VILNIUS UNIVERSITY
BUSINESS SCHOOL

DEEPTECHENTREPRENUERSHIP PROGRAMME

MD MASHRUR, ALAM

RAHAT, SULTANA

THE FINAL MASTER'S THESIS

TITLE	TITLE
DIRBTINIS INTELEKTAS IR TALENTAI DEEPTECH STARTUOLIUOSE: KAIP BESIFORMUOJANČIOS ĮMONĖS KURIA ATEITIES DARBO JĖGĄ	AI AND TALENT IN DEEPTECH STARTUPS: HOW EMERGING VENTURES BUILD THE WORKFORCE OF THE FUTURE

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Name, surname, academic title, scientific degree

Vilnius, 2025

SUMMARY

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AI AND TALENT IN DEEPTECH STARTUPS: HOW EMERGING VENTURES BUILD THE WORKFORCE OF THE FUTURE

Supervisor –Professor, Doctor of Management Sciences, Dr. Tadas Limba

Master's thesis was prepared in Vilnius, in 2025

Scope of Master's thesis – 29 pages.

Number of tables used in the FMTP – 1 pc.

Number of figures used in the FMTP – 23 pcs.

Number of bibliography and references – 71 pcs.

The FMTP is described in brief:

This research explores how resource-constrained DeepTech startups strategically use AI within talent management systems to sustain innovation. Operating in fields such as quantum computing, biotechnology and AI, these firms face ongoing shortages of capital, specialized expertise technological infrastructure and established organizational processes. Against this backdrop, the research investigates how AI is used strategically to attract, develop and coordinate cross-disciplinarity human capital rather than serving as a purely operational support tool.

Using a mixed method approach, this research combines an extensive review of academic and industry literature with qualitative interviews involving founders, HR professionals, venture capitalists and accelerator representatives. The analysis was completed in three stages. First, investigate the nature of the resource constraints common to DeepTech startups and show how these constrains encourage phased AI adoption, resilience in the innovation ecosystem and selective use of off-the-shelf AI solutions. Second, it highlights the role of AI in strengthen innovation capacity by accelerating R&D, supporting knowledge integration across disciplines. Third, the findings emphasize the importance of external ecosystems, revealing that coordination gaps among academia, investors, policymakers and incubators often limit effective AI talent integration.

The main theoretical contribution of this study is the AI Orchestrated Innovation Capacity Model, which reframes human capital as a dynamic AI-supported capability rather than a strategic resource. Practically, the research offers guidance for founders, HR professionals, investors and policymakers on how deliberate AI use and ecosystem coordination can

transform constraints into sustained competitive advantage.

Problem, objective and tasks of the FMTP:

Problem

Although AI is increasingly transforming business functions, there is still little research on how it is used strategically in talent management within DeepTech startups. These startups often have limited resources and operate in specialized, interdisciplinary areas, which makes attracting, developing and retaining key talent especially challenging. Most existing studies focus on traditional tech companies or general AI applications in HR, leaving a gap in understanding how DeepTech ventures apply AI to their specific talent needs. This study aims to fill that gap by exploring how DeepTech startups use AI to support talent acquisition, development and engagement. It also looks at how they manage limited resources, handle ethical and organizational challenges, and adopt AI-driven HR tools to maintain innovation and stay competitive.

Objective

The object of this research is AI enabled talent management practices in DeepTech startups. Specifically, it focuses on how these ventures operating in fields such as quantum computing, biotechnology and advanced engineering attract, develop and retain interdisciplinary talent through the strategic integration of AI in human resource management.

Tasks of the FMTP

The primary goal of this research is to examine how DeepTech startups strategically use artificial intelligence (AI) to attract, develop and retain interdisciplinary talent in resource-constrained, innovation-driven environments.

The goal will be achieved through the following set of tasks**:**

1. To analyse how startups address resource constraints when adopting AI-enabled HR strategies.
2. To assess how AI contributes to sustaining innovation capacity in DeepTech ventures.
3. To explore expert insights on how external ecosystem factors influence AI–HR integration and sustain innovation capacity in DeepTech ventures.
4. To develop a conceptual framework linking human capital theory and resource orchestration theory.

Research methods used in the FMTP:

This research adopts a mixed methods approach to capture both empirical depth and theoretical breadth. It integrates the following components:

- **Qualitative case studies** of selected DeepTech startups in Europe to examine real world applications and challenges of AI enabled talent strategies.

- **Expert survey with startup founders, HR** professionals and AI specialists to gather nuanced insights into the intersection of AI and human resource practices.
- **Comprehensive literature review** covering over 30 empirical and conceptual studies related to artificial intelligence in human resource management (HRM), DeepTech entrepreneurship and talent development.
- **Secondary data analysis** began with a thorough analysis of the available academic literature on DeepTech and AI in human resources. This involved reviewing journal articles, case studies and relevant books to map the existing knowledge and identify key themes. Through this review, a clear gap was recognized: a lack of focus on how resource-constrained DeepTech startups implement AI for talent management. The insights from this literature directly informed the design of the subsequent primary research phase.

Research and results obtained:

Research Design

The study is structured into three sequential phases, each serving a distinct purpose:

1. **Exploratory Phase:** A scoping review is conducted to identify current trends, conceptual limitations and emerging practices in AI driven talent strategies within startup ecosystems.
2. **Empirical Phase**: This phase involves in depth case studies and semi structured survey with key stakeholders in DeepTech startups. The focus is on understanding how AI tools are deployed for talent acquisition, upskilling and workforce development.
3. **Synthesis Phase**: Drawing on resource orchestration theory and human capital theory, this phase develops a Talent AI Integration Framework. The framework offers strategic and actionable insights for startups and their ecosystem partners.

Results Obtained

The analysis made it possible to get several key findings, organized below by the original research objective:

First Objective: Analyse how startups address resource constraints when implementing AI-based HR strategies.

- Startups like to adopt an adaptive, phase implementation approach (e.g, “crawl-walk-run) more than large-scale deployment.
- By forming ecosystem partnerships, they gain access to tools, data and expert knowledge.
- Artificial intelligence serves as a force multiplier by automating routine HR tasks and enabling data driven decision making despite small team sizes.

Second Objective: To Assess How AI Contributes to Sustaining Innovation Capacity in DeepTech Ventures

- AI enhances R&D efficiency by means of predictive modelling, generative design and faster synthesis of existing research.
- Tools such as knowledge graphs and natural language processing (NLP) promote cross-disciplinary cooperation and helps to reduce barriers between fields of specialization.
- Ongoing skill development is further supported by AI through tailored learning systems which allowing teams to keep pace with technological change.

Third Objective: Explore Expert Insights on How External Ecosystem Factors Influence AI–HR Integration and Sustain Innovation Capacity in DeepTech Ventures

- External stakeholders—including investors, policy makers and accelerators are playing a decisive role in either enabling or obstructing the integration of AI and human resources.
- A notable challenge identified is a lack of coordination among these actors.
- Those startups that proactively manage and align external partnerships show higher resilience and more enduring innovation outcomes.

Fourth Objective: Develop a conceptual framework linking human capital theory and resource orchestration theory

- An **AI-Orchestrated Innovation Capability Model** was developed, which merges principles from Human Capital Theory and Resource Orchestration Theory.
- In this model, artificial intelligence functions as a meta-orchestrator, continuously aligning human talent, internal resources and external ecosystem resources to foster sustained innovation.

Conclusions of the FMTP:

This study shows that for DeepTech ventures, long-term success depends on building organizations that can be innovative as their core technology. Using a mixed-methods approach—combining with literature review, concept analysis and expert surveys—this research explores how AI can strategically manage critical talent dynamics. The findings highlight both the possibilities AI brings and practical challenges of implementing it in a high shake resource constrained environment.

The first is that the constraints DeepTech startups confront — financial, human, technological and organizational — are unique and interdependent to determine the mode in which innovation can take place. Rather than allowing these constraints to be stumbling blocks, successful enterprises interpret them as drivers of entrepreneurial virtuosity. They employ AI not as a luxury, but as the cornerstone “force multiplier” and “meta-asset” that allows small teams to achieve sophistication in talent acquisition, development and retention which would otherwise be out of reach.

Second, the research confirms that AI's primary value extends far beyond automating administrative HR tasks. And its enduring contribution is that it enables continual and exponential innovation. By speeding up the R&D with predictive modelling and generative design, by integrating knowledge from outside their own discipline and creating data-driven decision-making, AI is placing an organization in location with its own learning loop. This turns innovation from something that sprays out of the nozzle into something that can be operated as a fine-tuned tool that moves startups to new sources of progress in technology under conditions like uncertainty and long development cycles.

Third, empirical research highlights an important but often underestimated aspect: the external innovation ecosystem is not merely a background feature, but an active co-creator of an AI-enabled talent strategy of start-ups. The feasibility, ethics, and trajectory of integrating AI and HR are deeply shaped by incubators, investors and policymakers. A lack of "coordination" was identified as the door, demonstrating that whether a startup succeeds or fails has more to do with orchestrating external relationships and resources than mastery over technical skills.

Fourth, the AI-Orchestrated Innovation Capacity Model is developed to combine these insights into an integrated theoretical model. AI-Orchestrated Innovation Capacity The model provides the link and extension between Human Capital Theory and Resource Orchestration. Theory by embedding AI as a transformational enabler, which connects continual nurturing of dynamic human capital with strategic coordination of a wide array of resources. It offers a compelling theoretical framework for how DeepTech ventures can develop a defensible competitive advantage based on the mutualism of human judgment and machine intelligence.

Information about the publication of FMTP results or adaptation for publication

The core results and conceptual model from this thesis may be adapted for submission to peer-reviewed academic journals or into a paper for academic publication.

Santrauka

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DIRBTINIS INTELEKTAS IR TALENTAI DEEPTECH STARTUOLIUOSE: KAIP BESIFORMUOJANČIOS ĮMONĖS KURIA ATEITIES DARBO JĖGĄ

Darbo vadovas – Profesorius, vadybos mokslų daktaras, Dr. Tadas Limba

Magistro baigiamasis darbas parengtas Vilniuje, 2025

Magistro baigiamojo darbo (projekto) apimtis – 29 puslapių.

Magistro baigiamajame darbe (projekte) naudotų lentelių skaičius – 1 vnt.

Magistro baigiamajame darbe (projekte) naudotų paveikslų skaičius – 23 vnt.

Naudotų literatūros šaltinių ir nuorodų skaičius – 71 vnt.

Trumpas magistro baigiamojo darbo (projekto) aprašymas:

Šis tyrimas nagrinėja, kaip ribotus išteklius turintys „DeepTech“ startuoliai strategiškai naudoja dirbtinį intelektą talentų valdymo sistemose siekdami išlaikyti inovacijas. Veikdamos tokiose srityse kaip kvantinė kompiuterija, biotechnologijos ir dirbtinis intelektas, šios įmonės susiduria su nuolatiniais kapitalo, specializuotų kompetencijų, technologinės infrastruktūros ir nusistovėjusių organizacinių procesų trūkumais. Šiame kontekste tyrimas analizuoja, kaip dirbtinis intelektas taikomas strategiškai – ne vien kaip operacinė pagalbos priemonė, bet kaip priemonė pritraukti, ugdyti ir koordinuoti tarpdisciplininį žmogiškąjį kapitalą.

Taikant mišrių metodų požiūrį, tyrime derinama išsami akademinės ir pramonės literatūros apžvalga su kokybiniais interviu, atliktais su steigėjais, žmogiškųjų išteklių specialistais, rizikos kapitalo atstovais ir akseleratorių atstovais. Analizė vykdoma trimis etapais. Pirma, nagrinėjama „DeepTech“ startuoliams būdingų išteklių apribojimų prigimtis ir parodoma, kaip šie apribojimai skatina etapais vykdomą dirbtinio intelekto diegimą, priklausomybę nuo inovacijų ekosistemų ir selektyvų paruoštų komercinių dirbtinio intelekto sprendimų naudojimą. Antra, pabrėžiamas dirbtinio intelekto vaidmuo stiprinant inovacijų pajėgumą, spartinant mokslinius tyrimus ir plėtrą bei palaikant tarpdisciplininę žinių integraciją. Trečia, empiriniai rezultatai išryškina išorinės ekosistemos svarbą ir atskleidžia, kad koordinavimo spragos tarp akademinės bendruomenės, investuotojų, politikos formuotojų ir inkubatorių dažnai riboja veiksmingą dirbtinio intelekto ir talentų sistemų integraciją.

Pagrindinis šio tyrimo teorinis indėlis – Dirbtiniu intelektu grindžiamas inovacijų pajėgumo orkestravimo modelis, kuris perinterpretuoja žmogiškąjį kapitalą kaip dinamišką, dirbtinio intelekto palaikomą gebėjimą, o ne kaip statinį strateginį išteklių. Praktiniu požiūriu tyrimas pateikia rekomendacijas steigėjams, žmogiškųjų išteklių specialistams, investuotojams ir politikos formuotojams, kaip sąmoningas dirbtinio intelekto naudojimas ir ekosistemos

koordinavimas gali padėti paversti išteklių apribojimus tvaraus konkurencinio pranašumo šaltiniu.

Magistro baigiamojo darbo (projekto) problema, tikslas ir uždaviniai:

PROBLEMA

Nors dirbtinis intelektas (DI) vis dažniau transformuoja verslo funkcijas, vis dar trūksta mokslinių tyrimų, nagrinėjančių jo strateginį taikymą talentų valdyme „DeepTech“ startuoliuose. Šie startuoliai dažnai veikia turėdami ribotus išteklius ir specializuotose, tarpdisciplininėse srityse, todėl pagrindinių talentų pritraukimas, ugdymas ir išlaikymas tampa ypač sudėtingas. Dauguma esamų tyrimų orientuojasi į tradicines technologijų įmones arba bendrą dirbtinio intelekto taikymą žmogiškųjų išteklių valdyme, todėl trūksta supratimo apie tai, kaip „DeepTech“ sterculia taiko DI spręsdami jiems būdingus talentų valdymo iššūkius. Šiuo tyrimu siekiama užpildyti šią spragą, analizuojant, kaip „DeepTech“ startuoliai naudoja dirbtinį intelektą talentų pritraukimo, ugdymo ir įsitraukimo palaikymui. Taip pat nagrinėjama, kaip šios įmonės valdo ribotus išteklius, sprendžia etinius ir organizacinius iššūkius bei taiko DI pagrįstas žmogiškųjų išteklių valdymo priemones, siekdamos išlaikyti inovatyvumą ir konkurencingumą.

TYRIMO OBJEKTAS

Šio tyrimo objektas – dirbtiniu intelektu grįstos talentų valdymo praktikos „DeepTech“ startuoliuose. Tyrime analizuojama, kaip šios įmonės, veikiančios tokiose srityse kaip kvantinė kompiuterija, biotechnologijos ir pažangioji inžinerija, strategiškai integruoja dirbtinį intelektą į žmogiškųjų išteklių valdymą, siekdamos pritraukti, ugdyti ir išlaikyti tarpdisciplininius talentus.

TYRIMO TIKSLAS

Pagrindinis šio tyrimo tikslas – ištirti, kaip „DeepTech“ startuoliai strategiškai naudoja dirbtinį intelektą (DI), siekdami pritraukti, ugdyti ir išlaikyti tarpdisciplininius talentus ribotų išteklių ir inovacijomis grindžiamoje aplinkoje.

Tyrimo tikslui pasiekti keliami šie uždaviniai:

1. Išanalizuoti, kaip „DeepTech“ startuoliai sprendžia išteklių ribotumo iššūkius, diegdami dirbtiniu intelektu pagrįstas žmogiškųjų išteklių strategijas.
2. Įvertinti, kaip dirbtinis intelektas prisideda prie inovacinio potencialo palaikymo „DeepTech“ įmonėse.
3. Išnagrinėti ekspertų įžvalgas apie tai, kaip išoriniai ekosistemos veiksniai daro įtaką DI ir žmogiškųjų išteklių integracijai bei inovacijų tvarumui DeepTech“startuoliuose.
4. Parengti konceptualųjį modelį, siejantį žmogiškojo kapitalo teoriją ir išteklių orkestravimo teoriją.

Magistro baigiamajame darbe (projekte) taikyti tyrimo metodai:

Šiame tyrime taikomas mišrių metodų požiūris, siekiant atskleisti tiek empirinį gilumą, tiek teorinį platumą. Tyrimas apima šiuos komponentus:

- **Kokybinius atvejų tyrimus**, atliktus pasirinktose Europos „DeepTech“startuoliuose, siekiant išnagrinėti realaus pasaulio dirbtiniu intelektu grįstų talentų valdymo strategijų taikymą ir su tuo susijusius iššūkius.
- **Ekspertinius apklausa su startuolių steigėjais,** žmogiškųjų išteklių specialistais ir dirbtinio intelekto ekspertais, siekiant gauti išsamias įžvalgas apie dirbtinio intelekto ir žmogiškųjų išteklių valdymo praktikų sąveiką.
- **Išsamią mokslinės literatūros analizę**, apimančią daugiau nei 30 empirinių ir konceptualių tyrimų, susijusių su dirbtinio intelekto taikymu žmogiškųjų išteklių valdyme (ŽIV), „DeepTech“verslumu ir talentų ugdymu.
- **Antrinė duomenų analizė** prasidėjo nuo išsamaus akademinės literatūros apie DeepTech ir dirbtinį intelektą žmogiškųjų išteklių valdyme ištyrimo. Tai apėmė mokslinių straipsnių, atvejo analizių ir svarbių knygų peržiūrą, siekiant susisteminti esamas žinias ir nustatyti pagrindines temas. Šio peržiūros metu buvo aiškiai nustatytas spragą: trūksta dėmesio tam, kaip išteklių riboti DeepTech startuoliai įgyvendina dirbtinį intelektą talentų valdyme. Šios literatūros analizės išvados tiesiogiai formavo vėlesnės pirminio tyrimo fazės planą.

Atlikto tyrimo rezultatai:

Tyrimo dizainas

Tyrimas struktūrizuotas į tris nuoseklias fazes, kurių kiekviena atlieka skirtingą paskirtį:

Ištyrinėjimo fazė: Atliekama apžvalginė literatūros analizė, kuria nustatomos esamos tendencijos, konceptualūs apribojimai ir naujos praktikos dirbtiniu intelektu grįstose talentų strategijose startuolių ekosistemose.

Empirinė fazė: Ši fazė apima išsamius atvejų tyrimus ir dalinai struktūruotus interviu su pagrindiniais DeepTech startuolių suinteresuotaisiais asmenimis. Dėmesys skiriamas supratimui, kaip dirbtinio intelekto įrankiai yra naudojami talentų pritraukimui, kvalifikacijos kėlimui ir darbuotojų skaičiaus planavimui.

Sintezės fazė: Remiantis išteklių orchestracijos teorija ir žmogiškojo kapitalo teorija, šioje fazėje sukuriamas Talentų ir dirbtinio intelekto integracijos modelis. Šis modelis siūlo strategines ir praktiškai pritaikomas įžvalgas startuoliams ir jų ekosistemos partneriams.

Gauti rezultatai

Atlikta analizė leido nustatyti keletą pagrindinių rezultatų, kurie toliau pateikiami pagal pirminius tyrimo tikslus:

Pirmasis tikslas: Išnagrinėti, kaip startuoliai sprendžia išteklių ribotumą diegdami dirbtiniu intelektu pagrįstas žmogiškųjų išteklių strategijas.

- Startuoliai dažniau taiko adaptyvų, palaipsniui įgyvendinamą diegimo požiūrį (pvz., „šliaužti–vaikščioti–bėgti“), o ne plataus masto sprendimų diegimą.

- Kurdami ekosistemos partnerystes, jie įgyja prieigą prie įrankių, duomenų ir ekspertinių žinių.
- Dirbtinis intelektas veikia kaip jėgos daugiklis, automatizuodamas rutinines žmogiškųjų išteklių užduotis ir sudarydamas galimybes priimti duomenimis grįstus sprendimus net ir esant nedidelėms komandoms.

Antrasis tikslas: Įvertinti, kaip dirbtinis intelektas prisideda prie inovacijų gebėjimo palaikymo „DeepTech“ įmonėse.

- Dirbtinis intelektas didina mokslinių tyrimų ir plėtros efektyvumą taikant prognozinį modeliavimą, generatyvųjį projektavimą ir spartesnę esamų tyrimų sintezę.
- Tokie įrankiai kaip žinių grafai ir natūralios kalbos apdorojimo (NLP) sprendimai skatina tarpdisciplininį bendradarbiavimą ir padeda mažinti atotrūkį tarp skirtingų specializacijos sričių.
- Nuolatinį kompetencijų ugdymą taip pat palaiko dirbtinis intelektas, pasitelkdamas individualizuotas mokymosi sistemas, kurios leidžia komandoms neatsilikti nuo technologinių pokyčių.

Trečiasis tikslas: Išnagrinėti ekspertų įžvalgas apie tai, kaip išoriniai ekosistemos veiksniai veikia DI ir žmogiškųjų išteklių integraciją bei inovacijų tvarumą „DeepTech“ startuoliuose.

- Išoriniai suinteresuotieji subjektai, įskaitant investuotojus, politikos formuotojus ir akseleratorius, atlieka lemiamą vaidmenį tiek palengvindami, tiek apsunkindami dirbtinio intelekto ir žmogiškųjų išteklių integraciją.
- Vienas iš reikšmingų iššūkių yra koordinacijos stoka tarp šių veikėjų.
- Tie startuoliai, kurie aktyviai valdo ir derina išorines partnerystes, pasižymi didesniu atsparumu ir tvaresniais inovacijų rezultatais.

Ketvirtasis tikslas: Sukurti konceptualųjį modelį, siejantį žmogiškojo kapitalo teoriją ir išteklių orkestravimo teoriją.

- Buvo sukurtas dirbtiniu intelektu orkestruojamo inovacijų gebėjimo modelis, apjungiantis žmogiškojo kapitalo teorijos ir išteklių orkestravimo teorijos principus.
- Šiame modelyje dirbtinis intelektas veikia kaip meta-orkestruotojas, nuolat derinantis žmogiškąjį kapitalą, vidinius išteklius ir išorinius ekosistemos išteklius siekiant užtikrinti tvarią inovacijų plėtrą.

Magistro baigiamojo darbo (projekto) išvados:

Šis tyrimas rodo, kad „DeepTech“ startuolių ilgalaikė sėkmė priklauso nuo gebėjimo kurti organizacijas, kurios būtų tokios pat inovatyvios kaip ir jų pagrindinės technologijos. Taikant mišrių metodų prieigą – derinant mokslinės literatūros analizę, konceptinę analizę ir ekspertų apklausas – tyrime nagrinėjama, kaip dirbtinis intelektas (DI) gali būti strategiškai pasitelkiamas valdant kritinius talentų dinamikos aspektus. Gauti rezultatai atskleidžia tiek DI teikiamas galimybes, tiek praktinius jo diegimo iššūkius itin nestabilioje ir išteklių ribotoje aplinkoje.

Pirma, nustatyta, kad „DeepTech“ startuoliams būdingi finansiniai, žmogiškieji, technologiniai ir organizaciniai apribojimai yra unikalūs ir tarpusavyje susiję, kartu lemiantys inovacijų kūrimo būdą. Vietoje to, kad šiuos apribojimus laikytų kliūtimis, sėkmingos įmonės juos interpretuoja kaip verslumo išradingumo variklius. Jos taiko dirbtinį intelektą ne kaip prabangą, bet kaip pagrindinį „jėgos daugiklį“ ir „meta-turtą“, leidžiantį mažoms komandoms pasiekti aukštą talentų pritraukimo, ugdymo ir išlaikymo lygį, kuris kitu atveju būtų nepasiekiamas.

Antra, tyrimas patvirtina, kad pagrindinė DI vertė gerokai peržengia administracinių žmogiškųjų išteklių užduočių automatizavimą. Ilgalaikis jo indėlis pasireiškia gebėjimu skatinti nuolatinę ir eksponentinę inovaciją. Pasitelkiant prognozinį modeliavimą, generatyvinį projektavimą, tarpdisciplininių žinių integravimą ir duomenimis grįstą sprendimų priėmimą, DI sukuria organizacijose nuolatinio mokymosi ciklus. Tai leidžia inovacijas paversti ne atsitiktiniu procesu, o tiksliai valdomu instrumentu, padedančiu startuoliams siekti technologinės pažangos net esant dideliam neapibrėžtumui ir ilgiems plėtros ciklams.

