VILNIUS UNIVERSITY
BUSINESS SCHOOL

DEEPTECH ENTREPRENEURSHIP PROGRAMME

HAMZA AALAM

Dirbtinio intelekto grindžiamos investicijos ir startuolių sėkmė: duomenų analizė giliųjų technologijų verslų plėtrai gyvybės mokslų sektoriuje	**AI-Driven Investment and Startup Success: Data Analytics for Scaling Deep Tech Ventures in Life Science Sector**

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SUMMARY

VILNIUS UNIVERSITY BUSINESS SCHOOL
DEEPTECH ENTREPRENEURSHIP STUDY PROGRAMME

HAMZA AALAM

AI-Driven Investment and Startup Success: Data Analytics for Scaling Deep Tech Ventures in Life Science Sector

Supervisor: ROBERTAS SKLIAUSTAS

Master's thesis was prepared in Vilnius, in 2026
Scope of Master's thesis – 58 pages.
Number of tables used in the FMTP - 9pcs.
Number of figures used in the FMTP – 5 pcs.
Number of bibliography and references - 65pcs.

The FMTP described in brief:

Biotech startups operate in a highly uncertain, capital-intensive, and regulated environment, which makes investment decision-making and scaling particularly challenging. Recent advances in Artificial Intelligence (AI) and data analytics have introduced new possibilities to accelerate research processes, reduce risk, and improve transparency for investors in the life science sector.

Problem statement:
Biotech startups face difficulties in attracting investment and scaling efficiently due to long development cycles, high scientific and regulatory risks, and limited visibility of future outcomes. Traditional evaluation methods are often insufficient to assess early-stage biotech ventures, increasing uncertainty for investors.

Objective and tasks of the FMTP:
The objective of this master's thesis is to explore how AI driven data analytics can support investment readiness and scalable growth in biotech startups within the life science sector

Specific objectives:

- To review scientific literature on AI use in biotech innovation and investment readiness.
- To examine how AI is applied in biotech startups to improve research and decision-making processes.
- To analyze investor perceptions of AI as a tool for risk reduction and value assessment
- To evaluate the role of AI in supporting startup scalability through empirical evidence

Research methods used in the FMTP:

The research is based on a qualitative approach Semi structured interviews were conducted with biotech founders investors and AI specialists In addition 5 case studies of AI driven biotech startups were analysed The collected data were examined using thematic and cross case analysis .

Research and results obtained:
The study used interviews and case studies to analyze how AI affects research efficiency, investment decisions, and scalability in biotech startups. The results show that AI improves productivity, reduces risk, and increases investor confidence.

Conclusions of the FMTP:
The FMTP concludes that AI acts as a strategic enabler that enhances investment readiness and sustainable growth in biotech ventures. Its effectiveness depends on ethical use, data quality, and human oversight.

Information about the publication of FMTP results or adaptation for publication:

The results are suitable for adaptation into an academic or professional publication on AI-driven innovation and investment in life sciences.

SANTRAUKA

VILNIAUS UNIVERSITETO VERSLO MOKYKLA
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STUDENTAS: HAMZA AALAM
Dirbtinio intelekto grindžiamos investicijos ir startuolių sėkmė: duomenų analizė giliųjų technologijų verslų plėtrai gyvybės mokslų sektoriuje

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Magistro baigiamasis darbas (projektas) parengtas Vilniuje, 2026
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Panaudotų literatūros šaltinių ir nuorodų skaičius – 65

FMTP aprašymas trumpai:
Biotechnologijų startuoliai veikia labai neapibrėžtoje, daug kapitalo reikalaujančioje ir reguliuojamoje aplinkoje, todėl investicinių sprendimų priėmimas ir plėtra yra ypač sudėtingi. Naujausi dirbtinio intelekto (DI) ir duomenų analizės pasiekimai atvėrė naujas galimybes paspartinti mokslinių tyrimų procesus, sumažinti riziką ir pagerinti skaidrumą investuotojams gyvybės mokslų sektoriuje.

Probleminė situacija:
Biotechnologijų startuoliai susiduria su sunkumais pritraukiant investicijas ir efektyviai plečiantis dėl ilgų kūrimo ciklų, didelių mokslinių ir reguliacinių rizikų bei riboto būsimų rezultatų matomumo. Tradiciniai vertinimo metodai dažnai yra nepakankami ankstyvosios stadijos biotechnologijų startuoliams vertinti, todėl investuotojams didėja neapibrėžtumas.

FMTP tikslas ir uždaviniai:

Šio magistro darbo tikslas – ištirti, kaip dirbtiniu intelektu grindžiama duomenų analizė gali padėti užtikrinti investicinį pasirengimą ir mastelio didinimą biotechnologijų startuoliuose gyvybės mokslų sektoriuje.

Konkretūs uždaviniai:

- Išnagrinėti mokslinę literatūrą apie dirbtinio intelekto taikymą biotechnologijų inovacijose ir investiciniame pasirengime.
- Ištirti, kaip dirbtinis intelektas taikomas biotechnologijų startuoliuose siekiant pagerinti mokslinių tyrimų ir sprendimų priėmimo procesus.
- Išanalizuoti investuotojų požiūrį į dirbtinį intelektą kaip rizikos mažinimo ir vertės vertinimo priemonę.
- Įvertinti dirbtinio intelekto vaidmenį palaikant startuolių plėtrą remiantis empiriniais duomenimis.

FMTP tyrimo metodai:
Tyrimas pagrįstas kokybiniu požiūriu. Buvo atlikti pusiau struktūruoti interviu su biotechnologijų startuolių steigėjais, investuotojais ir dirbtinio intelekto specialistais. Papildomai buvo išanalizuoti penki dirbtiniu intelektu grindžiamų biotechnologijų startuolių atvejų tyrimai. Surinkti duomenys buvo analizuojami taikant teminę ir tarpatvejinę analizę.

Tyrimas ir gauti rezultatai:
Tyrimo metu, remiantis interviu ir atvejų analize, buvo nagrinėjama, kaip dirbtinis intelektas veikia mokslinių tyrimų efektyvumą, investicinius sprendimus ir biotechnologijų startuolių plėtrą. Gauti rezultatai rodo, kad dirbtinis intelektas didina produktyvumą, mažina riziką ir stiprina investuotojų pasitikėjimą.

FMTP išvados:
FMTP išvadose teigiama, kad dirbtinis intelektas veikia kaip strateginis veiksnys, didinantis investicinį pasirengimą ir tvarų biotechnologijų startuolių augimą. Jo efektyvumas priklauso nuo etiško naudojimo, duomenų kokybės ir žmogiškosios priežiūros.

Informacija apie FMTP rezultatų publikavimą ar pritaikymą publikavimui:
Gauti rezultatai yra tinkami pritaikyti akademinei arba profesinei publikacijai, nagrinėjančiai dirbtiniu intelektu grindžiamas inovacijas ir investicijas gyvybės mokslų sektoriuje.

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LIST OF ABBREVIATIONS

AI – Artificial Intelligence

R&D – Research and Development

USD – United States Dollar

NLP – Natural Language Processing

FDA – Food and Drug Administration

EMA – European Medicines Agency

VC – Venture Capital

ML – Machine Learning

IP – Intellectual Property

INTRODUCTION

Medical advancement and technological breakthroughs are impossible without biotech innovation, yet the industry is characterized by high uncertainty and levels of capital intensity. Drug development usually takes between 10 and 15 years from early discovery to market approval and often costs more than two billion US dollars per approved drug, while fewer than ten percent of drug candidates eventually succeed (Oliveira et al., 2023). These long timelines, high costs, and low success rates make biotech ventures difficult to evaluate and risky from an investment perspective. As a result, many investors prefer opportunities with faster and more predictable returns, leaving biotech startups facing serious challenges in securing funding and growing sustainably.

In recent years, Artificial Intelligence has attracted increasing attention as a possible way to reduce some of these challenges. AI technologies such as deep learning, predictive modeling, and natural language processing are already being used to accelerate drug discovery, support clinical decision-making, and analyze large volumes of scientific literature (Gupta et al., 2021). Large pharmaceutical companies, including AstraZeneca and Roche, have started integrating AI into their research and investment strategies, while many biotech startups still struggle with limited resources and restricted access to advanced AI tools (AstraZeneca, 2021). Learning how AI can be applied as a strategic element in startup operations and investment evaluation is therefore becoming increasingly important for the competitiveness of biotech ventures (Stephen, 2025).

The relevance of this research lies in the gap between the strong scientific potential of biotech startups and their ability to attract long-term investment. Early-stage biotech ventures often operate without revenue, face unpredictable outcomes, and require highly specialized expertise, which makes traditional investment assessment methods insufficient (Corea et al., 2021). From a scientific perspective, AI can support innovation by predicting drug–target interactions, identifying biomarkers, and enabling in silico clinical trials (Kumar & Sadashiva, 2025). From a business perspective, AI-driven analytics can help assess startup pipelines, scaling potential, and market readiness. In practice, machine learning models may allow promising drug candidates to be identified at earlier stages, helping startups save both time and capital (Javid et al., 2025). Predictive analytics can also help demonstrate potential returns to investors, which may increase confidence and reduce perceived risk.

However, most existing studies focus on AI applications either from a scientific or a technological perspective, without sufficiently examining how these AI-driven research outcomes influence investment readiness and scaling decisions in biotech startups. In particular, there is limited empirical research that connects AI-supported research efficiency with investor evaluation processes and strategic growth decisions in early-stage biotech ventures. This gap highlights the need for research that links scientific AI applications with their practical and financial implications in the startup context, which this master's thesis aims to address.

This research analyzes the role of AI in the development and success of biotech startups due to improved research findings, operational efficiencies, and investment choices. It focuses on entrepreneurial ventures in the area of genomics, synthetic biology, personalized medicine, and computational drug discovery. Particularly, this final master's thesis examines the application of AI technologies, including deep learning, natural language processing, and predictive modeling, to assess scientific potential, find market opportunities, and optimize the allocation of resources to scale. The topic at hand thus informs the strategic AI position in defining the science and business aspect of biotech enterprises.

The biotech startups have not been successful in attracting enough investment due to their high risks as they have a long-development process and cannot be assured of success, and their use of AI has not been fully exploited as a solution to supplement the research results and investor assessment.

The objective of this master's thesis is to examine and evaluate how Artificial Intelligence can support biotech startups in achieving investment readiness and market readiness within the life science sector.

To achieve this objective, the study pursues the following tasks:

1. To identify the main challenges biotech startups face in becoming investment-ready and market-ready
2. To analyse existing and potential applications of Artificial Intelligence in addressing these challenges
3. To investigate how biotech startups are adopting Artificial Intelligence, based on industry reports, case studies, and founder perspectives
4. To explore investor views on the role of Artificial Intelligence in enhancing biotech startups' investment attractiveness and market readiness
5. To develop a conceptual framework illustrating how biotech startups can strategically leverage Artificial Intelligence to accelerate investment and commercialization readiness

The research follows a qualitative approach and combines semi-structured interviews with investors, biotech managers, and AI experts, along with case studies of selected AI-driven biotech startups. This approach allows the research to capture practical experiences and different perspectives on how AI is used in practice and how it influences research processes, investment decisions, and scaling strategies.

This thesis starts by explaining the research context, problem, and approach. It then reviews key literature on biotechnology, investment readiness, and the role of AI. The methodology section outlines how the data was collected and analyzed, followed by a discussion

of findings from interviews and case studies. The thesis concludes with key insights and practical recommendations for biotech startups and investors.

This study has several limitations. The qualitative sample size is relatively small and may not represent the full diversity of biotech startups. Access to data may limit the depth of analysis, and the fast-evolving nature of AI means that the findings reflect current practices rather than long-term developments. Despite these limitations, the study provides useful insights into the strategic role of AI in biotech innovation and investment readiness and offers a basis for future research.

Key Words: *Artificial Intelligence (AI), biotech startups, deep tech ventures, life sciences, data analytics, predictive modeling, drug discovery, investment strategy, startup scaling, personalized medicine, genomics, synthetic biology, natural language processing (NLP), machine learning, clinical trials, investor confidence, entrepreneurial innovation*

1. THEORETICAL PART

This chapter conducts a review of the available literature to describe the structural nature of biotechnology ventures, the concept of investment readiness in biotechnology, and how Artificial Intelligence (AI) helps to minimize scientific and investment uncertainty. By shifting the nature of the biotech industry to investor evaluation problems and consequently to solutions powered by AI, the chapter provides a clear theoretical background to the empirical analysis that is subsequently depicted.

1.1 Biotech as a Sector and Technology

Biotechnology has been generally harshly characterized as a high-technological and capital-intensive business with massive scientific and governmental uncertainty. It is also called as deep technology since innovation relies on serious scientific studies, lengthy development cycles, and wide-ranging verification (Gregory and Trump, 2023). Biotech startups have a long process of research and development, a need to adhere to complex data protection regulations, and go through clinical trials before getting into the market, unlike digital startups which parallels their development with software design and user acquisition. Such requirements add a substantial amount of delay to commercialization, raise the capital requirement, and subject ventures to high technical risks (Ali et al., 2024). Moreover, biotech innovation is quite interdisciplinary and can incorporate human biology, chemistry, engineering, and data science in one iteration. Whereas this integration makes high-impact solutions in the areas of healthcare, agriculture, and environmental sustainability possible, it simplifies the development trajectories and makes coordination more complex (Pagani, 2024).

These features of the sector have a significant implication on the perceptions and valuation of biotech ventures in the mind of investors. The investment decision in biotechnology not only relies on the business models and market potential, but also on scientific validation, protection of intellectual property and their feasibility. Since scientific developments are not usually linear and results are unpredictable, investors struggle to estimate schedule and payments. Biotech has therefore been often considered as a high-risk and a long term area of investment, as the financial success of biotech is subjected to the technological validation and regulatory authorization instead of early financial gains. Recent sources indicate that AI is already starting to corrupt this classic line of development, as it helps make the discovery, simulation, and validation processes faster. Molecular screening, predictive modeling, and patient stratification are some of the tasks automatized by AI applications and make research easier and correctly decide (Bisogni, 2023). But the researchers warn that the quality of data is a major predictor of AI results, is frequently poor in early research, and that performance will decrease with AI, but never vanish (Gregory & Trump, 2023).

Table 1 : Key Characteristics of Biotech Ventures vs. Digital Startups

Dimension	Biotech Ventures	Digital Startups
Development Cycle	Long (10–15 years typical)	Short (6–18 months)
Capital Requirements	High – R&D, labs, trials	Low – mainly software development
Risk Type	Scientific, regulatory	Market and user adoption
Time-to-Market	Slow; dependent on validation	Rapid; iterative product release
AI Utility	Predictive analytics, molecular discovery	Customer personalization, automation

Source: Adapted from Gregory & Trump (2023) and Ali et al. (2024).

These structural characteristics directly shape how investors assess risk and readiness in biotech ventures, which is discussed in the following section.

1.2 Investment Readiness in Biotech Ventures

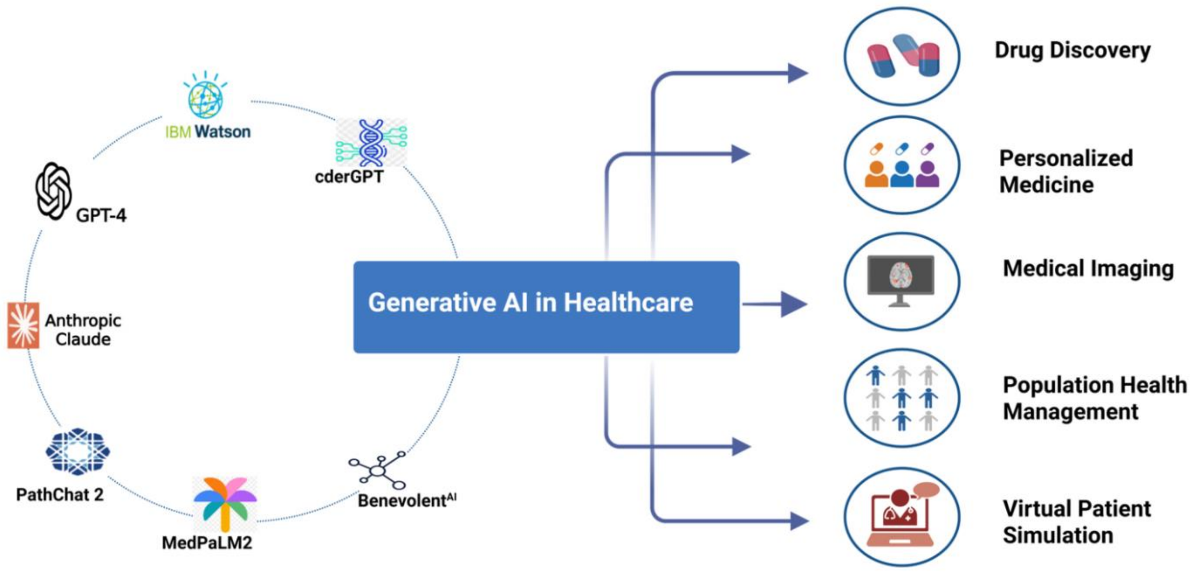
Biotechnology has a high level of uncertainty and long period of development which has made scholars to embrace a wider outlook on investment readiness. Investment readiness is the capability of a venture to fulfill, handle and effectively utilize external funding as a method to contribute to development and innovation (Dupont, 2025). In the biotech reality, this idea is not limited solely to financial metrics but considered scientific plausibility, regulatory development, operational maturity and strategic alignment of the needs of the market (Pagani, 2024). Since biotech products may take years of laboratory work, clinical trials and ethics approval before they make it to the commercial side, investment readiness is not a one-time step. Rather it is dynamic in nature by developing into a venture with early discovery to clinical validation and market entry.

The criteria applied by investors alter as the company of biotech startups moves through the stages of its development. Early-stage preparedness can manifest itself in robust experimental outcomes and secured intellectual property but later-stage preparedness is based on clinical effectiveness, production upscaling, and business approaches. This paradigm shift evaluation model renders the issue of investment decision-making especially difficult and leads to the gap in funding, especially in the initial stages when there is scientific promise and scanty market evidence. Consequently, the literature highlights the necessity of developing mechanisms capable of converting complex scientific developments in credible, comparable and meaningful signals to investors. Given these evaluation challenges, the next section examines how Artificial Intelligence can support and strengthen investment readiness in biotech startups.

