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Scaling Startups Smarter: A Conceptual Framework for Data-Driven Growth

Abstract

Background and purpose: Adapting Smart Data analytics, a refined approach from Big Data, has great potential for a startup's internal processes, market understanding and growth support. While the use of Big Data is well described for conventional companies, its description for startups remains fragmented. This knowledge gap highlights the need for a conceptual framework developed for the development stages and strategic needs of startups. The aim of the study is to develop a theoretical framework for the adaptation of Smart Data in startups and to formulate possible implementation strategies taking into account the development stages of the startup.
Design/methodology/approach: The usefulness of Smart Data in the context of startups will be assessed using a SWOT analysis based on scientific articles published after 2019 in Q1 and Q2 journals, according to Journal Citation Reports. Based on the SWOT results and using the associated TOWS tool, recommendations will be made for the implementation of this approach in startups.
Findings: The key finding is that Smart Data implementation is most impactful during the growth and development phases, when adequate operational maturity and resources are available. Early-stage startups may face significant barriers such as resource constraints, data security risks and technical risks. Addressing these risks and adapting Smart Data provides the startup with improved market insight, streamlined processes and enhanced decision-making capabilities.
Value and limitations: The study fills an existing gap in startup scaling theory by providing a detailed framework for Smart Data integration. It extends startup and Big Data theory by providing practical guidance for founders, and serves as a foundation for future empirical research. The study shows that a well-timed and strategically phased implementation of Smart Data can significantly increase a startup's capabilities and potential.

Keywords: *start-up, big data, data-driven innovation, strategic decision-making, conceptual framework*

JEL Classification: M13, O32, D83, C88, L26

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1. Introduction

The development and scaling of a startup represents a pivotal moment in the startup's history. Having endured numerous challenges, the company has demonstrated resilience in navigating market barriers, securing sales, and positioning itself for further expansion. Many business models espouse a commitment to continuous learning (Blank, 2013; Ries, 2011), aiming to gain deeper insights into customer needs and respond with greater precision. In addition, startups, like any business, are subject to the laws of scaling. This law assumes a power-law relationship between the growth of macroscopic variables (e.g. revenues, expenses, total liabilities) and their size (e.g. turnover, total assets, number of employees). This means that as the company grows, the variables shown will change in a predictable way, but the growth will not be linear (Kobayashi et al., 2019, 2021; Xu et al., 2023). One proposed approach to accelerate the scaling cycle is to leverage the concept of Smart Data, which has emerged from the field of Big Data.

The topic of the article was chosen because there is a gap in the literature. The topic of Big Data has already been addressed in the literature, and the concept itself has been recognised as valuable for startups and their development (Juma & Silver, 2020). Among other things, the concept has been used to study the impact of Big Data on business models (Hartmann et al., 2016) and to develop frameworks for specific industries (Behl et al., 2019). However, there is a lack of studies that point to implementation strategies at specific stages of a startup's development. The following article fills this gap by providing a theoretical framework for how Smart Data works at each stage of a startup's development, taking into account strengths and barriers.

The usefulness of Smart Data in the context of startups is assessed through the lens of a SWOT analysis. Given the advantages of this method, namely the potential for strategic for strategic assessment and positioning (Helms & Nixon, 2010), as well as its simplicity and universality and universality (Pickton & Wright, 1998), recommendations for the implementation of this approach in startup contexts are based on the TOWS tool, which is linked to the strategic interpretation of the SWOT analysis results (Weihrich, 1982). The SWOT analysis was based on an analysis of scientific articles. The selection of articles was based on a number of characteristics, including the date of publication, with only articles published after 2019 in peer-reviewed scientific journals ranked Q1 or Q2 on the Journal Citation Reports scale.

The paper is structured as follows. The theoretical overview deals with the characteristics of Smart Data. The methodological chapter describes how the data were collected and the methods used to analyse them. The results include an analysis of the literature using the tools presented. Discussion includes the development of a theoretical framework for the concept of Smart Data functioning in each of stages of development in startups. The conclusion deals with the final summary of the findings, proposed hypotheses and the value brought by the article, limitations and future research directions.

The aim of this article is to detail the strengths, weaknesses, opportunities and threats of using Smart Data in startups. Furthermore, implementation strategies will be proposed based on the TOWS analysis carried out. The whole will be related to the different stages of startup development with a proposal to apply a specific strategy at a specific stage of development.