Trečia, empiriniai duomenys išryškina svarbų, tačiau dažnai nepakankamai įvertintą aspektą: išorinė inovacijų ekosistema nėra vien foninis veiksnys, bet aktyvus DI pagrįstos talentų strategijos bendrakūrėjas. Inkubatoriai, investuotojai ir politikos formuotojai reikšmingai formuoja DI ir žmogiškųjų išteklių integracijos galimybes, etiką ir kryptį. Tyrime identifikuotas „koordinacijos trūkumas“ kaip esminė problema, rodanti, kad startuolio sėkmė ar nesėkmė dažnai labiau priklauso nuo gebėjimo orkestruoti išorinius santykius ir išteklius nei vien nuo techninių kompetencijų.

Ketvirta, siekiant apjungti šias įžvalgas, buvo sukurtas Dirbtiniu intelektu orchestruojamo inovacijų gebėjimo modelis. Šis modelis sujungia Žmogiškojo kapitalo teoriją ir Išteklių orkestravimo teoriją, integruodamas dirbtinį intelektą kaip transformuojantį veiksnį. Jis susieja nuolatinį dinaminio žmogiškojo kapitalo ugdymą su strateginiu įvairių vidinių ir išorinių išteklių koordinavimu ir siūlo įtikinamą teorinį pagrindą, kaip „DeepTech“ įmonės gali kurti tvarų konkurencinį pranašumą, paremtą žmogiškojo sprendimo ir mašininio intelekto sinergija.

Informacija apie magistro baigiamojo darbo (projekto) rezultatų publikavimą arba pritaikymą publikavimui:

Pagrindiniai šio darbo rezultatai ir konceptualusis modelis gali būti pritaikyti pateikimui recenzuojamuose akademiniuose žurnaluose arba parengti kaip straipsnis akademinei publikacijai.

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AI	Artificial Intelligence
API	Application Programming Interface
BI	Business Intelligence
BERT	Bidirectional Encoder Representations from Transformers
CVC	Corporate Venture Capital
DCT	Dynamic Capabilities Theory
DHCT	The Dynamic Human Capital Theory
DI	Dirbtinis Intelektas (Artificial Intelligence in Lithuanian)
EU AI Act	European Union Artificial Intelligence Act
GDPR	General Data Protection Regulation
GPT	Generative Pre-trained Transformer
HCT	Human Capital Theory
HR	Human Resources
HRM	Human Resource Management
IP	Intellectual Property
IT	Information Technology
LLMs	Large Language Models
LMS	Learning Management System
MVP	Minimum Viable Product
NER	Named Entity Recognition
NLP	Natural Language Processing
RBV	Resource-Based View
R&D	Research and Development
ROI	Return on Investment
ROT	Resource Orchestration Theory
SaaS	Software as a Service
SMEs	Small and Medium-sized Enterprises
VC	Venture Capital
VRIN	Valuable, Rare, Inimitable, Non-substitutable
VUCA	Volatile, Uncertain, Complex, Ambiguous

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AI and Talent in DeepTech Startups: How Emerging Ventures Build the Workforce of the Future

Introduction

DeepTech startups founded on scientific advances in artificial intelligence biotechnology and quantum computing are critical to solving profound global challenges in climate energy and healthcare. Unlike conventional technology ventures these companies emerge from extensive academic research requiring long development cycles specialized infrastructure and highly skilled interdisciplinary teams. While technological innovation is their core the strategic management of talent especially within AI driven contexts has become equally vital for their success.

Current research recognizes AI’s role in enhancing business innovation and operational efficiency, yet a significant gap remains in understanding how resource constrained DeepTech startups orchestrate AI driven talent strategies. For instance, studies such as Wang, S., & Zhang, H. (2024) demonstrate that, generative AI’s utility in knowledge acquisition for green ventures but do not fully explore how startups mobilize and retain the human capital needed to leverage such technologies. Similarly, while resource orchestration theory explains how firms align technological resources its application to talent development in AI centric startups is underdeveloped.

Human capital theory highlights investment in skills and learning as a driver of innovation performance, in DeepTech contexts these investments must be accelerated adaptive and interdisciplinary. Startups must be seen not merely as resource limited but as agile orchestrators of talent technology and partnerships. Connecting this perspective with AI based tools could help overcome barriers like smaller size weaker employer branding or inability to match large tech salaries instead of startups can cultivate talent strategies built on flexibility data and culture. This is increasingly urgent as governments prioritize DeepTech entrepreneurship affecting education labour policy and economic resilience.

AI is reshaping team building and management at a rapid pace. Research including work by Babina, T., Fedyk, A., & He, A. (2024) indicates AI investment fuels growth through product innovation particularly in large firms. However, DeepTech startups in fields like quantum computing and biotech face distinct challenges. They operate with fewer resources compete directly with giants like Google and IBM and require teams that span multiple scientific domains. Reports from McKinsey & Company (2024) and the OECD (2023) underscore this tension. Consequently, there is limited insight into how young DeepTech ventures employ AI in talent management to build robust innovative teams.

The global talent market is also evolving. Workforce mobility, digital nomadism and remote collaboration tools create more flexible but uneven labour landscapes. Talent is geographically dispersed yet access remains constrained by borders culture and regulation as noted by the ILO. While hybrid work offers startups new global hiring opportunities. It introduces challenges in building cohesive creative teams across distances while safeguarding intellectual property and sensitive data.

Competition with established tech giants presents an acute challenge, their aggressive AI talent acquisition strategies inflate salaries and intensify sector-wide shortages, worsening retention risks for startups. This pressure forces startups to innovate in how they attract and engage talent.

Multiple research strands emphasize AI's growing role in talent acquisition development and strategic workforce planning AI driven HR tools such as predictive hiring platforms and personalized learning systems have been shown to boost productivity reduce attrition and cut time to competency by up to thirty percent. However most evidence comes from traditional IT or corporate settings overlooking how DeepTech startups with unique needs and constraints implement such systems.

Moreover, integrating AI into HR raises ethical structural and human centric concerns issues of algorithmic bias, data privacy and transparency are especially critical in high stakes DeepTech environments, where recruiting involves scarce expertise and sensitive research. Despite the proliferation of AI powered HR tools from screening to analytics little research examines their adaptation for DeepTech ventures.

DeepTech companies also face pressure to embed diversity equity and inclusion principles into their talent strategy. This is not only a social imperative but a driver of cognitive diversity essential for breakthrough innovation. Therefore, AI enabled HR systems must balance efficiency with strong safeguards against bias, particularly given the complexity of scientific domains and emerging disciplines.

Emerging research highlights the importance of integrating ethics into AI talent systems to mitigate bias and promote accountability. As DeepTech startups rely more on AI for talent orchestration, balancing innovation with ethical stewardship becomes paramount.

Topol, A., Koumpan, E., (2025, January) propose a multi agent AI framework using generative AI to support talent management stages from requisition to continuous learning. These agents can scan labour markets in real time, debias skills matching and guide applicants. While promising in large organizations their adaptation to DeepTech where ethical sensitivity knowledge intensity and IP security are heightened remains poorly understood.

Evidence suggests startups adopt AI in varied patterns such as the Dedicated Optimizer Cautious Cost Saver and Selective Enhancer. However, their focus is broad tech startups not DeepTech firms, which must manage high knowledge intensity, long timelines and specialized workforce development. Similarly, studies on corporate venture capital show how external partnerships fuel innovation but often neglect the accompanying human capital strategies.

Talent scarcity is a severe bottleneck in quantum technology. Alone demand drastically outpaces supply and traditional recruitment pipelines are inadequate. Although universities and governments have launched training programs. Startups still need agile interdisciplinary approaches to attract and retain researchers across fields like physics and systems design. This complexity is seldom addressed in AI HRM studies which typically examine functional roles in established companies rather than nascent ventures.

The pressure to understand DeepTech talent needs is escalating. New roles in AI quantum and biotech are emerging faster than the supply of skilled professionals. A shift toward skills-based hiring prioritizes practical ability over degrees and enabling faster recruitment. Yet the broader job market offers fewer entry level positions as AI automates tasks that once supported internship pathways. This intensifies the difficulty for startups competing with large firms that can offer premium salaries.

Insights from broader organizational settings provide reference points AI HR tools can shorten hiring time by 35% to 42% increase diversity by around 10% and reduce costs by over 25%. However, these findings originate in large companies leaving open the question of how small innovation focused startups can use such tools responsibly and effectively. Implementing chatbot prediction models and recommendation systems in DeepTech is more complex. Concerns regarding ethics, algorithmic bias, high knowledge demands and IP protection create challenges not prevalent in typical corporate environments.

Topol, A., Koumpan, E., (2025) stress that explainability, transparency and trust are crucial in AI aided recruitment. Generative AI can reduce inefficiencies and improve decisions but in startups success depends on careful management user cantered design and adherence to local labour regulations within the broader innovation ecosystem.

Existing startup AI adoption categories do not fully address the unique talent challenges of DeepTech Similarly corporate venture capital research highlights resource sharing for innovation but overlooks how investors influence startup workforce development.

This study aims to fill these gaps by examining how DeepTech startups utilize AI for talent acquisition workforce development and employee engagement across interdisciplinary fields. It investigates how limited resources high innovation demands and ethical considerations shape the adoption of AI based HR tools. The study also explores how external ecosystem actors including universities, policymakers and venture capitalists help shape talent strategies and support sustainable growth.

From a broader economic perspective, the way DeepTech startups employ AI in talent management influences national innovation systems and regional economic clusters. Governments and innovation agencies worldwide are investing in links between universities, research institutes, startups and large firms to accelerate technology transfer and skill development. Understanding how startups use AI within this ecosystem can inform policies that build strong inclusive innovation hubs and promote long term economic growth.

This research also highlights the continuous iterative nature of talent management in DeepTech. Unlike traditional firms, these ventures must perpetually develop their workforce as technologies evolve often pivoting business models in response to new scientific discoveries. AI powered talent management is therefore not a onetime implementation but a dynamic process reliant on constant learning, feedback and adaptation.

AI does not replace human judgment rather it acts as a collaborative partner enhancing decision making with predictive insights and freeing HR professionals to focus on strategic and relational tasks. This synergy enables more flexible and adaptive talent strategies in fast moving startup environments.

As technology advances skill requirements in DeepTech change continuously making ongoing upskilling and reskilling essential. Organizations must integrate continuous learning pathways directly into their talent management strategy.

By synthesizing insights from generative AI DeepTech entrepreneurship and strategic HR management, this research seeks to develop a practical framework for talent management and innovation focused startups. It illustrates how the ethical, automated and personalized use of HR technology can help maintain innovation velocity in uncertain high-pressure environments. Ultimately the framework aims to assist DeepTech ventures in building agile, inclusive and future ready teams.

Scientific Issue

Although AI is increasingly transforming business functions, there is still little research on how it is used strategically in talent management within DeepTech startups. These startups often have limited resources and operate in specialized, interdisciplinary areas, which makes attracting, developing and retaining key talent especially challenging. Most existing studies focus on traditional tech companies or general AI applications in HR, leaving a gap in understanding how DeepTech ventures apply AI to their specific talent needs. This study aims to fill that gap by exploring how DeepTech startups use AI to support talent acquisition, development and engagement. It also looks at how they manage limited resources, handle ethical and organizational challenges, and adopt AI driven HR tools to maintain innovation and stay competitive.

Scope of the study

This research is focused on a narrow intersection of technology and strategy within a specific type of venture. Its boundaries are set to allow for a deep and contextual investigation.

The study is exclusively concerned with early-stage DeepTech startups ventures. Whose core innovation is rooted in advanced science or engineering, such as quantum computing or biotechnology. It examines how these resource constrained firms adopt artificial intelligence specifically for talent management functions, including recruitment, development and retention.

The inquiry is grounded in a qualitative dominant, mixed-methods approach, primarily drawing from literature synthesis and expert insights gathered within the European DeepTech ecosystem. The theoretical focus is on contributing to Human Capital Theory and Resource Orchestration Theory, culminating in a conceptual framework for understanding organizational capability.

This scope excludes AI applications in large corporations, non-technical SMEs or the technical development of AI tools themselves, ensuring a targeted analysis of strategic people operations in high-innovation, resource-scarce environments.

The Object of the Research

The object of this research is AI enabled talent management practices in DeepTech startups. Specifically, it focuses on how these ventures operating in fields such as quantum computing, biotechnology and advanced engineering attract, develop and retain interdisciplinary talent through the strategic integration of AI in human resource management.

Goal of the Research

The primary goal of this research is to examine how DeepTech startups strategically use artificial intelligence (AI) to attract, develop and retain interdisciplinary talent in resource constrained, innovation-driven environments.

The goal will be achieved through the following set of tasks**:**

1. To analyse how startups address resource constraints when adopting AI-enabled HR strategies.
2. To assess how AI contributes to sustaining innovation capacity in DeepTech venture.
3. To explore expert insights on how external ecosystem factors influence AI–HR integration and sustain innovation capacity in DeepTech ventures.

4. To develop a conceptual framework linking human capital theory and resource orchestration theory.

The Methods and Resources of Research

This research adopts a mixed methods approach to capture both empirical depth and theoretical breadth. It integrates the following components:

- **Qualitative case studies** of selected DeepTech startups in Europe to examine real world applications and challenges of AI enabled talent strategies.
- **Expert survey with startup founders, HR** professionals and AI specialists to gather nuanced insights into the intersection of AI and human resource practices.
- **Comprehensive literature review** covering over 30 empirical and conceptual studies related to artificial intelligence in human resource management (HRM), DeepTech entrepreneurship and talent development.
- **Secondary data analysis** began with a thorough analysis of the available academic literature on DeepTech and AI in human resources. This involved reviewing journal articles, case studies and relevant books to map the existing knowledge and identify key themes. Through this review, a clear gap was recognized: a lack of focus on how resource-constrained DeepTech startups implement AI for talent management. The insights from this literature directly informed the design of the subsequent primary research phase.

Research Design

The study is structured into three sequential phases, each serving a distinct purpose:

1. **Exploratory Phase:** A scoping review is conducted to identify current trends, conceptual limitations and emerging practices in AI driven talent strategies within startup ecosystems.
2. **Empirical Phase**: This phase involves in depth case studies and semi structured survey with key stakeholders in DeepTech startups. The focus is on understanding how AI tools are deployed for talent acquisition, upskilling and workforce development.
3. **Synthesis Phase**: Drawing on resource orchestration theory and human capital theory, this phase develops a Talent AI Integration Framework. The framework offers strategic and actionable insights for startups and their ecosystem partners.

Practical Significance of the Research

This study delivers value across multiple stakeholder groups within the innovation ecosystem:

- **Startup founders and entrepreneurs** will benefit from low cost, scalable approaches to AI driven recruitment and retention of high skill talent.

- **HR and talent management professionals** in DeepTech ventures will gain frameworks for designing AI enabled talent systems suited to resource constrained environments.
- **Policy makers and academic institutions** can leverage the findings to design collaborative training initiatives, interdisciplinary talent pipelines and policy incentives to address DeepTech talent shortages.
- **Investors and corporate partners** will acquire tools to assess the talent readiness and organizational maturity of DeepTech ventures during funding, partnership or acquisition decisions.

By integrating theoretical foundations with practical applications, this research contributes to building inclusive, agile and ethically aligned talent strategies that are essential for sustaining innovation in DeepTech environments.

1. Analyse how startups address resource constraints when adopting AI-enabled HR strategies

DeepTech startups are a distinct category of enterprises that convert leading-edge scientific and engineering innovations into tangible products and solutions. These companies, on the bleeding edge of areas like artificial intelligence, biotechnology, quantum computing and nanotechnology are fundamentally different from software-focused digital startups. Their products tend to have long development cycles, high capital requirements and high technological uncertainty. As a result, effectiveness, success and survival depend not only on pure scientific excellence but also on effective management of limited resources.

In today’s fast-paced, technology-driven world economy, DeepTech startups have become significant drivers of advancement and sustainable competitive edge. They are granted the mandate to ‘push scientific boundaries’ but operate with only a small fraction of the resources big business or public research organizations have at their disposal. That scarcity in capital, high quality talent and institutional support presents serious challenges. This is especially relevant when implementing AI-enabled HR systems which are crucial today to attract, develop and retain the unique interdisciplinary talent on which these ventures rely.

Managing this interface of scientific complexity and resource scarcity means that strategic resource management is a key skill for founders to learn. It is therefore critical to understand how DeepTech startups can perform advanced, AI-driven HR practices in a very constrained environment and thus explain their survival as innovators, resilience and competitiveness in the uncertain context of high-stakes technology markets.

1.1.1 Nature of Resource Constraints in DeepTech Startups

The resource constraints that a DeepTech startups are multidimensional, spanning financial resources, human capital and technology to knowledge. Every dimension comes with its own set of concerns that fundamentally shape what's practical, how it should be done and the speed at which AI tools can reasonably make their way into HR processes. Due to the reason for limited financial resources, an investment in advanced systems, talent shortage mitigation implementation, difficulty in integrating with current technologies and a lack of organizational skill sets required for their proper use. These are the borders of the picture in which DeepTech startups need to innovate systemically when it comes to their added HR value.

1.1.1.1 Financial Constraints

Financial challenges might be the first and most obvious hurdles for DeepTech start-ups. Substantial amounts of capital are spent on extended R&D, prototype creation and working through the regulatory process, which causes cash flow restrictions. The investors are cautious about the apparent high level of risk associated with long time-to-market and technological uncertainty makes traditional venture capitalists cautious, forcing startups to adopt exceptionally lean financial strategies. In HR, this means that low-cost, modular AI is the preferred option over pervasive enterprise software, such as open-source machine learning libraries or subscription models for cloud-based HR analytics as opposed to integrated applications.

This prudent financial behavior, though essential for survival, comes with costs. It can slow down the hiring of potentially transformative AI tools and prevent companies from offering competitive pay, an important factor in drawing top talent to startups when competing with deep-pocketed tech giants. When the budget is tight, investments in sophisticated HR tech or competitive salaries or a structured long-term training program are often delayed and then there's a talent deficit just when you need it most, in the critical points of growth.

Ironically, those economic constraints also serve as a spur to innovation. Startups are chasing even more non-dilutive funding sources to fill that resource gap. Government innovation grants, university research collaborations and accelerator programs are become invaluable lifelines. These external resources aren't just capital, but are also considerations about complementary assets: mentorship, technical expertise and access to professional networks. By using those ecosystems, startups can introduce AI in HR processes step-by-step, aligning IT adoption with long-term innovative goals without compromising finances.

Empirical Evidence:

A study shows that the cost of deployment is the biggest impediment to adopting AI, mentioned by 55% organizations. For a startup, that's not only the cost of software itself but the hidden costs of integration, training and operation disruption.

Startups don't have much access to capital, so they become conservative and ROI focused on every technological spend. This includes both the price of software, as well as hidden costs of integration training and disruption to daily operations.

1.1.1.2 Human Capital Constraints

Lack of talent is the most well-known challenge of DeepTech ventures. They need teams with a deep grounding in areas such as physics, data science and engineering combined with business acumen and entrepreneurial skills. It can be hard to find and keep such people, as startups often can't offer a salary, stability or structured career paths of established businesses.

This is further complicated by the lack of formal dedicated HR activities as well. In early-stage startups, the HR function often finds its way to founders and operations teams were hiring processes along with development and performance management are done on an informal, ad-hoc basis. This discrepancy can result in missing out on strategic talent development. In this case, HR tools powered by artificial intelligence (AI) like automated recruiting platforms, predictive attrition analytics and skills gap identification programs–which could provide a solution. They can aid in more consistently making decisions, automate some administrative overhead and fill-in for the lack of full-time HR staff.

Yet there's a fundamental paradox that emerges effectively in practice, even just using and maintaining these AI tools effectively requires trained human professionals. That is why startups turn to AI as a remedy for talent shortage if they can have or bring someone in who does AI. Overcoming this circular challenge will require thoughtful sequencing and commitment to a strategy for AI as a supportive layer in the broader category of talent management, not a substitute for human judgment on its own.

Empirical Evidence:

DeepTech startups often operate under resource constraints and have relatively small learning bases or immature processes in place. They tend to rely on informal routines, operate on slim budgets and possess weak documentation practices. Such constraints can result in knowledge of silos and expose the company to a potential loss of essential knowledge.

A significant skills gap persists, particularly in the field of AI and business intelligence. HR departments in DeepTech startups also are not yet fully ready to shift towards data-driven HR practices and it is an even bigger challenge for them to implement AI successfully.

1.1.1.3 Technological Constraints

AI implementation needs solid tech fabric: high-performance computing, dependable data pipelines and interconnected information systems. Due to budget constraints and limited in-house technical expertise reserved for the core product R&D, most early stage DeepTech startups do not have this infrastructure.

Another significant challenge is the availability and quality of data. AI-generated models in HR analytics, predictive hiring and performance management are only as good as the proprietary, high quality or relevant datasets they're built upon. Startups typically do not have enough historical HR data, which may be consistent to train the trustworthy models. As noted in related sectors, the development of any new technology or minimum viable product (MVP) "hinges access to comprehensive, high-quality data," often necessitating trusted partnerships. In addition, there are pressing, complex demands due to data privacy and cybersecurity. The management of sensitive employee data requires that privacy legislation such as the GDPR is followed closely. But setting up enterprise-level security and privacy systems can be expensive and challenging for cash-strapped startups, who often don't have the technical expertise to do it themselves or afford a specialist.

To overcome these hurdles, startups are increasingly relying on cloud-based AI-services, shared data infrastructure and collaborating with external technology suppliers. With these solutions, we can get cost-effective scalable access to advanced analytics without extensive up-front investment. But by doing so we add new dependencies, risks of vendor lock-in and intentionally put ourselves at risk with control over proprietary and sensitive data. Balancing these opportunities and risks becomes a major strategic decision for startups who wish to enable AI in HR on any scale, while maintaining the integrity of their operations.

Empirical Evidence:

The lack of proprietary, high-quality data is a major barrier created by AI-driven startups across sectors, which is directly impacting their ability to develop effective models for internal processes like HR.

IT systems are weak or fragmented; DeepTech startups are increasingly struggling to make them work because it is difficult to integrate AI tools into a robust IT system. To enable the execution of AI-powered HR operations, systems must be effective in combination with each other, but many startups do not have that infrastructure or technical expertise at its core.

1.1.1.4 Knowledge and Organizational Constraints

Combination of knowledge of asymmetry and organizational immaturity is a significant challenge for DeepTech startups in transitioning to AI-enabled HR policies. If we are the founder or one of the early team members, it's likely that our technical expertise in artificial intelligence, biotech, robotics or quantum computing is deep, but we have limited training in Human Resource Management, Organizational Development or Strategic Planning. This asymmetry makes it extremely challenging to develop business goal-aligned AI-driven HR systems that can underpin and sustain innovation. Startups can deploy AI machine learning tools without having a complete grasp of how to fit them into existing processes, which restricts the effectiveness and therefore, potential positive impact on workforce development.

Many DeepTech start-ups suffer from what is called the liability of newness. They don't have the growing track record and consistency of process that more mature companies can rely on and it is this that makes it difficult to hire and keep capable practitioners. For the talent, if they know where their career is going, they will sometimes opt for a more certain long-term path with clear HR practices in place. The absence of formal transparent HR frameworks codified roads, daily routines and captured best practices make it even impossible to collect consistent data about the workforce, which is crucial for AI systems to provide reliable insights and forecasts.

Fragmentary or invalid internal data is another major bottleneck. Many of the startups do not have standardized HR metrics, organized performance data or formal documentation on staff expertise. This makes it challenging to successfully train AI models or build predictive analytics for hiring, workforce planning and talent management. Internal resistances can also represent obstacles to the adoption of organizational change. If workers are not acquainted with digital tools or worry about AI taking their job away, they may push back on using the new systems, leading to slower adoption and less than full value from those investments.

To close these gaps, DeepTech startups increasingly leverage external knowledge networks such as incubators, accelerators, industry partnerships and academic mentors. These communities offer best practices guides in AI deployment of HR innovation and strategic workforce planning. Some startups even use AI powered learning management systems (LMS) to improve in-house digital acumen, reinforce lifelong learning and track skill growth across longer periods. Mentorship and external partnerships support in filling knowledge gaps and bringing structure in the form of decision making and governance frameworks.

Even when startups seek to use AI, governance creates both ethical and operational risk due to a lack of proper internal monitoring. Most DeepTech startups lack clear guidelines and processes around the use of AI. Scarce resources make it difficult to verify that bias has been checked in validating algorithms or to guarantee that AI systems are easy for people to understand and use. As such, AI tools can be discriminatory against certain people, underrepresenting certain groups to decrease employee trust and come into conflict with rules like GDPR or local labor laws.