1.3 The Role of AI in Strengthening Investment Readiness

To address these challenges, AI has become a topic of more and more discussion as a strategic instrument that aids in scientific creation as well as investment analysis in the biotech enterprises. Scientific, genomic, and clinical data can be analyzed with AI-based analytics at large-scale levels allowing making more informed judgments about technical performance, development progress, and market potential (Wheeler, 2025). Practically, AI predictive models have the ability to take experimental data in the early stages of the drug behavior and potential efficacy and safety risks, estimating these characteristics, thus assisting in the identification of promising candidates and avoiding uncertainty at an earlier developmental stage. The advancements in the field of AI allow improving the degree of transparency and evidence-based forecasting of startups which brings the latter to a new stage of proving improvement and enables the investors to estimate possible returns more confidently.

Figure 1 Generative Artificial Intelligence in Healthcare:



***Source:* Wheeler (2025)**

Risk management is another area of vital importance of AI. Analyzing historical data of the failed drug candidates and regulatory submissions, AI systems can define the patterns that predict the success or failure in particular therapeutic fields. This assists the entrepreneurs as well as investors to make more informed decisions. In the same manner, machine learning applications have the ability to evaluate the patent portfolio, competitiveness, and technological innovativeness of a startup, which are major factors of investment readiness in the biotech sector (Ali et al., 2024). These AI-based evaluations offer the degree of accuracy that is inaccessible to conventional market research or human analysis.

Moreover, AI-based portfolio management systems currently assist venture capitalists and institutional investors in tracking the current performance of their biotech investments. Automated dashboards have the capability of monitoring such measures as R and D productivity, publication activity, and patent citations. This provides a level of transparency between biotech start up and their investors so that the decisions to provide funding are grounded on quantifiable performance outcomes instead of speculation or personal favour.

Despite these advantages, the increasing reliance on AI in investment decision-making raises important questions about human judgment, bias, and ethical responsibility, which are discussed in the following section.

1.4. The Human Factor and Ethical Considerations

Although artificial intelligence is increasingly important in investment decisions, researchers caution investors against relying on software. Gregory & Trump (2023) also warn that AI models may recreate the bias of algorithms, in which data-driven predictions tend to give preference to companies that already have more data or greater visibility, without necessarily considering small, but innovative companies. As an illustration, a start-up, which is operating in the field of rare diseases, may be underestimated by AI models that were trained primarily on data of large pharmaceutical companies. This bias may skew the priorities of funding, instead of funding breakthrough innovations it may fund safer and more established projects.

The second issue is an exaggeration of AI-created metrics. Participants in the field can build too much trust in AI forecasting and believe that a high model accuracy guarantees a successful business. Nevertheless, AI gives clarity, but not certainties as Dupont (2025) notes. Biotechnology investment decisions remain based on human judgment, ethical consideration and situational insight into science. Even a drug candidate whose forecasts are well trained based on AI may fail because of unexpected biological or regulatory events. Hence, investment preparation should be a compromise between technology effectiveness and human sense.

The availability of ethical and regulatory preparedness is also an important component of investment preparedness in biotechnology. The more ethical data is gathered, reports made transparently and AI is responsibly used, the more investors believe in the venture. The ethical responsibilities should be on human decisions, as compliance can be ensured with the help of AI that is automatically checking the research data against regulatory standards, but the ultimate decision-making should be considered ethical. According to Pagani (2024), investors are seeking more biotech projects that can bring in financial profits, as well as more aligned with the values of the larger society, including patient safety, sustainability, and data integrity.

These ethical and human considerations directly influence how AI-driven insights are translated into strategic and practical decisions within biotech ventures, which is examined in the next section.

1.5. Strategic and Practical Implications

Strategically speaking, AI-based insights enable biotech firms to reduce their time-to-market - one of the largest factors of investment preparedness. AI will also make startups more financially and operationally appealing to the extent that it will help the impact of drug discovery cycles and make clinical trials less expensive. Educating partnerships with other companies on how AI minimizes development risks would help the companies find more venture capital and partner with higher-ranking pharmaceutical companies. Indicatively, other startups that have been able to raise hundreds of millions in funds through launching demonstrations of how their AI platforms can simplify the target discovery and preclinical research are Benevolent AI and Insilico Medicine.

To the investors, AI enhances due diligence. It allows them to consider not only the science of a start-up but also data management procedures, supply chain preparedness, and business potential. This broad disclosure minimizes the information asymmetry between entrepreneurs and investors- a long-term problem of biotech financing. Nevertheless, according to Ali et al. (2024), AI tools can be as effective as the analyzed data. The bad quality of data or incomplete data may lead to misleading an investor, which is why it is essential to monitor data constantly and make sure that it is checked by a human.

While these strategic and practical implications demonstrate the current value of AI in biotech ventures, they also raise important questions about how investment readiness will evolve in the future, which is explored in the next section.

1.6. The Future of Investment Readiness in Biotech

In the future, AI-based investment preparation in the biotech sector will be reliant more on hybrid solutions that integrate AI with human experience. The data-intensive tasks, including the modeling of clinical outcomes or the analysis of patent landscapes, will be performed by AI, whereas the interpretation of the results in the ethical and strategic frameworks will be provided by investors and scientists (Mirakhori, F., & Niazi, S. K. (2025). It also is foreseen that regulatory authorities will put forward more articulate rules on the application of AI in drug discovery and investment appraisal, which will assist in standardization of the readiness measurement within the industry. More AI may also democratize biotech investment by making smaller investment opportunities available via such a crowdfunding platform, which operates on the basis of transparent data analytics (Savioz et al., 2025). Nontraditional investors might have access to such systems and use the AI-generated risk profiles to assess biotech opportunities. However, the same principle holds that technology is not to replace the human judgment but rather to complement it.

To sum it up, investment preparedness in biotechnology is a complex term that incorporates financial, technological and ethical preparedness. AI can increase preparedness through the capacity to offer more timely and information-based insights, augmenting transparency, and minimizing risks in investment decision-making (Elisa et al., 2025). Nevertheless, overreliance on AI can create bias and overconfidence, and it is necessary to strike the right balance between AI and human judgment. However, the riskiest bets which are likely to attract funding are those that have integrated scientific validity, responsible use of AI and foresight- making them attractive in creating investor trust without sacrificing ethical and regulatory standards.

This future-oriented perspective provides the foundation for a deeper examination of how Artificial Intelligence is integrated across biotech innovation processes, discussed in the following section.

1.7. AI Integration in Biotech Innovation

1.7.1 .The Transformative Role of AI

Artificial Intelligence (AI) has emerged as one of the most radical ideas in the current biotechnology, which allows discoveries faster, increased precision, and reduction of the cost at each stage of research and development. Bisogni (2023) notes that AI contributes to the development of biotech, facilitating the use of patterns in molecular and genomic data, predicting compound behavior, and increasing the speed of laboratory experiments. These have enabled the discovery-to-validation cycle to be made shorter, and innovation has made it more efficient, causing the time and risk involved to be minimized. Dupont (2025) goes on to clarify that AI is no longer an assistant analysis tool but has been found to become a strategic infrastructure facilitating scientific discovery and commercialization.

Practically, AI technologies transformed the functioning and the competition of biotech startups. Protein structures, which could be predicted in years previously, can now be predicted using machine learning models in several hours. It was also demonstrated in particular by DeepMind AlphaFold which has transformed the prediction of protein folding and provided structural information that researchers can use at once in drug design. Likewise, chemical synthesis optimization with the assistance of AI algorithms is performed to determine the most economically efficient routes to synthesize compounds of the highest yield and purity (Pagani, 2024). These developments not only improve the accuracy of an experimental result but also reduce the expenses and errors incurred by trial and error research. AI also plays a very important role in real-time decision-making. Predictive models give scientists the opportunity to dynamically change parameters of an experiment on the basis of simulation feedback. An example is when a model predicts low efficacy of a drug compound, one can modify its molecular structure and proceed with expensive in-vitro or in-vivo experiments. It is what allows making data-driven real-time adjustments and enhances productivity and shortens the route between discovery and preclinical validation. Therefore, the incorporation of AI has now become a significant consideration towards the scalability, attractiveness in funding, and readiness to enter the market of a biotech startup.

1.7.2 Challenges and Risks of AI Integration

Although it is obvious that AI has certain advantages to biotechnology, researchers warn that the contribution to this field should not be overestimated. According to Gregory & Trump (2023), the quality of input data and the dependability of algorithms to process it are the most significant factors that determine the success of AI systems in biotech innovation. Lack of good curation of data can lead to false results that can result in scientific and financial losses. An example is that a model that is being trained on a biased or incomplete genomic data points may falsely predict an association between a disease or drug response, resulting in a failed trial or detrimental effect.

The other significant issue is reproducibility. Biotech AI models can be black-box, i.e. the inner decision-making mechanisms of the model are hard to read. With this obscurity, researchers can hardly establish the reason behind a model reaching a certain conclusion. This may be an issue in drug discovery, particularly when the outcomes are to be used to generate regulatory filings or solicit investments. Thus, Dupont (2025) emphasizes the need to test AI predictions with strict laboratory validation in order to gain scientific reliability.

1.7.3 Ethical and Regulatory Dimensions

The bioethical and legal framework of AI-based biotechnology remains confusing and disjointed, and is changing rapidly at inter-jurisdictional levels (Floridi et al., 2018). According to Wheeler (2025), regulatory uncertainty has been described as one of the greatest impediments to the expedited biotech solutions utilizing AI. In comparison with the traditional approaches toward drug development, AI-based discoveries have a propensity to blur the line in regard to which human and machine input to be regarded as the intellectual property, and who is legally held responsible in the eventuality of discoveries. To take an illustration, in case an AI algorithm identifies a new drug compound, who should patent the researcher, or the creator of an AI, or both? Such indistinctness challenges the legal provisions as they are there and makes licensing a difficult procedure. Also, the key ethical issues are data privacy and consent. When AI models apply the patient genomic or medical data to determine disease risk or drug response, there are concerns on how this data is gathered, stored and shared (Ali et al., 2024). Unless protection measures are in place, anyone may fall prey to discrimination or abuse of their genetic data by the employer, their insurance company or a third party. Thus, it is crucial to keep the consent process transparent and anonymize the data as the means of preserving the rights of the participants.

Other emerging concerns include discrimination and fairness. The AI models can be trained only on specific population data, which can result in the reinforcement of the existing health disparities. As an example, a model that has been largely trained on European genetic data may not be as accurate on African or Asian population, thereby providing unfair healthcare advantages. The regulatory authorities, such as the U.S. Food and Drug Administration (FDA) and the European Medicines Agency (EMA) have started lamenting this issue by imposing more diverse and representative datasets on AI-based medical studies. The other field of ethics governance is environmental and social responsibility. The computer systems required in AI modelling consume a lot of energy that adds to carbon emissions. With green computing becoming the focus of attention across the world, biotech companies should think of how to incorporate the element of green computing within their AI activities, including utilizing renewable energy resources or creating a more energy-efficient algorithm.

1.7.4 Balancing Innovation and Regulation

To make biotech sustainable in the long term, there is a need to strike the balance between the fast development of AI and the adequate regulation of it. On the one hand, excessive regulations may potentially slow down the innovation and deter start-ups in their experiments with new models. Conversely, absence of regulation may cause abuse, breach of ethics or loss of investor confidence. According to Wheeler (2025), the most effective strategy is adaptive regulation, in which the policies will be adjusted as technology is improving. Regulators may also offer sandbox environments, in which companies may test AI-based applications to understand sandboxes in a controlled environment before scale deployment. These ethical and regulatory challenges are also of interest to investors in the way biotech startups are managing them. Investments that are also proactive in compliance and open AI governance are viewed as less risky investments. Trust and accountability, as Dupont (2025) notes, are now as crucial as the process of innovation in itself when it comes to establishing long-term investor relations. Thus, AI startups should not only address the performance metrics, but also convey the idea of their ethical integrity and information security.

1.7.5 Future Directions

In the future, AI applications in biotechnology will most probably be used in all the value chain steps such as identifying the target, conducting clinical trials, production, and monitoring the market. The black-box issue is being solved with the development of emerging technologies like explainable AI (XAI) to make AI decision-making transparent and interpretable. Also, federated learning systems can facilitate the learning of AI models that utilize distributed data without transmitting sensitive information to enhance privacy but retain the capacity to analyze information. The partnership between AI creators, biotech scientists, and policymakers will also play a central role in creating a common set of rules on responsible innovation (Li et al., 2023). These criteria might encompass ethical AI practice certification, compulsory bias examination and quality of data parameters. These frameworks would over time mitigate risk besides boosting the overall credibility of AI-driven biotechnology.

Together, these developments highlight that effective AI integration is not only a driver of scientific innovation, but also a critical enabler of scalability in biotech ventures, which is examined in the next section.

1.8. Scaling Biotech Ventures through AI

1.8.1 Challenges of Scaling in Biotech

BI scaling is completely different than software or digital start up scaling. Biotech startups have a very complex environment in contrast to software companies who can develop at a very rapid rate with a minimum amount of physical infrastructure. They require advanced laboratories, equipment, and access to biological samples all of which are planned and expensive to invest in. Scaling biotech is posed by one of the primary challenges in dealing with the lengthy development cycles which are unpredictable. Scientific research can take years to leave the laboratory and go through preclinical tests and further to clinical testing and in the process, startups are unable to make revenues (Garcia, 2022). The long time span makes it hard to attract investors and strategy business growth. Moreover, the other major challenge is regulatory compliance. Strict regulations have to be followed by Biotech ventures in ensuring that their research and products are safe, ethical and legal (Singh et al., 2023). Commercialization may be hindered by unpredictable regulatory procedures that are slow in nature.

Also, the biotech scaling is built on the restricted assortment of highly qualified researchers and technicians. Talent recruitment and talent retention is costly and competitive and start ups tend to lose a team with the necessary expertise in terms of research, development and commercialization. There is also an access barrier in that a good portion of the information necessary to create drugs or therapies is held by hospitals, research centers or pharmaceutical companies. The absence of good relationships can make startups slow down in terms of gathering data meaning that research is slowed down and this means that a venture can grow slowly. Lastly, expanding biotech venture involves massive investment in production facilities, equipment and supply chain management. Startups can be forced to invest in dedicated drug or biologics scale manufacturing, which further increases operational and financial burdens. All this coming together makes the process of setting up biotech a high-risk and complex task that needs planning, strategic collaborations, and long-term investments (Pagani, 2024).

1.8.2 AI as a Catalyst for Scalability

AI has become an influential instrument to handle most of the issues related to scaling biotech startups. To enable startups make better decisions in a shorter time, AI technologies have the potential to optimise key processes, including resource allocation, planning production and demand forecasting. Indicatively, by using machine learning models, large datasets of experimental findings, clinical trials and molecular data may be analyzed and results inferred about the probability of the most success in compounds or therapies. The early detection of potential candidates saves time and money due to the fact that AI minimizes wastage of human effort and speed up research (Dupont, 2025). The automation provided by AI can be used in a laboratory setting, where repetitive or time-consuming tasks, including data analysis, sample tracking, and initial modeling, will be performed with a high level of accuracy. This minimizes human error, standardization and researchers are in a position to concentrate on complex scientific issues, leading to greater productivity. Outside the lab, AI can also be used to assist in regulatory compliance and quality control, monitoring the processes of the experiment, keeping records and identifying the problems that may emerge before turning into expensive tasks. Predictive algorithms can also be used to model the effects of expanding production or conducting a set of experiments to allow startups to plan how to allocate resources well and prevent supply chain bottlenecks. Talent optimization is another field in which AI can be applied to enhance scalability. Startups can apply AI to give priority to tasks, allocate projects to the most competent employees and even anticipate when they need to hire or train more employees (Aliyev, 2024). This assists small groups to do more without having to hire people at an alarming rate.

AI is also used to aid decision-making as it sends real-time information about the trends of the market, its competitors, and the progress of clinical trials. Analyzing external data, AI may assist startups in choosing the most strategic directions to expand and grow, minimize risk, and make superior investment choices. Although these benefits exist, AI is not some sort of magic. Its efficiency is determined by quality of input data, strength of algorithms and human supervision to give appropriate meaning to the results. However, the integration of AI has demonstrated significant gains in performance of biotech scaling in terms of speed, efficiency and cost-effectiveness, and is the key element of the current biotech venture strategy. To sum up, AI is a technical enabler as well as a strategic partner to biotech startups to enable them to surpass most of the inherent challenges of scaling and position themselves to grow sustainably in a complex, competitive industry (Dupont, 2025).

Table 2: Comparison of Traditional and AI-Enhanced Scaling Models in Biotech Ventures

Feature	Traditional Scaling	AI-Enhanced Scaling
R&D Process	Sequential and manual	Parallel and automated
Decision-Making	Based on expert judgment	Data-driven and predictive
Time-to-Market	10–15 years	5–8 years (average reduction)
Risk Profile	High uncertainty	Managed through predictive modeling

Source: Adapted from Dupont (2025) and Wheeler (2025).

By enabling more efficient and predictable scaling, AI also strengthens the investment readiness of biotech startups, a relationship that is explored in the following section.

1.9. AI-Driven Scalability and Investment Readiness

Scalability AI impacts directly and directly on the readiness to invest in biotech. Investors can also see clear data-driven evidence of progress in startup ones that take up predictive analytics, automation technologies, and AI-based decision-support systems. To use an example, predictive models can predict the success rates of potential compounds, regulatory challenges, and production outcomes in advance and forecast before a company commits substantial investments (Ali et al., 2024). Laboratory automation tools decrease errors, standardization, and real-time recording of results to give clear view of scientific and operational performance. This openness gives greater confidence to the investors since they will be in a position to trace quantifiable signs of a venture development as opposed to the use of reports or oral information. It goes without saying that in a highly risky and capital-intensive industry such as biotechnology, access to reliable data available in real-time to facilitate decision-making would go a long way in drawing funding. Companies that effectively apply AI technologies in their scale will tend to be a prototype of the so-called algorithmic scalability, in which expansion is directed by data, forecasts, and automated technologies instead of just human judgment. Such a model reduces uncertainty, perceived risk to investment and improves start-up attractiveness to venture capital companies, corporate partners and other stakeholders requiring both innovation and accountability. Scalability through AI allows startups to demonstrate that they are sustainable, quantifiable, and predictable - this is the type of confidence that deep-tech investors want in their business (Nguyen et al., 2024).

Although AI can rule over transparency and efficiency, AI-based scaling comes with a lot of organizational adjustments as well. The introduction of AI into the daily business is not a technical problem but a cultural one. The teams need to develop new digital skills like the ability to analyze results from AI, be able to run automated systems, and embrace predictive models. This could include hiring or training staff with a different domain expertise in data science, machine learning or bioinformatics. Apart from technological skills, there are also ethical practices of AI which organizations must maintain. The danger of introducing AI tools is that they may introduce biases, may over-rely on the outcomes of an algorithm, or use sensitive information for other causes, which can be of clinical, financial and reputational impact in the event that they malfunction (Koponen, 2025). It is important to have clear governance and ethical standards established thus to make sure that AI integration contributes to sustainable growth as opposed to posing unknown issues (Gregory & Trump, 2023). Also, new companies have to deal with the cultural change between the traditional workflow with laboratories and the digital-first operations. Researchers and scientists who were used to practical experimentation will have to adjust to settings where AI-based simulations and automated analyses and predictive dashboards take over day-to-day decision-making. This change may be difficult to manage, but with a proper approach, it will enable human skills to collaborate with AI solutions, increasing productivity and scalability, in general.