The novelty and added value of the article is the creation of a theoretical framework for how Smart Data works in startups. Given the lack of studies on this topic, the article will serve as a basis for further academic reflection. The value of the article is both theoretical and practical. The article is an extension of big data theory and startup theory. Furthermore, it is an attempt to show startup practitioners a new tool to help them scale their business.

The article attempts to answer the following research questions:

- From which stage of a startup's development can Smart Data be used effectively in practice? (RQ_1)
- What are the barriers to the practical implementation of Smart Data in startups? (RQ_2)

2. Theoretical background

The concept of Smart Data has evolved in conjunction with the emergence of Big Data, particularly in the context of broader digital transformation. In contrast to Big Data, which is concerned with the volume, variety and velocity of data, Smart Data prioritises the provision of:

- trusted,
- contextualised,
- relevant,
- cognitive,
- predictive,
- consumable

information at any scale (Zeng, 2017). This enables more informed decision-making and strategic planning.

The concept of trustworthiness in Smart Data refers to ensuring the reliability, security and privacy of data. Data assurance can be achieved through a variety of techniques, including the use of blockchain technology or smart contracts. These methods can guarantee the integrity of data by ensuring that only authenticated data is collected and processed (Ardagna et al., 2021; T. Li et al., 2021).

Contextualisation, in the context of Smart Data, is of paramount importance for improving the efficiency and accuracy of data-driven processes. By taking into account contextual factors (Mikalef & Krogstie, 2020), improving data quality (Ghasemaghaei & Calic, 2019) and leveraging fine-grained contextual information (Pentland et al., 2020), organisations can achieve enhanced innovation capabilities, decision quality and predictive accuracy.

The transformation of raw data into actionable insights depends on the use of Smart Data. The use of key techniques, including data pre-processing, integration with the Internet of Things (IoT) and Big Data, machine learning, data fusion, relevance-based prediction, and the use of ontologies for data interoperability, are essential for achieving this goal (Bagozi et al., 2019; Munawar et al., 2020; Surbakti et al., 2020). Furthermore, addressing the challenges associated with data imbalance is a prerequisite for the success of Smart Data applications. Taken together, these approaches enhance decision making, operational efficiency and sustainability in various smart environments.

The cognitive and predictive capabilities of Smart Data are critical for increasing organisational productivity, optimising data processing efficiency and predicting future trends (S. Gupta et al., 2020). The development of these capabilities requires a combination of advanced analytics, efficient data processing techniques and a supportive organisational culture that is responsive to external pressures (Dubey et al., 2019).

The usability of data in Smart Data depends on overcoming technical challenges, using robust frameworks and tools, and creating value by generating practical insights (Hulsen et al., 2019; Munawar et al., 2020). Effective use of Smart Data requires a systematic approach that considers data quality, security and organisational factors (Surbakti et al., 2020). By addressing these aspects, organisations can more effectively harness the potential of Smart Data to drive innovation and improve decision making across disciplines.

The key characteristics of Smart Data serve to highlight the key differences between it and Big Data. In the context of the Smart Data concept, the authenticity and integrity of data are of paramount importance. The quality of decisions and the ability of companies to innovate depend on the volume and quality of the data in question. Of particular importance is the combination of advanced business analytics capabilities and an organisational culture that is conducive to the responsible use of Smart Data. Given the above, i.e. the greater 'precision' of Smart Data compared to classic Big Data, which is achieved by reducing the volume of data, improving its quality and relevance, and making it more consumable. This makes it a better fit for startups who, due to resource constraints, need more flexible solutions that don't break the bank, while providing valuable opportunities for scaling and learning.

3. Methods

The main objective of the article is to explore the usefulness of smart data in start-ups and to provide a theoretical framework. The article answers the two research questions:

- From which stage of a startup's development can Smart Data be used effectively in practice? (RQ_1)

- What are the barriers to the practical implementation of Smart Data in startups? (RQ_2)

The potential of smart data is explored using a SWOT analysis and a complementary TOWS analysis. The SWOT method was chosen because of its universality in strategic analysis and its ease in identifying the internal and external factors that influence the use of Smart Data in startups. The TOWS analysis was chosen to design the basic strategies that a startup can adopt when implementing Smart Data. SWOT/TOWS analyses can be used to determine with a high degree of accuracy at what stage a startup is ready to implement Smart Data, and which elements the startup needs to optimise in order to make the implementation successful. The methodology also allows the identification of threats and external challenges that may hinder this process. TOWS enables the SWOT results to be translated into concrete, practical, action-oriented implementation strategies that can help startup founders in their implementation decisions. In addition, both analyses are easy to conduct, which is crucial for startups operating in a resource-constrained environment. This method can be used by startups to quickly and cheaply analyse the usability of Smart Data in the context of their business. It is because of the pragmatism and simplicity of this solution and its fit with the realities of startups that the study is based on this methodology.