These gaps can reach beyond simple compliance. They can also be damaging to the company culture, slow down the uptake of new technology and create staff retention problems. Addressing these gaps is critical not just to responsibly apply AI, but to establish the great human resource practices necessary for promoting learning innovation and long-term survival. Startups that establish clear governance, easy oversight and open communication can AI safely – keeping in mind their employees, while also enhancing the ability to grow and innovate.

1.1.2 Why Resource Constraints Matter for AI Adoption

A DeepTech startup is a company that deeply converges hardcore technology and traditional business, wherein resource constraint is a dominant issue in the organization model, one of the greatest difficulties they face while AI for HR. With the value that AI can bring to efficiency, scale and data informed decision making, operationalizing such systems typically requires substantial investments in terms of financial, technical and human capital. Most early-stage startups can't afford these. Consequentially, resource constraints are not only manifest as operational challenges but also influence how startups pursue AI adoption.

Due to the lack of resources, DeepTech companies tend to employ selective, adaptive and iterative approaches. AI tools are not an after-market add-on that they take or leave, but how they can extend what they have. This notion is consistent with the Resource Based View and Dynamic Capabilities Theory that suggest competitive advantage arises from developing efficient use of scarce resources. AI is not a labor substitute for DeepTech startups. Instead, it continues to enhance and build on what we already have.

In HR, AI helps startups do more with less. And software that can automatically recruit, predict performance with analytics and match skills to roles aid small HR teams with tight budgets. With the help of AI recruitment tools, local information can be mined in a job pool from around the world and the cost, cycle time and quality ratings of hiring can thus be optimized. Analytics can predict early signs of disengagement or turnover risk, allowing startups to retain key talent necessary for innovation.

The key challenge for the AI in HR is to become a part of a large and innovative ecosystem. AI alone is something DeepTech startups can’t just apply to. They depend on collaboration with universities, research institutions, accelerators and AI vendors for expertise, cloud infrastructure and training data. That’s how AI becomes a joint effort. Outside relationships expand inner strengths, not core.

1.1.2.1 The Adoption Paradox

For DeepTech startups, expensive or failed AI implementation is not an option. They tend to be short on cash and even smaller in terms of highly specialized staff, meaning every investment must show crystal clear measurable results in the shortest possible time. While established companies absorb failed projects or distributing costs across multiple initiatives, startups work on a shoestring in both cash and operations. Thus, well thought out planning and rigor with prioritization and capacity is critical for survival and growth.

Due to these constraints, DeepTech startups rarely utilize legacy enterprise AI models, which are often structured around heavyweight, static deployments. Instead, they are taking a lean and incremental approach to AI by quickly rolling out AI in small bites. This enables startups to develop through trial and error, iterate after learning from the results and adjust accordingly. They typically start with a few high impact areas like automating candidate screening, predicting employee turnover or optimizing skills allocation. Starting with these relentless use cases reduces exposure to financial and operational risks but captures initial proof of value.

This early-win confidence boost can also tilt the odds in favor of further investment in other AI projects.
Startups also must make careful decisions about betting risk and return. They also value AI initiatives which boost productivity, inform better decisions and reinforce innovation. Leveraging Iterative exploration and continuous feedback, it's by doing so in concert with iterative experimentation, continuous feedback and tying these to your core business goals. AI can serve as a force multiplier for DeepTech startups. It enables small, scrappy teams to do more with less. It is a strategic approach that enables AI adoption to serve immediate operational needs while building the groundwork for long-term competitiveness without overstressing limited financial and human resources.

1.1.2.2 Exacerbated Risks

Limits of knowledge and legitimacy are very high barriers to the acceptance of AI. Startups without a formal background in HR or technical governance frameworks could roll out AI tools with biased, unfair or opaque results. An algorithmic hiring tool, for instance, could indirectly discriminate against applicants who don’t fit a traditional profile, running afoul of GDPR, local employment laws and the like while frightening away investors and talent with bad publicity in its wake.
The people’s side of change management is just as important. But, without clear communication about how AI will be integrated into the work environment, workers may feel their jobs or lives are under attack and respond with recalcitrance, disengagement or attrition of high-value talent. For a small company, losing a key scientist or engineer to this resistance can even be fatal.
So thoughtful, open and people centered is not an option but a necessity. Startups will need to be upfront about the role of AI tools (as an augmentation rather than replacement), engage employees in any automation and cultivate a culture of trust and learning. Dealing with these human and organizational aspects is arguably equal, if not more important than managing the technology per se to mitigate operational, ethical and reputational risks.

1.1.2.3 Strategic Imperative

For DeepTech startups, the question is no longer whether to use AI but how they can efficiently implement it with their limited resources. The strategies familiar to big companies don’t tend to be successful for these startups. In contrast, DeepTech startups need to adopt an agile and resource-light methodology leveraging AI as a "force multiplier" expanding the limited bandwidth of small teams far beyond their reach and a "meta-resource" transforming constraints into opportunities. By using AI intelligently, startups can better leverage their resources, increase efficiency and make more informed decisions while not overstretching budgets or teams.

Startups can turn their disadvantages into opportunities with this model. For example, AI can be used to detect and attract global talent, lead complex projects or predict potential operational risks. When AI is employed like this, it's more than a tool. It becomes central to the startup's innovation strategy. By using AI to solve both short-term operational challenges and long-term strategic objectives, DeepTech startups can build a sustainable competitive edge for attracting interdisciplinary talent on the global stage.

1.1.3 Linking Resource Constraints with Sustainable Innovation Capacity

While resource scarcity is often considered an obstacle to innovation. However, constraints can also push forms towards more creative solutions and sustainable innovation. When the resources are limited in a DeepTech startup, the founders must think creatively, adapt continuously and make well planned choices on how the limited resources will be used. These circumstances drive them to develop leaner and more robust methods of technology, including AI implementation.

By this way, AI empowered HR practices are increasingly significant drivers for innovation. By taking over these essence HR operations and providing them with data driven decision making, AI also helps startups to use/ extract the potential of their workforce despite small teams and tight budgets. Automation of HR processes via algorithmic talent analytics, which is ready to use onboarding and learning platforms. Startups can increase productivity, keep employees engaged and increase productivity. Such systems foster not only life-long learning in the enterprise but also building a culture which will support innovation from bottom to top.

This results in a self-reinforcing loop of sustainable innovation. Constraints reduce slack, motivate efficiency seeking effort and greater efficiency raise firm's ability to innovate. Instead of investing in traditional, expensive organizations, startups create lean, data-driven and collaborative engines of innovation. And take some relevant principles to avoid the dark side of scarcity and encourage experimentation, rapid iteration and adaptive learning that are essential for long term competitiveness.

The external environment is also a key to innovation. Startups that collaborate with research institutions, accelerators, corporate partners and government programs will have access to pooled knowledge, resources, funding and digital infrastructure. These alliances supplement in-house resources, keeping startups relentless on the innovation path that doesn't saddle with limitations.

Thus, Resource Management is not just surviving with fewer resources. It's a matter of using and combining scarce resources to best effect on both internal and external networks.

DeepTech startups can turn limitations into levers of strategic renewal and competitive advantage by treating scarcity as an enabler for creativity, problem solving and collaboration.

1.2 AI as a Strategic Enabler Under Resource Constraints

AI for DeepTech startups is more than a technology – it's a strategic enabling factor to scale through the constraint of resources. Besides its technological role, AI supports decisions, automation of HR process and optimizes talent allocation across tech startups lifecycles. By reducing limitations of capital, team size and organizational capacity, AI enables DeepTech ventures to grow smoothly and continue to innovate.

1.2.1 AI-Driven Decision-Making: From Intuition to Data- Driven Strategy

Depending on founder intuition to navigate uncertain conditions is dangerous in high-uncertainty settings. AI, especially when integrated with Business Intelligence (BI) tools, provides evidence-based decision-making. In the HR world, this would be to get rid of gutfeel hiring and promotion decisions in favor of data-based insights.

AI powered systems can evaluate candidates based on their skills, cultural fit and long-term performance potential. They can use workforce metrics to model different scenarios. As a result, this change allows HR to routine administrative tasks to play an active role in planning and supporting workplace future needs.

Empirical Evidence: Studies on technology startups indicate that the combination of AI with Business Intelligence tools can speed up decision making process up to 50% and reduce time to market. This support is crucial for small teams that must make high impact decisions with limited information.

1.2.2 AI driven Automation: The "Force Multiplier" for Lean HR Teams

Automation provides a huge benefit of AI for DeepTech startups with a limited number of resources. By acting as a "force multiplier", it reduces the routine process and increases productivity and allows them to manage more tasks with limited resources.

Function Automated: Resume screening. Interview scheduling, candidate communicating, onboarding workflow, payroll processing, and basic attendance monitoring.

Impact: This allows employees to spend less time on routine administrative work and can perform more strategic activities, such as, designing effective structure, training and development and building organizational culture which leads to better growth and innovation.

Real Life Examples:

- At Uniliver, the use of recruitment AI reduced the hiring cycle from 4 to 6 months to approximately 4 weeks. That's also reduced the recruitment cost by around 25% without compromising the candidate's quality.

- Similarly, SoftBank reported that 75% of the time was reduced in their document screening process and this is achieved through automation.

Besides recruitment, AI also improves payroll processing, document screening, performance monitoring and attendance tracking. AI is handling routine administrative tasks and now HR team and AI enable founders to focus on improving the organization, employee development, culture and supporting innovation. This enhances operational efficiency and strengthens startup's ability to retain talent and focus on long term sustainability.

1.2.3 AI in Talent Acquisition and Retention: Competing Without Brand Power

Sometime it's difficult for startups attract and keep good employees because of lacking in strong brand image and large HR team. AI can handle repetitive administrative tasks and giving small teams tools they don't normally have. It can personalize candidate and employee experience. Also suggest who might leave and suggest ways to keep them. AI helps employees to move into various role, where they will do their best. It's also reduced the need for hire external employees. This strategy helps startup managers move smartly, save money and grow their team effectively.

1.2.3.1 Hyper-Personalized Engagement

AI paves the way for any small company to answer custom questions that employees and job candidates might have, giving personalized attention at a level of scale usually only achieved by extensive HR teams. Through the analysis of personal preference, work behavior and career aspirations, AI can draw up personalized engagement campaigns. These interventions could also feature personalized learning journeys, timely feedback loops and growth opportunities tailored to individual employees' wants and needs. Personalizing the employee experience from the start keeps high engagement of employees. In a small startup, AI can ensure employees stay motivated, satisfied and retention with limited HR resources.

1.2.3.2 Proactive Retention and Internal Mobility

Predictive analytics is a game changer for retention. AI models can look at a multitude of data points to identify employees with a high probability of leaving, sometimes long before they're actively thinking about it. This enables retention efforts to be timely and focused. Such people, once identified, can be re-purposed in other areas of the organization to suit current needs rather than hiring somebody new and risking that it might not work out this time.

Evidence: Studies show that generative AI and predictive analysis can improve employee retention (Example: from 72% to 85% in documented cases). This helps the organization more stable and preserves institutional knowledge.

1.2.3.3 Enhanced Quality of Hire and Workforce Performance

AI improves hiring, employee training and performance management with great accuracy in startups. AI assists HR teams in making more informed decisions about who to hire and how to develop the workforce. Studies have shown that implementing AI, performance review accuracy rose from 60% to 90% and the effectiveness of training programs climbed from 70% to 88%. These findings illustrate how AI is helping startups achieve the most out of their limited HR resources, ensuring that employees are in roles where they can perform at their highest potential and development programs are aimed to maximize learning and performance.

1.2.4 Strategic Implications of AI Adoption

AI is not just about being more productive; it is a strategic integrator that brings together operational efficiency, ethical governance and human capital maximization. Its effectiveness also cuts across strategic alignment to achieve organizational goals and a good degree of managerial supervision to mitigate biases, privacy issues associated with data and compliance (Sony et al., 2025; Deepa et al., 2024).

1.2.4.1 Resource Constraints as Strategic Determinants

Fundamentally, the limitations startups face will influence how they adopt AI:

- ***Financial Constraints:*** Few financial options regarding the allocation of funds for AI implementation or ethics auditing (Madanchian & Taherdoost, 2025).
- ***Human Capital Constraints:*** Small, multitasking teams with limited managerial bandwidth (Deepa et al., 2024).
- ***Technological Constraints:*** Disintegrated IT structure and poor integration capability, Madanchian, M. (2025).
- ***Knowledge Constraints:*** Organizations lack AI- or data analysis-capabilities that raise ethical and compliance issues (Sony et. al., 2025).

These limitations are not merely barriers to pass but considerations that necessitate strategic innovation, requiring startups to wield AI in the most precise and meaningful way.

1.2.5 AI for Strategic Agility and Proactive Workforce Planning

AI enhances strategic accuracy, enabling startups to seek opportunities. AI seizes them rapidly and reconfigures resources dynamically. This flexibility builds resilience in a volatile environment (Cai et al., 2024).

AI also facilitates proactive planning of the workforce by scenario modeling and predictive analytics to enable startups anticipate talent shortages, maximize on internal resources and ensure business' continuity without having to involve expensive external consultants (Adam & Ali, 2020).

In the end, AI turns scarcity into strategy and this helps to establish DeepTech startups leveling barriers to transformation by turning constraints into competitive advantage in an intelligent, adaptive approach to lean human capital management.

1.3 Challenges in AI Adoption for DeepTech Startups

Although AI offers a promising competitive edge, this path to adoption for DeepTech startups is also riddled with large, interrelated barriers. These obstacles are not only operational but also exist at the heart of the resource constraints that characterize the startup context, leading to a complex adoption paradox.

1.3.1 Data Scarcity and Quality: The Foundational Barrier

For AI solutions to be effective, machines must process massive amounts of high-quality and relevant data. This is a serious and basic restriction for startups.

Lack of Proprietary Data: Most of the time startups do not have enough proprietary historical data, which makes it difficult to train AI models accurately. According to Zahlan (2025), "in order to develop an MVP or any product, startups need reliable data." In HR terms, this means poor internal data on employee performance, tenure and turnover - all making it hard for accurate predictive modelling of attrition or skills gap analysis.

The "Black Box" Problem: Even if data is available, startups frequently lack the expertise to ask intelligent questions about it. Sony et al. (2025), state that "The black box nature of much algorithmic technology makes it hard for candidates and HR professionals to comprehend or challenge decisions". Small, non-expert groups have difficulty in challenging or interpreting these opaque outputs carrying high compliance and reputational risk.

1.3.2 Cost Barriers: The Direct Financial Constraint

In addition to software subscription fees, costs should encompass systems integration and employee training as well as maintenance and possible business disruption. This is particularly costly for startups as AI spending diverts resources from R&D. In addition to proactively monitoring ethical AI deployment, constantly investing in bias audits and governance is a significant ongoing resource drain.

High Implementation Cost: Mishra et al. (2025) write that high implementation cost' was identified as major challenge by 55% of companies. For startups costs would not only be purchase of software but also integration, training and potential interruption of work.

Ongoing Oversight and Auditing: Ethical AI deployment requires continuous investment. Sony et al. (2025) point out that bias audits require time, money and resources away from the development of the core product and creating high opportunity costs for startups.

1.3.3 Skills Gap: The Critical Human Capital Deficit

This is arguably, the most deeply difficult pose. Startups face a dual deficit:

1.3.3.1 Lack of Technical and HR Data Skills:

Start-ups deal with a double skills gap. There is an "AI/BI Expertise Gap" in the overall workforce (Mili et al., 2025). Indeed, HR departments are often "ill-equipped for the transition to data-driven HR" and fall short with respect to being able to use available data generated by AI systems (Collings, D. G., & McMackin, J, 2025). This creates an environment for the enterprise that has a tool, but no one uses it strategically.

1.3.3.2 Managerial Capability Gap:

Deepa et al. (2024), review a set of management competencies necessary for AI adaptation, which are generally lacking in lean startups. These are ***"technical expertise"***, ***"digital savviness"*** and ***"institutional configuration capacity"*** to catalyse technological maturity. But without competent managers in place, AI initiatives are doomed to fail.

1.3.4 Ethical and Regulatory Barriers: The Compliance and Trust Dilemma

Startups are especially exposed to the ethical and regulatory traps of AI, as there is only limited governance in place.

1.3.4.1 Algorithmic Bias and Fairness:

AI models that were trained on historical data inequalities with disproportionate impact on women, minorities and people with disabilities (Sony et al., 2025). Startups that rely on off-the-shelf hiring software might create automated discrimination without the means of identifying and amending these biases.

1.3.4.2 External Regulatory Pressure:

New regulations, such as blind recruitment policy or the EU AI Act, impose compliance burdens. Lim, H.-M., & Lee, C (2026) also illustrate how AI can be used to promote fair hiring, but startups need to allocate resources to put in place conformity checks and documentation, which seems difficult as they lack money or additional employees.

1.3.4.3 Resource Trade-Off for Ethics:

Madanchian, M., & Taherdoost, H. (2025) point out that giving priority to ethical boundaries may lead to higher complexity and costs, reducing the immediate efficiency gains of AI. So, startups should choose between immediate efficiency gain and long-term ethical consideration.

1.4 Adaptive Strategies Adopted by Startups

Based on organization size, age and success, businesses operate in tough economic times and sometimes face the challenge of rapid technological advancement.

In the face of these challenges, DeepTech startups are diametrically opposed to “copy and paste” corporate strategies. They use a range of lean; agile and collaborative strategies suited to their context of scarcity and flexibility.

1.4.1 Strategic Prioritization and Phased Implementation: The "Crawl-Walk-Run" Approach

Startups reduce risk by avoiding "big bang" rollouts and instead introducing AI gradually. And allowing them to learn and adopt minimal upfront cost step by step.

1.4.1.1 Evidence from Expert Interviews:

(Collings, D. G., & McMackin, J 2025), based on nearly 150 interviews with HR professionals, they see successful companies promoting a “bite-sized implementation” of AI. **"Those who reported the most progress in their implementation journeys strongly advocated piloting skills-first HR in critical areas of the business... a pilot can be used to refine tools and processes... and build positive momentum."** This enables a startup to concentrate on their limited resources on a single, high-impact role such as recruiting before scaling.

1.4.1.2 Evidence from Conceptual Frameworks:2

Kamidin, N. A. A. B. (2025, January) presents a modelized framework with these steps in distilled caricature, acknowledging that each of them corresponds to the phase of maturity and accumulated resources of a startup venture:

Digitization: The first and most basic step, involving the conversion of analogue information such as converting paper record into a digital format. This creates a low-cost foundation for storing and managing data efficiently.

Digital transformation: Building on the digital foundation, this step uses technology to improve or streamline existing processes. For example: automating payroll or other routine administrative tasks.

Digital Transformation: The goal of digital transformation is to involve a comprehensive redesign of process and operations. This is often powered by advanced technologies like AI-driven predictive analysis. By approaching it in stages, even startups with limited resources can manage the financial and operational impact effectively.

1.4.2 Leveraging Strategic Alliances and Ecosystem Partnerships

For startups, a key strategy is joining strategic partnerships to get essential resources they do not have specifically data, know-how and legitimacy.

1.4.2.1 Evidence from Case Study (AI-Healthcare):

A readily used model that forms another sector is offered by Zahlan (2025). AI healthcare startups bypass the barrier of their lack of proprietary data by entering partnerships with ***"Hospitals & Clinics"*** (for patient data), ***"Medical Schools & Research Centers"*** (for clinical validation) and ***"Physicians"*** (for data labeling and institutional connections). The paper stresses that "the development of an MVP … depends on access to a complete set of high-quality data owned by the alliances." For an AI-HR startup, this could be through aligning HR tech platforms, collaborating with universities for their research or leveraging industry benchmarks so the data they need to build their models.

1.4.2.2 Evidence for Accessing Specialized Support:

According to Zahlan (2025), startups circumvent financial and knowledge constraints by identifying the right ***"sector-specialized incubators and investors."*** A founder from the RZIN case study confirmed the benefit, stating that collaboration with established healthcare entities is **"advantageous because they provide access to essential resources... they had teams that could help us do that without expanding my staff"** (Zahlan, 2025, p. 10). For an AI-HR startup, this likely means identifying HR tech vendors that have put in place other startup programs or grants aimed at workforce innovation.

1.4.3 Building Cross-Functional Teams and Ad-Hoc Governance

To bridge expertise gaps without making new hires, startups embed AI responsibility into the operations of cross-functional teams. One popular model is a founding team that consists of domain science, business expertise and AI/technology expertise. For ongoing governance, they could set up lightweight, ad-hoc committees consisting of representatives from technical, HR and legal functions to monitor AI projects, taking in multiple viewpoints without adding too much bureaucracy.

1.4.4 Utilizing Cost-Effective, Off-the-Shelf and "Good Enough" AI Solutions

Startups prioritize practicality and speed. They leverage SaaS platforms, open-source tools and modular AI services that solve very targeted use cases (such as e.g. a standalone recruitment analytics tool). Adopting a “Good Enough” Philosophy by utilizing skills taxonomies from outside or even working from initially less-than-perfect skill data like employee self-assessments data to launch more quickly rather than waiting to craft perfect proprietary solutions.

1.4.5 Securing Non-Dilutive Funding and De-risking Development

To monetize AI without throwing away equity, startups spend a lot of time seeking non-dilutive funding: government grants, innovation prizes and research fellowships. It enables critical early-stage capital to de-risk development, prototype and prove technological concepts before seeking larger venture investment.

1.4.6 Fostering a Human-Centric Culture and Transparent Communication

Considering trusting a critical resource, startups rely on transparent communication to support change. AI in a supporting role, its limits and reasons for its adoption help to reduce employee concern. Consequently, many startups adopt a hybrid HR model, where AI supports initial process while final decision remains human authority over final outcomes.

1.5 Theoretical and Conceptual Implications

The adaptive behaviors of DeepTech startups to adopt AI-based HR under significant resource constraints are not only pragmatic solutions but also represent a rich context for testing and advancing extant management theories. Empirical evidence strongly supports ***RBV (Resource-Based View)*** and vividly expresses in the mechanics images the ***DCT (Dynamic Capabilities Theory)*** and codesign ***Lean Startup Methodology.***

1.5.1 Resource-Based View (RBV): From Ownership to Orchestration

The classical RBV focuses on obtaining VRIN resources (valuable, rare, inimitable and non substitutable). Startups demonstrate that in a constricted and dynamic environment, the advantage comes not via ownership but through the ability to orchestrate resources.
AI itself acts as a "meta-resource" that amplifies other assets. For Deeptech startups, this shift VRIN resources to intangibles such as social relationships that enable collaboration, drives human capacities within teams and organizational culture build on trust. When firms rely on external resources (SaaS tools, partner data, grant funding) or data, competitive advantages arise from the ability to integrate and manage resources effectively.

1.5.2 Dynamic Capabilities Theory (DCT): The Engine of Adaptive Strategy

The life of the startup itself evidences dynamic capabilities – sensing, seizing and transforming.

- ***Sensing:*** Using AI and BI tools to sense talent trends, skill gaps and employee sentiment. The "Diverse founding team, which offers a combination of skills (Domain, Business and AI)" is identified as a VRIN asset. This resource can make the overall adoption process possible (Zahlan 2025).
- ***Seizing:*** Phased pilots and 'good-enough' solutions are implemented to rapidly leverage identified potential.
- ***Teaching AI/Reconfiguring:*** To reconfigure into an adaptive-human resource, skill matching the challenges. Stratified technology maturity model. The staged approach to the digital maturity model is a systematic corridor of change.

1.5.3 Lean Startup Theory: Principle of "Good Enough" and Iterative Learning

This Lean Startup cycle of Build-Measure-Learn is rampant throughout the book. The MVP, it is the "good enough" pilot AI tool. Lessons learned are validating the pilot in terms of its effect on hiring speed or retention. The overall phased rollout process is a set of iterative loops, where each loop feeds into the next. This emphasis on agility, experimentation and learning from MVP is the operational expression of surviving under constraints.

Summary and Transition

This viewpoint demonstrates that AI enabled HR is more than just a technology purchase for resource-constrained DeepTech startups, but an exercise in strategic creativity. Through adaptive behavior like ecosystem leverage and flexible organizational structure, careful tool selection and open communication despite operation with limited resources. In doing so, they turn AI from a potential cost center into a “force multiplier” and “meta-resource,” which makes it possible to multiply their constrained resources in human and capital terms.