1.10. Data-Driven Investment in Biotech

In the contemporary biotech business, the AI is termed as a blood of innovation. Earlier, biotech development has been dependent on isolated experimentation, professional intuition, and tedious manual methods. Nowadays, Artificial Intelligence (AI) has altered the situation and modified raw scientific data into actionable insights. This knowledge can be used to facilitate decision-making at each phase of venture progression, starting with initial discovery and testing in the preclinical phase, through clinical trials and ultimately commercialization (Pagani, 2024). AI can help startups to handle large volumes of molecular, genetic, and clinical data in a manner they could not prior to the development of the technology. This is what Dupont (2025) refers to as the data value chain. The first stage is the collection of raw data, then the cleaning of the data to eliminate errors or inconsistencies, analysis to identify patterns and trends, and lastly the application of findings to enhance the work of the research and minimize the risk. Adhering to such value chain, biotech ventures will be in a position to make more rapid, evidence-based decisions, allocate resources more effectively and respond to either scientific or market pressures. This systematic attitude to information does not only result in a more efficient process but also enables firms to react in a more fluid manner to the problems, including the unexpected outcomes of the trial or regulatory postponements.

When the quality and integrity of data are high, investment preparedness with respect to AI-driven ventures relating to biotech is augmented. Investors will most likely invest in startups that can create clean, reliable and well-analyzed datasets because this transparency will eliminate uncertainty and create trust. Most of the biotech firms currently implement AI dashboards to provide real-time progress. Such dashboards are able to monitor progress in research, clinical results, patent applications and even market forecasts, providing investors with a clear understanding of how they are spending their money (Wheeler, 2025). This degree of transparency cuts down the information disparity that has always existed between biotech startups and investors. Historically, venture capitalists and corporate partners were not able to see complex research pipelines, as these reports or infrequent updates may not show the whole picture. AI technology can be used to track projects in real-time, establish potential risks in the early stages, and make evidence-based decisions, which may hasten financing and collaboration. By doing so, data integrity and AI-based analysis has become a key parameter to venture attracting and retaining investment.

1.11. Predictive Analytics and Investment Forecasting

One of the most effective AI uses in biotech investment is predictive analytics. The tools apply historical data to model the possible future of a new project, like regulatory status, patient reactions, or market acceptance (Bisogni, 2023). Through the examination of past clinical trials, laboratory outcomes, and commercial performance, AI algorithms can make deductions as to the probability of a new therapy or product succeeding. This data enables the investors to focus on investing in those projects which have the largest chance of success in order to maximize resource investment and to reduce financial risks of investing in biotech projects. Scenario test is also possible using predictive analytics. An example is that investors can investigate what-if cases, a delay in clinical trials, or a shift in regulatory needs, or an unexpected competitor action. Such simulations help in advising on the manner in which the investment strategies and research priorities can be adjusted to enhance the overall process of decision-making.

Although the benefits of predictive analytics seem obvious, researchers warn that such analytics must never fully eliminate human judgment. AI predictions are also probabilistic, that is, they are based on trends in current data. These models may undervalue or misrepresent projects which are indeed novel, unconventional or fall outside the scope of historical experience (Gregory & Trump, 2023). E.g. a breakthrough therapy with a totally new mechanism of action would be considered high-risk by predictive algorithms only because there is not much previous information to back it up, despite having a potentially substantial scientific payoff. Thus, the most effective investment choices will involve the AI-based quantitative data and qualitative experience of the best scientists, clinicians, and business strategists. This equilibrium guarantees the fact that the decisions are not only supported by data but also undergo the scientific and business understanding of the world.

1.12. Reducing Time-to-Market: The Core of AI Advantage

Time-to-market has turned out as one of the most significant performance indicators of biotech startups. Time-to-market is the duration of time to pass following the initial discovery of a new therapy, diagnostic tool or biotech product through research, development, clinical trials and finally to commercialization. The pace with which a new venture break into the market is a major factor in determining the confidence of investors, strategic alliances, and general competitiveness in the market in the current competitive and capital intensive biotech landscape. Companies that are able to reduce this time are in a qualified position to receive early-stage capital, market share, and become responsible actors in the market (Arampatzi et al., 2025). Conversely, any delay in development may raise the cost, investor interest, and give competitors a good footing. Consequently, time-to-market management is a strategic necessity as well as an issue of operational efficiency that influence financial and scientific success.

Artificial Intelligence (AI) has transformative effects in lessening time-to-market in biotech ventures. AI systems are effective at almost every phase of the product development process, starting with its discovery to supply chain management (Helo & Hao, 2022). In the discovery phase, AI will have the ability to process tens of terabytes of molecular and genetic data to provide probable compounds, possible drug targets, or novel therapeutic solutions. It takes weeks to do what used to require months or even years of manual experimentation. Machine learning models can identify trends in chemical reactions or sequences, how compounds may act in a biological process, and they can pick those candidates most likely to be effective. This is achieved through the automation of such initial phases, making AI a great deal faster in the distance between concept and proof-of-concept validation (Pagani, 2024).

In addition to discovery, AI helps to enhance the development speed by designing trials and doing predictive models. The conventional method of clinical trial planning is complicated, too costly, and time-consuming and may need repetitive cycles to derive optimal protocols. Before the trials are initiated, AI can recreate various situations of trials, optimize patient selection, and forecast potential outcomes. Such simulations enable researchers to create more powerful trials, minimize unwarranted cycles, and identify possible failures at an earlier stage. According to Dahmen et al., 2023, the startups that apply AI-based simulations may validate themselves about 40 times as quickly as the ones that rely on the traditional means. It is also a valuable speed in the early-stage biotech projects, where proving a concept fast can be the difference between finding the crucial funding and halting the business. As an instrument to offer predictive information, AI will guide ventures to look ahead, streamline resources, and synchronize trial strategy to both scientific and regulatory standards. There is also enhancement of operational efficiency in the later stages of development by AI. Considering biotech, supply chains are complicated and delicate, which means sourcing of specialized material, keeping of strict storage conditions, and production with regulatory compliance.

Scholars, however, warn that quicker development is not always associated with improved results. The discovery and trials should take place as fast as possible, which may be associated with inadequate testing or safety concerns and unethical activities. According to

Wheeler (2025), sustainable acceleration should be provided in a way that balances efficiency and scientific rigor and ethical control. The Biotech ventures should not sacrifice clinical assessment, compliance with regulation and patient safety at the expense of pace. Regulatory bodies and investors are becoming more accountable in terms of ethics, and this is forcing them to report clearly, create comprehensive records, and ensure that they abide by the best practices. Thus, the impact of AI on the time-to-market reduction must be interpreted as a strategic. The aim is to pursue regulated, fact-based advancement that is of high standards and reduces the time period.

Moreover, the connection of AI and investor preparedness is linked to the time-to-market strongly. Start-ups involving AI to speed up development are efficient in their operations and have evidence-based decision-making. Predictive modeling, automated analytics, and optimized workflow give real time tangible indicators of progress that investors can observe. The transparency will minimize uncertainty, enhance belief in the potential of the venture, and have a higher chance of raising funds or strategic alliances. Practically, according to Challoumis, 2024), the acceleration of AI enhances the scientific and financial preparation, which is a virtuous circle in which the speed, credibility and the appeal to investment reinforce one another.

In summary, this chapter discussed biotechnology as the industry, what is meant by investment readiness, and how Artificial Intelligence (AI) can be used to facilitate biotech development, growth, and investment decision-making. It is always indicated that biotechnology is a risky capital intensive industry whose development cycles are lengthy, there is complexity in the regulations, and a high dependence on scientific validation. Biotech startups cannot scale fast like their digital counterparts and they have to prove scientific, regulatory, and intellectual property competence before they get to the market. These structural conditions clarify the presence of the unresolvable funding problems of biotech startups and the inadequacy of traditional evaluation approaches to investments.

Riding on the above sector background, investment preparedness in biotechnology was examined as a multi-dimensional and dynamic concept in the chapter reviewed. Investment preparedness goes beyond financial performance to encompass scientific advancement, business maturity, ethical business, and alignment to the future market requirements. Since evaluation criteria vary within development stages, the investors find it difficult to evaluate early biotech venture and this is a factor that creates disparities in funding. The literature hence brings out the significance of instruments capable of transforming the complicated scientific data into signals that are trustworthy and comparable to the investors.

One of the mechanisms that are available to overcome these challenges is AI, which appears in the literature. In the discovery, development, scaling, and investment assessment, AI can be used to analyze data faster, predictively model, risk mitigate and operate more efficiently. AI-based analytics mitigate uncertainty because they generate evidence-based prescriptions regarding drug efficacy, regulatory risks, the scalability of production, and market opportunities. Meanwhile, researchers warn that AI should not be trusted, so the quality of the data, human expertise, ethical oversight, and legal adherence must be prioritized ((Martins, 2024).

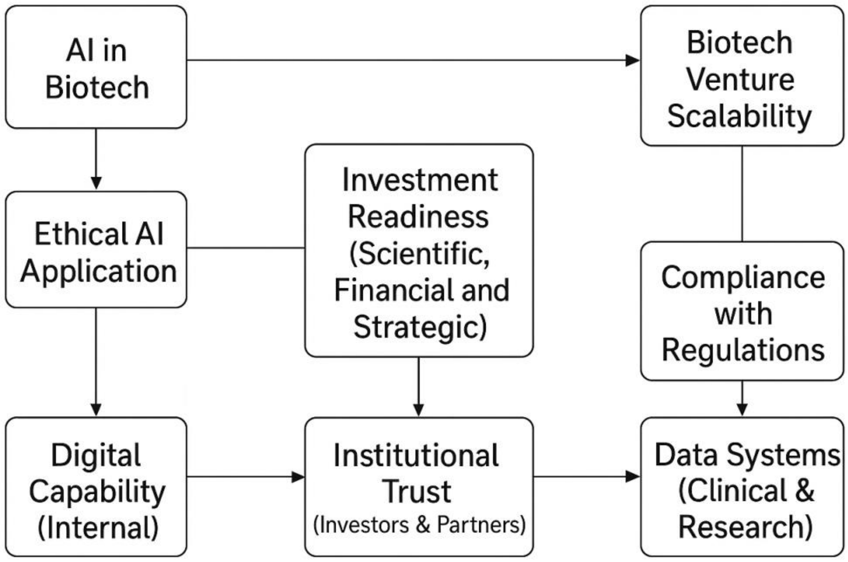
1.13. Conceptual Synthesis and Framework

1.13.1 Synthesis of Literature

The literature review indicates a dynamic interaction between artificial intelligence, investment preparedness, and the scalability of biotech ventures. Biotech startups face several structural challenges, including long research and development phases, regulatory uncertainty, and high capital intensity, which delay time-to-market and complicate investor risk assessment. To address these challenges, AI improves the accuracy of predictions related to clinical trial outcomes, research success rates, and market potential, while also providing greater operational transparency for startup managers and investors and increasing efficiency in research processes, data analysis, and resource allocation (Bisogni, 2023; Dupont, 2025). Nevertheless, scholars emphasize that these benefits require careful implementation. Gregory and Trump (2023) argue that the effective contribution of AI depends on its ethical application, compliance with regulatory frameworks, and the use of robust and well-developed data systems. Consequently, investment preparedness in biotech ventures is not determined by technological capability alone, but by a combination of human expertise, institutional trust, and digital capability that allows AI to be used responsibly and strategically (Verhoef et al.2021).

1.13.2 Conceptual Framework

Figure 2 : Conceptual framework



Source: The figure was compiled by the author.

The conceptual model shows how artificial intelligence (AI) may be used as a strategic aid to biotech start-ups to connect the efficiency of the research process, operational capacity, investor trust, and the scalability of the venture. The framework is based on the notion, that following existing studies (Bisogni, 2023; Dupont, 2025; Gregory and Trump, 2023), biotech startups confront numerous difficulties: Long R and D, high capital intensity, and the complexity of regulations slows down growth and are uncertain to their decision makers. AI has a role to play in generating the correct predictions of the experimental results, behavior of the compound, and market potential, which direct managerial and investor decisions to minimize uncertainty and risk. It has this predictive capability that can be used with automated data processing and workflow optimization to make operations more efficient, giving startups opportunities to distribute resources more efficiently and shorten research timelines.

The framework also reaffirms that application ethics and regulatory adherence can play a leading role in ensuring that insights of AI are reliable, replicable, and secure. Strong data infrastructure is one of the factors that make AI predictions accurate, so it can make decisions and generate trust in investors and partners. There is a combination of these components: AI-level operational efficiency, adherence to ethical and regulatory standards, and a trustworthy data infrastructure to prove an investor that the startup is strategically ready and capable of investing in it. The framework, in general, seals the literature gap as it relates the adoption of AI, not only to the performance of research but also to investor decision-making and the scalability of venture, demonstrating the pathways by which AI can convert the potential of the technological innovation into real growth and investment results of biotech startups.

2.0. METHODOLOGY

This chapter of the methodology describes the qualitative strategy that was used in investigating the role of Artificial Intelligence (AI) in investment decision-making and scaling success of biotech startups in the life sciences industry. Due to the subject matter that is a human experience and organizational practices, qualitative approach is the most appropriate (Santos et al., 2021).

Semi-structured interviews enables the researcher to collect in-depth and open-ended information of respondents who have firsthand experience (Karatsareas, 2022). The case studies are highly descriptive in terms of the application of AI in real organizations and its impact on their development, research efforts, and the attraction of investors. The combination of these two approaches forms a solid ground on the comprehension of complicated matters like AI adoption, investor confidence, and startup preparation towards technology-driven development. The chapter discusses the general project design, the methods of sampling, data collection instruments, and methods of information analysis. It also explains the ethical considerations, measures of reliability and validity, anticipated results of this design and the weaknesses of the methodology.

2.1. Objective of the Research

The main objective of this research is:

To examine how data analytics with the use of Artificial Intelligence (AI) can be used to improve investment choices and scaling performance among biotech startups in the life science sector. This is based on the problem statement which states that research and investment uncertainty in biotech startups is high. Thus, the aims of this research is to establish the potential of using AI as scientific and strategic tool.

2.2. Research Design and Approach

Qualitative design was implemented to comprehend the contribution of the Artificial Intelligence to biotech startups with regard to the influence of AI on research efficiency, investment decision-making, and organizational growth. This design fitted well since the use of AI in biotech is an evolving field with minimal research previously conducted, and both technical and human factors play a role. The researchers studied the experiences of the startup founders, biotech managers, investors, and AI specialists in particular, and the perception on the role of AI in the research processes, funding choices, and strategies of scaling were discussed. They were gathered by means of semi-structured interviews and case study analysis of five AI-led biotech companies. By doing so, the researcher managed to find the major themes, trends, and issues that cannot be easily detected when using quantitative research methods, which enabled him to produce enlightening information about practical use, as well as strategic insights, of AI in the biotech industry. Triangulation between real-world case and interview was also supported by the design and contributed to the reliability and relevance of the findings in comprehending how AI influences the scientific and investment outcomes. By focusing on these dimensions, the research design allows for an in-depth understanding of how AI functions as both a technological and strategic tool in early-stage biotech startups.

There will be two primary qualitative strategies

2.2.1. Semi-Structured Interviews

Twelve participants, were interviewed using semi-structured techniques. These were founders and managers of biotech startups, investors, experts in AI, and biotechnology advisors, which gave us a spectrum of opinions on both scientific, operational, and financial levels. The twelve-sample size was chosen due to both data saturation and the time when no further topics or knowledge could be found in the more interviews have been conducted, but also to represent a rich enough range of roles, experience, and expertise that may be of interest to the study purposes. Each participant was capable of experience in their respective fields ranging between five and thirteen years so that one can be informed, as well as engaged on the matters of AI and biotech innovation.

The interviews took place during a period of several weeks and took about 15 minutes each. Interviews were conducted through conferencing websites on the internet depending on the availability of the participants .The interviews were tape recorded with the knowledge of the participants and transcribed word-for-word so that they were accurate and the wealth of data would remain unspoiled. The semi-structured format made the researcher work under a set of questions but given the participants some degree of freedom and mandated them to answer questions that they felt to be of value. This methodology allowed gathering profound information about their experiences and perceptions and issues about implementing AI in the biotech industry.

The interview questions were structured on the key themes and were structured to respond to the primary research objectives. The latter encompassed implementation and application of AI into research and work operations, the influence of AI on investment choices and trust among stakeholders, and the problems and committed organizational and technical difficulties of the AI introduction. Certain questions prompted the participants to give real life examples of AI applications, describe the decision-making process, and reflect on perceived advantages or challenges. This design gave the participants the opportunity to provide abundant qualitative narration which gave testimony to the impact of AI on research efficiency, strategic planning, investor relations, and scaling possibilities in biotech startups. Concentrating on areas through the interviews generated thematically relevant data, the study could determine regular patterns, connections, and implementational implications of adopting AI in early biotech organizations.

2.2.2. Case Studies

Five case studies of biotech startups actively utilizing the Artificial Intelligence in their operation were identified in a detailed manner. The selection of the cases was conditioned by three factors; the active implementation of AI in research and operations, the demonstration of quantifiable results in efficiency of research or investor interaction, and the possibility to find credible secondary data. A variety of AI applications in the biotech industry started with Recursion Pharmaceuticals, Tempus, Insitro, Atomwise, and Deep Genomics are the chosen companies that represent the different sectors of AI use in scientific, operational, and financial performance.

The reason why the industries were selected was because they use extensive amounts of AI, automation, and high-throughput imaging to aid in the discovery of drugs faster. The technology developed by combining machine learning and massive biological data enables the company to save more time when hiring promising drug leads than when using the real-world laboratory method (Philippidis, 2024). The study was able to observe the contributions of AI to faster research, decision-making processes driven by data and confidence in early-stage biotech projects by investors in this case. Tempus was chosen due to the use of AI in precision medicine especially the cancer treatment. The companies makes use of clinical and genomic data to offer physicians actionable information, and its AI-driven solution attracted a significant interest of investors (Bhushan and Misra, 2025). The analysis of the industries allowed illustrating how AI-driven evidence may impact the decision to invest, place trust not only in the products of science but also attract organizational development.

