack of structure makes it difficult for the startups and other stakeholders to validate the business idea and causes challenges in the later stages.

Furthermore, the results show that there are various impact factors that determine the adoption of (big) data in the early stage of a startup. These include but are not limited to lack of a structured process and resources, reluctance, data availability etc. Additionally, other factors such as the type of startup context, business models, and products also effect (big) data adoption. For example, Sigma did not use (big) data for market research in the early stage but rather used it for the improvement of the product during the market testing phase. The data was continuously collected during the test. This data helped Sigma improve its product by continuously analyzing the data. However, during the early stage, this was difficult to do due to limited resources. Meanwhile, Gamma has not yet found any significant use for (big) data. The authors collected and analyzed secondary data during the EVU testing on Gamma, but this was also very limited. Their product does not collect data as Sigma's does, and so they are unable to continuously improve their product. However, Gamma can nonetheless use (big) data to analyze the market trends and scale the usage of the product's outputs.

This study shows that early-stage startups realize the importance of (big) data but they are not willing to adopt it in the early stage. They have set their priority on the development of the product and acquiring the necessary funding instead. This short-term approach makes it hard for them to integrate (big) data and commit resources to it early on. Interestingly, the interviewed startups with a more experienced team were more open to the idea of (big) data adoption than the startups initiated by young entrepreneurs. Moreover, the constraints of adopting (big) data make startups reluctant to use it in the early validation process. For example, limited resources hamper the ability of startups to spend too much time analyzing data. Representative from Delta mentioned that if they start analyzing (big) data at the start, they can get too immersed in it. This leads to other problems such as delay in market entry, loss of crucial funding, and control over the product itself.

The results from the interviews show that startups require a user-guide that can make it easier for them to adopt (big) data strategies in the early stages. Importantly, they should know when to start using (big) data in their research and when to stop. They need to continuously adapt to changes, and have iterations embedded in their business models to be able to respond to an external stimulus quickly. Their reluctance assumes that they will lose time and resources by using (big) data early on. A guide could help them use agile principles and iterations to use (big) data in certain phases of the early validation process and thus give them a clear pathway. Based on this, the EVU was created which can make it easier for startups to adopt (big) data in the early stage. The results show that adopting (big) data in the early stage can act as a support but is not the solution to the problem. It comes with its challenges and hence should only be adopted based on the context of the startup and its requirements.

5.1 Limitation and Future Research

There is a need for improvement in the EVU to make it more adaptable to startups in different industries. The data sources and tools are context-dependent; therefore, more relevant sources and types should be included. Moreover, the authors of the study are no professionals in data analytics and hence the testing of the EVU may be limited. However, this study serves as a starting point for further investigation into the use of (big) data as a means of facilitating the early validation processes of these organizations, while also helping incubators and investors in their decisions. Further research is proposed related to innovation ecosystems to get a better understanding of how different stakeholders help startups in early validation and whether these stakeholders could play a role in reducing the challenges of (big) data adoption.

6 Conclusion

This study examines the value (big) data could provide during the early stage of high-tech startups that follow the market pull strategy with a B2B model. Based on the case studies, it was observed that startups do not follow a structured approach for validation in the early stage. High-tech startups usually rely on direct interviews or industrial visits with potential customers to define the value proposition. They spend less time on secondary data research as their focus is to develop the product and attract investors. The study also identifies constraints that hinder the adoption of (big) data in the early stages. These are data availability, limited resources, priority, short-term goals, and knowledge. To address these challenges, and the need of the startups, an early validation user guide (EVU) is proposed. The EVU rests on agile principles and supports startups in adopting (big) data during the early validation process. The phases and steps provided in the EVU help startups determine when to use big data and when to stop. Additionally, iterations are provided in each phase that allows the startups to decide when to pivot if there is a need.

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