The introduced theorems are theoretically consistent; these observation strategies align with an orchestration focused RBV and purposeful use of capabilities and lean learning practices. This combination allows startups to transform limitations into a flexible and adaptive approach to manage human capital.

2. To Assess How AI Contributes to Sustaining Innovation Capacity in DeepTech Ventures

Innovation plays a vital role in survivable DeepTech ventures. Especially as their business models are focused on moving scientific research into real product or service. However, this process is not so smooth. As analyzed in task 1, it illustrates that long development timelines and substantial capital needs already pose major challenges. These challenges are much compounded by limited access to cross disciplinary skills and uncertainty linked to emerging technology.

Under this challenging condition, AI does not appear as a mere operating instrument but as a system enabler and capability multiplier. Strategically, AI architecturally keeps open innovation capacity by carrying on a self-sustaining process that cancels out the typical limits in funding, humans and info binding DeepTech ventures.

Beside its isolated applications, AI’s main value always lies in its role as a general-purpose technology influencing innovation process. Through the transformation of data into strategic capital and the interrogation of feedback loop in R&D. AI always support in learning and reinforcement of a cycle of faster discovery, improved prediction and strong innovation performance (Feng et al., 2025).

Furthermore, AI is the common thread across scientific, engineering and business domains that enables the convergence of information that is necessary for breakthrough innovation. In the process, it solves the chronic expertise of bottlenecks that under-capitalized startups suffer.

At the highest strategic level, AI imparts agility and accuracy to decision making processes that can also operationalize strategic foresight—the capacity of aligning technological capabilities with new market openings (Capatina et al., 2024). With predictive analytics and scenario modeling, AI helps startups de-risk innovation, optimize scarce capital and talent, and make data-driven decisions that extend their competitive runway.

This analysis suggests that AI not only supports innovation but plays an active role in making robust and adaptive environments. Driving R&D acceleration, enhance collaboration, data driven foresight, contentious learning, AI forms the foundation of DeepTech ventures long term competitive advantage. The bellow section will describe how this mechanism turns innovation capacity into a strategic asset.

2.1 Defining Innovation Capacity in DeepTech Ventures

Innovation capacity can be understood by the ability to generate and apply novel ideas, technologies or discoveries. In DeepTech startups, it represents a dynamic capability that supports the long-term transformation of scientific research into marketable or technologically advanced products and services (Kask, J., & Linton, G. 2025). However, this capability is chronologically affected by a triadic set of ecosystem challenges that jointly limit long-term innovative performance.

- ***Long R&D Cycles & High Cost:*** The road between the laboratory and productization is "neither direct nor short" (Pacher et al., 2025, p.1), sometimes lasting a decade or longer. The long development process and the high capital requirements for prototypes and testing intensify financial constraints, creating a extended capital drain that hinders process across the valley of death and pressure to venture timelines and allocations (Kask, J., & Linton, G. 2025).
- ***Scarce Interdisciplinary Experts:*** The intersection of advanced scientific fields that is the hallmark of DeepTech requires a combination of rarely found deep technical expertise, business development prowess and strategic as well as market acumen. Such "T-shaped" professionals are in very short supply - the human capital constraint, with far-reaching bottlenecks not only for technical implementation, but more importantly knowledge of creation and integration. This scarceness hinders the synthesis of distinct knowledge areas which is fundamental for disruptive innovation (Capatina et al., 2024; Pacher et al., 2025).
- ***Technological Uncertainty & Limited Data:*** DeepTech ventures operate in a "volatile, uncertain, complex and ambiguous (VUCA) environment" where basic technologies are often untested on a scale that matters and market trends are uncertain (Capatina et al., 2024, p 2). This is the combination of technological and knowledge constraint, as the absence of historical data, established benchmarks and predictable development pathways makes it incredibly hard to de-risk R&D decisions, forecast timelines effectively and garner conviction from stakeholders. A key obstacle however is a simple "disconnect between R&D efforts and general market understanding," which means the two parts are often completely isolated, creating an often-insurmountable "gap between DeepTech startups' sound technological solutions and lack of marketing skills" (Capatina et al., 2024).

Thesis Statement: This section argues that Artificial Intelligence serves as a 'capability amplifier', directly addressing these constraints to sustain and even accelerate innovation capacity where it is most vulnerable. AI helps DeepTech ventures sustain and enhance innovation. It coordinates rare resources, scales human capital and enable teams efficiently while predictive insight s helps mitigate risks in R&D. These tools, details bellow, creates a cycle of learning and adaptability and reinforcing the ventures competitive advantage.

2.2 AI as a Driver of Knowledge Creation and R&D Efficiency

Artificial Intelligence (AI) is revolutionizing the scientific method for DeepTech start-ups by systematically compressing time and cost to discovery & experiment. This shift is not just about automation but rather envisions AI as a cognitive partner for collaboration in the R&D phase that increases both the volume and radicalness of innovation (Feng et al., 2025).
As identified by Feng et al. (2025), AI is a two-way process fostering the generation of new knowledge and facilitating the reuse of previous knowledge. This dual process directly enhances innovation of a venture, especially under financial and knowledge constraints. The main mechanisms by which AI accomplishes this are unpacked in the subsequent subsections:

2.2.1 Accelerated Literature Review and Hypothesis Generation

The first phase of any R&D project — understanding and mapping the science and suggesting hypothesis — becomes significantly accelerated with AI. NLP and transformer models advance in NLP and transformer-based models like BERT/GPT can systematically extract information from large unstructured text datasets, such as scientific publications, technical documentation or evidence (Rodrigues et al., 2025).
Services like Elicit, Semantic Scholar and LLMs such as ChatGPT now serve as force multipliers for small research shops by "elevating summaries over thousands of pages," pulling out key nuggets in mere seconds – those previously were reported to be a painful undertaking (Budige, R. R. 2025).

For example, a quantum computing startup might use AI to scour chemistry and materials science databases in search of overlooked compounds that increase the stability of qubits. The AI augmented cross-domain knowledge synthesis allows start-ups to get a jump ahead of the scientific frontier in R&D, instead of reinventing the wheel — directly benefiting an enhanced knowledge creation channel of innovation.

2.2.2 Predictive Modelling for Experimental Prioritization

For sectors like biotech and advanced materials, laboratory experiments are ludicrously resource intensive. AI is a predictive filter, providing predictions on the outcome of complex biological or chemical processes to prioritize which experiments need real-world testing.

AI and ML are used in such “multivariable, nonlinear and noisy systems” as algal biorefineries as “data-driven approach to replace complex mechanistic models,” thus obtaining highly accurate predictions of experimental results (Pusuluru et al., 2026, p.2).
For example, a biotech start-up could use AI tools such as AlphaFold to predict protein structures nearly as accurately as a lab can. This screens many thousands of potential compounds in silico and dramatically decreases the number of wet-lab experiments that need to be performed. The outcome is sensational increase in experimental throughput and cost—drastically cutting down financial and human resource constraints without losing the innovative tide.

2.2.2.1 Accelerated Literature Review & Hypothesis Generation

AI has condensed the basic, R&D “prep work” that needs to be done on any project, for example understanding what’s happening scientifically in a field including forming new hypothesis. Advanced NLP and transformer models with BERT and GPT are capable of systematically analyzing huge repositories of unstructured data, for instance research papers, technical reports or patent documents toward uncovering hidden themes and correlations (Rodrigues et al., 2025). In short, tools like Elicit or Semantic Scholar are force multipliers for small teams: they "summarize big, long technical reports" and "get that insight out to me in a second," which is normally a "big headache" of manual processing (Budige, R. R. 2025, p.12-13). For example, a quantum computing setup could be using AI to scan chemistry and material science databases to identify missed compounds that improve qubit stability. By supporting cross domain knowledge integration, AI allows R&D to begin closer to scientific frontier and directly supporting knowledge creation.

2.2.2.2 Generative Design & In-silico Testing

Physical prototyping is an important factor in the long development cycles and high costs. AI driven generative design and digital twin simulation significantly transform this process. Engineers established design and criteria. AI system evaluates and produces thousands of optimized design options through simulation. As, Hölsä et al. (2025) argue that these physics-based simulations can be used to inform AI systems across the product lifecycle and enabled advanced machine learning optimization for more complex multi objective problems. (pp. 83, 103). This approach allows startups, especially robotics startups, to explore and simulate high performance, light weight components before creating any physical prototypes and lowering development cost significantly.

2.2.2.3 Predictive Modelling for Wet-Lab Replacements

In biotechnology or advanced materials science, lab work is notoriously costly and slow. AI acts as a predictive filter, analyzing potential biological or chemical interactions and prioritizing those most worth testing in the lab. This is important for “multivariable, nonlinear and noisy systems” common in DeepTech domains such as algal cultivation-based biorefineries in which AI serves as a “data-driven surrogate to complex mechanistic models” (Pusuluru et al., 2026, p. 2). For example, models like AlphaFold can accurately predict protein structures, which allow startups to screen thousands of potential drug compounds computationally. this reduces the need for costly wet lab ‘trial and error’ to identify promising candidate drugs for further development. This approach accelerates the R&D timeline and makes the most of the limited lab resources and expert time. That's makes both financial and human capital constraints easy.

Link to task 1: Cloud-based AI to simulation also bypasses the requirement for multi-million-dollar lab equipment, enabling lean DeepTech teams that were historically only available at large corporations.

2.3 AI and Cross-Disciplinary Collaboration and Knowledge Integration

AI is bridging with some advanced fields like gene editing, synthetic biology and drug discovery, breaking silos that limit knowledge sharing. By using tools like AI powered knowledge graphs, startups can connect insight across disciplines, find out hidden patterns, and help to make better decisions. This reduces the dependence on source interdisciplinary experts and allows the small teams to innovate effectively even with small human resources.

2.3.1 Knowledge Graphs for Mapping Interdisciplinary Landscapes

The AI powered dynamic knowledge graphs are a central enabler for this integration. Unlike traditional databases, such semantic networks constantly evolve due to learning and linking data, concepts and methods across research areas (e.g. molecular biology, semiconductor physics or machine learning).

For instance, a neurotechnology startup could use a knowledge graph to link patterns of neural signals (neuroscience) with sensitivity of sensor materials (materials science) and computational load for algorithms (computer science); in turn helping team members discover dependencies and reason about design trade-offs. This mapping demonstrates latent connections and novel trajectories that are often obscured by the strictures of discipline, thus augmenting exploratory power as per innovations.

Link to Task 1: By connecting and contextualizing knowledge across different fields, AI knowledge graphs enable interdisciplinary collaboration without relying on rare, all in one expert. In doing so, they help ease human capital constraints and support continued innovation even when access to hybrid talent is limited.

2.3.2 AI-Powered Upskilling and Personalized Learning

In addition to linking existing knowledge, AI builds interdisciplinary team capability. It can detect individual skill gaps and recommended tailored learning paths. Which helping highly specialized workers grow into a broader, T-shape contributor. (Katona, J., & Gyonyoru, K. I. K.2025). For example, a materials scientist could be provided with a customized module on machine learning for experimental optimization and work seamlessly with data scientists.

Result: This ongoing, AI-catalyzed skill enhancement begets a virtuous innovation cycle—one where the skill set of human capital adapts in real time with technology. By institutionalizing workforce adaptability as a sort of an infrastructural capability, AI enables the survival of long-term innovation capacity in resource-poor DeepTech ecosystems.

2.3.3 NLP for Democratizing Access to Unstructured Knowledge

In DeepTech companies, vital knowledge is frequently stuck in unstructured sources: research papers, lab notebooks etc. These silos of information compound the human capital constraint, with highly skilled practitioners unable to reach down to access the foundational work in other fields. Natural Language Processing (NLP) is a transformative method that can help transform unstructured text into structured and actionable knowledge patterns.

Advanced Tools for Knowledge Extraction and Integration

- ***Deep Text Mining and Semantic Analysis:*** Transformer-based NLP models (e.g., BERT, GPT) semantically analyzed to deduce concepts, relations and implications across-multidiscipline. For instance, a materials science article may be cited in physics research.
- ***Automated Entity Recognition and Relationship Mapping:*** Extracting the entities with Named Entity Recognition (NER), NLP identifies and classifies chemical compounds, biological processes and algorithms from sentential or multi-sentential information contained in relevant datasets showing a map of their interactional flow amongst themselves discovers hidden connections (Rodrigues et al. 2025).

- ***Cross-Disciplinary Summarization and Insight Generation:*** Generative NLP models generate summary of technical documents, transfiguring complex domain-specific knowledge into approachable insights for collaboration between interdisciplinary collaboration.

2.3.4 Tangible Outcomes for Innovation Capacity

- ***Accelerated Onboarding and Context Sharing:*** New team members can quickly understand the years of research, reducing knowledge acquisition from months to days.
- ***Proactive Identification of Convergent Opportunities:*** The NLP system proactively informs teams about likely advances through scanning internal and external publications, enabling unconventional uses.
- ***Enhanced Problem-Solving Through Knowledge Recombination:*** Teams can strategically--use and recombine existing knowledge that is scattered across disciplinary silos, unlocking solutions (Feng et al., 2025).
- ***Preservation of Institutional Memory:*** NLP enables the team to retain its learnings from insights and failures even as people move on, reducing knowledge loss.

Link to Task 1: AI is a force multiplier that digitally enhances collaboration, alleviating human and knowledge limitations by allowing small interdisciplinary teams to sustain and integrated innovative R&D front.

Link to Task 2: NLP-driven knowledge integration strengthens the venture's capacity to innovate continuously, a critical component forming of sustained DeepTech innovation.

2.4 AI driven Decision-Making and Strategic Resource Allocation

Building of AI role on knowledge integration and cross disciplinary collaboration (in Section 2.3), it also increases innovative capacity through data at the level of strategic resource allocation and decision-making. For resource-constrained startups, AI converts intuition-driven guessing to systematic, portfolio-guided optimization of strategic decisions, so every dollar and hour is spent on the most promising innovation pathways. In deep tech, which capital starved and misspending could compromise a venture.

2.4.1 Predictive Analytics for De-risking R&D Portfolios

The predictive power of AI enables startups to foresee technical/operational/market risks before they escalate into a major problem, Machine learning algorithms are fed with internal

R&D data as well as external market signals, predicting outcomes with great precision. (Mahabub et al. 2025) AI is capable of "reducing the average time it takes to make critical business decisions by 40%" and improve "the accuracy of predicting corporate trends by 32%" (p.328). For example, one can now imagine a biotech startup being able to predict which drug candidates are most likely to succeed (based on the molecular and historical trial information available) and create an R&D portfolio that is weight for risk of technical success and dead-ending costs.

2.4.2 Dynamic Resource Orchestration and Project Prioritization

It goes beyond prediction to allow continuous resource optimization by intelligent prioritization engines for projects. These platforms assess many different dimensions—technical feasibility, investment requirement, market potential, IP environment and its fit with strategic priorities—which results in objective and data-supported project rankings. This creates additional ways to think and act effectively, but it should not think of as a conclusion. The AI dynamically updates these priorities over time when new data arises (maintaining strategic agility). (Capatina et al. 2024) point out that this represents strategic foresight in practice and the conversion of technological capability to market relevance.

2.4.3 Enhancing Strategic Foresight Through Environmental Scanning

AI systems powerfully enhance a firm's capacity to sense and respond to external changes—a basic ingredient of dynamic capabilities. By continuously sifting through a wide range of sources—ranging from scientific literature, patent filings and regulatory postings to market reports. AI can identify emerging threats and opportunities well in advance of the appearance that would typically arrive via traditional routes. This forward-looking environmental scanning covers the "strategic constraint" of technological uncertainty found by (Capatina et al. 2024), giving advance warning of market needs, competition or regulation trends that would affect R&D trajectories. The implications of the resulting intelligence are such that ventures can modulate their innovative strategies preemptively, remaining competitive within fast-rate technological spaces – as opposed to reacting to changes in technology.

2.4.4 The Hybrid Leadership Model: Augmenting Human Judgment

AI does not substitute human based decision-making, rather it complements it by what (Mahabub et al. 2025) apply the term "hybrid leadership model," where "AI gives data-based tips. But CEOs employ critical thinking in making final decisions" (p. 330). This framework proves particularly useful in DeepTech domains where machine learning and qualitative scientific judgment are needed. While the AI system takes in massive amounts of data to recognize patterns and draw conclusions, human leaders contribute contextual knowledge, moral judgment and strategic insight. So, combining human and conceptual judgement leads to more robust resource allocation decisions.

2.4.5 Project Prioritization Engines: Systematic Resource Allocation

Project selection in startups typically depends on founder intuition and partial information. AI Powered Project Prioritization Engines change this dynamic by establishing a systematic, multi-factor evaluation framework for ongoing evaluation and ranking of innovation initiatives. Based on multiple data sources, including internal R&D project data and results of experiments, as well as external market data and growth trends, patent databases, scientific publications and projected resources availability and timeline constraints, these advanced algorithms consolidate different inputs into objective scores for projects based on pre-determined weights of the factors technical feasibility (internal vs competitors ecosystem state-of-the-art), market potential (current vs future size / growth) IP landscape competitiveness (significance of the technological advance - patent-covered inventions not just publication), R&D investment needed.

For example, a quantum computing startup could employ such a system to evaluate multiple research paths. By analyzing scientific trends, patent signals and resource constraints, the system ranks options according to strategic priorities, grounding decisions in evidence rather than institutions.

2.4.6 De-risking Through Predictive Analytics: Proactive Risk Mitigation

AI’s ability to anticipate is arguably the most critical tool of all for navigating risk in DeepTech. Machine learning Model can discover potential breaking points on so many facets before a break occurs. Research by (Mahabub et al. (2025), suggests that AI based decisions drive "a reduction of 40% in the average time spent making critical business decisions and increases precision in predicting company trends by 32%".

Applications include predicting technical failures, where AI detects patterns in empirical data and signals where projects are likely to encounter fundamental scientific limits and assessing supply chain risk assessment, such as monitoring global supplier networks and materials availability to anticipate disruptions. For instance, a semiconductor startup working on next generation of gallium nitride chips could use AI to foresee which fabrication techniques were more at risk of failing at scale, allowing them to pivot before it’s too late and they hit expensive dead-ends. This risk management yields immediate conservation of limited resources, energy and momentum rather than recovery from catastrophic loss through loss aversion.

2.4.7 Dynamic Capabilities Framework: Institutionalizing Strategic Adaptation

The infusion of AI in decision-making processes improves an organization's dynamic capabilities - its ability to sense, seize and transform when it's shifting environment. This serves as a foundational structure for maintaining the ability to innovate:

Sensing Capability Enhancement: AI based solutions use Natural Language Processing (NLP) to monitor global research, patent and competitive activity. This automated environmental scanning contributes to discovering new opportunities and threats that cannot be done effectively by human teams which help answer the call (Capatina et al. 2024) point to the necessity of the strategic foresight in DeepTech projects.

Seizing Mechanism Optimization: Once opportunities are unearthed, prioritization engines with AI capabilities make quick decisions on where to place resources in the most promising acts of good. This flexibility allows firms to act quickly on new opportunities while keeping multiple innovation options open. AI helps to allocate limited resources to projects that combine strong technical viability, market promise and strategic revenge.

Transforming through Institutional Learning: When projects fail or underperform, the data from that failure gets fed back into those AI systems, so they are better next time around at making predictions and prioritization. This process reflects what (Feng et al. 2025) is the process of "data assetization" in which accumulates learning through repeated experimentation, enables firms to adapt without locking into risky, unchangeable strategies.

This AI-infused approach to dynamic capabilities represents a significant departure in how DeepTech ventures orchestrate innovation. By utilizing data to guide the decision of which paths to explore or abandon on the basis of potential payoffs and also how best to utilize limited resources, AI transforms (non-human) decision-making from a purely reactive activity into an inherently future-oriented one that can in principle optimize capacity for sustaining innovation despite uncertainty about technology and a lack of appropriate incentives. By integrating AI's data-driven insights with human critical judgement that speaks a new model, a "hybrid leadership model;" whereby the human and machine expertise together would be able to take better long-lasting decisions (Mahabub et al., 2025).

2.5 AI for Continuous Learning and Adaptive Innovation

Sustainable innovation capacity is a result of an organization learning faster than market changes. AI in continual learning for a DeepTech venture, from isolated pockets of success and failure to institutional capabilities. This constitutes the final achievement in AI's history as a capability amplifier: this is what Sinap (2026) defines "an innovation meets product system where outcomes keep evolving via data every time you use it". By programmatically recording knowledge, tracking results and shaping team growth, AI keeps the company's human and machine capabilities in sync with what is expected of them by the innovation landscape.

2.5.1 Personalized Upskilling: Building Adaptive Human Capital

For the self-employed or existing employees, there is an urgent need to develop personalized upskilling strategies as individuals are unlikely to be viewed as a mere appendage of a future robot system and so will have a more active role in directing their skill development.
The constant development of DeepTech areas leads to ongoing skill obsolescence, exacerbating the already prevailing human capital limitation identified in Task 1. AI-based learning platforms provide a solution to this by detailed, individualized development plans for each team member based on performance strengths and weaknesses. Based on adaptive learning models (Katona, J., & Gyonyoru, K. I. K. 2025), these systems process the knowledge gaps of everyone, as well as their learning patterns and those ministry project specific requirements to deliver targeted upskilling.
When a materials scientist moves on to quantum-resistant cryptography, for example, AI recognizes that knowledge is needed for lattice-based algorithms and assembles the corresponding resources and exercises. This is a way of turning the traditional one-size-fits-all approach to professional development into a precision instrument for building interdisciplinary T-shaped professionals. It builds adaptive human capital that spans specialisms and preserves disruptive technology and business change.

2.5.2 Institutionalizing Failure: Transforming Setbacks into Strategic Assets

In traditional R&D, failed experiments are typically sunk costs with little organizational learning. AI changes that this systematic evolution by implementing structured feedback loops but where negative results are optimized for maximum value. Every failed experiment, flawed prototype or abandoned research pathway creates structured data that informs the venture's AI models, over time compiling what (Feng et al. 2025), refers to this adaptation and transformation as service-data assetization i.e., making data an asset from which services are created.

The protocols are standardized and contain both quantitative results and specific contexts such as experimental conditions, environmental variables or comments made by the researchers. The failure patterns are then analyzed by machine learning algorithms, which can identify root causes, correlations and early warnings that could evade human attention. For instance, if a biopharma startup has invested in a drug candidate, which had to be abandoned due to its toxic nature, the recorded data can then be used to enhance predictive accuracy for future candidates. This becomes a virtuous cycle in which every failure contributes to the learning of an organization, reduces the cost of trying again and normalizes cautiously taking risks.

2.5.3 Dynamic Strategy Reformation: Pivoting with Precision

The capacity for a DeepTech venture to pivot or reverse strategy based on new feedback without existential risk is the fundamental gauge of innovative power. AI can do this by constantly validating and adjusting strategies. By continuously contrasting the real against the projected along several dimensions — technical milestones, marketplace feedback, competitive equilibria — AI systems give early-warning signals of strategic drift and propose evidence-driven alternatives.

This ability to do is essentially operationalize the 'Transforming' part of dynamic capabilities. If external conditions change or internal tests show the limits of intuition, then the experiment shifts not by pivoting toward intuition alone but rather by reconfiguring based on what has been already learned and encoded in AI systems. Abandoned projects feed the next strategic initiatives; their also-ran status doesn't mean that they are not part of the evolving knowledge of technology and market.

2.5.4 Personalized Upskilling Platforms: Building Adaptive Human Capital

The fast evolution of DeepTech disciplines leads to a constant skill of obsolescence and an increased human capital chokehold described in Task 1. AI-powered learning platforms directly challenge this by through individual, dynamic development paths for all users. These platforms use advanced evaluation algorithms to align current capabilities with developing project demands and market trends to discover crucial skills gaps on-the-fly.

It works by dynamically analyzing several data streams: individual performance metrics, project requirements, research trends and competitive analysis. Leveraging adaptive learning models (Katona, J., & Gyonyoru, K. I. K.2025), these platforms customized an individual's learning narrative by administering specifically chosen micro-courses, research papers and technical documentation and applied exercises to bridge gaps. One example is when a quantum computing startup pivots to work on error correction techniques, the AI will immediately surface which team members require a more in-depth understanding of topological quantum codes and share tailored resources to plug that gap quickly.

This takes the traditional, one-size-fits all model behind professional development and turns it into a precision instrument for creating the interdisciplinary T-shaped specialists DeepTech innovation requires. The result goes beyond the individual skills accumulation for an organizational ability of continuous human capital growth, leaving a team of expertise that will keep pace with technology evolution.