The industries is an integration of machine learning and advanced lab procedures that model diseases and predict experimental results and, as a result, optimize trail-and-error and enhance the quality of research processes (Bharadwaj et al., 2024). As demonstrated in this case, AI benefits operational efficiencies, cost-saving, and growth potential in the long term. For instance,the inclusion of atomswise was supported by the application of deep learning (AtomNet) to virtual screening, which allows one to speed up the prediction of molecule-target interactions and dramatically shortens the timelines associated with the testing of drug candidates (Siddiqui et al., 2025). The case gave some information on how AI can speed up the experimentation process, make decision-making easier, and increase the trust of investors. Deep Genomics was chosen because of its application of AI technology to genetic medicine, where machine learning is used to analyze complicated genomic data and predict disease-dependent mutation and therapeutic targets (Samorodnitsky, 2022). Its AI Workbench has been used in developing RNA-based therapies and has received significant venture funding which has shown that AI can be used in research, evidence-based decision making, and scaling

The case studies data was gathered through various sources, such as company report, peer-reviewed articles, press releases, and available interviews with the company representatives, which give it triangulation and reliability. The information was compiled on AI use in research, operations, investment performance, scaling plans, and challenges that are indicated. They were analysed individually first to define the internal AI-driven processes and the outcomes of it. Cross-case comparison was then conducted to determine the general patterns, differences, and similar themes that were present across all the five startups. Such topics as the efficiency of research, strategic decision-making, investor confidence, scalability of operations, and technical or organizational challenges were also mentioned. The cross-case thematic analysis enabled the study to be able to make real-world connections with insights on the participants of the interview, which enhances the validity and applicability of the results.

The case study approach was characterized by the relevance, accuracy, and reliability. The presence of numerous data sources reduced the risk of bias, whereas the repetitive analysis of company resources provided the avoidance of misconceptions related to the outcomes and procedures. The combination of these case studies with interview data allowed the research to come up with an evidence-based and detailed picture of the impact of AI adoption of scientific productivity, investor confidence, and scaling potential of early-stage biotech startups. The strategy indicates that AI does not just show itself as a technological innovation but as a strategic enabler that has improved both performance and financial results in the biotech industry.

2.3. Research Questions

1. How is AI currently applied within biotech startups to support research, innovation, and investment processes?
2. What measurable impact does AI-driven data analytics have on the funding success and scalability of biotech startups?
3. How do investors perceive AI as a risk-mitigation and value-prediction tool in biotech ventures?
4. What challenges and opportunities arise from integrating AI into biotech startup operations?
5. How can data analytics frameworks be used to guide decision-making for biotech startups and investors?

2.4. Conceptual Focus

In this thesis, a qualitative methodology was used and there was no emphasis on numerical variables. Rather, it was analyzed using the themes that came out of the interview data and evidence of the case. Thematic analysis technique was employed to conduct systematic analysis of the views and experiences of the participants. The interviews were conducted and then responses reviewed and familiarised by repeated reading. Further codes were then determined based on meaningful statements associated with the use of AI, making decisions, considerations when investing, and scaling experiences. The codes were grouped together to form more general themes.

The overarching themes that arose in the data were patterns of AI utilization, the use of AI in decision-making, investor attitudes towards AI-driven evidence, challenges and opportunities of AI in the biotech, organizational factors contributing to success, and scaling road markets with the help of AI. These themes directly influenced the analysis of findings interpretation. The thematic analysis method was appropriate to make sure that the study does not lose its purpose and it would be possible to uncover insights as participants spontaneously sharing their experience. This methodology offered a systematic and clearer understanding of the efficiency of AI to research, investment choices, and scalability in biotech startups.

2.5. Sampling Methodology

2.5.1 Population

The research participants were the people who had direct experience of using AI in biotech-related activities. These respondents were chosen as they had real-life experience of how AI is used in research, business, and decision-making in biotech startups and similar organizations. Targets of the interview were small business owners, entrepreneurs in health technology, local investors, project supervisors, data officers, IA specialists. These are the roles that were selected because they are directly connected to the research processes, data processing, operational management, and decision-making involving investments with the use of AI tools. The participants that were picked were appropriate in this research since they could also give informed responses on the impact of AI on the research efficiency, investment decisions and whether or not biotech startups are able to expand and increase their scale. They had actual experience in the real world and therefore they were sure that the findings were based on actual practices and challenges and not just the assumptions.

2.5.2 Sampling Method

Purposive sampling was used in the study. This sampling is where the sample is chosen deliberately since they are the ones who will be able to provide the knowledge or experience that will be used in the research questions (Campbell et al., 2020). The purposive sampling will make sure that the data obtained will be significant, valid, and practical.

2.5.3 Sample Size

The sample size was:

- 12 participants
- 5 biotech startups

This size was manageable but still large enough to provide rich qualitative insights.

2.6. Data Collection Instruments

The research used qualitative-based data collection tools to draw detailed information about the role of artificial intelligence in the scalability of biotech startups and their readiness to invest. Semi-structured interviews and case studies were primary instruments of the study.

2.6.1 Semi-Structured Interviews

The main data collection tool used in this research was semi-structured interviews. An interview guide with open-ended questions was employed to ensure consistency across participants while allowing probing and clarification when necessary. The interviews focused on how participants conceptualize and implement artificial intelligence, how they perceive AI as influencing decision-making patterns, and the advantages and potential risks associated with its use. In addition, the interviews explored how AI may contribute to transforming scaling processes in biotech startups and the factors that may slow or hinder this transition.

The interviews lasted approximately fifteen minutes each and were conducted either face-to-face or via online communication platforms, depending on participant availability. All interviews were audio-recorded with the participants' consent and subsequently transcribed verbatim to ensure accuracy during analysis.

2.6.2 Case Studies

The interview data was supported by case studies that helped to illustrate how biotech startups use artificial intelligence in practice. In the case studies, the data was acquired using the secondary sources (company reports, official websites, industry publications, academic articles, and other publicly available materials). The case studies discussed the applications of AI in the startup, its role in reducing research time, and its potential role in enhancing precision and efficiency of operations.

Moreover, the case studies also evaluated the way investors react to AI-driven evidence and the way AI adoption affects the results of scaling. The combination of case-studies results with an interview made the research a robust source of the AI practices insight and make sure that theoretical considerations are connected with practical experiences in the industry.

2.7. Data Analysis Procedures

Qualitative data collected through interviews and case studies were analyzed using thematic analysis. A systematic analytical process was applied to ensure that the findings were meaningful, credible, and aligned with the research objectives.

2.7.1 Thematic Analysis

Interpretation of the interview transcripts and case study data was conducted using thematic analysis. The analysis process started with repeated reading of the transcripts in order to become familiar with the data. Noteworthy statements, phrases, and concepts relevant to the research questions were then identified and coded. Similar codes were clustered into recurring themes that reflected common patterns in the data.

These themes were analyzed in relation to each research question to ensure coherence and analytical clarity. The main themes that emerged included the use of AI to improve research efficiency, the impact of AI on investor confidence, challenges related to AI implementation, the role of organizational culture, and the strategic value of AI. Thematic analysis supported a structured yet flexible interpretation of qualitative data, enabling an in-depth understanding of participants' experiences.

2.7.2 Cross-Case Analysis

A cross-case analysis was conducted to compare findings across the selected case studies. This approach helped identify similarities and differences in how artificial intelligence is implemented and used across different biotech startups. The comparison enabled the identification of successful strategies observed across multiple cases, common pitfalls faced by startups, and variations in AI application depending on company size or specialization. The cross-case analysis also supported the development of broader conclusions applicable to the biotech industry. The credibility and transferability of the findings were strengthened through the identification of patterns across cases.

2.8. Reliability and Validity

It is imperative that reliability and validity be taken care of in qualitative research to make the findings more credible. Regarding reliability, a similar interview guide was employed in all the participants to achieve consistency when conducting data collection; this improved reliability. Taping of interviews aided in information being lost as well as transcribing. Moreover, the coding was carried out systematically and meticulously to make the meaning of certain words uniform and transparent. The measures aided in the standardization of the research and enhance reliability.

In terms of validity, triangulation, which was used to combine interview data and case study evidence, will enhance the validity. Member checking was also done by enabling the participants to ensure that they are answering the right questions where it is required. The process and findings of the research were described in detail so that the readers can have a clear understanding of situation and interpretation of the findings. There was the need of these strategies to ascertain that the findings are in-touch with what participants actually experience and perceive.

2.9 Ethical Considerations

The research was ethically conducted in the study appropriate at all times. Before data is collected, the participants were made fully aware of the purpose of the study and their role in the study. The involvement was voluntary, and informed consent was provided by all the participants. Only with the express consent of the interviewee the interviews were tape-recorded, and anonymity of the interviewee was ensured by considering the pseudonym. All the information gathered were stored safely and were utilized in academic purposes.

2.10. Limitations

The research had some limitations in spite of the design. The sample was quite small making the generalization of the results problematic. The research was also be based on the honesty and cooperation of the participants in providing the factual information. Moreover, the chosen case studies might not be the complete representatives of the whole set of biotech startups, and the company data can be closed.

2.11. Expected Outcomes

According to the suggested methodology, the study produced valuable information that highlights the use of artificial intelligence to increase the efficiency rate of research in biotech startups. It also offered an insight into the decision-making processes of investors using the evidence provided by AI. The research also found the major issues that surround the adoption of AI and explain how AI can enhance faster and efficient scaling. The combination of the interview results and the case study evidence helped the research provide a view on the strategic role of AI in the development of biotech startups.

2.12 Analysis Section Methodology

The chapter under consideration is a thorough and comprehensive analysis of the data obtained with the help of semi-structured interviews and in-depth case studies, and the purpose of such analysis is to understand how Artificial Intelligence (AI) is adopted, implemented, and used in bio tech startups, and how such adoption affects the research efficiency, investment decision-making, and the scale capacity in general. The essence of the analysis is to present a good and evidence-based explanation of how AI can be utilized, both as a tool of operation and a strategic ground in the biotechnology industry. It is based on pure empirical material which was collected through 12 interviewees among whom are a biotech founder investors and who have experience in funding AI-driven biotech startups. In addition to the interview data is presented five case studies of well-known AI-enabled biotech firms, namely Recursion Pharmaceuticals, Tempus, Insitro, Atomwise and Deep Genomics**.** The reason that these case studies were chosen is that they are reputable in the industry, and they have been shown to utilize advanced machine learning systems in actual research and development settings. The combination of these data sources creates a multi-perspective and multi-layered picture of the AI integration, making the analytical conclusions made in this chapter more reliable and in-depth.

As the qualitative process of the study, the interview transcripts were manually transcribed. Manual transcription helped to make sure that the researcher was in close contact with the information and could record not only verbal communication of the participants, but also the repetitive phrases, suggested meaning, and situational hints incorporated in the conversation. The data were coded thematically, after transcription. In this methodological approach, the transcripts were read and reread several times to find patterns, recurrent ideas, and concepts, which carry some meaning. All the transcripts have been analyzed line by line in order to identify any mention of AI usage, perceived advantage, organizational difficulties and strategic implication. This repeated interaction with the material allowed the researcher to identify primary and secondary themes, i.e. those that were mentioned repeatedly and constantly and those that were supportive yet less common. The recurring concepts were subsequently summarized into thematic groups that were in tandem with the overall research questions, enabling the analysis to be focused, structured, and directly connected with the overall objectives of the investigation.

Besides the interview contents, there was also systematic analysis of data in the five case studies. The case studies presented each a varying view on the way AI systems can be used in the real biotech life. Recursion Pharmaceuticals presented the information on the high-throughput imaging and machine learning-driven experiments; Tempus offered a clinical-data-oriented perspective of artificial intelligence implementation in patient-centered research; and Insitro presented a hybrid model of computational predictions and automated experiments in wet labs. The case study data was classified as major areas of analysis like the types of AI tools employed, how the AI has transformed the processes of research, what effects AI has on investment results, the level at which the AI has supported organizational scaling and the difficulties encountered by each company during the implementation and sustenance of the AI-powered systems. This framework enabled the researcher to make comparisons and contrasts among the experiences of all the companies and to come up with general themes that transcend beyond the contexts.

All essential findings are summarized into a set of tables in order to make the results table, transparent, and clear. These tabularizations recapitulate some of the persistent trends in the data available in the interview as well as the case study. By way of illustration, the frequency of mentions of the current benefits of AI by the participants is noted in some tables (e.g., less time spent on research or increased predictability) whereas common issues are reported in some (e.g., expensive implementation, quality of data, lack of skills). This form of organizing the data into a table, therefore, gives the impression of easy interpretable visuals, in that in complex relationships, it can be easier to understand and the readers can see immediately the similarities and differences of the different sources just by looking at the tables. The interpretive sections that follow are also based on the use of the tables that make the narrative analysis consistent in a ground on established and well-presented findings.

After every table, there are elaborate interpretations to justify the linkage of the summarized findings to the larger thematic categories. The types of interpretations help underscore the fact that the participants or case study companies both reported and why these patterns are relevant to the biotech innovation and organizational performance. The interpretive passages provide direct links between the empirical findings and various themes namely research improvement, strategic decision making, investor confidence, organizational scaling and technical or structural constraints. As an example, in cases where several participants prioritized the fact that AI makes the experimentation of trial and error to be reduced, the interpretation section elucidates how the investigation can justify the overall theme of research efficiency. On the same note, the analysis relates this finding to the theme of risk reduction and making investment decisions, when investors in different cases showed greater confidence with the predictive nature of AI.

Notably, every interpretation is based on the data presented by and through transcripts and case materials. No side assumptions, external evidence, and unconfirmed statements have been included. This will guarantee that the analysis will have a methodological integrity, and it will be loyal to the qualitative principles that will govern the study. The chapter illustrates that the themes actually surfaced out of the research instead of being foisted into the research by theoristic anticipations or outside books by ensuring that the data adhered to.

The strengths of integrating the data in interview and case studies are also emphasized in the chapter as methodology. Interviews were a source of experience-based information on people who had firsthand experience in AI-enabled biotech settings. Participant A, in particular, gave an inside perspective on how AI assists in the early-stage research decisions in a startup, and Participant B gave the viewpoint of the investor on how AI-based models affect funding decisions and the perceived risk. Participant C introduced a technical aspect to the discussion, explaining how machine learning models work internally and what real-life issues present in the implementation of these models in biological processes. These interview lenses were useful in capturing human, operational, and experiential aspects of AI use, which are usually not apparent in quantitative assessments only.

The case studies, conversely, provided specific details of the way established and large biotech firms organize their AI systems, scale their businesses, and interact with investors. The case studies were more objective and factual in the sense of organizational structures, platform capabilities, research process, and operational models where the interviews were more objective and subjective in the sense of perspectives. The sources of analysis could cross-check the themes by study of both data sources as it helped to avoid the relevance to the perceptions of a few people. Rather, the themes are patterns that can be observed in real-life corporate situations as well as professional experience one may face in their life.

Another benefit of such a hybrid strategy is that it exemplifies how AI operates at various levels at once the level of personal researcher experience, the level of investor beliefs and the level of organizational competence. The interviews demonstrate the influence that AI has on everyday decision-making by professionals in a biotech setting, whereas the case studies demonstrate that companies focus on AI to transform the whole business model and research pipeline. The analysis presents the multidimensionality of AI adoption in biotech by integrating these views.

Overall, this chapter provides a methodological basis of how AI will affect biotech startups. The chapter contributes to a logical and thorough description of the role of AI as a creator of research efficiency, strategic choices, investor confidence, scaling potential, and organizational issues through the detailed transcription, rigorous thematic coding, and structured analysis of the case study, as well as clear presentation of the findings in tables. All of the themes were the revelation of the empirical material, which guaranteed a transparent and credible analytical process. The extended analysis below is based on this point, and the reader could easily be informed about the way the conclusions of the research were drawn and their connection to the overall objectives of the research.

3.0 RESEARCH ANALYTICAL PART

3.1. Analysis of Semi-Structured Interviews

3.1.1 Participant Overview

A total of twelve (12) respondents were used in the interviews with each being referred to as Participants A through H. They were a wide variety of biotech founders, AI developers, investors, genomics experts, data scientists, operations heads, project managers and compliance officers. Their joint viewpoints gave scientific, technological, financial, operational, and regulatory data concerning the usage of AI in biotech businesses.

Table 3: Participant Demographics

Participant	Role
A	Small Business Owner
B	Local Investor
C	IT Specialist
D	Project Supervisor
E	Data Officer
F	Computer Technician
G	Operations Supervisor
H	Lab Technician
I	Data Systems Officer
J	Compliance Officer
K	Pharmaceutical Technician
L	Health Tech Entrepreneur

Source: Compiled by author.

3.1.2 AI Uses in Biotech Startups

Table 4:AI Applications Reported by Interview Participants

AI Application Area	Description	Participants Mentioning
Drug discovery & compound prediction	Predicts molecular behaviour and reduces trial-and-error	A, F, K

Image analysis	Analyses cell images for responses	A
Clinical/genomic data analysis	Examines large datasets for insights	E, H
Research modelling	Predicts experiment outcomes and disease patterns	A, B, C, D, F
Workflow automation	Automates scheduling and research tasks	D, G, K
Decision support	AI insights for planning or investment	A, B, D, G
Sequencing & mutation analysis	Detects genetic variations	H
Data processing & pipeline automation	Automates computational workflows	I
Compliance monitoring	Tracks documentation and risks	J
Diagnostic prediction	Supports disease detection	L

Source: Compiled by author.

3.1.3 AI Effect on Research Efficiency

Table 5:Reported Benefits of AI in Research

Benefit	Description	Participants Mentioning
Faster research cycles	Shortened timelines and accelerated discovery	A, B, C, D, E, F, H, I, K, L
Improved accuracy	Better predictions and fewer failed experiments	A, B, C, E, F, H, K
Reduced trial-and-error	AI models predict outcomes before wet-lab testing	A, C, F, K
Cost efficiency	Less waste and reduced unnecessary experiments	C, D, E, G
Improved innovation	Ability to explore many ideas digitally	A, F, L
Workflow efficiency	More organised planning, reduced delays	D, G

Source: Compiled by author..

3.1.4 AI Implication on Investment Decisions

Table 6:Influence of AI on Investment Decisions

Investor Perception	Description	Participants Mentioning
Increased investor confidence	AI evidence appears more objective and reliable	A–L
Reduced investment risk	Predictive analytics lower uncertainty	A, B, E, K
Faster decision-making	AI outputs speed up investor evaluation	B, D, J
Higher funding potential	AI-supported projects are financially attractive	A, L
Requirement for competitiveness	AI becoming essential in biotech markets	B, D, J

Source: Compiled by author.