To ensure the robustness and relevance of the conceptual framework presented in this study, a systematic literature review was conducted. The selection process adhered to strict inclusion criteria, focusing exclusively on peer-reviewed journal articles published after 2019 in journals classified as Q1 or Q2 according to the Journal Citation Reports (JCR) ranking. This decision was motivated by the need to capture the latest advances in smart data applications in startup environments, ensuring alignment with current research trends and high-impact academic discourse.

A total of 82 articles were analysed, primarily sourced from leading databases such as Scopus, Web of Science and IEEE Xplore, among others. The selection criteria included studies that explicitly addressed the intersection of Smart Data analytics, startup growth strategies, and digital transformation. In addition, articles that explored the theoretical underpinnings of data-driven decision making in early-stage ventures were included to ensure a holistic understanding of the topic. The literature analysis was structured around a SWOT framework, which enabled the identification of key strengths, weaknesses, opportunities and threats associated with the adoption of smart data in startups. The extracted insights were then synthesised using the TOWS matrix, which facilitated the derivation of strategic recommendations tailored to different stages of startup development.

Despite the methodological rigour, it is acknowledged that limiting the scope of the literature to post-2019 publications may have omitted foundational studies that have shaped earlier discourse on Smart Data in entrepreneurship. However, given the rapid evolution of data analytics methodologies and the increasing prevalence of AI-driven approaches, prioritising recent high-impact studies was considered essential to ensure the relevance and applicability of the study. Future research could address this limitation by conducting a longitudinal bibliometric analysis, integrating both historical and contemporary perspectives to track the evolution of smart data adoption in startup ecosystems.

4. Results

4.1. Strengths

The main benefit of using Smart Data in the context of startups is the ability to streamline organisational processes. In addition, the use of Smart Data has an impact on the decision-making process by enabling inferences to be drawn from large data sets. This not only streamlines the decision-making process itself, but also facilitates the formulation of strategic plans (Saura et al., 2021; Saura, 2021). Furthermore, the use of Smart Data analytics enables a startup to gain a deeper understanding of market dynamics and customer needs, which can subsequently lead to an improvement in the quality of the product or service offered (Grimaldi et al., 2021; Prüfer & Prüfer, 2020). Improved decision making also has implications for optimising productivity and performance. A variety of data science techniques are used to assess and improve productivity in many business processes. These techniques facilitate the allocation of resources and the comparison of performance metrics, ultimately leading to improved overall efficiency (Charles et al., 2021).

4.2. Weaknesses

A notable shortcoming in the use of Smart Data in startup companies is the lack of explicitly delineated goals and a comprehensive vision regarding data science initiatives. This deficiency often leads to the expenditure of unwarranted effort and the misallocation of resources (Martinez et al., 2021; Saltz & Krasteva, 2022). Furthermore, startups often prioritise the technical intricacies of data science at the expense of addressing internal organisational challenges that hinder the effective implementation of data-driven strategies (Fayyad, 2022; Martinez et al., 2021). In particular, startups in the early stages of development may find it difficult to integrate Big Data analytics into their day-to-day operations. Barriers to implementation include inadequate and untrained operational methodologies and a lack of guidance on how to use the analysed data effectively (Ahmed et al., 2023). Using data in this way can lead to a reduction in both productivity and the quality of the outcomes derived from the data in question (Ebert et al., 2019).

4.3. Opportunities

The opportunities for startups lie primarily in their ability to anticipate and respond to market uncertainties, thereby reducing the risk of failure. The use of Big Data for early validation can facilitate the acquisition of critical insights into market needs and customer preferences. However, it is important to note that this is not a stand-alone solution and needs to be complemented by other strategies (Ahmed et al., 2023). In addition, data science can be used to examine labour market trends and assess the demand for entrepreneurial and digital skills, which are critical to the success of a startup. Insights from data science can help startups identify the most in-demand skills and adapt their hiring strategies to meet the identified needs (Prüfer & Prüfer, 2020). Data science in startups has demonstrated the potential to drive innovation and introduce disruptive change in numerous fields, including entrepreneurship (Grossi et al., 2021; Obschonka & Audretsch, 2020).