2.5.5 Institutionalizing Failure via Feedback Loops: Transforming Setbacks into Strategic Assets

In conventional R&D, failed experiments are sunk cost which rarely contributes to organizational learning. AI changes this by creating structured feedback loops that extract insights from every negative result. Failed experiments, prototypes or cast-off research paths generate data that feed AI models, gradually achieving what (Feng et al. 2025) term "data assetization"—the process of systematically transforming raw data into a strategic asset.
Recognition of failure with standardized protocols, including matric conditions and observations-machine learning, can detect correlation, root cause and early warning signs that humans might miss. For example, a biopharma startup whose drug accelerates fills due toxicity can use this data to better predict risk in future compounds, flagging potential issues earlier in development.

Link to Task 1: This involves overcoming knowledge and organizational constraints by creating an adaptive, self-learning organization capable of evolving its own capabilities throughout the long R&D cycle.

2.6 Measuring the Impact of AI on Innovation Capacity

The disruptive power of AI on innovation capability can be measured as a mix of quantitative efficiency improvements and qualitative growth in strategic agility. Beyond traditional R&D, a full measurement framework would have to consider both the short-term efficiency gains and long-term adaptive capabilities made possible by AI extending DeepTech activities. This multidimensional perspective permits a more comprehensive consideration of how AI supports and augments innovation capacity on several organizational dimensions.

Table: Comprehensive Metrics for Assessing AI's Impact on Innovation Capacity

Category	Metric	How it Demonstrates Sustained Innovation
Quantitative Metrics	R&D Velocity (experiments/week)	Increased output with same resources, demonstrating enhanced efficiency in knowledge generation
	Idea Throughput (viable concepts/quarter)	Enhanced creativity and screening capabilities, showing improved innovation pipeline health
	Reduction in Cost per Prototype	Direct efficiency gain from AI simulations and generative design
	Patent Citations & Technological Breadth	Quality and influence of innovation output, reflecting knowledge creation and reuse (Feng et al., 2025)
	AI driven Innovation Efficiency Ratio	Patents or publications per R&D dollar, measuring resource optimization
Qualitative Metrics	Cross-Functional Collaboration Score	Improved knowledge integration and breaking down of disciplinary silos
	Strategic Pivot Speed	Enhanced dynamic capability and organizational responsiveness to change
	Employee Skill Diversification Index	Growth of internal human capital and adaptive learning capabilities
	Failure-to-Learning Conversion Rate	Effectiveness in institutionalizing lessons from setbacks
	Ecosystem Connectivity Index	Strength and diversity of external knowledge networks and partnerships

2.6.1 Quantitative Efficiency Metrics: Measuring the Direct Impact

This data shows that AI accelerates innovation by scaling resources and increasing R&D velocity. This number is directly proportional to how quickly the venture can iterate despite being resource constrained. No Less Important, the Reduction in Cost per Prototype The economic influence of AI driven simulations and generative design can also be measured with transformed business operations that tackle financial threats head on.
Innovation quality of the output can be captured by Patent Citations and Technological Breadth, considering the capability of the firm to create and reuse knowledge as discussed under (Feng et al. 2025). An upward trajectory in each of these metrics suggests that AI innovation is becoming faster, but also more impactful and varied—than ever before.

2.6.2 Qualitative Adaptive Metrics: Capturing Strategic Transformation

The qualitative measures express the less tangible, yet important ways AI support by increasing organizational capabilities. The Cross-Functional Collaboration Score, via organizational network analysis and team surveys—is an indicates how AI acts as the “connective tissue” to dissolve knowledge silos across specialized areas.
Strategic Pivot Speed tracks how quickly resources are reallocated across projects, reflecting the venture’s flexibility and ability to seize opportunities. Diversification of employee kills shows how AI powered upskills builds versatile cross functional teams, addressing talent shortages. The conversion rate from failure to learning following the idea of "data assetization " (Feng et al., 2025), to improve decisions continuously.

2.7 Theoretical and Practical Implications

The introduction of Artificial Intelligence (AI) as an enhancer in the mission profiles of DeepTech ventures has profound implications for the theoretical understanding and practical management of innovation under conditions of high constraint. Such implications are not limited to short-term tactical enhancements but will go on to challenge the way we think about resource-based considerations and organizational learning in technology-based enterprises.

2.7.1 Resource Orchestration Theory (ROT) Extension

ROT focuses on qualitative description of resource orchestration qualitatively but a dynamical systems method that can extend it to qualitatively model and predict how these mechanisms behave, using activation inhibition or excitation inhabitation systems.

This research represents a significant development of Resource Orchestration Theory in framing AI as a ‘meta-orchestrator’ beyond traditional resource management frameworks. In contrast to traditional methods, which exploit and organize existing resources, the AI entities constantly reshape the quality and capacity of resources dynamically. AI converts raw data into insights, augmented human expertise and dynamically reallocate resources across the organization. The AI re-organizes combination of resources constantly in response to new emergent opportunities and constraints, a process what (Feng et al. (2025) superior resource orchestration leads to higher performance, thus better capability of orchestrating more and/or better resources.

2.7.2 Human Capital Theory (HCT) Advancement

The findings highlight how AI enabled learning and collaboration tools are a game changer for human capital development in DeepTech ventures. Traditional human capital investments offer decreasing returns and a limited scope of scalability, especially in the case of highly specialized knowledge workers. AI powered platforms overcome these limitations by offering high-return, scalable investments in human capital that can catalyst the cultivation of precisely the interdisciplinary talent that will fuel DeepTech innovation. These platforms provide “personalized learning pathways” (Katona, J., & Gyonyoru, K. I. K. 2025) thus allowing teams to build cross functional skills more quickly while maintaining institutional knowledge. This is a profound extension to human capital theory by showing that technological enhancement can very rapidly magnify both the productivity and efficiency of human capital development in knowledge-based environments.

2.7.3 Practical Implications

The results of this analysis provide important strategic recommendations to both DeepTech players, thus revolutionizing the current way of thinking and planning related to AI incorporation in innovation-led companies. For entrepreneurs and investors, in both companies that are developing and applying AI, this should leave no doubt about the fact that money put into AI is essentially not just an operational expense but directly a strategic bet made on the core innovation moat of the venture.

This new way of thinking has a number of important implications for how we think about making strategic decisions:

Strategic Resource Allocations Framework: Leadership must rethink investment in AI through a strategic lens favoring implementations working as force play multipliers for business most scarce resources. This requires a focus on AI solutions that directly speed up R&D by predictive modeling and simulation, that increase the pace at which decisions are made through advanced analytics and that improve the productivity of interdisciplinary teams with intelligent knowledge integration systems. This framework for evaluating such investments should explicitly measure their impact in addressing the underlying constraints identified in Task 1, with a focus on long-term innovation potential rather than short-term cost reduction.

Organizational Transformation for Augmented Intelligence: Success will require the redesign of incentive structures, organizational processes and collaborative frameworks to maximize human-AI synergy. This is an important move beyond simply more of the old automation toward a commitment to intelligence augmentation as a central strategy for interacting with intelligent systems. Startups need to cultivate habitats in which human expertise and AI competences mutually interact by exchanging knowledge dynamically, to generate what (Mahabub et al. 2025) call the "hybrid leadership model" which best combines data-informed insights with human strategic judgment.

Human Capital Development Reimagined: The investment in AI-powered learning platforms and knowledge management systems should be viewed as critical for human capital development, rather than optional training costs. These systems allow continuous and targeted upskilling which is essential in DeepTech sectors where knowledge is outdated quickly and interdisciplinary skills are often scarce.
For investors, the maturity of AI adoption offers a useful tool for evaluating ventures with long-term innovation capacity. Besides assessing the core technology, investment decisions should also consider how effectively AI is used across the innovation process. Technological excellence and AI supported innovation are getting more difficult to separatable.
However, the success of this approach also depends on the wide environment. Academic institutions, policymakers and venture capital mechanisms influence the environment in which DeepTech startups grow. The support of DeepTech startups to apply AI strategically, sustain innovation capacity and remain competitive in the global market.

Transition to Task 3:

While AI broadly increases the ability to innovate within DeepTech startups, its effectiveness ultimately depends on the surrounding ecosystem. Task 3 examines how academia, policymakers and the venture capital shape the conditions under which AI-enables innovation capabilities develop, identifying systematic enablers and barriers that influence sustained competitive advantage.

3. Explore Expert Insights on How External Ecosystem Factors Influence AI–HR Integration and Sustain Innovation Capacity in DeepTech Ventures

Issue of research. Despite the growing use of artificial intelligence in human resource management, there is a lack of empirical research on under the influence of external ecosystem actors how DeepTech startups integrate AI into talent management. Operating in resource constrained and innovation driven environments, these ventures are significantly affected by the support of incubators, investors and policymaker but insufficient attention has been given to how such external influences shape AI-enabled HR practices. This study addresses this gap through a questionnaire-based analysis of practitioner's perspectives.

The object of the research. Examine the influence of external ecosystem actors on the integration of artificial intelligence into human resource management in DeepTech startups and its impact on innovation sustainability.

Goal of research. According to the experts, to explore how external ecosystem actors (incubators, investors and policymakers) influence the integration of Artificial Intelligence (AI) into human resource (HR) management and its impact on innovation sustainability within deep-tech ventures.

The tasks of the research:

1. To examine how external ecosystem actors (incubators, investors and policymakers) influence the integration of artificial intelligence into human resource management in DeepTech ventures.
2. To assess the perceived impact of AI-enabled HR practices on innovation sustainability in DeepTech startups.
3. To identify key challenges related to AI–HR integration under the influence of external ecosystem actors.

Both the quantitative and qualitative research method was chosen by ecosystem actors survey by structured questionnaire form. This method was chosen to dig deeper into the problem. Quantitative research allows us to understand the point of view of experts on given statements and qualitative research allows obtaining various information, broadening the issue and analyzing it in a broader context. A survey is considered one of the most effective qualitative research methods, which provides detailed answers, especially to open questions where there is no boundary. The survey was carried out according to pre-formulated questions and respondents were asked by the same procedure to provide their thoughts and experiences.

3.1.1 Organization of the research

The experts have been chosen according to the activity areas; it was important that experts would be related to human resource management, incubators, investors and policymakers in

DeepTech startups. The information has been looked at on the Internet. After selecting the experts, they were contacted personally. The researcher proposed to the experts, as well as the problem of the research and the goal according to the experts. Experts wanted to stay anonymity but agreed to specify the occupied functions. To keep the anonymity the experts are named anonymous, such as Expert A, Expert B, etc.

The survey was carried out between 2025 October 16 and 2025 November 17. The questionnaire was sent to twelve experts. However, three of the respondents did not provide the answers. In the end, nine experts' opinions are analyzed. Moreover, the accuracy of decision and evaluation is sufficiently high when the number of experts reaches nine, so this number of experts is enough to obtain accurate information.

The questionnaire is structured into four sections, containing a total of ten main questions. Some of these main questions are included sub-questions to gather more detailed information. Four of them are open-ended nature, six closed: on them respondents three questions are asked to evaluate the formulated statements by the assessment scale from 1 to 5 (5 means "strongly agree", 4 – "agree", 3 – "Neutral", 2 – "disagree", 1 – "strongly disagree").

In the first question (closed question), respondents were asked to select their primary role in the deep-tech ecosystem.

In the second question, the size of the organization you represent (closed question), respondents were asked to provide information from the given option about how many years of experience you have in the deep-tech or AI sector.

In the third question (closed question) the size of the organization you represent.

In the fourth question, (open question) provide information about their Country of operation.

In the fifth question (closed question) under this question, there are six sub questions. respondents were asked to evaluate the formulated statements about:

a. Our organization uses AI-based tools for recruitment and talent acquisition.

b. AI is applied to analyse employee performance or engagement data.

c. The HR department leverages data-driven insights from AI for strategic decisions.

d. Employees receive training to effectively use AI-enabled HR systems.

e. The adoption of AI in HR has enhanced fairness, efficiency and transparency.

f. AI adoption aligns closely with our organization's innovation strategy.

In the sixth question (open question) the respondents were asked to provide information about the key barriers your organization faces when integrating AI in HR processes.

In the seventh question (closed question) under this question, there are six sub questions. respondents were asked to evaluate the formulated statements about:

a. Incubators/accelerators provide strategic HR or AI adoption guidance.

b. Investors actively support startups in building AI-driven HR capabilities.

c. Policymakers encourage responsible and ethical AI use in HR.

d. Collaboration among ecosystem actors enhances startups' ability to integrate AI and manage talent.

e. The lack of coordination among ecosystem players creates barriers to AI–HR integration.

f. public funding or regulatory frameworks significantly affect AI–HR integration decisions.

In the eighth question (open question) the respondents were asked to provide their point of view about how ecosystem actors can (e.g., investors, incubators, policymakers) better enable AI–HR integration in deep-tech ventures.

In the nineth question (closed question) under this question, there are five sub questions. respondents were asked to evaluate the formulated statements about:

a. AI–HR integration strengthens our organization's capacity for continuous innovation.

b. AI-driven HR systems help us attract and retain innovative talent.

c. The combination of human creativity and AI tools enhances organizational adaptability.

d. Over-dependence on AI can limit creativity and critical thinking among employees.

e. External ecosystem support contributes to long-term innovation sustainability.

By tenth question (open question) the respondents were asked to provide their perspective on what practices can ensure the sustainable coexistence of AI systems and human talent in deep-tech startups.

The questionnaire was sent by e–mail to the respondents with additional explanations about the questions.

3.1.2. Characteristics of survey respondents

From the experts who were performing in the survey, nine experts were chosen:

- Expert A – Human resource Manager
- Expert B – Startup founder.
- Expert C – Incubator. He is a representative of a startup and supports that startup by providing mentorship, resources and access to funding opportunities to help that grow and scale.
- Expert D – Researcher.
- Expert E – Incubator. He is a representative of a startup and supports that startup by providing fund.
- Expert F – Investor.
- Expert G – Human resource Manager.

- Expert H – Startup founder.
- Expert I – Project Manager.

Since the goal of the research is to figure out how external ecosystem actors (incubators, investors and policymakers) influence the integration of Artificial Intelligence (AI) into human resource (HR) management and its impact on sustainability innovation within deep-tech ventures, the experts above have been chosen from different activity areas. By formulating questions of the survey, the aim was to find out the opinions of experts about the integration of artificial intelligence into human resource management in DeepTech startups and its impact on innovation sustainability.

3.2. Data analysis

First Question: What is your primary role in the deep-tech ecosystem? The results indicate a varied range of professional roles among the respondents within the DeepTech ecosystem. The largest proportion of participants (33.3%) identified as startup founders or managers, reflecting strong representation from individuals directly involved in leading and scaling DeepTech ventures. Incubator representatives made up 22.2% of the sample, while researchers, project managers and investors each accounted for 11.1% of respondents. This distribution is presented in the following Figure.

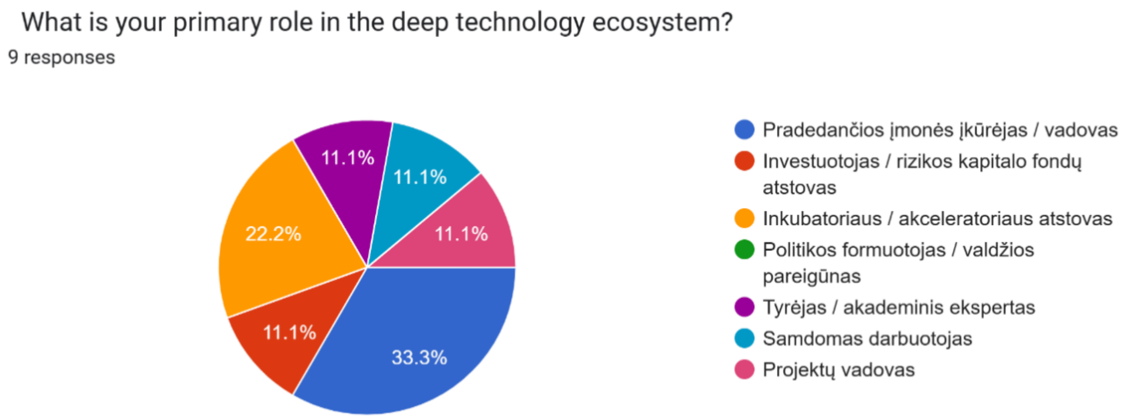

Figure 01: 'Primary role in the deep-tech ecosystem'

In between 11.1%, Expert A respond this answer, and she is working as a HR manager now and she is responsible for hiring employees**.** In between 33.3%, Expert B and H respond this answer and they are working as startups founder. Expert G is working as a HR manager and she is responsible for organizational structure and company policy making**.** In between 22.2%, Expert C and E working as an incubator**.** They are representative of a startup and supports that startups by providing mentorship, resources and access to funding opportunities to help that grow and scale. In between 11.1%, Expert I respond he is a project manager and he is handling DeepTech projects. In between 11.1%, Expert D respond that she is a researcher and she is working as a researcher in DeepTech company. In between 11.1%, Expert F respond that, he is a startup investor.

Second Question: How many years of experience do you have in the deep technology or AI (artificial intelligence) sector?

The findings show a wide range of experience levels among respondents working in the deep technology and AI fields. When we asked them this question, then we found most participants (55.6%) reported having less than two years of experience, indicating a strong presence of relatively new professionals in the sector. In contrast, 11.1% of respondents reported more than ten years of experience, representing a smaller group of highly experienced experts. Additionally, 11.1% of participants indicated having between two and five years of experience, while 22.2% reported six to ten years of professional experience.

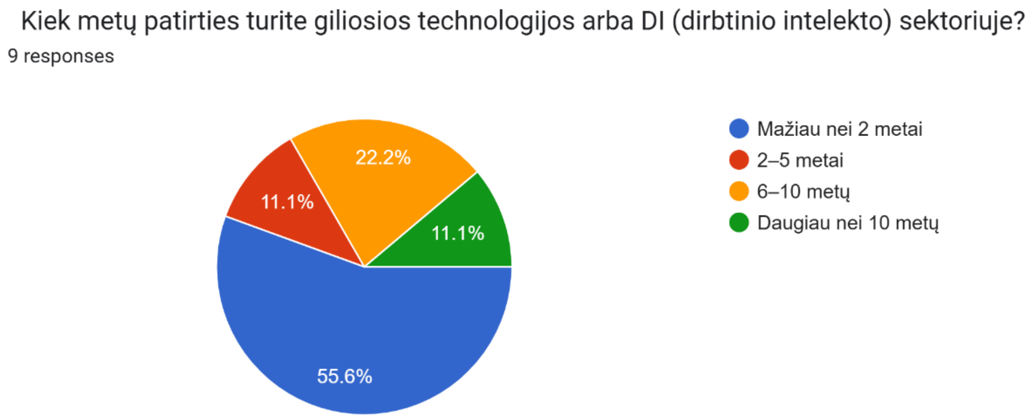

Figure 02: ‘working experience in DeepTech and AI sector’

Third Question: What is the size of the organization you represent?

The responses reveal variation in the organizational sizes represented in the study. When we asked them this question, then we found more than half of the respondents (55.6%) indicated that they work in organizations with over 200 employees, suggesting significant representation from large and established entities within the DeepTech ecosystem. Meanwhile, 22.2% of participants reported working in organizations with between 10 and 50 employees, while the remaining 22.2% represented very small organizations with fewer than 10 employees.

This distribution highlights the presence of both large institutions and early-stage ventures, offering a balanced perspective across different organizational scales within the DeepTech landscape.

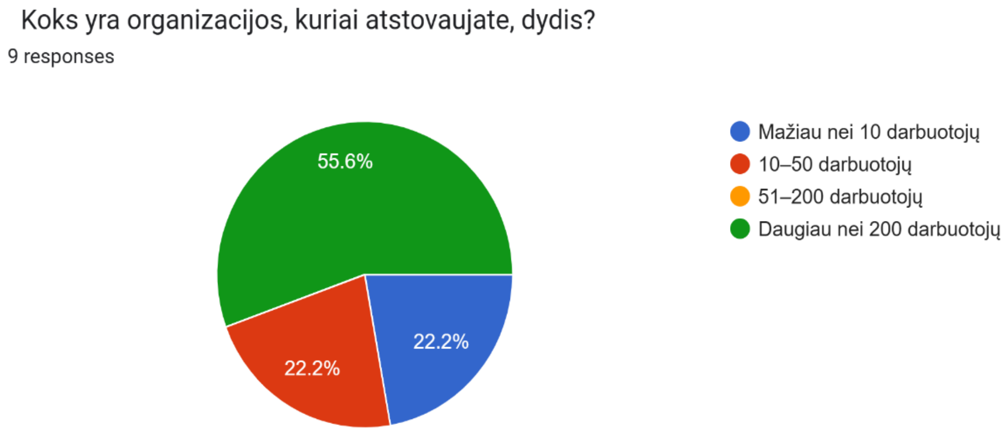

Figure 03: 'size of the organization'

Fourth Question: Country of operation

When we asked them this question, then we found that, the responses indicate that most participants operate primarily in Lithuania. Specifically, 77.78% of respondents reported Lithuania as their main country of operation. A smaller proportion, 11.11%, indicated operating in Spain. Another 11.11% reported conducting activities across multiple countries, namely Spain, Germany and Lithuania.

This distribution suggests a strong concentration of DeepTech activity within Lithuania, while also reflecting a degree of cross-border operational presence among some participants.

Fifth Question: **In this question they were given 6 statements and asked them to indicate how much they agree with the statement.**

a) Our organization uses AI-based tools for employee selection and talent acquisition.

When we asked this question, the responses showed a range of opinions. Specifically, 11.1% of participants disagreed with the statement, while another 11.1% agreed. A larger proportion, 33.3%, strongly agreed and the majority of respondents (55.6%) remained neutral regarding the statement.

This distribution suggests that while some participants hold a clear position, most are undecided or perceive the statement as context dependent, highlighting a diversity of perspectives within the sample.

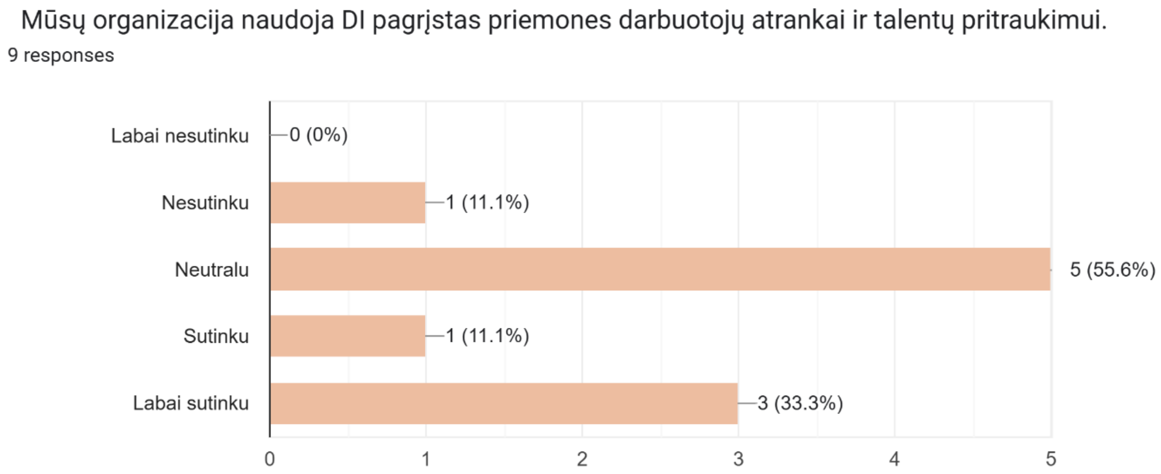

Figure 04: ‘Our organization uses AI-based tools for employee selection and talent acquisition’

b) AI is used to analyse employee performance or engagement data. When we asked this question, respondents expressed varying levels of agreement. Specifically, 11.1% strongly agreed with the statement, 55.6% agreed and 44.4% remained neutral.

This result indicate that most participants recognize the use of AI for analysing employee performance or engagement, while a notable portion remains uncertain or perceives its application as limited within their organizations.