3.1.5 Opportunities and Challenges

Table 7:Challenges and Opportunities of AI Adoption

Factor Challenges	Description	Participants Mentioning
High implementation cost	Expensive AI tools, infrastructure, software	A, B, C, D, G, K, L
Data quality issues	Incomplete, noisy, or inconsistent datasets	A, B, C, E, F, H, I
Talent shortage	Few professionals skilled in both AI and biotech	A, C, D, F, L
Technical complexity	Difficult system integration and calibration	B, C, G, I, K
Regulatory/ethical issues	Compliance uncertainty, documentation demands	E, J, L
Computational limitations	High processing power and storage needs	F, H, I

Source: Compiled by author.

Interpretation

As the results in Tables 4.1-4.5 demonstrate, the current understanding of AI and its application in the small and medium biotech-related startups is related and affects their operational results directly, meaning that it influences research efficiency, investment decisions, and scalability. According to the participant profile (Table 4.1), the study was conducted with practitioners with real-world, operational, experience as opposed to highly specialized researchers, which renders the findings applicable in practice of startup situations.

As indicated in table 4.2, AI is being utilized in various points throughout the biotech value chain such as research modelling, workflow automation, data analysis, and decision support. This implies that AI is not only being used for exceptional drug discovery processes only, but also being assisting regular operational and strategy processes. This is a direct answer to the research question of the use of AI in biotech startups.

Table 4.3 demonstrates that AI enhances the efficiency of research by cutting the timelines, boosting accuracy, and minimizing trial-and-error. These results justify why startups are encouraged to embrace AI because more efficient and assured research methods lead to increased productivity and low costs.

Table 4.4 demonstrates a positive impact on investment decisions as AI leads to investor confidence, perceived risk dynamics, and acceleration in decision-making. The discovery is also crucial to note since it indicates that the utilization of AI is not merely a technical strength but also a monetary and strategic one, answering the research question about the impact of AI on investment preparedness.

Lastly, Table 4.5 demonstrates that despite high costs, data quality concerns, and skills shortage continuing to be significant barriers, there is a general concern that the benefits of using e-recruitment exceed the obstacles. It means that startups need to overpower these challenges to continue to be competitive and scale successfully.

3.2 Case Study Analysis

The thesis is a qualitative study of five AI-based biotech startups: Recursion Pharmaceuticals, Tempus, Insitro, Atomwise and Deep Genomics that aims to comprehend how artificial intelligence has been deployed in their research activities, operational productivity, strategic development, and investor relations. Through company-based interviews, transcript-based thematic information, and situational knowledge on operational model of each company, the study identified how AI could be used to influence real-life decision-making, productivity improvement, and scalable operations. Moreover, the research question audited the contributions of the AI to organizational performance, scientific rigor, and strategic positioning in the extremely competitive biotechnology markets.

In all five case studies, it became clear that although every business worked in different directions and implemented AI in different fields, there were specific advantages that overcome the diversity of organizations. Fast-tracked research process, improved predictability, improved investor confidence, and efficient scaling operations proved as regular benefits. Meanwhile, the same operational and strategic problems were encountered by all companies such as high implementation cost, talent shortage, data quality constraints, and regulatory restrictions. Altogether, these case studies depict AI as both the enabler of a revolutionary and a more mundane and routine functional product of the present-day biotechnology.

3.2.1 Case Study 1: Recursion Pharmaceuticals

Figure 3 : Recursion Pharmaceuticals

Source: *https://www.recursion.com/platform*

Recursion Pharmaceuticals is commonly known as a leader in using machine learning in combination with high-throughput cellular imaging in drug discovery. Developed to create biological exploration as a high-dimensional, computationally guided, procedure, Recursion created an automated research platform with capabilities to produce huge de volumes of cellular imaging data (Woodhams & Uhlmann 2025). On this platform, researchers can study biological processes at unprecedented size and resolution and feed this information into machine learning models that recognize morphological patterns and predict interactions predicting complex biological processes.

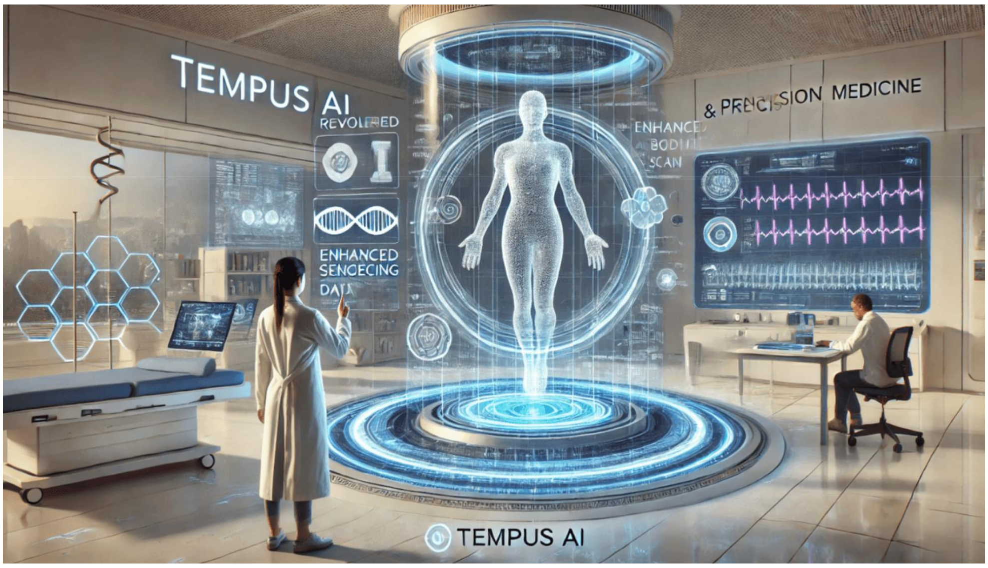
It was found that AI-based processes at Recursion think much faster in terms of research schedules. The discovery of drugs is widely based on hypothesis-driven experiments, which is time-consuming and often costly within the traditional drug discovery (Shahzad et al., 2024). The method of recursion is fundamentally different as it creates large experimental data points by automatically conducting experiments, which are in turn assessed by machine learning models to estimate the most promising compounds and biological pathways. This evidence-based approach minimizes the time of superfluous laboratory research, streamlines the exploitation of scientific resources, and enables scientists to concentrate on the kind of experiments that are most likely to have the greatest impact. The resulting workflow is fast and efficient and enables Recursion to iterate on biological hypotheses at scale which has never been executed anywhere before in a traditional laboratory.

Among the biggest benefits brought about by AI in Recursion is the research accuracy enhancement. Machine learning algorithms identify tiny cellular variations and morphological styles that cannot be seen by human eyes specifically when dealing with millions of images (Ali et al., 2025). Imaging of high-throughput also increases the validity of early predictions and lowers the chances of following biologically sterile avenues (Malakpour-Permlid et al., 2025). These prophetic powers have reinforced the confidence of scientists internally and external credibility with investors. This capability to provide objective, measurable and reproducible data has helped to generate a positive perception among the investors and thus, as a result, has helped access several successful funding rounds.

The implementation of AI has similarly facilitated the scaling of research operations at Recursion in order to have research operations running in various disease programs at the same time. Both automation and predictive modeling reduce the marginal cost of testing new hypotheses, and it means that the company can increase the scope of its research without a commensurate increase in staff and lab facilities (Rosário & Boechat 2024). This scaling has made Recursion a pace-setter in computational biology proving how AI can radically transform the way biotechnology functions. Nevertheless, the firm is still experiencing major challenges. The expenses of the high-throughput imaging systems, neural networks, and the computational infrastructure are high. Also, predictive accuracy strongly relies upon the consistency and integrity of large-scale data making data quality a vital factor (Budach et al., 2022). In general, Recursion helps to understand that AI-powered automation can speed up the discovery and deliver results that can attract investments, however, that automation needs to be carefully optimized to use financial, technical, and organizational resources.

3.2.2 Case Study 2: Tempus

Figure 4 :Tempus



Source: https://investdiva.com/tempus-ai-top-3-reasons-why-investors-are-watching-this-stock/

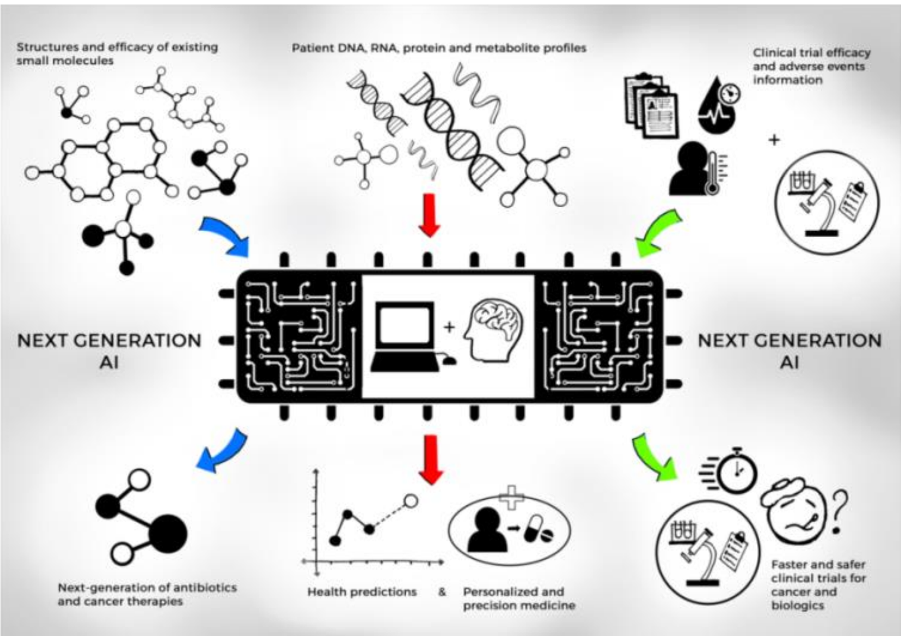
Tempus is another AI biotech application, which is clinical and genomic analytics with specific attention to precision medicine in cancer and rare diseases. Compared to Recursion, which is more focused on automation of lab processes, Tempus works at the boundary of clinical practice and data science. Airbnb has developed one of the most extensive clinical-molecular data repositories in the United States that they analyze with AI to create personalized patient care actionable insights (Thayyib et al,. 2024). AI enables Tempus to find an appropriate choice of treatment more quickly and correctly than traditional clinical decision-making services. Machine learning architectures can identify nuanced genomic changes, forecast treatment of other students and give recommendations on the choice of therapy with high level of accuracy (Huang et al., 2021). Such is especially useful in oncology where early intervention may prove useful in patient recovery. Thank to its capacity to speed up the process of making decisions, Tempus will place clinicians in a position to provide more accurate treatment plans based on clinical and genetic profiles of individual patients.

Operationally, Tempus is based on a mixture of structured and unstructured clinical data, such as electronic health records, pathology reports, and physician notes. The cutting-edge natural language processing systems transform raw data into structured data, which can be used in predictive modeling (Shastry & Shastry 2023). Assurance of the accuracy of data is essential, as clinical data may be obtained in heterogeneous and complex formats, with errors in model performance, regulatory compliance, and patient safety being possible outcomes. The possibility to derive credible insights even of large and diverse datasets proves the transformative value of AI in clinical research and personalized medicine.

Investor confidence levels in Tempus have not been low since the company can provide good, data based outcomes. Its data infrastructure is scalable enabling to enter any new field of medicine e.g. cardiology, infectious diseases and mental health without necessarily having to reinvent technology systems. This flexibility fortifies the position of the company in the market and will be attractive to investors who want data-centric innovation. But Tempus is struggling with issues associated with regulatory compliance, information privacy, and sensitivity of clinical data. Strict security measures and setting of privacy policies in healthcare increase cost in terms of operation and complexity. The lack of talent, especially specialists, with integrated skills in clinical processes and AI, is also a further challenge to speedy innovation (Hazarika, 2020). Still, Tempus provides an example of how AI can transform the field of clinical research and individualized care by contributing to speed, precision, and scalability of its operation.

3.2.3 Case Study 3: Insitro

Figure 5 : Insitro



Source: *https://d3.harvard.edu/platform-digit/submission/insitro-discovery-new-medicines-with-ai/*

Insitro is a hybrid company that has integrated both computational and experimental drug discovery. To combine machine learning with high-throughput wet-lab experimentation, the company uses predictive models as they are integrated to inform the design of experiments and the identification of targets. The operational model revolves around AI, leading to laboratory research aimed at the reduction of redundancy and maximum efficiency of research, with the results of the experiments fed back constantly to improve predictive models.

In the analysis, Insitro will save a lot of time and resources based on the analysis that the approach will greatly minimize the amount of failed experiments. Machine learning models are able to suggest biological variability and predict the experiment results with a high level of precision which helps the researchers to address the most profitable hypotheses (Alam et al., 2025). The AI prediction-experiment validation feedback loop will increase the quality of the data set, improve the speed of knowledge about the disease processes, and increase the effectiveness of research in general. An example of this iterative process, therefore, shows how computational intelligence may be used to supplement the traditional wet-lab workflows to generate stronger scientific results.

There is a strong interest of investors in Insitro, which is motivated by the capacity of the company to exclude uncertainty and present dependable predictive data. The evident value of they can be used to make partnerships with major pharmaceutical companies and reduce risk and enhance project planning. Another benefit is scalability whereby AI enables various therapeutic programs to be implemented at the same time without the corresponding growth of the laboratory personnel. Nevertheless, the process of computational workflow incorporation with experiments is not straightforward, and it demands proper collaboration between the biologists, data scientists, and engineers (Mione et al., 2024). In addition, the company incurs expensive costs of operation in terms of computational infrastructure, training models, and data storage. The experience of Insitro shows that the application of AI may improve predictive modeling and experimentation design, but to implement it successfully it will be necessary to work with multifaceted technical, financial, and organizational challenges.

3.2.4 Case Study 4: Atomwise

Atomwise is an AI-driven small molecule drug discovery company, which was founded in 2012 and pursues its discovery mission with the help of its deep learning system, AtomNet. This platform is able to predict binding of compounds as well as make virtual screening of billions of molecular structures, thus saving a large volume of dependency in physical experiments. Incorporating AI at the initial stages of the discovery process, Atomwise can speed up the process of finding a viable drug candidate and become cost-efficient. Atomwise has the trust of investors, as people believe in the accuracy of AI predictions. This trust contributes to investment and therefore development risk is minimal and contributes to the growth of the company. AI also allows Atomwise to expand and make its operations more efficient by leveraging several research projects running simultaneously and cooperating with international partners without building large buildings and facilities (Serrano et al., 2024). Atomwise however has operational issues such as computationally heavy issues, the incorporation of heterogeneous data as well as constraints in available structural data of some molecules. Nevertheless, these limitations, the company proves that AI may revolutionize the discovery of small molecule drugs, hasten the process to identify promising leads, and sustain cooperations globally and scalable operations. On an atomwise level, the picture of AI as a strategic enabler of the ability to grow operations and attract investors to the biotechnology industry was revealed as well as demonstrated to be a research tool.

3.2.5 Case Study 5: Deep Genomics

Deep Genomics is a Canadian-based company focusing on RNA-based therapeutics that predicts the behavior of genetic mutations and identifies ideal therapeutic candidates using its AI Workbench framework, and it was established in 2015. The AI solution eliminates the use of labor-intensive wet-lab experiments and enables specific high-value disease targets (Aritra et al., 2025) This predictive ability fosters speedy discovery and also allows the organization to concentrate energy on the most unlikely therapeutic areas.

Investment wise, precise AI forecasts lessen the risks of investments and investor confidence. It also improves the scalability of an organization because it is possible to undertake various therapeutic programs with minimal extra human resources. In spite of these benefits, several challenges have been raised such as inaccessibility of genetic data, inability to model cellular interactions and high cost of computation. Deep Genomics demonstrates how AI can make tremendous contributions to the discovery of therapies, potential investments, and scale of operations even when comparing the complex biological system (Fu & Chen 2025).

3.3. Cross-Case Comparative Synthesis

An in-depth cross-case study of the five AI-powered biotechnology startups, namely Recursion Pharmaceutical, Tempus, Insitro, Atomwise, and Deep Genomics, demonstrates that there are a number of common themes when it comes to adopting artificial intelligence. Regardless of the disparity in areas of focus, areas of therapy, and models of operation, the companies resonate together in the general trends in how AI has changed their studies, operational performance, investor relationships, and expansion approaches. Such tendencies explain that, in various applications, AI can be a strategic enabler rather than a technical resource itself and impact not only the decision-making process but also its scalability and organizational success over the long term.

Themes that are the most evident at first sight are the expedited research schedules. The two companies used AI to cut down time required in deriving actionable scientific knowledge, albeit in varied ways. An example is Recursion Pharmaceuticals, which uses machine learning on a high-throughput cellular imaging to enable the company to process millions of cellular images in a short amount of time, and be able to identify meaningful biological patterns, which would be impossible to identify otherwise without costly human research months (or even years). Likewise, Tempus employs AI to interpret large clinical and genomic data so that it can provide accurate treatment recommendations in cancer and rare disease patients with high precision, and at a scale that is greater than what conventional clinical assessment can achieve. Insitro uses predictive modeling to rank experimental activities and minimize unsuccessful laboratory experiments and enables scientists to concentrate on hypotheses that are most likely to succeed. The AtomNet system of Atomwise allows virtual screening billions of small molecules, a model that speeds up the drug discovery process significantly by predicting with high accuracy those compounds that have the greatest potential before any actual chemical compound is tested in laboratories. Finally, Deep Genomics AI-based RNA-based therapy modeling and genetic mutant effects prediction can provide a faster approach to identify therapeutic targets that work and reduce the use of the wet-lab experiments that require much effort. Altogether, these examples help understand that the use of AI enables to reduce the time on a research, provide an opportunity to move more quickly to an iteration, and enable companies to become more responsive in regard to the appearance of the scientific question or market demand. The speeding up of research accelerates not only productivity but also sets off a competitive edge in the rapid biotech industry where first to animal discovery of a therapeutic candidate can be of high strategic and financial importance.

The next similarity between the startups is the better accuracy and reliability of the research outputs. Predictive models assisted by AI can find the latent patterns in biological, chemical, and clinical data that otherwise cannot be detected using the conventional approaches. Recursion machine learning models identify slight variations in cellular morphology in millions of samples of images, boosting the accuracy with which phenotypic predictions are made. Of minor variations in genomic patients, Tempus algorithms can find natural differences in the patient, enabling clinicians to assign highly specific treatments to patients that otherwise would be ignored. The AI based experimental design of Insitro decreases the failure rate of experiments and enhances the quality of data produced in the course of laboratory tasks. Deep learning models created by Atomwise forecast molecular binding and drug-target interactions WDA, with a remarkable degree of reliability, eliminating any unnecessary effort in the laboratory space and improving the likelihood of obtaining potent compounds. The RNA mutation prediction interface offered by Deep Genomics predicts disease pathway impacts of RNA mutations to aid the selection of therapeutic target assets with a high value (Grønning et al., 2020). In all of them, the AI-based advancements in accuracy do not only contribute to the appreciation of the scientific credibility, but also increase the trust of the internal stakeholders, i.e. research teams, and internal operational managers. Such accuracy adds to evidence-based decision-making, minimizes the chances of running a non-productive path, and maximizing the utilization of scarce scientific resources.