4.4. Threats

The main concerns associated with the use of Smart Data relate to security, particularly the potential for external interference with the confidentiality of sensitive corporate data. The entire Big Data cycle, from initial data collection to final data destruction, is characterised by a number of significant security and privacy issues. Each stage of the data lifecycle has the potential to lead to the exposure of personal data, which in turn can lead to privacy risks (Koo et al., 2020). Startups, particularly those in the early stages of development and lacking the capacity to adopt Smart Data, may be inclined to resist the introduction of this type of analytics due to the inherent risks and costs involved (Cabrera-Sánchez & Villarejo-Ramos, 2020). Early-stage startups often face difficulties in validating the implementation of Big Data-related techniques, due to the numerous barriers they face. Although Big Data can facilitate preliminary validation, it is not a panacea and requires overcoming numerous obstacles (Ahmed et al., 2023).

A tabular summary of the above analyses, in the form of short bullet points, gives the following results:

Table 1. **SWOT Analysis**

STRENGTHS	WEAKNESSES
• Efficiency in organisational processes • Gain insights into market dynamics • Optimise performance	• Lack of clear goals and vision for Data Science initiatives • Too much focus on technical aspects • Barriers to integrating Big Data analytics (early-stage)
OPPORTUNITIES	**THREATS**
• Anticipate market trends • Assess labour market trends • Harnessing the potential to drive innovation	• Exposure of sensitive corporate and personal information to privacy risks • Reluctance to adopt Smart Data due to associated risks, costs and lack of resources • Need to overcome significant barriers despite the potential benefits of Smart Data

Source: own study

1. An aggressive strategy (labelled S/O - Strengths/Opportunities in the TOWS matrix) implies an emphasis on greater insight into the market, its characteristics, trends and the needs of potential customers, as well as the availability of potential new employees. It is also assumed that improvements in the efficiency of processes within the company will lead to an increased level of market analysis and responsiveness to market needs, which can be achieved through product or service customisation. This, in turn, can lead to the development of a startup's performance.
2. A conservative strategy (labelled S/W - Strengths/Weaknesses in the TOWS matrix) involves using the initial resources and time available at the start of the venture to define the purpose and scope of the use of Smart Data and the technical security measures required to implement Smart Data analytics within the organisation. The strengths of this approach, namely process improvements and market insights, enable the startup to overcome the security concerns and resistance to adopting Smart Data that are typical of early-stage startups.
3. A competitive strategy (labelled W/O - Weaknesses/Opportunities in the TOWS matrix) is to address any internal weaknesses that may arise when attempting to

integrate Smart Data with the opportunities that its implementation presents. It is expected that initial doubts about the feasibility of achieving the desired objectives and the technical aspects involved will be resolved favourably, given the availability of the necessary knowledge and staff capable of performing the required Smart Data analyses. The implementation of an appropriate analytical methodology (assuming the barriers to its use are overcome) will facilitate the acquisition of superior market intelligence and create the potential for more significant innovation.

4. A defensive strategy (labelled W/T - Weaknesses/Threats in the TOWS matrix) is based on the assumption that an organisation operates in conditions that are unfavourable to its interests and that it lacks the capacity to adequately prepare its internal processes and measures to withstand the impact of these conditions. It also assumes that data can be stolen or corrupted relatively easily, despite the implementation of measures to protect it. At this stage, it is prudent to focus on the core business of the emerging company. Once the company has reached a more advanced stage of development, or has accumulated sufficient resources, it can begin to use Smart Data, ensuring that data security and anonymity are maintained throughout the process.

5. Discussion

The SWOT/TOWS analysis provided a theoretical framework for the use of Smart Data in startups and strategies for its implementation. Strengths include increased efficiency in decision making. Weaknesses relate to the lack of vision in the introduction of Smart Data and the limitations in the incorporation of Smart Data by young startups. Opportunities relate to helping startups analyse market trends and assess ideas and values at an early stage. Threats relate to data security and privacy risks.