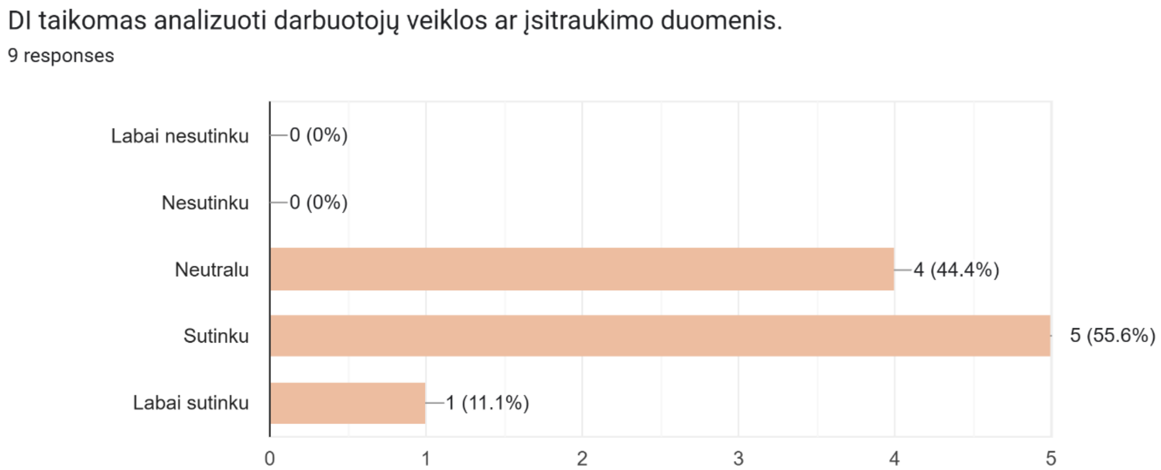

Figure 05: ‘AI is used to analyse employee performance or engagement data’

c) The Human Resources (HR) department is leveraging AI-based data insights to make strategic decisions.

When we asked this question, respondents expressed varied opinions. Specifically, 11.1% strongly disagreed and another 11.1% disagreed with the statement. A further 33.3% remained neutral, while 33.3% agreed and 22.2% strongly agreed.

This result suggests that while a majority of participants recognize some use of AI insights in HR strategic decision making, a considerable portion either remains neutral or perceives limited implementation, indicating variability in AI adoption across organizations.

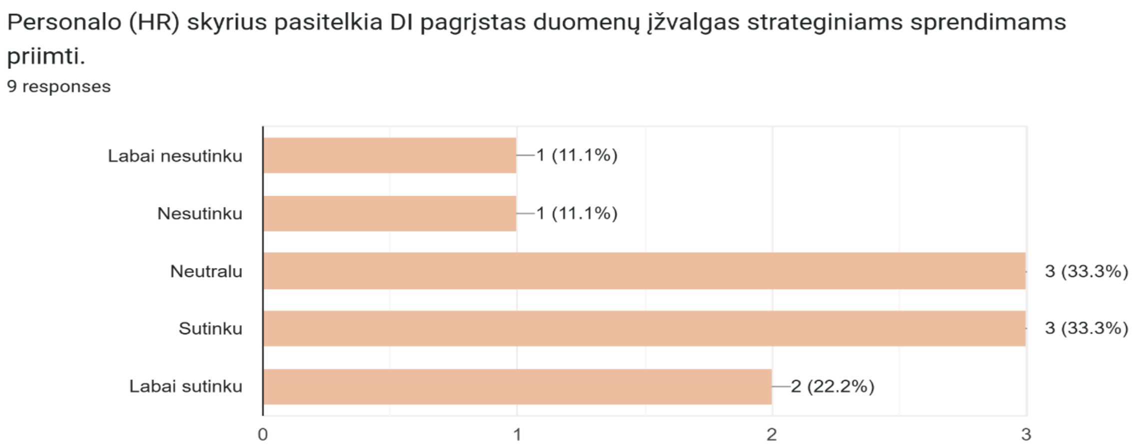

Figure 06: ‘The Human Resources (HR) department is leveraging AI-based data insights to make strategic decisions’

d) Employees receive training on how to effectively use AI-enabled human resources systems.

When we sked this question, respondents showed varied responses. Specifically, 22.2% disagreed with the statement, while 44.4% remained neutral. Additionally, 22.2% agreed and 22.2% strongly agreed.

This finding indicates that while some organizations offer training on AI-enabled HR systems, a considerable portion of employees either do not receive training or consider it insufficient. This highlights potential gaps in AI adoption and workforce readiness across the sampled organizations.

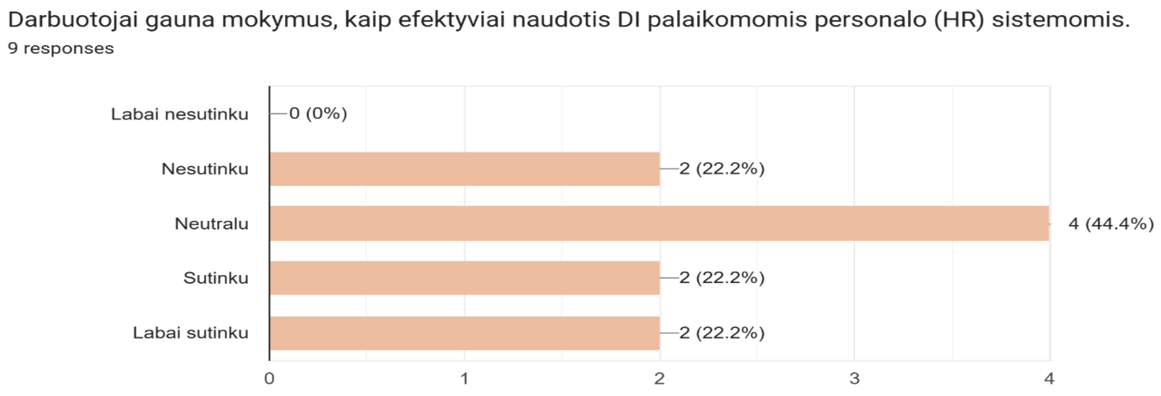

Figure 07: ‘Employees receive training on how to effectively use AI-enabled human resources systems’

e) “Implementing AI in human resources (HR) has increased fairness, efficiency and transparency”

When we asked this question, respondents provided varied perspectives. Specifically, 11.1% strongly disagreed and 22.2% disagreed with the statement, while 33.3% remained neutral. In contrast, 44.4% agreed and 22.2% strongly agreed.

This finding suggests that most participants perceive AI implementation in HR as enhancing fairness, efficiency, and transparency. However, the presence of neutral and dissenting responses indicates that experiences and perceptions of AI’s impact on HR processes can differ across organizations.

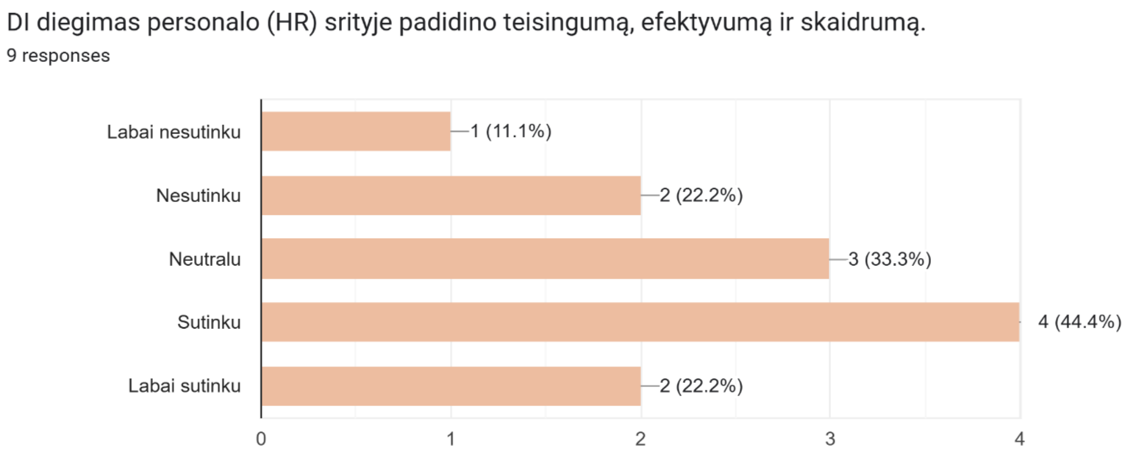

Figure 08: ‘Employees receive training on how to effectively use AI-enabled human resources systems’

f) "The implementation of AI closely aligns with our organization's innovation strategy."

When we asked this question, respondents provided a range of perspectives. Specifically, 33.3% remained neutral, 22.2% agreed and 44.4% strongly agreed with the statement.

This finding suggests that majority of participants perceive AI implementation as closely aligned with their organization's innovation strategy. However, the neutral responses indicate that some participants are uncertain or see the alignment as partial, reflecting differences in how AI initiatives are integrated across organizations.

Figure 09: 'The implementation of AI closely aligns with our organization's innovation strategy'

Sixth Question: "What are the main obstacles your organization faces when implementing AI in human resources (HR) processes?"

This was an open-ended question. When we asked them this question, the respondents are providing answer, which are given bellow:
Expert A- "Data Privacy and Security Concerns, Bias and Fairness, Integration with Legacy System, Employee Resistance, Lack of Skilled Talent, Ethical Consideration, Cost of Implementation, Quality and Accuracy of Data, Change Management"
Expert B- "Searching for new tools to make daily tasks easier"
Expert C- "Knowledge"
Expert D- "The main obstacles include limited data quality, lack of AI expertise among HR staff, high implementation costs, concerns about data privacy and bias and resistance to change from employees and management."
Expert E- "Skills"

Expert F- "The main obstacles are GDPR and compliance constraints, integration with global HR systems and ensuring ethical, bias-free use of AI while maintaining employee trust." Expert G- "I am not the suitable person to talk about the HR, but in the department, we still believe the selection should be made by human, while search could be automated, by using targeted groups for potential candidates, etc"

Expert H- "Compliance with information security and fair use standards" Rest one of them did not provide any response. These findings suggest that organizations face a combination of technical, ethical, regulatory and human-related challenges when adopting AI in HR. Addressing these obstacles requires not only technological solutions but also workforce training, change management and careful consideration of ethical and compliance issues.

Seventh Question: In this question they were given 6 statements and asked them to indicate how much they agree with the statement.

a) "Incubators/accelerators provide strategic guidance on HR or AI implementation." When we asked this question, respondents provided varied responses. Specifically, 11.1% disagreed, 33.3% remained neutral, and 55.6% agreed.

These results indicate that most participants perceive incubators and accelerators as offering strategic guidance on HR or AI implementation, though some respondents remain neutral or unconvinced, suggesting variability in the level of support provided.

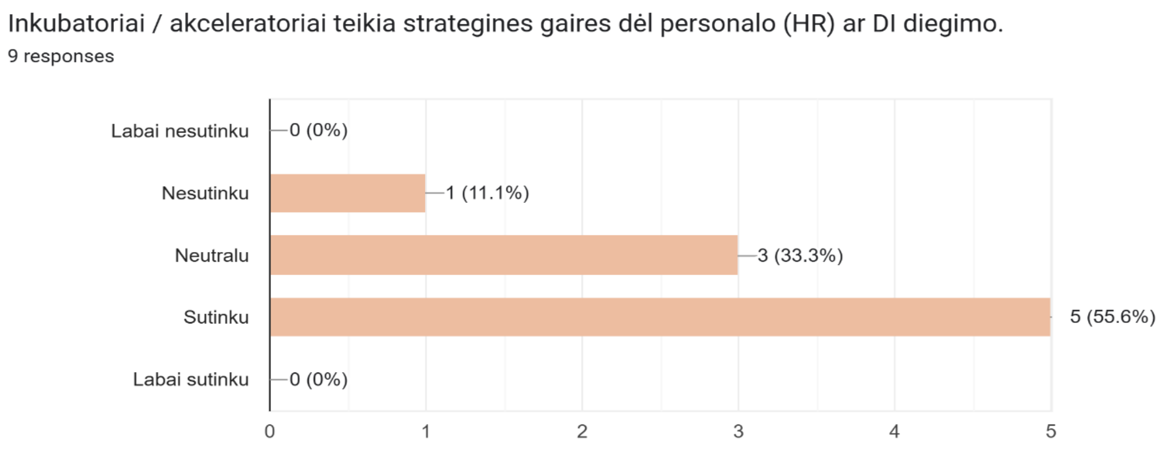

Figure 10: 'Incubators/accelerators provide strategic guidance on HR or AI implementation'

b) "Investors are actively backing startups in developing AI-based HR capabilities."

When we asked this question, respondents provided a range of opinions. Specifically, 22.2%

disagreed with the statement, 33.3% remained neutral, 44.4% agreed and 22.2% strongly agreed.

This result suggests that while many participants perceive investors as supporting the development of AI-based HR capabilities in startups, a notable portion remains neutral or disagrees, indicating that investor involvement in this area may be inconsistent across the DeepTech ecosystem.

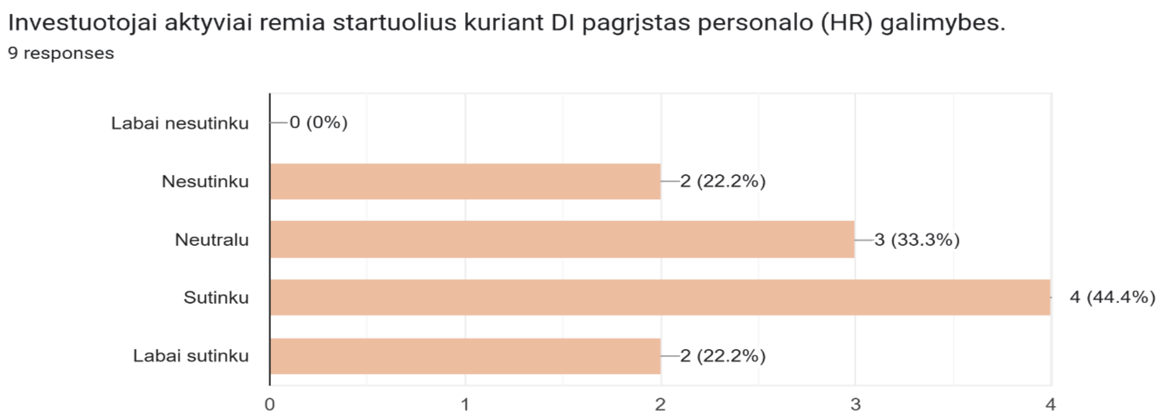

Figure 11: ‘Investors are actively backing startups in developing AI-based HR capabilities’

c) “Policymakers are promoting the responsible and ethical use of AI in human resources (HR).”

When we asked this question, respondents expressed varying perspectives. Specifically, 11.1% disagreed with the statement, 22.2% remained neutral, 66.7% agreed and 11.1% strongly agreed with the statement.

These results indicate that majority of participants perceive policymakers as actively promoting the responsible and ethical use of AI in HR. However, the presence of neutral and dissenting responses suggests that the impact of such policies may not be equally recognized or experienced across all organizations.

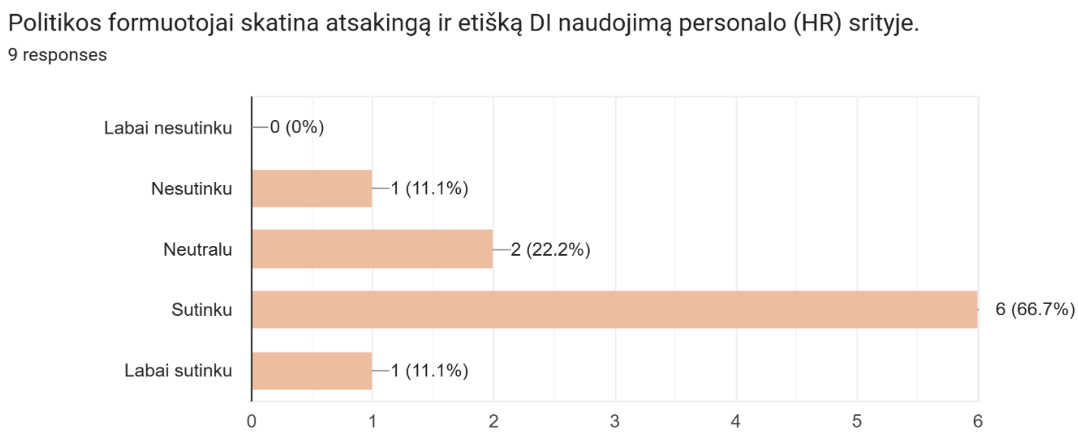

Figure 12: ‘Policymakers are promoting the responsible and ethical use of AI in human resources’

d) “Collaboration between ecosystem players increases startups' ability to integrate AI and manage talent.”

When we asked them this question, they respond that 22.2% of them are disagree with that statement. 11.1% of them are natural with the statement. 66.7% them are agree with that statement and 22.2% them are strongly agree with that statement.

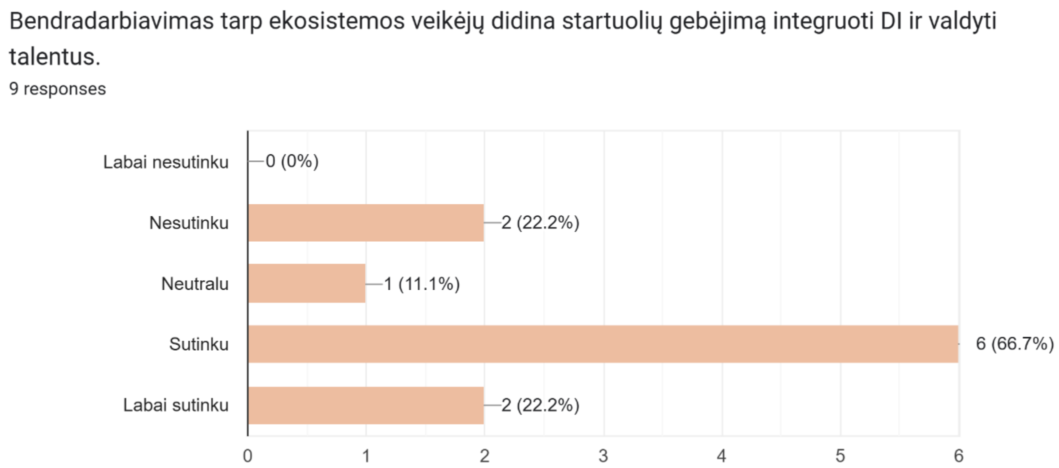

Figure 13: ‘Collaboration between ecosystem players increases startups' ability to integrate AI and manage talent’

e) “Lack of coordination among ecosystem participants creates obstacles to the integration of AI and human resources.”

When we asked this question, respondents provided varied responses. Specifically, 11.1% disagreed, 22.2% remained neutral, 22.2% agreed and 44.4% strongly agreed.

This result suggests that a significant portion of participants perceive a lack of coordination among ecosystem participants as a key barrier to integrating AI into HR processes. The strong agreement among nearly half of the respondents highlights the importance of collaborative efforts to overcome these obstacles.

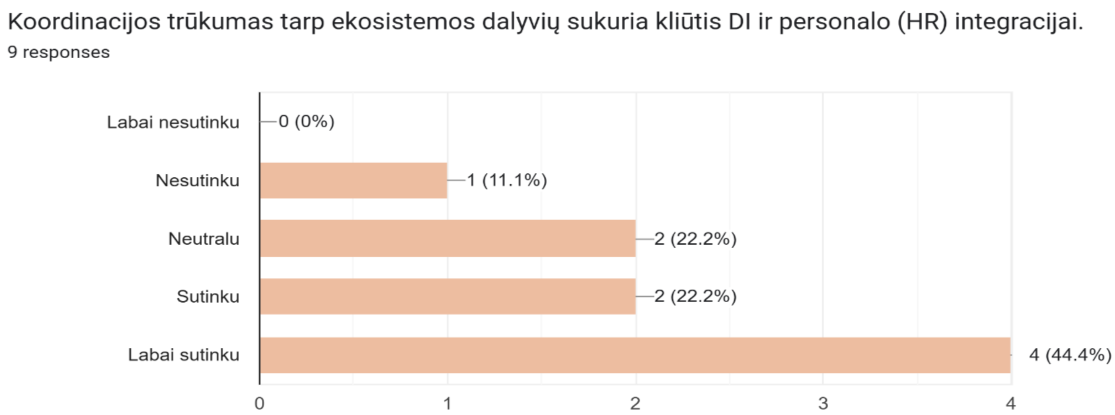

Figure 14: ‘Lack of coordination among ecosystem participants creates obstacles to the integration of AI and human resources’

f) “Public funding or the regulatory framework significantly influences decisions regarding AI and human resources integration.”

When we asked this question, respondents shared their perspectives as follows: 11.1% disagreed, 11.1% remained neutral, 77.8% agreed and 11.1% strongly agreed.

This result suggests that a clear majority of participants perceive public funding and regulatory frameworks as playing a significant role in shaping decisions related to AI integration in HR. The high level of agreement underscores the importance of external support and policy in facilitating AI adoption within organizations.

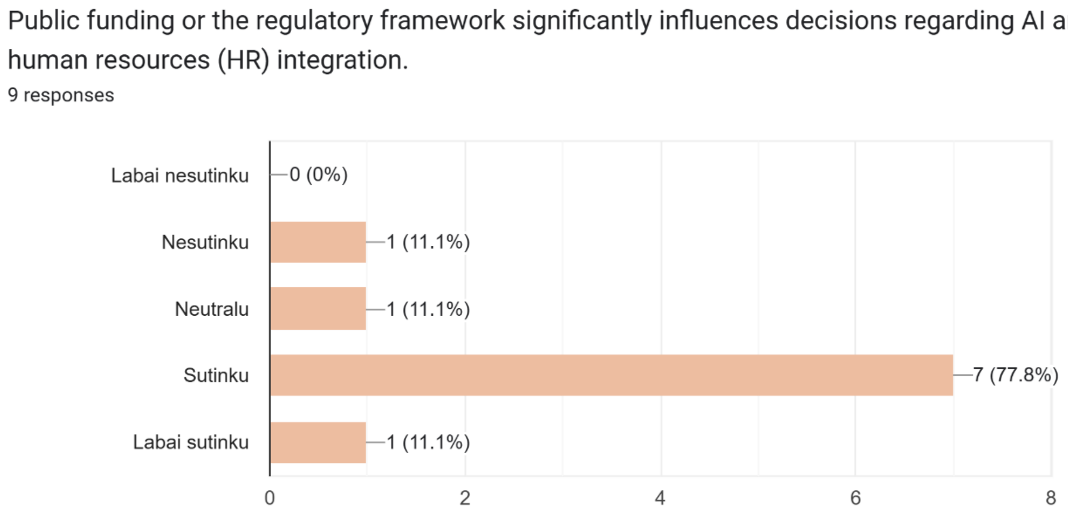

Figure 15: 'Public funding or the regulatory framework significantly influences decisions regarding AI and human resources integration.'

Eighth Question: "In your opinion, how could ecosystem actors (e.g. investors, incubators, policymakers) better promote the integration of AI and human resources (HR) in deep tech companies?"

When we asked them this question, the respondents are providing answer, which are given bellow:

Expert A- "Encourage investment in AI-powered HR solutions"

Expert B- "I have no opinions on this matter."

Expert C- "Investments"

Expert D- "Ecosystem actors can promote AI–HR integration by providing targeted funding, practical training and mentorship, clear ethical and regulatory guidelines, shared data and AI infrastructure, and by encouraging collaboration between deep tech firms, academia, and HR technology providers."

Expert E- "Training"

Expert F- "Ecosystem actors can promote AI–HR integration by funding applied pilot projects, providing regulatory and ethical guidance and offering targeted HR-AI expertise through incubators and accelerators to help deep tech firms adopt AI responsibly and at scale."

Expert G- "I do not see a direct relation between the ecosystem actors and Ai in HR. Ecosystem actors affect the management, they affect HR department, so its not a direct connection"

Expert H- "Send staff to train to deepen their knowledge in the field of AI"

One respondent does not provide any answer.

This result suggests that investment, training, regulatory guidance and collaborative support from ecosystem actors are viewed as key enablers for integrating AI into HR in deep tech companies. However, the presence of neutral and dissenting responses highlights that perceptions of ecosystem influence may vary depending on organizational context and experience.

Nineth Question: In this question they were given five statements and asked them to indicate how much they agree with the statement.

a) “The integration of AI and human resources strengthens our organization's ability to continuously innovate.”
When we asked this question, respondents expressed varied levels of agreement. Specifically, 33.3% remained neutral, 44.4% agreed and 22.2% strongly agreed.

This result suggests that majority of participants perceive the integration of AI and HR as positively contributing to their organization’s capacity for continuous innovation. The neutral responses indicate that some participants are uncertain or have not fully experienced the benefits of AI-HR integration in driving innovation.