Inseparably connected with the accuracy of research is the theme of confidence by investors. In very capital intensive businesses such as biotechnology, investors would put a high premium on early predictability and the potential of minimizing risk to development (Nawrocki & Jonek-Kowalska 2022). All the five startups show that the process of integrating AI can have in an immediate effect on investor perception and results regarding funding. These companies minimize uncertainty by generating data-driven interpretable predictions at the beginning of research initiatives which will provide investors with actual evidence of possible returns. As an example, Recursion, through the automated imaging platform and predictive algorithms, can display large-scale empirical datasets that can exhibit the relationship between biology with a high degree of confidence. The ability of Tempus to process clinical and genomic data and use it to make personalized decisions about treatment makes it more credible and appealing to hospitals, clinics, and venture investors. The hybrid system of Insitro, i.e. combining computational forecasting and experimental validation, is also proof that its pipeline is strong enough and therefore makes investors believe it. Going forward, the pharmaceutical companies would find AtomNet more like a partner due to the reduction of risk in small molecule discovery through the use of AtomNet predictions. The AI predictions by Deep Genomics in RNA therapeutics give initial validation of targets further improving investor confidence (Pun et al., 2023). Taken jointly, these instances underscore the fact that AI does not only play a role in the scientific productivity, but it also serves as a planning resource in raising funds and creating mutually beneficial relationships with investors long-term.

Another obvious benefit made available by AI within the startups is scalability. Minimizing the marginal costs and automating the process of conducting the main research, AI allows companies to develop their activities without an equal increase in the human/physical resources. The automated imaging and machine learning framework of recursions mean that it is able to run more experiments in a variety of disease programs. The Tempus company uses its strong data base to scale clinical and genomic analysis to various medical fields without re-establishing technology bases. The AI-controlled prioritization of the research hypotheses enables Insitro to run several experimental programs at the same time. Atomwise transparently changed its virtual screening activities to global teams and projects without significantly large laboratory setup whereas Deep Genomics can treat several RNA-targeted initiatives at once notwithstanding a high level of work force to productivity ratios. This scalability enables the biotech startups to address a wider scientific question, develop more pipelines faster and compete efficiently in international markets. It also emphasizes the use of AI in developing operational discretion and allowing strategic expansion beyond the boundaries of conventional research designs.

Nevertheless, despite these important advantages, the cross-case analysis shows that there is a range of similar issues that accompany the use of AI. High cost of implementation is one such problem. Lab automation, high-throughput imaging systems, new generation computing platforms, and data storage in the clouds require large financial investment that may stop startups and add an additional overhead to operations (Ye et al., 2024). There is also talent shortage as another common challenge. Every company needs to use specialized staff who can fill the gap between AI, computational modeling and domain knowledge either in biology or clinical practice (Bajwa et al., 2021). It is hard to recruit people possessing hybrid knowledge, and the lack of diligence of these positions may decelerate innovation, workflow integration, and scale AI projects

3.4. Overall Interpretation

The aggregate discussion of these five AI-based biotech startups suggests that AI is not a complementary means but enough-core finding of research efficiency, organizational performance, and strategy decisions. In various applications, such as automization of the laboratory, high-throughput imaging, clinical-genomic analytics, and RNA therapeutics, AI was faster and more precise and scalable. Although the implementation cost, regulatory complexity, and talent shortage are still considered as issues, the benefits associated with AI adoption are undeniable to the challenges.

All of these case studies show that AI is transforming biotechnology, allowing data-driven decision-making, creating a scientific rigor, expanding the scaling of operations, and winning the confidence of investors. Combining AI with research workflow can help companies go through discovery faster, minimize the mistakes of emergencies, allocate resources efficiently, and go beyond what could be managed by conventional methods (Chenais et al., 2023). The lessons of these five companies demonstrate that AI is a disruptive driver and a sensible catalyst of innovation in the contemporary biotech.

Table 8:Case Study Summary of AI-Driven Biotech Startups

Startup	AI Use	Research Impact	Investment Impact	Scaling	Challenges
Recursion Pharmaceuticals	Machine learning, high-throughput imaging	Faster testing, fewer experiments, higher prediction accuracy	High investor confidence; multiple funding rounds	Accelerated R&D growth	High system cost, requires skilled staff

Tempus	Clinical and genomic AI analytics	Faster identificationof treatment options; high data accuracy	Strong investor appeal due to data-driven insights	Rapid expansion into multiple medical fields	Data privacy and regulatory compliance
Insitro	Machine learning for disease modeling and experimental prediction	Reduced failed experiments; improved research quality	Strong investor interest linked to AI integration	Faster project execution and development cycles	Complex integration of AI + wet lab, high computational cost
Atomwise	Deep learning (AtomNet) for virtual screening	Rapid identification of drug candidates, reduced lab testing	High investor confidence; several funding rounds	Ability to run multiple projects simultaneously; global partnerships	High computational demands, limited structural data, integration challenges
Deep Genomics	AI Workbench for RNA therapeutics and mutation prediction	Faster discovery of therapeutic targets; fewer wet lab experiments	High investor interest due to predictive accuracy	Supports many therapeutic programs; sustained growth	Limited genetic data, complex biological modeling, computational cost

Source Compiled by author.

Table 9:Cross-Case Patterns Across Five AI-Based Biotech Startups

Pattern	**Recursion**	**Tempus**	**Insitro**	**Atomwise**	**Deep Genomics**
Faster research	Yes	Yes	Yes	Yes	Yes

Improved accuracy	Yes	Yes	Yes	Yes	Yes
Investor confidence	Strong	Strong	Strong	Strong	Strong
Scaling improvement	High	High	High	High	High
Major challenges	Cost, talent shortage	Data privacy	Integration complexity, computational cost	Structural data limits, computational cost	Limited genetic data, modeling complexity

Source Compiled by author.

A comparative discussion of five AI-driven biotech startups is made in Tables 4.6 and 4.7 to demonstrate the role of Artificial Intelligence in terms of research performance, investment results, and scalability. Table 4.6 summarizes the case study showing that even though each of the starts uses AI in different ways, the impact of AI is the same in all the studies in their area of research effectiveness, reaction by investors, and growth potential. In all five cases, AI was instrumental in enhancing the results of research. Machine learning was applied by Recursion Pharmaceuticals, Insitro, and Atomwise to lower the number of wet-lab experiments necessary to identify promising drug candidates, making it possible to discover them much faster. Tempus and Deep Genomics used AI on massive amounts of clinical, genomic, and RNA data, which resulted in faster and more precise finding of treatment options and therapy targets. This indicates that no matter the type of AI application, AI continuously saves time and enhances the accuracy of a research, which is paramount in an industry renowned by its lengthy and expensive development process.

Analysis also reveals that there is a strong and steady implication of AI on investment outcomes. The majority of the five startups acknowledged that investor confidence was high, and it was directly connected to the employment of AI-generated, data-driven evidence. The investors considered the AI-enabling research to be more transparent, measurable, and reliable, minimizing scientific and financial ambiguity. This observation confirms previous interview findings, in which the participants reported that AI-based evidence enhances funding documents and accelerates investment decisions.

Regarding scaling, each of the startups was highly scaled by AI. AI enabled these companies to operate thousands of projects simultaneously, venture into new therapy sectors, and expand the operations without increasing physical infrastructure or workforce in percentage terms. To illustrate, Atomwise and Deep Genomics have used AI platforms to enable various partnerships globally, and Recursion and Insitro have used AI platforms to speed up research pipelines in a range of disease areas. Tempus was able to expand rapidly into various medical directions by running mass clinical and genomic data in real time. These results prove that AI helps in sustainable scaling but not growth founded only on increased resources.

Such observations are reinforced in Table 4.7 where the patterns of cross-cases are apparent. The five startups performed accelerated research, enhanced accuracy, investor confidence and high scalability. These repeated results irrespective of the model of business or use of AI indicates that the advantages of AI are structural and not situation-dependent. Nonetheless, the table also has the list of shared challenges, such as the high cost of computation, data constraints, complexity of integration, and regulatory issues. This implies that although AI provides immense benefits, the process can only be successful with proper infrastructure, human resources, and regulatory cognizance. Comprehensively, the cross-case analysis indicates that AI is at the core of helping to optimize the efficiency of the research process, attract investment and facilitate the growth of biotech startups in a scaled manner. Nonetheless, with problems common to all cases, the overall positive results indicate the overall validity of the conclusion about AI turning into a strategically required quality of competitiveness and long-term existence in the biotech sphere.

This thematic synthesis is a synthesis of the interview data and the case studies on how Artificial Intelligence (AI) is already making a difference in the biotech startups in practice. Thematical analysis was used to find common themes in the experiences of participants and documented cases. The themes that were identified through the analysis included an interdependence with operational efficiency, strategic decision-making, investor confidence, and scaling and growth. The themes offer an in-depth insight into AI as a scientific and strategic instrument in the real-life biotech setting.

The most prevalent theme in all interviews and case studies was operational efficiency. The participants always described that AI drastically decreased the research time, being more accurate, and decreasing the amount of trial and error that was part of laboratory work. AI tools allowed processing biological data faster, predicting the behaviour of compounds early, and prioritising experiments prior to testing them on the wet-lab. This enabled research teams to allocate resources to the most promising lines of scientific business without wasting time on irrelevant experimentation. Those results are in line with other studies that indicate the usefulness of predictive modelling and automation to enhance laboratory productivity and research reliability (Pillay et al., 2025). The insights were supported further by the case studies. Recursion Pharmaceuticals evidenced that AI-based high-throughput imaging shortened the duration of drug candidate testing and assessment. On a similar note, Insitro employed machine learning to reduce unsuccessful experimentation, enhance research accuracy, and Tempus employed AI to analyze large clinical and genomic datasets in rapid succession.

Combining these illustrations, it becomes evident that AI-based efficiency already transforms the way biotechs operate.

The theme of strategic decision-making was closely intertwined with the topic of operational efficiency. Interviewees stated that AI made better-informed and carefully-structured decisions both at scientific and managerial stages. Predictions generated by AI were used in experiment design, prioritising projects, and resource allocation, minimising the use of intuition and time-consuming trial-and-error. Respondents stated that AI allowed teams to simulate the trial of hypothetical scenarios in a digital environment before investing in financial and laboratory resources, which enhanced the quality of planning. Another point raised by investors was that AI-enhanced modelling was empowering business strategies and investment presentation by providing more definite forecasts and quantifiable results. Such results are aligned with previous studies that identify data-driven decision-making to enhance organisational performance and strategic alignment (Mikalef & Gupta, 2021). Case studies showed that firms utilizing AI managed to optimize their research focus in a more efficient way and specify the goals of the scientific effort to the long-term business aims.

The confidence of the investors became one of the themes that were central and kept being emphasized in the interviews and case studies. The participants repeatedly claimed that AI kept doubts at bay and this is a significant obstacle to the investment in biotechnology. The results produced by AI were perceived to be more transparent, measurable and reproducible as compared to classical experimental outputs. This boosted investor confidence in the science and maturity of operations of startups. According to investors, AI-driven evidence minimised due diligence time and enhanced risk analysis by offering forewarnings of success. These results are consistent with the literature sources that refer to AI being a credibility indicator in high-risk innovation settings (Lou et al., 2025). Examples of cases, including Recursion Pharmaceuticals, Tempus, and Insitro, demonstrated that powerful AI can be useful in raising funding, business collaborations, and institutional backing. AI was not regarded as just a technical benefit but as an indicator of strategic readiness and the scientific competence.

The issue of upsizing and expansion was directly linked to effectiveness, decision, and investor trust. Respondents discussed that with AI, startups are able to grow both research processes and pipelines without increasing research costs and headcount at the same pace. Automation of data processing, better prediction accuracy, as well as waste lessening, help small teams with a variety of research programs simultaneously with the help of AI. This encourages growth and diversification of projects which are sustainable. Investors also outlined that AI-based startups reach the development milestones more quickly, enhancing their competitiveness on the market and further development. Such results can be explained by the prior research conducted by other researchers who claim that AI reduces the time spent on discoveries and provides better scalability in biotech research (Gangwal & Lavecchia, 2025).

According to Case study data, Tempus increased its clinical and genomic services because it could handle complex data in real-time, and Recursion Pharmaceuticals applied AI to scale the research on numerous disease areas. Insitro also illustrated how the implantation of AI in the early modelling aided the growth of portfolios without physically incremental resources.

Throughout all sources of data, the themes identified had an interrelating interaction to create a consistent image of the role of AI in biotech startups. The superior strategic decisions were made using the operational efficiency which were then advanced to create confidence in investors and facilitate scalable expansion. The results are in line with current studies that have pointed to AI in enhancing predictability and minimizing uncertainty in innovation-driven sectors (Gyau et al., 2024). The importance of AI in biotech investment settings can be attributed to its capacity to make research more scientific and increase the financial plausibility thereof.

In total, the thematic synthesis proves that the role of Artificial Intelligence is the key to facilitating research efficiency, investment preparedness, and growth opportunities in biotech startups. Although data quality, cost, and regulatory compliance continue to be problematic, the data indicates that AI is gaining more acceptance as a fundamental capability instead of an optional tool. These results support the previous analysis presented in this study and show that AI is a necessity to biotech startups that would like to maintain a sustainable development, investor confidence, and competitiveness in the long-term in the life sciences field.

3.4.1. Strategic Decision-Making

The other theme that was eminent in the data is strategic decision-making. Participants several times mentioned the usefulness of AI to allow more informed and calculated decisions at various levels of biotech operation. According to the Participant f, AI tools assist in the process of deciding which experiments are worth following up so that the research groups focus on high-value business endeavors. To illustrate, predictions based on AI suggest the compounds that have the greatest likelihood of exhibiting the desired biological activity, and the researcher saves time by not screenings poorly potential compounds. Participant A claimed that internal organizational planning had been impacted by AI, which provided data-driven information upon which to steer the project direction. Investors explained the strategic implications of AI in financial terms in detail. They emphasized in the interview that AI-generated data are used to assist startups in preparing more compelling and powerful investment presentations. When startups model the results of the research and analyze large data dimensions with the help of AI, they can also clearly illustrate possible successful cases and forecasted returns. This degree of transparent gives investors the opportunity to make better decisions and less uncertainty is created when funding early-stage biotech research. They described AI as being useful in planning experiments, resources, and modeling disease pathways. Through predictive modelling, scientists are able to test hypothetic conditions without necessarily testing them in a laboratory environment. This allows the teams to polish their approaches prior to committing resources and chances of positive results increase. These strategic advantages were depicted in the case studies.

3.4.2 Investor Confidence

The confidence of the investor was found to be one of the most summative and persistent themes of all interviews and evidence based on case-studies. The entire supply comprised of the 12 participants who attended and participated in the interviews, including the startup founders, investors, and AI experts, all arrived at the notion that the inclusion of AI to any biotech start up significantly enhances trust, perceived risk reduction, and translates to scientific maturity. The introduction of AI was mentioned over and over as a strategic asset, which enhances transparency, gives measurable evidence, and allows more predictive research results. These attributes have a direct effect on the way investors weigh the opportunities of early-stage biotech, an industry whose uncertainty is traditionally high and growth path extremely costly.

The story varied between the startup founders (Participants 1-4), but it was more of the same: with the help of AI, they could come up with measurable, reproducible, and transparent research outputs. Participant 1, who also oversees a biotech as a co-founder and CTO, said that the investors were receptive to AI due to the (quantifiable) measures of performance that their predictive models yield. This quantifiability was understood by investors as an indicator that the startup had entered into the next stage of experimentation beyond concepts and could produce dependable scientific data. Likewise, Participant 2 described that AI was able to offer efficiency and improvement in the workflow that led to a higher confidence level among investors in the ability of the company to scale. The opinion that AI lessens the amount of guesswork and promotes more effective data-driven choices was also reflected by the computational scientists themselves. As an example, Participant 3 stated that AI thrives ambiguity given the fact that it discovers biological patterns that human tools are often blind to, and thus, this increases the plausibility of research results that are reported to investors.

This theme was further supported by investor views (Participants 5 08). Participant 5, a nine-year deep-tech and biotech venture capitalist, said AI would largely contribute to eliminating scientific ambiguity, which is among the gravest causes of investor reluctance in the biotech industry. This participant states that AI can provide startups with validated models, powerful data pipelines, and a quantifiable increase in accuracy which can reduce the time spent on due-diligence and enhance believing the timelines projected to them. The participant 6 is an angel investor who also noted that AI enhances scalability where he argued that an AI-powered research platform can grow significantly faster than the conventional methods. Participant 7 representing a partner of a pharmaceutical firm stated that AI-enabled solutions are ideal to establish a partnership given that they would integrate effectively with the workflow of the industry. Participant 8 further stated that investment analysts can understand AI-generated results better and more readily than conventional datasets which in many cases are not structured and cannot be used at scale.

The AI specialists and data scientists (Participants 912) also confirmed that AI provides startups with the ability to provide evidence that is better organized, reproducible, and convincing. These respondents stressed out how AI could do predictive modeling, enhance the precision of biological understanding, and draw attention to mechanistic clarifications that would be good in the technical due diligence to investors. Indicatively, Participant 9 said that AI forecasts protein interactions months quicker than laboratory investigations, illustrating how the acceleration of computations can turn presumptive, early-stage concepts into leads that have been verified. Participant 11, who is an expert in genomics, contributed that AI is more capable of finding disease-related variants with a more specific resolution that offers scientific clarity to investors. Collected collectively, the testimonies of experts proved that AI minimizes the ambiguity of the research results directly related to the investor confidence.

The general belief that AI is an imminent expectation and not differentiating advantage was another trend that was common among all investor participants. All participants whose numbers are 5, 6, 7, and 8 cited that the existence of AI is an indicator of scientific maturity and strategic ability. They stressed that companies that do not have an AI strategy might face more difficulties in raising funds, particularly when investors are changing investment models to focus on data-based choices. This changing expectation recommends alteration in the structure of the biotech investment environment, making AI literacy a key competitiveness factor.