Theoretical analysis has shown that the implementation of Smart Data will yield the best results at a more mature stage of the startup's development. The use of Smart Data by startups has great potential, enabling the identification of the most useful data, pattern recognition and the use of new algorithms. This capability improves decision making, increases efficiency and encourages the creation of innovative business models, helping to turn barriers into opportunities (Sedkaoui, 2018). Research shows that analytics based on Smart Data (and broadly defined Big Data), can significantly improve a startup's performance and competitive advantage (Behl, 2020). Big Data can create value on multiple dimensions, including informational, transactional, transformational, strategic and infrastructural. This approach can be particularly beneficial for startups looking to leverage data for strategic advantage (Elia et al., 2020). Big Data can also be used by startups to analyse web search traffic data to understand growth trajectories and market trends. Successful startups, particularly those in the consumer sector, show a strong correlation between web search activity and venture capital valuations, suggesting that data-driven insights can influence strategic decisions (Malyy et al., 2021). Smart Data can also assist a startup in early-stage validation by helping it overcome external challenges. However, it is not a one-size-fits-all solution, and startups need to overcome many barriers to effectively use Smart Data's validation capabilities (Ahmed et al., 2023).

Smart Data also presents barriers and drawbacks to its implementation in startups. Many startups struggle with a lack of skilled personnel who can effectively analyse and interpret data extracted from Big Data (Li et al., 2019; Sandhu, 2022). The use of any form of Big Data (not just Smart Data) involves the use and storage of large amounts of sensitive data, which poses significant security and privacy risks. Issues such as unauthorised access to data, data confidentiality and data integrity are particularly important for startups to consider before deciding to implement (Anwar et al., 2021; Khan et al., 2021; Venkatraman et al., 2019). These safeguards are not a one-size-fits-all problem. Each phase of the Big Data lifecycle, from data collection to deletion, presents unique security issues. However, protecting personally identifiable information (PII) and ensuring the trustworthiness of the data is critical (Kantarcioglu & Ferrari, 2019; Koo et al., 2020). There is also the challenge of integrating Smart Data with existing systems and ensuring adequate scalability. Data migration, vendor lock-in and compliance issues need to be addressed before an implementation decision is made (Sandhu, 2022).

The proposed model can comprehensively highlight the benefits proposed in the literature. The SWOT analysis and the identified benefits show significant similarity. The main benefits of using Smart Data in startups are greater insight into market characteristics and learning about real customer demand, ways of communicating with customers and thus greater opportunities to learn and adapt products and secure sales. Smart Data can also benefit internal business processes. Adapted data can positively influence the development of business models and performance optimisation. Data can also be used to enhance labour market research for talent acquisition. The barriers listed may also be addressed by the proposed implementation strategies, depending on the position of the start-up on the SWOT map. Each of the proposed strategies has the potential to cover potentially emerging barriers. If these are low, an aggressive strategy will make the most of favourable external conditions and favourable internal processes. A conservative strategy uses the company's strengths to cover emerging internal problems. Personnel and technical deficiencies can be covered by a competitive strategy. On the other hand, if the emerging problems and barriers prove to be overwhelming, a defensive strategy involves delaying the implementation of Smart Data and focusing on the startup's core business. The applicability of the model needs to be analysed in terms of the capabilities of the startup during the different phases of development. The seed phase is mainly characterised by the creation of the business foundations. Networking, refining the product prototype and market research are particularly important at this stage. Each of these activities is particularly important because of the need to raise finance (Venugopal & Yerramilli, 2022) and build an appropriate business model (Ghezzi & Cavallo, 2020). Based on these characteristics, it is possible to relate the SWOT analysis to the seed stage. A startup in the seed stage does not have the potential to profitably optimise its performance or gain advanced insights into the market because it has not yet learned how the market works and what its characteristics are. Weaknesses are identified due to a lack of resources to develop additional development methodologies. There is a lack of vision for the use of Smart Data because the vision for the whole business is only just being formed. Emerging market opportunities relate only to the development of the core product, and the potential use of Smart Data is effectively tempered by the risks of introducing this methodology. According to the proposed TOWS strategies, seed stage startups should focus primarily on the development of the company's core product and processes.

After the seed phase, startups enter the early development phase. This is characterised by the implementation of a go-to-market strategy and the stabilisation of the startup's operational capabilities. A good go-to-market strategy is a combination of intensive market scoping, strategic project management and strong market orientation (Chen et al., 2024; Khan et al., 2023; Molner et al., 2019). Equally important is early fundraising from investors. This is crucial for the continued growth and survival of the startup. The two main sources of funding are venture capital (VC) funds and business angels. Startups can also turn to alternative sources such as incubators, accelerators or crowdfunding platforms (Bonini & Capizzi, 2019; Jeong et al., 2020; Lange et al., 2024). In terms of SWOT analysis, startups at this stage focus mainly on product development and a deeper understanding of the rules and characteristics of the market in which they operate. Some potential is offered by the intensity of the founders' and the startup's learning; however, the lack of funding and product development effectively blocks the possibility of effective Smart Data implementation.