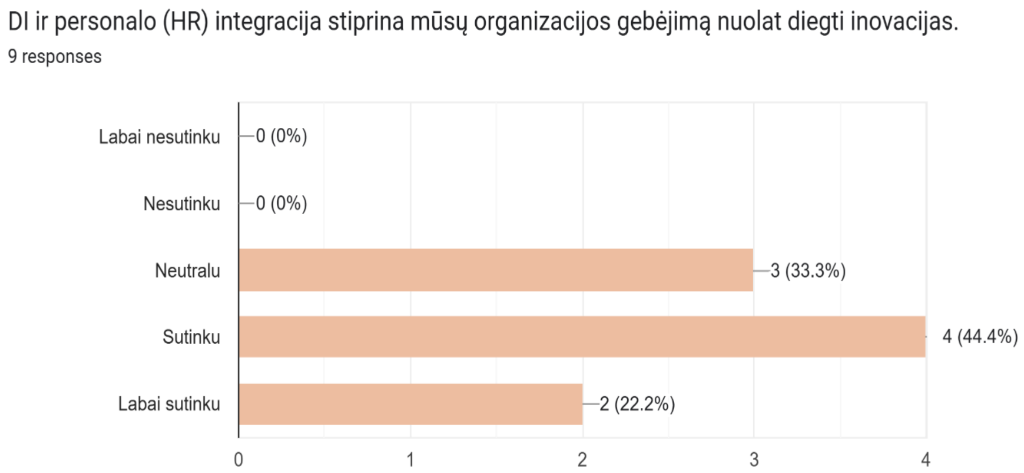

Figure 16: ‘The integration of AI and human resources (HR) strengthens our organization's ability to continuously innovate’

b) “AI-based human resources systems help us attract and retain innovative talent.”

When we asked this question, respondents provided a range of perspectives. Specifically, 44.4% remained neutral, 22.2% agreed and 33.3% strongly agreed.

This result suggests that while a significant portion of participants recognize the role of AI based HR systems in attracting and retaining innovative talent, many remain neutral, indicating either uncertainty or limited experience with the practical benefits of such systems.

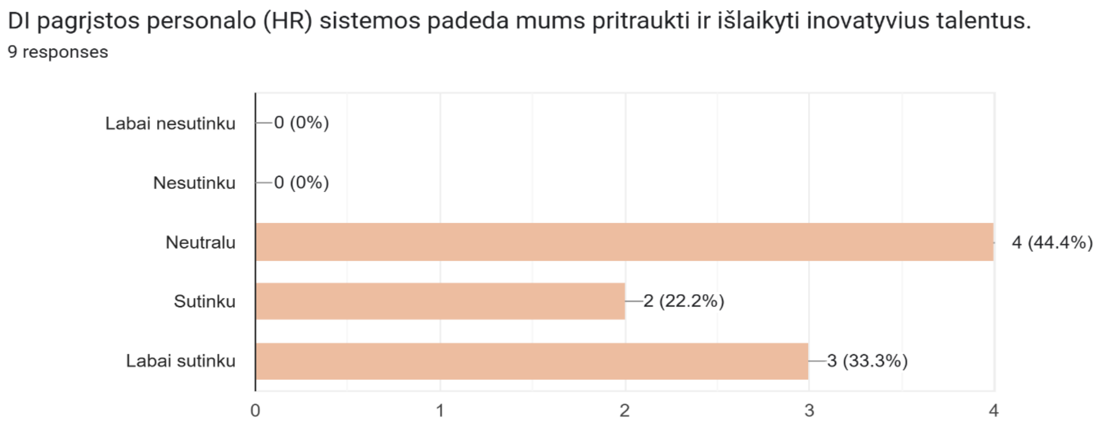

Figure 17: ‘AI-based human resources (HR) systems help us attract and retain innovative talent’

c) “The combination of human creativity and AI tools increases an organization's ability to adapt.”

When we asked this question, respondents expressed varied perspectives. Specifically, 22.2% remained neutral, 55.6% agreed and 33.3% strongly agreed.

This result suggests that most participants perceive the synergy of human creativity and AI tools as enhancing their organization’s adaptability. The neutral responses suggest that a small portion of respondents are either uncertain or have yet to fully experience the impact of this combination on organizational flexibility.

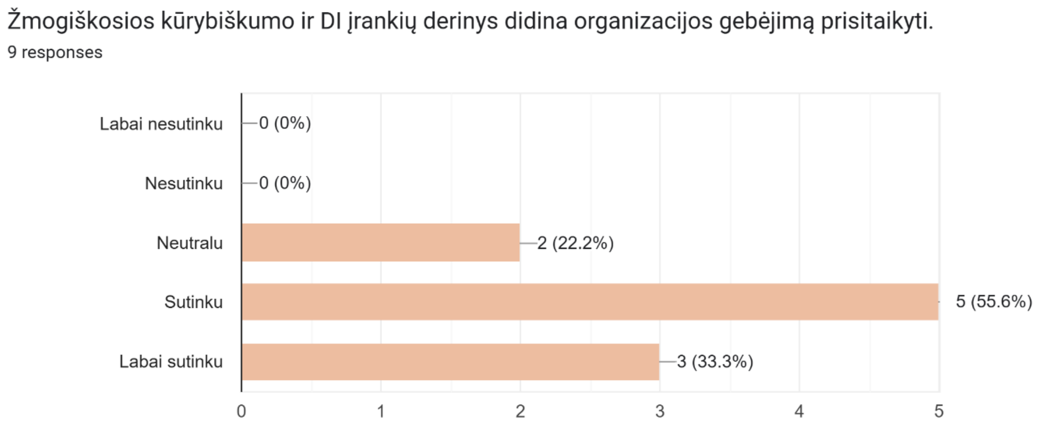

Figure 18: ‘The combination of human creativity and AI tools increases an organization's ability to adapt’

d) "Overreliance on AI can limit employees' creativity and critical thinking."

When we asked this question, respondents expressed varying perspectives. Specifically, 11.1% disagreed, 22.2% remained neutral, 66.7% agreed, and 22.2% strongly agreed.

These results suggest that the majority of participants recognize the potential risks of overreliance on AI, particularly in limiting employees' creativity and critical thinking. The neutral and dissenting responses indicate that some participants either perceive minimal risk or are uncertain about the impact of AI dependency on employee cognitive capabilities.

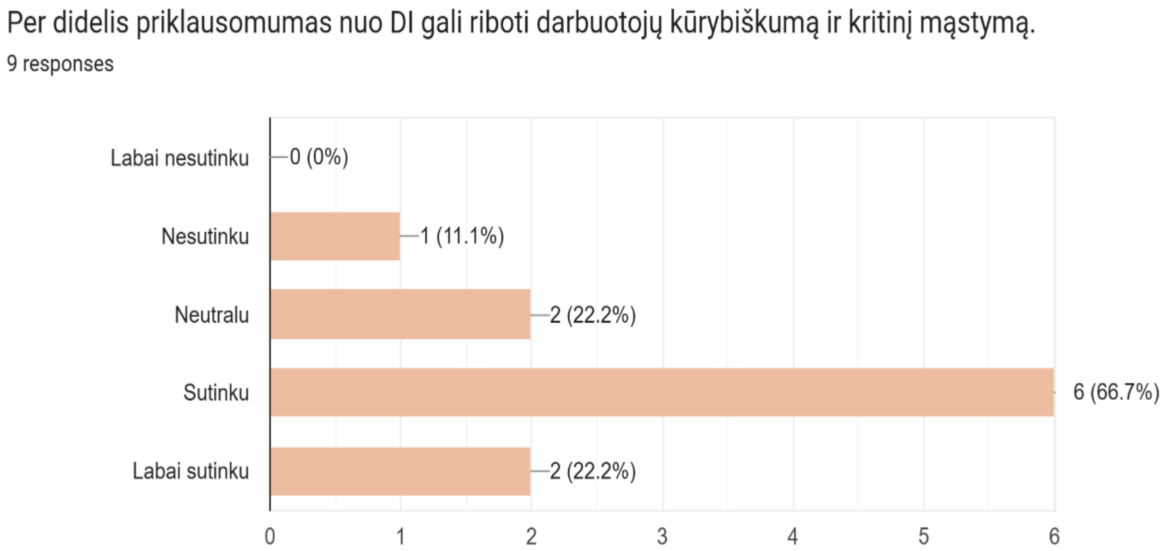

Figure 19: 'Overreliance on AI can limit employees' creativity and critical thinking'

e) "External ecosystem support contributes to the long-term sustainability of innovation."

When asked this question, all respondents agreed with the statement.

These results indicate a unanimous perception among participants that external ecosystem support such as from investors, incubators and policy makers is crucial for sustaining long term innovation. This highlights the recognized importance of collaborative networks in strengthening the innovation capabilities of organizations.

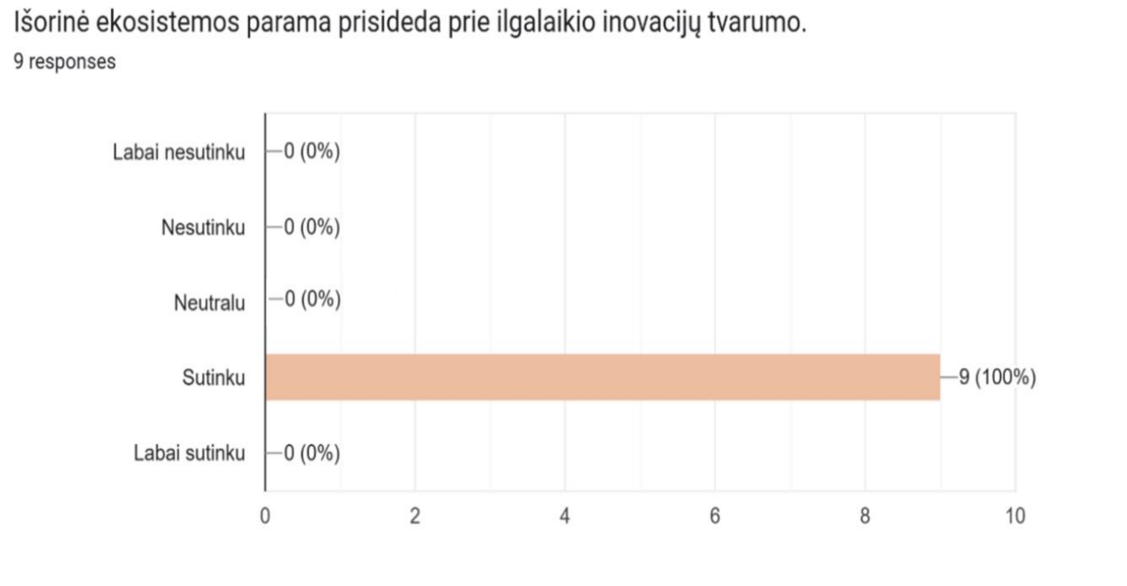

Figure 20: ‘External ecosystem support contributes to the long-term sustainability of innovation’

Tenth question: In your opinion, what practices can ensure sustainable collaboration between AI systems and human talent in deep technology startups?

When we asked them this question, the respondents are providing answer, which are given bellow:

Expert A- “continuous upskilling, promoting hybrid decision making.”

Expert B- “I have no opinion”

Expert C- “Training on how to properly use AI systems”

Expert D- “I have no opinion.”

Expert E- “Sustainable collaboration can be ensured by keeping humans involved in decision-making, using AI as a support tool rather than a replacement, investing in continuous upskilling, ensuring transparency and fairness in AI systems, and fostering a culture of trust and adaptability.”

Expert F- “Training”

Expert G- “Keeping humans in the decision loop, training employees to work alongside AI and establishing clear ethical, transparency and accountability frameworks so AI augments do not replace human talent.”

Expert H- “I do not know the specifics of DL startups so I can not say”

Expert I- “Properly selected training”

These findings suggest that sustainable collaboration between AI and human talent requires a combination of training, ethical governance, human-in-the-loop decision-making, and cultural adaptation, ensuring AI enhances rather than replaces human capabilities.

Conclusion of Task 3 & Transition to Task 4

The evidence from the empirical study reported in this task is grounded, practitioner-driven and supports as well as refines the theoretical propositions developed earlier. Based on the structured expert survey with relevant actors in the DeepTech ecosystem, several important patterns can be identified:

- ***The External Ecosystem is an Active Force:*** The challenge of embedding AI in the HRM function with success can't be seen as just a question for internal tech resolution only. It is strongly shaped by – and even dependent on – the focus of incubators, investment capital and investor expectations and policy regulation. The survey reveals that a clear "coordination deficit" is a prominent issue (designated by 66.7% of experts) where there is no real harmonization between these external actors which negate smooth AI-HR adoption.
- ***Adoption is Nuanced and Contextual:*** Though AI is celebrated for its potential to promote fair, efficient and strategic fit initiatives, current adoption varies. Complications Organizations are confronted with a set of barriers: data protection (GDPR) and costs of implementation/calendar time, lack of HR's skills on the one hand and employees' fear of algorithm transparency and bias on the other. This issue highlights the results from Task 1 where it was shown that resource constraints are complex and interdependent.
- ***The Imperative of Human-AI Symbiosis:*** The experts agreed wholeheartedly (88.9% combined agreement) that the fusion of human creativity with AI tools helps organizational adaptability. But there is also a strong and simultaneous warning (66.7% agreement) not to rely too much on AI, which was something that can limit critical thinking and creativity. This attests to the hybrid leadership model presented in Task 2, that is supported by empirical evidence: instead of replacing it, AI complements human judgement.
- ***A Unanimous Call for Ecosystem Support*****:** What is also abundantly clear from the findings is that 100% of experts surveyed believe that external ecosystem support is necessary for the preservation and success of innovation in the long run. That notion clearly sets ecosystem actors not just as contributors on the fringe, but rather as co-creators of the venture's ability to innovate.

Although these data provide insight into what are the key influentials, barriers and perceived consequences, it appears as if this is a complex picture interconnected in some way and not easily applied in practice. The insights, while very powerful, are still like a gear or two of a machine and we're still looking for the machinery schematics. There is a wide spectrum that separates such discrete pieces of understanding from a systemic model that explains how they dynamically interact to foment or discourage sustainable versus disruptive innovation.

Thus, the journey from diagnostic illumination to prescriptive focus will now require that the research integrate these empirical realities with extant theoretical underpinnings "profiles. This synthesis will be completed in Task 4 with a new conceptual framework. This will represent a formal connection between the ***Human Capital Theory*** (focusing on the micro-level development of adaptive talent) and ***Resource Orchestration Theory*** (focusing on the macro-level structure of internal and external assets). Through leveraging the established role of the ecosystem and the human-AI symbiosis principle, ***AI-Orchestrated Innovation Capacity Model*** will offer a cohesive framework for interpreting, diagnosing and crafting resilient innovation systems required for DeepTech venture success.

4. Develop a Conceptual Framework Linking Human Capital Theory and Resource Orchestration Theory

Drawing on the insights developed in the preceding section; this task introduces a new conceptual model: the AI-Orchestrated Innovation Capacity Model. This next section builds a bridge between the studies empirical and thermotical findings by integrating Human Capital Theory and Resource Orchestration Theory through the practical role of AI. It’s a model that shows how AI dynamically aligns three crucial elements: talent, resources and ecosystem ties. In practice, this alignment lets startups keep innovating even when resources are thin.

4.1 Introduction and Purpose: Synthesizing Micro and Macro Foundations

The preceding tasks have systematically constructed a multilayered understanding of innovation in DeepTech. We began by diagnosing the systemic resource constraints that threaten venture survival (Task 1), then explored how AI acts as a strategic enabler to transform these constraints into a sustainable innovation capacity (Task 2). Task 3 grounded this exploration in empirical reality, revealing that the integration of AI into critical functions such as talent management is not an isolated internal process but is profoundly shaped and often hindered by the surrounding ecosystem of incubators, investors and policymakers.

This cumulative analysis presents a complex picture: a venture’s ability to innovate durably depends on the internal augmentation of its human capital, the strategic orchestration of scarce resources and the effective navigation of an external ecosystem with Artificial Intelligence mediating all three domains. While these insights are valuable, they remain interconnected yet discrete findings. To advance both theory and practice, a unifying model is required one that can explain how these elements cohere into a functional system and provide a roadmap for building one.

Therefore, the purpose of this task is to synthesize the literature based and empirical insights into an original conceptual framework. This framework, termed the **AI Orchestrated *Innovation Capacity Model***, formally bridges the microlevel focus of ***Human Capital Theory (HCT)*** with the macro level perspective of ***Resource Orchestration Theory (ROT)****.* It achieves this by placing ***AI augmented human capital*** at the heart of the orchestration process and explicitly modelling the external ecosystem as an active, constitutive component of a venture's resource base. The framework incorporates two key empirical realities from Task 3: first, that the ecosystem functions as a cocreator of capability, not merely a funder and second, that the only sustainable model is a hybrid human–AI symbiosis, where technology amplifies rather than replaces human judgment and creativity.

This model moves beyond description to provide a structured, actionable lens. It serves as a **d*iagnostic tool*** for founders to audit their venture's innovation engine, a ***strategic map*** for ecosystem actors to understand their leverage points and a ***theoretical contribution*** that clarifies how next generation ventures build enduring advantage in conditions of extreme scarcity and uncertainty.

4.2 Theoretical Foundations Revisited & Bridged: Human Capital, Resource Orchestration and the Catalytic Role of AI

The proposed framework is not built from new theoretical first principles but from a novel synthesis and extension of established theories, reconfigured for the reality of AIdriven, ecosystem dependent DeepTech entrepreneurship.

4.2.1 Human Capital Theory (HCT): From Static Stock to Dynamic, AI Cultivated Flow

The foundational premise of Human Capital Theory, articulated by Becker (1964), conceptualizes human capital as a static stock—an accumulated reservoir of knowledge, abilities and health acquired through upfront investments like formal education and training. This stock is expected to depreciate slowly and deliver long-term returns through enhanced productivity. While instrumental for understanding industrial-era economies, this static model becomes profoundly inadequate when applied to the environment of DeepTech ventures. Here, the core assumption of knowledge stability collapses. In sectors such as quantum hardware, CRISPR-based therapeutics or neuromorphic computing, breakthrough publications and patent filings can redefine entire sub-fields within quarters, not decades. The specialized expertise possessed by a researcher today may face significant obsolescence within 18 to 24 months, trapped in what (Pacher et al. 2025) identify as the "rapid decay cycle" of DeepTech knowledge. A venture relying on a static stock of human capital is, therefore, investing in an asset guaranteed to depreciate at an accelerating rate.

As the analysis in Task 2 made clear, the central human resource challenge in DeepTech is not simply a numerical shortage of scientists, but a qualitative scarcity of a specific cognitive profile: the integrative innovator. Success depends on individuals who combine deep, vertical expertise in a core scientific discipline (e.g., molecular biology) with the broad, horizontal ability to collaborate with and understand experts in adjacent domains like data science, regulatory affairs and hardware engineering the quintessential "T-shaped" professional (Capatina et al., 2024). Traditional HCT, focused on the initial production of specialists through degrees, fails to account for the continuous, post-formal-education investment required to develop and, crucially, *maintain* this integrative capacity. It views the PhD as the culmination of investment, not its starting point.

Consequently, Human Capital Theory requires a fundamental reconceptualization for the DeepTech context. Relevant human capital in this paradigm is defined by three intertwined attributes: ***adaptability, interdisciplinary fluency and AI literacy***. Its primary economic value migrates from *possession* of a known skill set to the *dynamic capability* for perpetual learning, timely unlearning of obsolete methods and creative recombination of knowledge across domain boundaries. This theoretical shift is powerfully corroborated by the empirical data from Task 3. Experts consistently identified "continuous upskilling" and "training on how to properly use AI systems" not as optional HR initiatives but as existential operational necessities (Expert A, C, E, F). One founder explicitly noted the need to "send staff to train to deepen their knowledge in the field of AI" (Expert H). This forces a strategic pivot in investment logic. Capital must be diverted from solely credentialing individuals to architecting embedded, AI-powered learning ecosystems that facilitate growth as an integral part of the daily work process.

In this refined theoretical view, human capital is best understood not as a stock, but as a managed flow—a continuous and directed stream of capability that is constantly replenished and redirected. AI is the pivotal technology that enables and accelerates this flow. It creates a recursive developmental loop: AI applications generate the demand for new meta-skills (e.g., prompt engineering for large language models, critical evaluation of algorithmic bias, collaboration with digital agents), while simultaneously supplying the scalable infrastructure to meet that demand. For example, an AI-driven project management platform might detect that a team's progress on a photonics problem is stalled. It could then analyse the team's demonstrated skills, cross-reference this with the latest research in meta-materials and computational photonics and automatically deploy a tailored series of micro-simulations and tutorial papers to bridge the precise knowledge gap all within the workflow (Katona, J., & Gyonyoru, K. I. K. 2025). This transforms the venture from an organization that has human capital into an adaptive learning organism that continuously cultivates it.

Ultimately, this dynamic model presents a significant evolution of Becker's original thesis. It posits that in hyper-dynamic technological landscapes, sustainable competitive advantage stems less from the human capital stock a venture owns at inception, and more from the superiority of its human capital cultivation system. In DeepTech, where AI both defines the frontier and builds the paths to it, the most critical investment is in the loop that allows human talent and artificial intelligence to co-evolve, ensuring the workforce not only keeps pace with change but actively drives it (Sinap, 2026).

4.2.2 Resource Orchestration Theory (ROT): From Internal Bundling to Ecosystem-Enabled Orchestration

Resource Orchestration Theory explains competitive advantage as the result of managerial actions (structuring, bundling, leveraging) applied to a firm's resource portfolio (Sirmon et al., 2011). The classic ROT lens tends to focus on the strategic combination of internal assets. However, our analysis in Tasks 1 and 3 fundamentally challenges this inward focus. DeepTech startups are characterized by a poverty of internal resources; their most critical assets specialized talent, frontier scientific knowledge, validation credibility and often early-stage capital are predominantly external, residing in universities, research labs, investor networks and government grant programs.

Thus, we must extend ROT to an Ecosystem Enabled Resource Orchestration perspective. The core managerial capability for a DeepTech founder is not the bundling of owned assets, but the orchestration of access to and integration of resources across organizational boundaries. Success hinges on the ability to attract an investor, leverage an incubator's network, comply with a regulator's framework and collaborate with an academic lab simultaneously and coherently. The "orchestration" is of a dispersed, heterogeneous network of resource holders, a process fraught with the "coordination deficits" empirically highlighted by experts (Task 3, Question 7e).

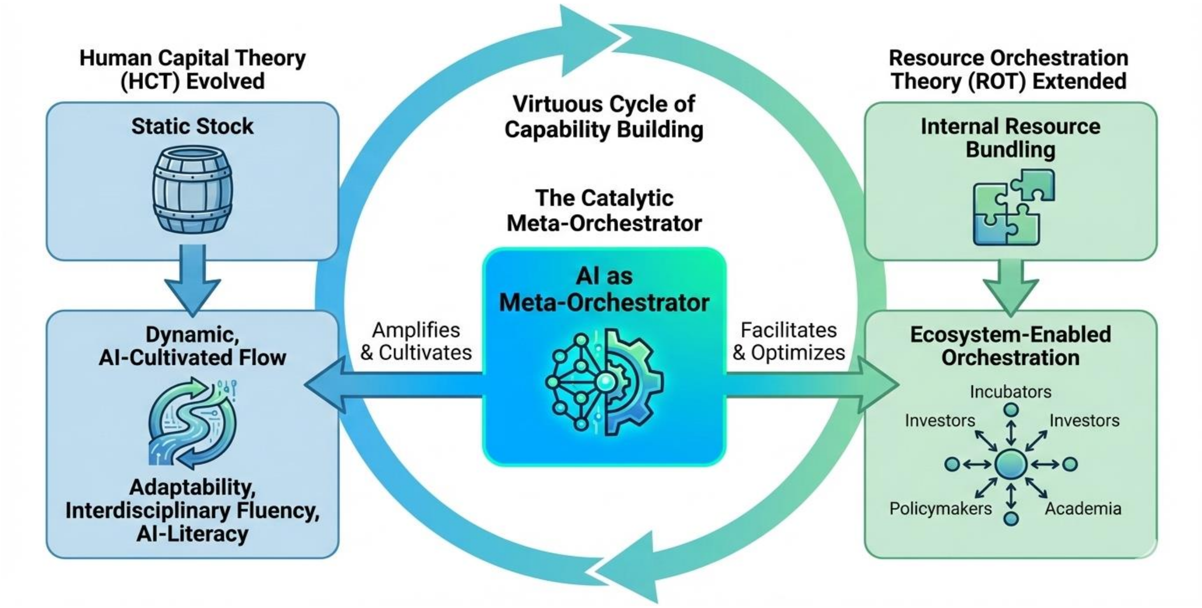

Figure 21: Bridging Human Capital; Theory and Resource Orchestration Theory in DeepTech: The Catalytic Role of AI

4.2.3 The Theoretical Bridge: AI as the Catalytic Meta-Orchestrator

The key underlying theoretical premise of this framework is that in the context of DeepTech reconstituted Human Capital Theory and Resource Orchestration Theory are not proximate or complimentary theories. Rather, they are imbricated and co-constitutive of each other, joined at the hip by AI's catalytic function. AI serves as the basic operational logic that connects the macro level of talent development to the macro level of strategic resource configuration and bridges two different theoretical lenses into an integrated theory system for constructing innovation capacity.