The close relation between AI and investor confidence was strengthened by the evidence provided by case studies. Recursion Pharmaceuticals was able to detail the application of AI-based high-throughput imaging and phenotype prediction models that enabled the firm to raise several rounds of funding. These computational platforms became reliable in the eyes of investors due to the scalability of the predictions, their repeatability, and the use of large data sets. Tempus also enjoyed good investor relationships thanks to its accuracy and speed in its AI-based clinical and genomic analytics that gave hospital clinicians and physicians real-time treatment information. Both medical and financial partners put their trust in Tempus because the accuracy and reliability of the AI tools would lead to institutional confidence. The success of Insitro also reflected that the structured, efficient, and data-rich models generated by AI-based disease modelling are attractive to one or another investor. As pointed out in the case study, pharmaceutical companies were ready to enter into high-value partnerships due to the fact that AI enabled Insitro to establish valid research predictions that are clear and validated. Also strongly associated with AI-first implications were Atomwise and Deep Genomics, where AI-first screens allow them to screen billions of molecules and analyze complex genetic data respectively, which they do with almost no inherent support of other scientific techniques.

Throughout all sources of data, the primary point is that AI boosts confidence among investors at two tiers: scientific and financial predictability. Scientifically, AI enhances the accuracy of experiments, enhances the visibility of data and makes predictive capabilities which investors find pertinent in alleviating risks. In terms of financial aspects, AI will help accelerate the development stages, decrease the number of resources lying unused and exhibit efficiency in the amount of operations therefore the interviews with the case studies reveal that AI is becoming a cross cutting influence in influencing the decisions by the biotech investors in terms of money. Thus, investor confidence is not a side effect of AI adoption, and is a force that allows it to become even stronger, as to why startups are still adopting evolved computational systems into the scientific and operational processes.

3.4.3 Scaling and Growth

Other main insights, which were pervasive in terms of how interviews and case studies reflected them, was the theme of scaling and growth. In unison, participants of the study recognized that AI is a trigger of faster growth, expansion in operations, and long term scaling in biotech startups. In contrast to traditional biotech research, which tends to be time-consuming and resource-heavy and involves a gradual process of experimental cycles, AI ushers in efficiencies with which early-stage organizations can meet their more ambitious objectives with less to hold back. Participants (14) related to the startup highlighted the fact that AI provides them with faster product development because of eliminating the trial-and-error phases. Participant 1 has mentioned that AI enabled the team to run numerous research programs without correspondingly increased lab staff, which means that computational bottlenecks are now automated manually. Participant 2 echoed this opinion by sharing that the combination of neural networks, automated imaging, and cloud analytics helped in opening up two new therapeutic fields. Participant 3 described that artificial intelligence enabled identifying a greater number of biological targets annually, which directly resulted in pipeline growth. Participant 4 focused on the fact that AI-mediated automation minimized the use of time-consuming manual processes so that their company experienced a growth in scale without incurring a net rise in costs. Overall, the startup voices demonstrated that AI enhances throughput, contributes to the diversification of projects, and allows allocating resources more efficiently, the key aspects of sustainable scaling.

The attitudes of investors (Participants 58) supported the opinion that AI enhances the scalability capacity of a startup by increasing efficiency in operations and research speed. According to participant 5, AI has increased the speed of research, so that startups are able to achieve major stages of development in shorter periods of time, a critical consideration in case of investment decisions that are sensitive to time. Person 7 emphasized the fact that AI-based workflow with the startups results in a faster integration into the pharmaceutical alliances, thus expanding their scope of operations. Investor 8 mentioned that by itself, AI-solutions are required to be scaleable since they can handle allegedly large quantities of data, which would otherwise remain unprocessed. These opinions of investors indicate that AI is not a technological benefit, but also an important catalyst of business scale and long term development. Additional information about how AI is used to scale was given by the respondents AI professionals and data scientists (Participants 9-12), who spoke about the ways AI is used to solve data complexity, help gain more predictive power, and minimize experimental waste. Participant 9 emphasized that AI makes time savings on critical steps like target identification, whereby the hospitality industry hypothesis-to-validation candidate is reduced in the timeline. Participant 12 clarified that AI-assisted simulations of biology allow businesses to demonstrate hypotheses within the laboratory through simulation, which saves both cost and complexity. The capabilities enable startups to continue a variety of research tracks at the same time with the ability to support broader and deeper pipelines at non-proportional costs and human resources.

Irrevocable evidence was offered in the case studies regarding the acceleration of growth and scaling provided by AI. Tempus showed that its AI-based clinical and genomic analysis could lead to accelerated growth in hospitals, clinics, and research collaborators. The fact that it provides real-time insights enabled the company to expand its services and increase its market presence. Recursion Pharmaceuticals demonstrated that AI imaging enabled by high-throughput realized significant shortening of the research process, with the company able to grow its research efforts in numerous disease domains in a remarkably short period of time. Insitro used AI to enable it to handle the several therapeutic programs in a single instance by automating core modelling processes that allowed it to expand outside tight focus areas. Atomwise called upon AI-based virtual screening to be used as a global operation that served researchers across the globe without the need to expand their physical laboratory setups. Deep Genomics employed AI to diversify its set of therapeutic candidates by speedily producing medicine against a wide variety of genetic disorders. In both the case studies and interviews, it was clear that there are a number of mechanisms by which AI facilitates scaling and growth.

3.4.4 Investor Confidence

Throughout the evidence presented in the interview and case study, investor confidence was continually noted to be a powerful theme that determined the relationship between artificial intelligence (AI) and biotech start-up development. The statistics showed that investors turn towards AI as a decisive measure of scientific quality, the level of operational maturity and strategic preparedness. AI was explained many times as a device that introduces informality to fields of biotech research that have always been associated with a lot of uncertainty, including early discovery, prioritising of candidates, preclinical efficacy prediction and interpretation of large biological datasets. Due to the traceability, quantification and validation of AI outputs, it opens up some sense of transparency, which was historically significantly more challenging to reach in experimental science. This openness was often linked to less risk in investing: where AI gives data-informed projections that have an underpinning systematic analysis, investors are more convinced that a startup can generate returns not founded on guesswork, intuit, or trial-and-error only. Rather, the organization is viewed as an institution with well-established and testable procedures applied to make scientific decisions. Consequently, AI can be used as a research tool but, more importantly, as a signaling system, signifying the competence, strategic maturity, and fundamentalism of science to both existing and prospective investors (Mikalef & Gupta 2021).

The interviews also hinted at a gradual realization among investors that the biotech startups would now require showing at least not just the obligatory technological tool but the necessity of the current standard of scientific competitiveness, that is, foundational AI competence. The current environment that investors work in today is where the time a drug discovery takes, how cost effective it is, and predictive accuracy are influential factors in funding decisions. Since AI assists in shortening research timeframes, minimizing redundant research, and detecting high-value targets at an earlier stage in the process, investors will view such utilization as a signifier that an organization is ready to respond to the industry pressure (Lou et al., 2025). AI enhances trust by offering predictive modelling, pattern recognition, and indicators of success early enough that enable investors to gauge the capability of a startup to effectively progress in the development of the concept into successfully tested biological insight. By so doing, AI will not supplant the work of laboratories but will complement them through reducing uncertainties prior to wet-labor success. This integration is viewed by many investors as a system of dual assuredness, in which AI determines the directions of promise and finds their validation in laboratory experiments. The result of this twofold guarantees is the establishment of a more stable information scenario that improves the willingness of the investor to invest huge sums of money. The decrease of uncertainty of different types: scientific, strategic, and financial, thus, turns into the primary means by which AI impacts the investment decision-making.

This relationship between AI and investor confidence is well supported in the case studies. Recursion Pharmaceuticals can be seen as the prime example of a company in the biotech industry that used AI-enhanced high-throughput imaging and predictive analytics to attract the massive investment in several fundraising rounds. Not only the scientific potential of Recursion attracted investors, but the observable fact of incorporating machine learning into the working structure, it indicated efficiency, scalability, and the reasonable attitude to risk management. The tens of millions of data points that the company was able to generate through automated imaging, accompanied with machine-learning interpretation, generated a degree of accuracy and speed that was perceived as performance of strong and reproducible research pipelines by investors. Such credibility was directly transferred to the investor confidence and financial support.

On the same note, Tempus showed that AI-powered clinical and genomic data analysis may gain the attention of Big Money by providing unprecedented precision in the patient-specific information. Investors often prefer to give dollars to organisations that are able to come up with clinically relevant productions within a very short period of time, and the AI-based model used by Tempus to analyse large volumes of real-life healthcare data represented just that. Turning complicated patient data into operational knowledge is what enabled the company to seem not only technologically progressive and highly developed, but also well-adjusted to the medical requirements of the future. This transparency and sensitivity to clinical issues hardened the investor beliefs on the sustainability of Tempus.

The situation with Insitro, another example, one more demonstrates how machine learning usage as strategy in disease modeling and experimental prediction can create a high investor interest. The intriguing area of Insitro working on AI to reduce uncertainty in initial experimentation, is something which resonated with investors who sought out businesses to decrease the likelihood of scientific failures. Taking the risk of installing the AI in the very heart of the hypothesis generation and planning of experiments made the startup appear as a very disciplined and advanced organization with its methodology. This capacity was seen by investors to decrease the chances of expensive research failure and enhance the chances of drug success. Combined, these case studies can be characterized by one common thread: in case AI produces structured, validated, and predictive inferences, investors will perceive them as technologically competent, as well as financially promising.

Overall, in both interviews and case studies, AI has been used as a two-sided tool in the biotech investment arena: to spur scientific accuracy and to increase investor confidence at the same time. AI is an encouraging practice to investors as it generates quantifiable and assessable results and minimizes uncertainty, proving that the startup is innovative and has a future plan (López-Solís et al., 2025). With AI being even more penetrated into the biotech industry, investor pressures begin to differ. Nowadays AI competence is often considered by various investors as a sign of scientific maturity and a prerequisite to becoming a competitor. This scientific plausibility concurrence and monetary assurance depict the progressively pivotal part of AI in influencing investment choices, impacting what startups are drawn to capital, how capitalists consider danger, how enduring collaborations are developed (Gyau et al., 2024). By doing so AI is not only changing the way research is conducted in the biotech industry, it is also changing the financial architecture of scientific innovation.

3.4.5 Scaling and Growth

The other critical theme that came out in the interviews and case studies is the application of AI in allowing the biotech startups to scale and grow. The traditional barriers of growth in biotech are long research periods, high validation costs, and the difficulty of biological systems, which typically act as slowing factors in getting startup pipelines to grow, diversifying projects, or reaching new markets. The statistics have remained consistent that AI has a transformational role to play in breaking most of these drawbacks. AI can also help make the discovery much faster, as it aids with faster experiments design, better prediction, and minimized redundant or low-probability research directions (Gangwal & Lavecchia 2025). Shorter discovery times imply that startups can produce more tested insights within shorter periods to produce faster product development, faster entry into clinical phases, and faster commercial milestones. This acceleration is another structural advantage: by adopting AI, startups can maintain various scientific hypotheses at the same time without scaling labor and laboratory resources in line with it, which enables them to grow more effectively than businesses that use only traditional approaches.

Other interviews also noted that the predictive modelling capability of AI contributes significantly to the growth of organisations. Predictive models assist groups in approximating which experiments have the greatest promise, which molecular candidates have the greatest viability, and which disease targets encompass the highest probability results (Toma & Wei 2023). The lowered rate of unsuccessful experiments with an aid of AI will help save resources (financial, human, material) and redirect them to other projects. This resource efficiency implies that the startups are not forced to expansion of their portfolio records exponentially in terms of the rise in expenditure or employees requirements. AI thus also serves as a multiplier: the same team can handle more activities as AI will take over analysis, prioritisation, and data interpretation assignments which would otherwise need larger research teams. The nature of this structure allows startups to grow operations without the normal scaling bottlenecks biotech growth enforces. Consequently, with the help of AI, companies have become able to remain flexible, diversify their research paths, and establish more holistic pipelines, which form a good foundation of long-term competitiveness.

The case studies are very graphic in showing how the AI-led efficiency becomes organisational growth. The high rate of growth experienced by Tempus in its various clinical and genomic service lines could not have been possible without the capacity to process large amounts of complex data in real-time at the speed and quality not possible by hand. This not only allowed the company to provide custom clinical insights, but also grow its operations in new therapeutic areas, teamups, and structure of services. The scalability of its AI systems enabled Tempus to service wider markets without an equivalent rise in labour or infrastructure expenses, which can reveal how AI systems can assist in rapid and sustainable growth.

Similarly, Recursion Pharmaceuticals demonstrated the ability of AI to reduce the duration required in an otherwise lengthy research process to increase hypothesis testing speed and cut the distance between initial discovery and candidate identification. This effective scientific advancement facilitated Recursion to expand its line of investigation and examine other programs of disease as well as to raise capital that enabled it to further enhance its expansive capacity. Due to the saved time created by AI when detecting promising biological correlation, the company was able to launch a larger number of projects at the same time and, thus, expand its overall capacity to carry out research studies and enter the market.

Another model of AI-enabled growth was proven to be Insitro. The company entrenched machine learning in the design and prediction phases of its experiments, which made the scientific process streamlined at the outset. This togetherness enabled Insitro to process growing amounts of data, take on a variety of disease programs, as well as refine its direction in experimentation much faster than would have been attainable as a consequence of relying exclusively on conventional laboratory-centric process. The fact that the company has been able to sustain a growing portfolio without comparative increase in physical resource offers a good example of the role of the AI in supporting scalability as well as operational disciplines.

In all data sources, growth that is facilitated by AI is associated with three key benefits: time saved, less resources wasted, and better accuracy in research. The higher the research cycle, the higher the product development and the higher the product development, the higher the market entry, the faster-based clinical trials, product development and launches, partnership agreements, service extension, among others. AI is thus integrated in a long term growth strategy and not just a diversionary research tool. All the results taken together point to the idea that AI will give startups the ability to grow effectively, meet changing scientific needs, and create competitive advantages that are sustainable. When these abilities are added together with investor confidence it results in an overall environment in which the biotech startups can grow faster, more efficiently, and can also maintain long term progress in an ever-growing competitive field.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This thesis has analyzed the influence of Artificial Intelligence on startups in the biotech industry based on scholarly literature, industry reports, and interview data from investors, managers, and AI professionals. The evidence indicates that AI is an important tool that enhances biotech innovation and supports research efficiency. Investigations reviewed in the study show that AI helps in discovering drugs faster, analyzing information more effectively, and evaluating risks more efficiently through deep learning, predictive modeling, and natural language processing. These technologies allow startups to reduce research uncertainty, improve experimental design, and generate insights that would traditionally take years of laboratory experimentation.

According to industry reports reviewed in the study, the adoption of AI by biotech startups is increasing, particularly in research modelling, workflow automation, and data processing. AI-based startups were reported to experience reduced research cycles, improved precision, and higher operational efficiency. However, adoption levels differ, and smaller startups face greater obstacles due to limited resources and capabilities. Despite these challenges, AI enables startups to better organize research activities and allocate scarce resources more effectively, helping them remain competitive in a demanding industry.

The interview findings further confirm that AI is already being used in practice to support research efficiency and decision-making. Participants indicated that AI-generated evidence simplifies project evaluation and reduces trial-and-error in research, which improves confidence in scientific and investment decisions. At the same time, they highlighted difficulties related to data quality, technical sophistication, high implementation costs, and regulatory compliance, all of which may slow down AI adoption in biotech startups.

With a synthesis of literature, reports, and interview findings, the research concludes that AI functions as a strategic instrument linking scientific development with investment preparedness in biotech startups. AI is not only a technical tool but also a support system that enhances planning, resource utilization, and operational growth. Although limitations such as a limited sample size and the rapidly evolving nature of AI technologies remain, the results indicate that AI has become a critical component for biotech startups seeking to stay competitive, attract capital, and achieve sustainable growth in the life sciences sector.

Recommendations

Developed upon the results of this study are a number of recommendations to the biotech startups, investors and policymakers and they are made in paragraph form here to represent a logical flow of story. In the case of biotech startups, AI is advised to be incorporated in the research and development pipeline as opposed to being perceived as an add-on. The implementation of AI in the early discovery would help startups to reduce the long research cycles, enhance the quality of predictions, and prevent expensive errors in experiments. In order to do so effectively, it is necessary that startups invest in robust data management routines, data which are clean, well structured and ethically collected since high-quality data is the foundation of credible AI outcomes. Balance between AI-generated insights and human expertise should also be adopted among startups because the expert judgment cannot be eliminated to interpret predictions and focus on managing uncertainty. In addition, startups are not only encouraged to apply the AI on scientific analysis but also to enhance the communication with the investors, providing data-driven projections, and scientifically-based reasons why the startup deserves to be financed.

Instead, investors must start adjusting their assessment model to consider increasing use of AI in biotech. This entails creating a better perception of AI functionality and restrictions that will enable investors to better understand the predictive models and to evaluate the quality of AI-enhanced start-up suggestions. Another noteworthy trend is embraced by investors who can promote startups by funding and mentoring specifically AI integration given that it enhances scientific validity and opportunities in commerce. Any investment decision should be made in a transparent manner and investors will prefer to invest in a startup that has an interpretable AI system and displays responsible data governance.

Policymakers and regulators need to come up with explicit policies that will define ethical, safe, and transparent application of AI in biotechnology. Rules must facilitate accountable data management, adherence to privacy regulations and transparency in algorithms, particularly ones pertaining to patient data. The policymakers will also think of promoting the innovation using the programs of public funding, which will assist startups at the initial stage to obtain AI tools which would not be accessible to them practically. Lastly, the collaboration between academic society, research centers and biotech entrepreneurs should be encouraged to contribute to the collective learning and allow more effective production of AI-based breakthroughs.

Overall, the recommendations state that the best way to make AI maximize its benefits of the biotech sector is to coordinate the efforts of all stakeholders. Startups need to implement AI in a certain strategic and responsible way, investors need to be ready to adjust their assessment systems, and the policymakers need to offer the friendly regulatory and ethical provisions. By acting in such a concerted and deliberate manner, AI can be completely used to revolutionize the biotechnology startup environment in a sustainable and material manner.

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ANNEX: CODED ANALYSIS OF INTERVIEWS

BIOTECH STARTUP INTERVIEW

PARTICIPANT 1 – Biotech Startup Founder

1. What is your role in the startup, and how long have you been in this space?

Yes, of course, it will give me great pleasure to answer your questions. First of all, my topics are very interesting. To answer your first question, in fact, I am a co-founder of the startup and I work in the field of AI, operational biotech application and technology actually, for about 8 years. Yes, it's been really 8 years.