The growth phase of a startup is characterised by increased customer acquisition. The acquisition of new customers and their subsequent retention is important from the point of view of the start-up and its growth. Increasing technological and marketing capabilities can have a direct impact on customer acquisition and business growth (Seo & Lee, 2025). In the growth phase, operational efficiency is equally important, especially through the use of technological innovation. Such efficiency helps to improve the efficient use of existing resources and to create new revenue streams, which are critical to securing growth and increasing the value of the startup (Ryu & Won, 2022). In addition, continued fundraising is key. Funds raised from VCs have a positive impact on the growth and performance of startups. In addition to funding, VCs also provide strategic advice and networking opportunities (Cavallo et al., 2019; Jeong et al., 2020; Singh & Hillemane, 2021). This stage is the first to show the startup's ability to build its infrastructure, develop its internal processes and increase its technological capabilities in order to start scaling its business. Compared to the SWOT model, startups in this stage will mainly focus on developing their future strengths, exploiting market opportunities and developing their business processes to attract and retain as many customers as possible.

The expansion phase of a startup is characterised by accelerated growth, increased market penetration and strategic scaling of operations. Market penetration requires customer involvement in product development. Involving them at different stages of development can lead to improved market performance (Chang, 2019; Steinhoff et al., 2023). Strategic scaling allows startups to achieve balanced growth by implementing a variety of techniques. To achieve this state, a startup must not only engage its customers, but also effectively put the knowledge gained from engagement into practice by creating value for its relevant market while adapting to change (Ireta-Sanchez, 2023). In addition, at this stage, the startup must be able to manage its risks, especially if it is uncertain about the maturity of the product. Scaling too early can increase the risk of failure by developing a product without the right market fit (Lee & Kim, 2024). At this stage, the startup begins to deepen its market presence, develop its business model and scale its business. This stage is suitable for the introduction of Smart Data because of the highly evolving nature of both the product and the processes within the company. In addition, the startup needs data for appropriate adaptation and product development. The introduction of Smart Data can significantly increase a startup's ability to know and respond to emerging demand.

The exit stage is the final stage, which is particularly important for startups. Exit can take the form of a merger, acquisition or various forms of going public, such as an initial public offering (IPO). A startup at this stage needs to pay particular attention to its financial health, market environment, strategic planning and timing. Financial health is extremely important as it affects the ultimate type of exit. However, current financial health is derived from past decisions. Startups that have developed healthy financial indicators at an early stage are more likely to have a successful exit (Fuertes-Callén et al., 2022). The second factor leading to a successful exit is the amount of funds raised. More funds lead to better exit results (Deias & Magrini, 2023). The choice of exit type is often dictated by market timing and macroeconomic conditions (Gupta & Arora, 2023), but also by strong market orientation. A good market orientation can lead to a higher probability of a startup being acquired. Therefore, the startup needs to focus on market orientation in order to increase the prospects of a future exit (Renko et al., 2022). Strategic planning at this stage allows startups to increase the value of the startup by determining the most optimal exit path, whether through secondary venture capital markets or financial harvests that can provide liquidity and divestment opportunities (Andrieu & Peter Groh, 2021; Elitzur et al., 2024). Strategic planning also improves the performance of the organisation, which is crucial when attracting potential buyers or investors (George et al., 2019). Exit stage startups are mature businesses with a strong focus on financial metrics and overall market orientation and management decisions. At this stage, a startup could use Smart Data to gain a deeper understanding of the market, support decision making and analyse its financial metrics. The startup has all the strengths identified in the SWOT analysis. Weaknesses related to the implementation phase are almost completely eliminated by the startup's sophistication. The continuous knowledge of the market and the deepening of the market characteristics lead to significant possibilities in the exploitation of opportunities. Through its sophistication, the startup has the right tools to respond to external threats. The choice of strategy for using Smart Data based on TOWS analysis would therefore depend directly on current needs and analysis.