2. Which AI systems or tools are currently utilized in research or operational activities at your company?

Okay. Mainly, we have deep learning models, automated data pipelines. So, these systems, we change the arrangement here and there of the research work arrangement, which sometimes also require modifications, adjustments. They are at the heart of our operations. So, it's unavoidable

3. What problem did your startup aim to solve by adopting AI?

In fact, the major problem or the main challenge that we have is the length of the research and discovery processes. And so, AI was adopted in order to accelerate these processes and obviously to improve the precision of decision-making

4. Have you noticed any improvement or setback in the rate or quality of your research as a result of AI?

In fact, there are improvements in the majority of cases. And so, to answer your question directly, we noticed a significant improvement. AI made it possible to increase precision and to improve development targets. Which allowed us to determine the research phases much faster than before.

5. Has AI helped attract investors or improve investor confidence? In what way?

Honestly, AI allows us to present clear data and measurable results. This is what strengthens investors' confidence and their credibility with regard to our work.

6. How has AI supported the growth or scaling of your startup?

As I always say, AI helped us to evolve by allowing us to carry out several research projects in parallel. Without significantly increasing laboratory staff. Okay. In order to have more efficient growth. That's it. That's one of the benefits of AI.

PARTICIPANT 2 – Head of research operation

1. What is your role in the startup, and how long have you been in this space?

I am the head of research operations. I work in a company and I have been working in computational biology for about 5 years.

2. Which AI systems or tools are currently utilized in research or operational activities at your company?

We use neural networks, mesh analysis tools, and cloud-based analytics platforms. These tools are integrated into our workflows in order to support the research activities.

3. What problem did your startup aim to solve by adopting AI?

The main problem was the volume of data being generated. By time, it became too large for teams to process efficiently. So AI was introduced to the company to handle complex and time-consuming data analysis tasks.

4. Have you noticed any improvement or setback in the rate or quality of your research as a result of AI?

Yes, of course. The research process has become much faster. Although we initially faced challenges related to data quality and organization, these issues have improved over time.

5. Has AI helped attract investors or improve investor confidence? In what way?

It will relate to investors, so I'm going to say yes. Investors now appear more confident because they see faster progress and clear growth potential, which increases their trust in the company. But it's not just because of the AI. Also, the validation and quality of the data and services we offer are good.

6. How has AI supported the growth or scaling of your startup?

The AI has enabled us to expand into two new research areas without significantly increasing staff numbers, allowing for faster and more efficient growth.

PARTICIPANT 3 – Computational Biologist and Technical partner

1. What is your role in the startup, and how long have you been in this space?

I would be happy to answer all your questions. Starting with how long I've been in this space and what is my role in this startup. Basically, I work as a computational biologist and technical partner in a new startup. And I have been in the industry for approximately 10 years..

2. Which AI systems or tools are currently utilized in research or operational activities at your company?

we use a lot of tools. Basically, we use image classification models and sequence analysis algorithms. These tools are generally very, very helpful. Although they sometimes require fine tuning or validations, Data is mandatory to ensure these models work perfectly and we are reliable with the results that we provide and also align with the company's research policies.

3. What problem did your startup aim to solve by adopting AI?

That's a great question. So, the main challenge is the scale and the complexity of biological data we have. So, we need AI, because manual methods were not effective in able to find that too much work. So, AI was introduced to handle the analysis part, to support the accuracy and to do the concession decision-making.

4. Have you noticed any improvement or setback in the rate or quality of your research as a result of AI?

AI has significantly accelerated hypothesis testing with the speed that it provides. However, it also requires staff to develop new technical skills, people to operate their models and algorithms, and need technical education and support so they can know how to use the tools. But yeah, OpenAI was significantly helpful for us.

5. Has AI helped attract investors or improve investor confidence? In what way?

Yes, yes. My answer would be yes. We attract a lot of investors since we started using AI. Investors have become more confident because we are able to use AI to achieve research outcomes, making the work more predictable and reliable for investors.

6. How has AI supported the growth or scaling of your startup?

AI allows us to evaluate a large number of potential targets this year without delay, or the delay that was introduced by using manual methods. So using OpenAI engines helps us a lot to evaluate and practice a lot of that. So now we need to make growth and scaling as easy as possible. So, definitely, yes.

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PARTICIPANT 4 – Chief Executive Officer (CEO) of a small startup

1. What is your role in the startup, and how long have you been in this space?

I would say, like, briefly, I am the CEO of the startup, and I would say I've been working in the biotech innovation for around, like, 10 years now.

2. Which AI systems or tools are currently utilized in research or operational activities at your company?

I mean, there are many tools. I would say we use predictive models, robotic automation systems, as well as the data integration tools. And we try to mix them together, so these technologies support both our research and operational processes.

3. What problem did your startup aim to solve by adopting AI?

I mean, I would say, like, the AI, like, we introduced it because laboratory work was, like, slow and, like, highly, like, manual. That's why the goal was, like, to improve the efficiency and also reduce, like, the delays in the research activities.

4. Have you noticed any improvement or setback in the rate or quality of your research as a result of AI?

That's why we keep using it. I would say the AI has made the prediction more reliable, but it also requires more careful data monitoring, which adds some additional responsibility from our part.

5. Has AI helped attract investors or improve investor confidence? In what way?

I would say we noticed that the investor's response has been very positive. With the increased productivity and the clearer performance indicators have strengthened the investor's confidence. That's why we acquired more.

6. How has AI supported the growth or scaling of your startup?

I mean I would say it's like in the operational level because like AI has like allowed us to scale our operations without proportional like increase in costs because that's the goal and making like the expansion I would say more efficient and also sustainable at the same time, yeah.

INVESTOR INTERVIEW

PARTICIPANT 5 – Venture Capital Investor

1. What kind of an investor are you, and how long has that been in biotech or deep-tech?

I am like a VC invest guy, i have been investing in biotech and deep tech for like nearly nine years now, during this period i was focusing on early stage startups or growth stage ones.

2. What is your opinion of AI affecting the innovation and research productivity of biotech startups?

In my opinion AI is making the startups work much faster and it also shorten the staff while increasing the productivity.

3. What AI capabilities or evidence do you consider when evaluating a biotech startup?

I always look for model that already proven their work, good data pipeline or we can say good data flow and also the accuracy of those numbers.

4. Is AI presence in a startup something that makes you more confident in investing in them? Why or why not?

The presence of AI of course it increase my confidence, especially when it is involved in thee research of the startups itself not just the workflow, basically i don’t have to wait long time to see some specific result to invest.

5. What is the impact of AI-generated data on your investment decision, as opposed to standard data?

Generally speaking, AI generated data often provide faster and more consistent result. So it has a positive impact on my investment evaluation.

6. Have you ever invested in a firm on the basis of its AI strategy or performance specifically?

Yes I already invest in a firm company that is based on AI , the AI strategy was strong and they shown so far a good performance with it.

PARTICIPANT 6 – Angel Investor

1. What kind of an investor are you, and how long has that been in biotech or deep-tech?

Okay, yeah. So, regarding like the direction, well, I work as an angel investor, as you know, because I mentioned that the last time when we talked, and I have been investing money in health, innovation stuff, like around six years now. And I have also invested in two startups, but not only like in a field, I invest in other domains as well.

2. What is your opinion of AI affecting the innovation and research productivity of biotech startups?

Well, I think AI becomes a reality now, you know, from my experience and from the seminars that I attended recently, I think AI helps startups to do new things more faster than it was before. And it helps also to take fast decisions in terms of science as well. And yeah, I mean, not like as it was before in the past, now it's more fast, of course, because of AI. Okay.

3. What AI capabilities or evidence do you consider when evaluating a biotech startup?

Actually, I think the model works good. If it explains itself in a more clean manner, I would say that their data management system is not too messy.

4. Is AI presence in a startup something that makes you more confident in investing in them? Why or why not?

Well, by us, it would be yes. Before, I was having a doubt, but now, absolutely, I would say yes, because it makes me more confident. And why? The reason why is that AI makes the research go bigger and more easier than it was before. So, more scale without too much trouble. And I guess the AI now helps us to correct our mistakes, the areas that we need to improve as well.

5. What is the impact of AI-generated data on your investment decision, as opposed to standard data?

Well the AI data gives more clear view, it's not like the generated data, because look, if we were talking about the two sides, I would say that the AI data gives more clear view on how the research is doing and what risk is there, more than the normal data, most time.

6. Have you ever invested in a firm on the basis of its AI strategy or performance specifically?

Well, I think this is... Okay, so I will make it exclusive for you because it's a kind of project that we are working on. Okay, but I will give you the answer. Yes, I already invested in that. And just to give you like a clear idea about it, the AI played a central role in our development, and they showed really miserable output that shows the cycle of the startup. So basically, this is what encouraged me to invest in a firm based on AI. Okay. Okay? Yeah, so this is what I can say because it's a project, it's a common project,

PARTICIPANT 7 – Corporate Pharma Investor

1. What kind of an investor are you, and how long has that been in biotech ?

If I recall very well, I started investing more than several years ago, like I think 10 years ago. I invested in many industries like tech and banking and everything. But for pharmaceutical companies, I've been doing that for, I think, 8 years now. And for me, it feels like kind of a long time in this biotech field, like investing in it. It's not rentable for me, so I'm still doing it for the moment.

2. What is your opinion of AI affecting the innovation and research productivity of biotech startups?

I think that AI makes the early stages of research, they make them go faster, they cut down a lot of waste experiments, they cut down the costs, which increases profitability, and so, as you know, we're in 2025, so things are not slow anymore, and I think that's the main reason I look for AI in the investment

3. What AI capabilities or evidence do you consider when evaluating a biotech startup?

So I'm gonna be honest, being an IT guy myself, so I work in IT, I know the field a little bit, so I look if the predictive models are proven already, and if they are good and supported, and if they got a strong bio-validation generally. Yeah, that's what I look for generally,

4. Is AI presence in a startup something that makes you more confident in investing in them? Why or why not?

Okay, so, in fact I think that AI makes me more confident because it accelerates the process of forming partnerships. It makes it easier for startups to align and collaborate effectively between them. And with AI now, startups can analyze and detect potential partnerships, maybe, I would even say, even better than humans, or maybe at least even faster. So, identifying compatible entities and optimizing integration. So, this ability doesn't only foster innovation, but I think also it strengthens the market position and enhances the growth potential, which is what I'm looking for as a growth investor.

5. What is the impact of AI-generated data on your investment decision, as opposed to standard data?

So I think like the AI data, it's like the other normal data, but AI data also shows if the platform can grow big enough, pharmaceutically speaking. So, and it's, I think it's more precise sometimes, but so it helps me to decide better than normal data. That's the, I think, the difference, like the precision. Although to be honest with you, I have to make sure that the data is accurate. And also if it's integrated, like, you know, how crazy it's going, the data these days, and it can be easily falsified. So I have to look for my own, sorry, it's my own strategy, but I have to look like if it's, if it's really accurate.

6. Have you ever invested in a firm on the basis of its AI strategy or performance specifically?

No, not particularly. It's not because of AI, but I just never had the idea of investing in a firm specifically because they use AI. But for me, if they do, it's a good sign, especially with the hype and craziness going all around AI lately, as you know. So yeah, I think it's a good sign for me.

PARTICIPANT 8 – Life-Science Investment Analyst

1. What kind of an investor are you, and how long has that been in biotech or deep-tech?

Thank you for having me. I've been an investment analyst, specifically biotech, let's see, from around 2020, so I guess five years now.

2. What is your opinion of AI affecting the innovation and research productivity of biotech startups?

I can say that AI makes the research faster. You know, we're a progressive, you know, technology is moving. So, we need to be actually moving with the technology. So, it actually makes the research faster, which makes the decision-making process more accurate. Yeah. So, it also helps when you're doing the analysis, it makes the data a bit faster.

3. What AI capabilities or evidence do you consider when evaluating a biotech startup?

First of all, I look at the model that I've been presented with. I have to check if it's clear enough. Then from there we check the dataset. I have to make sure it's not too small or rather too weak. And we also have to check how the AI is integrated into the research workflow. So those are some of the things that I'll consider when I'm evaluating any startup.

4. Is AI presence in a startup something that makes you more confident in investing in them? Why or why not?

yes, yes. I think I mentioned earlier, I said AI is the future. So yeah, AI shows how the startup can grow. And personally, I believe AI is the future. So I definitely, definitely have more confidence, especially, yeah, when investing.

5. What is the impact of AI-generated data on your investment decision, as opposed to standard data?

you see, for AI data, you see the platform is a bit bigger than the standard data. Okay. So, of course, the bigger the data, the more informed you can when you're making decisions. So, definitely, I prefer an AI-generated data compared to a normal data.

6. Have you ever invested in a firm on the basis of its AI strategy or performance specifically?

I think like three years ago, there was a metric company I did some investment in and we did actually incorporate some of the AI strategy. That's why I believe, that's why I strongly believe in AI.

AI EXPERT / DATA SCIENTIST INTERVIEW

PARTICIPANT 9 – AI Scientist in Biotech

1. How long have you worked on the AI related to biotech, and what is your experience in AI or data science?

I have been working with AI on biotic data like seven years or more, and my experience was great. Not everything is perfect, but I managed because the field is huge and we have different problems. I managed to analyze data science and data technic in the field of biotech, and we are trying to apply those techniques on the biotic data.

2. Which AI models, tools, or methods are used in biotech research most frequently now?

Like now people use graph network things and those multi-modal deep learning models, like neural network, like for, it depends for which goal we want, like for pattern recognition, we could use that. We could use this also for sequence analysis models. We can use them for genomic data. And we can also analyze images using image-based models.

3. How is AI used in biotech research in your experience?

Okay, what we're trying to do, we're trying to help make the research go faster, like find the target information more quickly. For example, machine learning now can analyze large genomic or protein datasets to detect or predict for us which genes, or for example, which protein is most likely involved in the datasets. This allows researchers to, of course, to focus more on the most relevant target instead of losing so much time.

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4. What is a good example of how AI has made one research outcome or insight much better?

I can remember one time we created a model that gives protein interaction way faster than traditional techniques.

5. What do you feel are the technical pitfalls in using AI on biotech data?

biotech data is really messy and really noisy. We have a lot of different data types in datasets, so sometimes the dataset itself, it's too small. So some models does not work good with this data. We need a huge number of datasets, and sometimes the data quality is poor. So we have, those elements can have a huge impact on the performance of models. So we try to deal with messy and small datasets also.

6. Why do most biotech startups not successfully adopt AI?

As I mentioned before, this domain is not huge as we know, so when we have a small domain like this, we will have very specific people that interact in generating data and working with data. So most startups, I think, they do not use AI good because they don't get proper data systems and not enough tech people who know how to do it right, honestly. So AI requires so much to do, it's difficult to implement effectively, but it's still a challenge that we are willing to do.

PARTICIPANT 10 – Machine Learning Engineer

1. How long have you worked on the AI related to biotech, and what is your experience in AI or data science?

So, I'm a machine learning engineer. I started this work for drug discovery like three years ago. Implementing AI in this field for like two years now.

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2. Which AI models, tools, or methods are used in biotech research most frequently now?

we commonly use like sequence models, we also use conventional neural networks, as we call them CNN, and we also use generative design tools for molecules and stuff. Most popular approaches that are widely used in the biotech research

3. How is AI used in biotech research in your experience?

AI makes everything faster, you can get so much more done with just a few clicks. It also eliminates boring work, so you don't have to do repetitive tasks all the time, and that's a major, major improvement. It also helps make the process more efficient and just faster overall.

4. What is a good example of how AI has made one research outcome or insight much better?

During the last project we just delivered, these models of AI helped us make a molecule that normal people would not even guess. So, that was really good, and the result was much better than using the old method.

5. What do you feel are the technical pitfalls in using AI on biotech data?

The model will not work as expected, especially if the data is messy and you don't have good data to work with. You can have errors in the data, like the wrong format, or it's labeled wrong, or something like that. That results in a performance drop, and you don't get the results you want. At the end of the day, I think training the model is the hardest part. That's one of the biggest challenges, and also data. You need good data.

6. Why do most biotech startups not successfully adopt AI?

So, most startups, like, they fail using AI and biotech because, like, they maybe think it's easier and cheaper to do, but, um, like, with time they actually find out that it's not that easy and it actually needs a lot of money and a lot of expertise to make it right, to, like, make it work in this industry.

PARTICIPANT 11 – Data Scientist in Genomics

1. How long have you worked on the AI related to biotech, and what is your experience in AI or data science?

I can say I have been working with AI an big data specially genomic data like 8 years now. So is more about machine learning, data science mainly in Genomics field.

2. Which AI models, tools, or methods are used in biotech research most frequently now?

People use genomic transformer, variant classify thing and some probabilistic model. Also deep learning and classification algorithms are common used for example to analyze genetics risks.

3. How is AI used in biotech research in your experience?

AI help make variant interpret faster and also make disease risk predict more correct than before.

4. What is a good example of how AI has made one research outcome or insight much better?

AI find some disease linked variant that normal lab never see, so it make research outcome much better, It leads to clear research insights and more confident conclusions.

5. What do you feel are the technical pitfalls in using AI on biotech data?

Data not balanced and no standard make model not always reliable, give problem for trust results.

6. Why do most biotech startups not successfully adopt AI?

You have to know that AI models and laboratory workflows works and developed separately , and that cause a big communication gaps , sometimes mismatched expectations , if data not collected properly from the lab , the AI system for sure won’t perform properly , and unfortunately that’s very common .

PARTICIPANT 12 – Computational Biology Specialist

1. How long have you worked on the AI related to biotech, and what is your experience in AI or data science?

Almost 6 years mix computational biology and AI system. I have earned practical experience in AI and Data science methods to biology research .

2. Which AI models, tools, or methods are used in biotech research most frequently now?

People use reinforcement learning, some generative models and bio simulate tools.but it always depend the startup or the company , for me I think the most common ones as I said , reinforcement learning that has many details as well , but I am sure you are not interested now to know all that details now .

3. How is AI used in biotech research in your experience?

AI help simulate bio response before lab test, so time is not wasted because usually it helps to avoid unnecessary experiments, AI is mainly used to analyze all this large and huge massive amount of data that's is mostly complicated to handle , and when it comes to biological datasets is more worst .

4. What is a good example of how AI has made one research outcome or insight much better?

AI is like a good biomarker signature that make experiment to be designed more efficiently , and this helps to reduce the time in reducing the trial and errors experiments.

5. What do you feel are the technical pitfalls in using AI on biotech data?

AI is limited in size, unbalanced and also cost a lot of time and money to process.

6. Why do most biotech startups not successfully adopt AI?

I think most startups don't get the proper system to collect, store and clean data, so everything is somehow overlapped sometimes.so that's why as result data is often incomplete or maybe inconsistent and can also be overlapped , and of course that's makes is difficult for AI models to work effectively as it supposed to .