Table 2. **SWOT analysis in the light of startup development stages**

SWOT Areas	Stages of startup development				
	Seed	Early Stage	Growth	Expansion	Exit
Strengths	None	Minor	During the development	Significant	Significant
Weaknesses	Significant	Visible	Visible, however opportunities to address them start to emerge	Visible, but the startup has the possibilities to effectively mitigate them	Mitigated, minor
Opportunities	Covered by threats and very early stage of development	Starting to emerge during the market learning	In the course of their closer search and the beginning of their covering	The startup is beginning to make full use of them and to find new	Startup has the tools to take full advantage of opportunities
Threats	Significant	Significant	Significant, however opportunities to mitigate them start to emerge	Startup's current capabilities make it possible to effectively mitigate their impact	Startup has the tools to effectively address emerging threats
Proposed Strategy	Defensive	Defensive	Competitive	Depends on the analysis and situation	Depends on the analysis and situation

Source: own study

The progression of a startup through its development stages is marked by sequential strategic realignments in data management and analytics that reflect increasing operational maturity and resource allocation. In the seed stage, startups adopt a predominantly defensive posture, emphasising core product validation through low-cost analytics tools (Rafiq et al., 2024; Velasco et al., 2024). At this stage, startups avoid premature investment in complex data infrastructure in favour of gathering qualitative insights from early adopters, while also implementing essential security measures such as data encryption and secure cloud storage. As companies move into the early development stage, there is a clear pivot from defensive to competitive strategies. Basic data capabilities are gradually established by integrating lightweight CRM systems and defining key performance indicators aligned with go-to-market objectives (Hsu et al., 2023; Mtau & Rahul, 2024), with technical constraints mitigated by strategic partnerships with freelance data analysts or the adoption of no-code visualisation platforms, accompanied by regular quarterly data audits to ensure compliance. In the Growth Stage, the focus shifts decisively to competitive strategies that scale data-driven decision making - leveraging predictive analytics and IoT sensors for real-time data collection (Gowrishankar et al., 2024) - while prioritising talent acquisition by hiring or upskilling dedicated data scientists and optimising infrastructure by migrating to scalable cloud solutions. The Expansion Stage is characterised by the aggressive deployment of advanced analytics, including AI-driven sentiment analysis and reinforcement learning for pricing optimization, augmented by robust data governance frameworks, such as blockchain-based immutable audit trails and geospatial analytics to support global market adaptation (Karunakaran et al., 2024). Finally, in the exit stage, strategic optimization becomes paramount as startups seek to maximize valuation by demonstrating data maturity in investor pitches and ensuring rigorous compliance through third-party data privacy assessments. Across all stages, the continued emphasis on security, cost management through pay-as-you-go cloud services, and fostering a data-centric culture underpins improved decision making, risk mitigation, and accelerated scaling - laying the groundwork for future empirical validation through longitudinal case studies.

6. Conclusions

The analysis showed that Smart Data plays a significant role in optimising startup processes and improving decision making. The implementation of Smart Data brings the greatest value in the later stages of startup development, when sufficient resources and skills are available to effectively exploit the potential of Smart Data analytics (addressed RQ_1). Startups implementing these analytics need to demonstrate adequate operational maturity, as adopting Smart Data too early may result in a lack of focus on the product and securing sales (addressed RQ_2). The above analysis advances the theory of scaling in startups by creating a framework for the use of Smart Data in startups. In addition, the article reinforces the creation of a strategic roadmap using SWOT/TOWS analysis as a guide for implementation. Two hypotheses requiring empirical confirmation emerge from the above analysis:

- startups that implement Smart Data strategies at their growth or expansion stages will achieve significantly higher operational efficiency and market adaptability than those implementing it prematurely,
- the effectiveness of Smart Data in enhancing startup performance is positively correlated with the startup's capability to manage data security risks and technical complexities.

The article also includes limitations of the research. The analysis was mainly based on literature published after 2019 in Q1 and Q2 journals. This means that the value shown in the earlier literature was not taken into account. The article is also theoretical in nature and the proposed framework needs to be empirically validated. Future research directions may include conducting empirical studies to confirm the framework presented. In addition, empirical research may address the impact of Smart Data on startup performance. Research may also address key success factors for the implementation of Smart Data in startups.

Authors' contribution

K.K.: article conception, theoretical content of the article, research methods applied, conducting the research, analysis and interpretation of results. **J.A.P.:** data collection, analysis and interpretation of results, draft manuscript preparation.

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