AI as the Engine of Dynamic Human Capital (DHCT). Deep learning AI ceases to be merely a passive instrument but instead emerges as the central proactive agent of creating the flexible, fluidic human capital DeepTech ventures need. It implements the transition from stock to flow through various concrete mechanisms:

- ***Personalized Learning Pathways:*** The engagement of AI-powered courses that go beyond the one-size-fits-all approaches. They design highly personalized upskilling paths by analyzing individual performance data, project requirements and skill gaps in real-time. This allows quantum algorithm specialists to establish the relevant area in lattice-based cryptography with minimal resources, while creating the horizontal line of the "T-shaped" profile in a focused and timely way (Katona, J., & Gyonyoru, K. I. K. 2025).

- ***Knowledge Synthesis & Integration:*** AI can act like a bridge between different worlds of knowledge. Using NLP, it links insights from scientific papers, patterns and internal notes (Rodrigues et al., 2025). For example, a biophysicist might discover that the methods used in protein folding simulation are similar to financial risk models. Such connections often lead to significant breakthroughs.
- ***Facilitation of Collective Intelligence:*** AI iimproves how people work together. AI powered performance moves beyond messaging, enabling teams to share knowledge and make decisions more efficiently. They can spot complementary expertise throughout a team, suggest just the right pairings for any given problem where they might collaborate most effectively and translate domain-specific jargon as a means of actively growing a 'T-shaped', collective entity out from under powerful pocketed specialists.

AI as the Meta-Orchestrator of Ecosystem-Enabled Resources (ROT). At the same time, AI also serves as the essential meta-layer that facilitates competent orchestration in a scarce-resource and ecosystem-dependent environment. It increases the founder's ability to perform the most important managerial activities of organizing, grouping and using:

- ***Proactive Resource Scanning and Matching:*** AI systems will be tracking the outside world – grant databases, investor portfolios, research results from academia — to find good matches without needing a deliberate search process. This proactively deals with the Task 3 characterized problem of "coordination deficit".
- ***Predictive Modelling of Resource Combinations:*** AI can also model potential outcomes and the associated trade-offs of different types of resource bundles beyond mere identification. For example, AI can help to explore questions about how accepting a certain grant with specific reporting requirements could affect R&D timelines or how working with one research institution over another affects the intellectual property landscape.
- ***Automation of Orchestration Overhead:*** The burden of managing eco-system relations compliance reporting for grants investor updates, ensuring regulatory adherence in HR practices is substantial for a lean team. AI turns these repetitive but important activities into automated functions, allowing people to concentrate on strategic relationship building and high-judgment decisions (Sony et al., 2025).

Hence the base-name of this framework: ***The primary resource to be orchestrated is dynamic human capital and the paramount goal of investing in that human capital is to***

enhance the firm's overarching capacity to orchestrate all other resources both internal and external. AI is the fuel to tighten this recursive, self-reinforcing loop.

This creates a virtuous cycle of capacity building: AI develops the adaptive, AI-literate human capital. This improved human capital, in turn, designs manages and strategically employs the more advanced AI systems. These sophisticated systems in turn open the door to a wider and higher quality range of financial, technological and knowledge resources in the ecosystem. Effective orchestration of resources results in materialized innovation outputs, which reinforce the new venture's legitimacy and increase ecosystem commitment and investment. This second feedback loop, fueled by AI itself on a constant basis radically shifts the venture from an entity with nothing but scarce resources into a lean organism that nurtures and orchestrates a fluid network of capabilities, which is what sustainable competitive advantage in DeepTech is all about.

4.3 Presentation of the "AI-Orchestrated Innovation Capacity" Framework

By integrating these bridged theories, we present the AI Orchestrated Innovation Capacity Model in Figure 22. It is composed of five elements and describes the dynamic relationships between them, with Sustained Innovation Capacity as output.

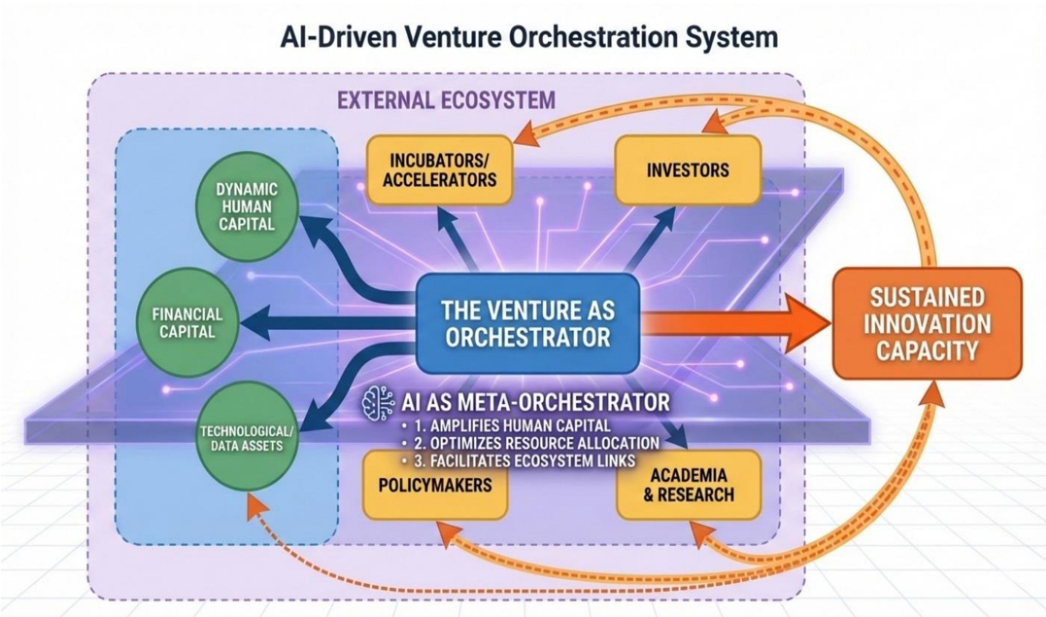

Figure 22: The AI Orchestrated Innovation Capacity Model

4.3.1 Core Component 1: The Venture as Strategic Orchestrator

At the center is all about the venture leadership team – the Strategic Orchestrator.

This module itself represents the "hybrid leadership model" (Mahabub et al., 2025) with human insight taking precedence. The Orchestrator: the leader who sets the vision, prescribes ethical rules and makes final strategic decisions based on AI generated insights as well as retains overall responsibility for creation of culture and relationships that sustain the whole. It is the human conductor of the AI-augmented orchestra.

4.3.2 Core Component 2: Internal Resource Pools

These three pools represent the foundational assets under the venture's direct managerial control and influence. However, within the framework of AI-orchestrated innovation, their nature, management and interdependence are fundamentally transformed from traditional conceptualizations.

4.3.2.1 Dynamic Human Capital: The Adaptive Core

This of course, is the primary asset - beyond simply looking at employees as static position-fillers. It consists of people and groups who have cognitive flexibility, interdisciplinarity fluidity and collaboration intelligence. As established in Sections 4.2.1 and Task 2, its value is not having a set of skills already known ahead of time; rather it lies in the ability to learn quickly, forget critically and repurpose knowledge across domain (e.g., a physicist capable of collaborating effectively with a computational biologist and someone from regulatory affairs). This capital is not fixed but is perpetually re-creating itself through AI-mediated processes: personalized learning platforms that focus on just-in-time skills gaps, NLP tools that democratize cross-disciplinary knowledge access and collaborative AI agents supporting team-based problem solving. This turns the workforce from a cost center to a living, learning system that accretes more value with each project cycle.

4.3.2.2 Financial Capital: The Constrained Catalyst

In DeepTech ventures, financial capital is limited and essential for long R&D cycles and expensive infrastructure. Its consistency is not just in terms of quantity but also quality — every distribution decision comes with existential risk. In this framework, the control of financial capital moves from intuitive, founder-driven budgeting to a data-informed, strategic optimization process. AI serves as a force multiplier for financial decision-making through: "Predictive analytics for R&D portfolio risk assessments", "Generative design tools that drastically reduce prototyping cost" and "Dynamic scenario modeling that projects the long-term burn rate implications of different strategic paths" (Mahabub et al., 2025).

This allows the venture to act as an active portfolio manager rather than simply a passive steward of budget, ensuring that scarce resources are allocated most likely to achieve both technical validation and subsequent investment by the ecosystem.

4.3.2.3 Technological & Data Assets: The Self-Reinforcing Engine

This pool consists of the venture technology, proprietary technology stack, including core AI algorithms, experimental datasets, functional prototypes and intellectual property (IP) portfolio. But crucially, within an AI-orchestrated system, these assets operate in a recursive, self-reinforcing loop. At the same time, all these aspects across every phase of the innovation cycle —whatever a successful experiment, a failed trial or a new research collaboration — there's new structured data or technology insight are generated simply through the process of doing. This continuous generation drives a process (Feng et al. (2025) term "data assetization," in which raw information's are systematically converted into a strategically a valuable strategic asset that enhances the venture's predictive capability, operational efficiency and IP moat. As an example, data from failed experiment trains more accurate AI models for future candidate selection and proprietary datasets become a significant competitive advantage when seeking partnerships. So, this pool serves as both the input and output of the innovation engine and it increases in volume as well as value with more running time.

4.3.3 Core Component 3: The External Ecosystem

As a context of envelopment, it is not so much a passive context as an active storehouse of vital resources. It comprises:

- ***Incubators/Accelerators:*** Sources of mentorship, validation and operation templates and network connection.
- ***Investors:*** Financial capital and strategic governance providers, seeking more and better data around talent health and maturity of innovation pipelines to enable more effective engagement.
- ***Policymakers:*** Who regulate the playing field (with regulation, e.g., GDPR, EU AI Act) and distribute non-dilutive funds in terms of grants, thus shaping the horizon for feasibility and ethics of AI adoption (Expert F).
- ***Academia & Research Institutions:*** The wellspring for frontier knowledge and an important pipeline of deep talent.

4.3.4 Core Component 4: AI as the Meta Orchestrator

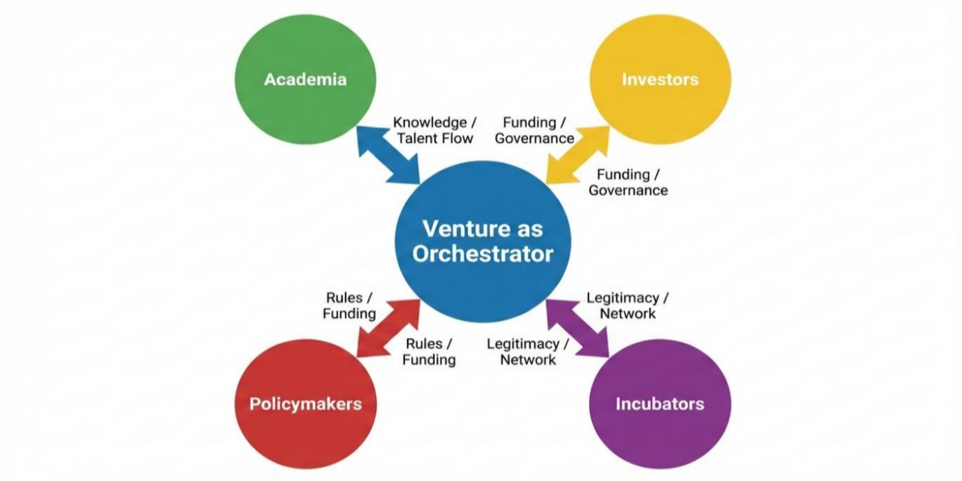

Figure 23: Core Component 4: AI as the Meta Orchestrator

Within the framework, AI isn't seen as a separate tool or a passive resource, but as the pervasive, intelligent layer that links everything else together. It acts as the brain of the model — enables the venture to perceive, think and act with some scale and precision that is not possible for humans to achieve on their own. This meta-orchestrator role is realized through three key inter-dependent activities:

- ***Amplifies Human Capital:*** AI directly enables the transitions of human capital from a static stock to a dynamic, continuous, evolving flow. It accomplishes this by laying out the foundation for ongoing, personalized learning. Adaptive learning platforms leverage diagnostic assessments and performance data to develop personalized upskilling pathways, thus building the horizontal bar of the "T-shaped" professional in real-time. NLP-powered knowledge management systems (e.g., tools such as Elicit or customized knowledge graphs) parse and link insights into large, unstructured internal and external data sources, facilitating interdisciplinary synthesis while disrupting traditional knowledge silos (Rodrigues et al., 2025). Moreover, smart collaboration tools can help map team-wide expertise, recommend ideal project pairings and aid in cross-disciplinary communication – all actively constructing a shared collective intelligence from a collection of experts.
- ***Optimizes Resource Allocation:*** This aspect deals with the main scarce and uncertain constraints. Artificial intelligence (AI) introduces data-driven decision making by allowing decisions that were once largely intuitive to be made more consistently and at scale. ***Predictive analytics*** model R&D portfolio risk and simulations of potential

outcomes enable leaders to de-prioritize low probability of success projects, while doubling down on the most promising opportunities to allocate scarce financial capital (Mahabub et al., 2025). ***Generative design and in-silico testing*** (e.g., digital twins) reduce time-to-market through the production of thousands of designs and assessments virtualized to provide earliest feedback on products possible, shortening lead times and cost associated with physical prototyping (Hölsä et al., 2025). Strategic foresight instruments are scanning technological and market landscapes, offering early-warning signals and proactive flexibility required to surf the disruptive waves in DeepTech sectors.

- **Facilitates Ecosystem Links:** A critical role in performing the ecosystem-driven resource orchestration needed for startup survival. AI automates and augments the venture's interaction with the outside world, thereby overcoming the "coordination deficit" referred to in Task 3. It automates the scanning and matching process for non-dilutive grants, investor thesis alignment and potential research partners, transforming a labor-intensive, unsystemetic search into a systematic sourcing operation. It further integrates regulatory compliance (GDPR, guidelines for the AI Act) directly into HR and data management systems-decreasing the legal risk and overhead of working with sensitive data (Sony et al., 2025). With routine partnership communications and reporting streamlined, AI reduces the costs of transacting relationships with many partners to enable small leadership teams to focus on valuable high-level strategic engagement.

Importantly, these three tasks are not performed in isolation. They form a synergistic loop: AI is operating from the central function at the platform where optimizing resource allocation, identifying emerging skills requirements, which then trigger tailored learning modules for the team these newly developed capabilities enable rapid prototyping aligned with investors' expectations, while ecosystem scanning AI simultaneously facilitates relevant external connections to support funding and collaboration. This is the integrative, whole-system enablement which warrants calling AI the meta-orchestrator—the catalyzing factor that unites and powers the entire model and transforms a conceptual map of resources it includes into an engine for sustained innovation.

4.3.5 Core Component 5: Sustained Innovation Capacity

This is the model's output: the demonstrated, repeatable capacity of the venture to produce commercially viable technological breakthroughs. It is one that can be measured in terms of faster R&D velocity, better quality patent output, effective market pivots and ultimately, growth and resilience (described in Section 2.6). It is as much the consequence of the system as it is its validation.

4.4 Explanation of the Framework's Dynamics: The System in Motion

A static model can describe components, but it takes a dynamic view to explain how innovation actually happens. This section moves beyond the framework's elements to detail the critical processes that bring it to life. Here, we examine the three core interactive flows—the Internal Augmentation Loop, the Ecosystem Orchestration Process, and the Innovation Feedback Loop. Together, they demonstrate how the model's components don't just coexist; they actively reinforce one another to build a venture's sustained capacity for innovation.

4.4.1 The Internal Augmentation Loop

This is a recurring process in the venture. For instance, the AI (Meta Orchestrator) was processing project data and discovered in general that a team's (Dynamic Human Capital) skillset lacked knowledge on a new regulatory mandate. It curates a microlearning module. The newly upskilled team subsequently designs a new experiment that generates better quality data (Technological Asset), enhancing the predictive model of the AI. This better-untested model helps to reallocate that R&D budget (Financial Capital) more wisely in favor of funding the next experiment. The loop is self-reinforcing AI builds human capital that makes for better assets and data, which trains smarter AI.

4.4.2 The Ecosystem Orchestration Process

This is an active engagement and two-way interaction between the VC and Ecosystem, facilitated by AI. Consider a venture building an ultra-sensitive biotech platform. The Population-based AI is notified of a pending regulatory consultation related to the use of genetic data (engaging Policymakers) which it could have an interest in (Facilitate Ecosystem Links). At the same time, it names a public grant opportunity for AI in life sciences to ensure they are ethical. The team (Orchestrator) makes use of the grant (Financial Capital) to conduct an ethics audit. The positive grant award and the proactive position regarding compliance become data points that make the project more appealing to a specialist bio focused Investor. The AI has not simply discovered resources; it has strategically arranged and packaged copies of them to construct legitimacy for the venture and de-risk its pathway (Zahlan, 2025).

4.4.3 The Innovation Feedback Loop

It is the learning mechanism of the complete system. As a result—continued success and important failure of the Sustained Innovation Capacity to feedback into the model. The structured data from an unsuccessful clinical trial becomes tuned and is input into the AI's predictive modes for better prospective candidate selection (Optimizes Allocation). How the team failed with failure story becomes a case study in learning platform that fosters resilience (Amplifies HC). Lessons learned around a particular regulatory barrier are documented and disseminated to the Incubator, thus formalizing and expanding that connection for future opportunities. This feedback results in the system learning and adjusting, rendering the dynamic capacity for innovation robust and responsive.

4.5 How the Framework Addresses Task 3's Empirical Insights

The AI-Orchestrated Innovation Capacity Model is not created from pure theory but has been created and specified to describe the complex realities as presented by expert practitioners (Task 3). The model acts as a potent interpretive guide, making isolated observations coherent as parts of a unified systemic story and giving an organized reasoning for the issue they point to.

4.5.1 On the "Coordination Deficit" as a Primary Barrier

Task 3's survey revealed that a significant majority (66.7%) of experts identified a lack of coordination among ecosystem participants as a critical obstacle. The framework diagnoses this not as a simple failure of communication, but as a systemic failure in the resource orchestration process. It argues that through the external ecosystem contains abundant resources, it inherently fragmented, with each actor group investors, incubators, policymakers and academic institutions operate under different incentives, time horaizons,p professional logics and languages.

The model assigns clear agency to resolve this: the onus is on The Venture as Orchestrator to proactively manage these connections. This is not a passive role but an active, strategic function. Crucially, the framework specifies the mechanism for this: the AI's Facilitate Ecosystem Links function. This AI capability is theorized to lower the transaction costs of coordination by automating scans for aligned grants and investors, translating regulatory requirements into operational checklists and managing the data flows for partnership reporting. Therefore, the empirical frustration expressed by experts is reframed by the model: it indicates a venture that either lacks a conscious orchestration strategy or possesses AI tools that are purely internally focused, lacking the external networking and intelligence-gathering features necessary for ecosystem navigation. The framework thus converts the finding from a complaint about the environment into a strategic imperative for the venture: to deliberately build dual orchestration capability, combining human relational skills with AI-powered ecosystem intelligence tools.

4.5.2 On the Necessity of the "Hybrid Human–AI Model"

The expert data offered a mixed perspective, with 88.9% agreeing that the combination of human-intelligence and AI would increase adaptability, while simultaneously cautioning against over-reliance on AI leading to a reduction in creativity and critical- thinking (66.7%, respectively). The bondage with this importance of symbiosis is inbuilt into the platform, making sure it never morphs into full automation. It does so by enforcing a hard ontological separation of two main actors: Venture as Orchestrator (a vision, ethical reasoner and ultimate judge in the form of a human leadership) from AI as Meta-Orchestrator (an augmenting force providing data, options and efficiency).

This structural separation is critical. It makes sure that AI is always framed as a tool in the service of human-determined ends. The conception visually and conceptually prevents AI from being confused with autonomy. For example, AI could suggest a candidate shortlist or portfolio prioritization, while leaving the final selection and ethical sanction to the human orchestrator. This design exactly reflects the expert-based guideline, e.g., the principle of "keeping humans in the decision loop" (Expert G) and utilizing AI as a support tool, rather than replacement (Expert E): As such, the framework offers a governance model that can be used to instantiate the equally balanced hybrid model, that experts argue is required for sustainable innovation.

4.5.3 On Compound Barriers and Ecosystem-Enabled Solutions

What emerged from the expert responses was a picture of intertwined barriers—where cost, skill shortages, ethics and integration challenges reinforce one another. The framework captures this complexity by locating each barrier across multiple components of the innovation system. For example, a deficit in Dynamic Human Capital (like AI literacy) doesn't just slow down tool adoption; it also amplifies regulatory risk and undermines investor confidence.

The framework's value lies in moving from diagnosis to integrated strategy. It provides a way to address several barriers simultaneously through what we term the Ecosystem Orchestration Process. Consider the case of adopting an AI-driven talent analytics system: a venture might combine an incubator's guidance on tool selection, a policymaker's innovation grant for funding and the system's own data to activate personalized upskilling. So, for building capability and ecosystem cohesion, the venture transforms compound obstacles into opportunities.

4.6 Theoretical Contribution and Practical Utility

This model serves two purposes. On the theoretical side, it reframes key concepts to better capture how innovation unfolds under the distinctive constraints faced by DeepTech ventures. On the practical side, it turns these ideas into a usable way of thinking, offering founders, investors, and ecosystem actors a shared reference point for identifying problems and shaping responses. Its main contribution lies in connecting these two dimensions: rather than remaining an abstract framework, the model links theoretical insights directly to concrete points of action.

4.6.1 Theoretical Contribution

The AI-Orchestrated Innovation Capacity Model proposed in this research contributes in three important interconnected ways to the management and entrepreneurship fields and specifically addresses the theoretical as well as empirical gaps mentioned above.

4.6.1.1 Evolution of Human Capital Theory: From Static Stock to Dynamic, Co-Created Flow

The Traditional Human Capital Theory, with its roots in the work of economists like Gary Becker (1964), has long viewed skills and knowledge as a kind of personal stockpile—something you build through education and then draw down over your career. But this view falls short in today's DeepTech sector, where specialized knowledge can become obsolete incredibly fast.

Our framework proposes a fundamental shift. Instead of seeing human capital as a static asset owned by an individual, we see it as a dynamic, system-wide flow. It’s a continuous process of developing capabilities, driven by the ongoing interaction between team members, advanced AI tools, and a supportive learning culture within the organization.

At the heart of this is what we call "AI-augmented adaptability." This is the proven ability of individuals and teams to use AI not just for tasks, but to rapidly learn new concepts, let go of outdated methods, and weave together insights from different fields. In practice, this moves the focus from the initial educational investment to the ongoing, integrated cultivation of talent. This new lens, we argue, better captures how innovation actually happens in fast-moving, science-intensive industries.

4.6.1.2 Extension of Resource Orchestration Theory: Integrating the Ecosystem and the Meta-Orchestrator

The model is a major extension to Resource Orchestration Theory (ROT) in the startup context as it addresses two identified limitations. First, it explicitly includes the external ecosystem—incubators, investors, policymakers, academia—as a constituent part of the portfolio that needs to be constructed and exploited; this is opposed to being merely an environmental setting. From an “ecosystem-enabled” perspective, this interpretation of ROT is critical for making sense of ventures that are resource poor yet network rich. Second, and more speculatively, it hypothesizes AI as the “meta-orchestrator”. AI faculty contends that AI is not simply a resource to be managed, but the fundamental enabler device that allows small managerial teams to perform complex sensing, bundling and leveraging mechanisms across internal and external pools of resources – at scale. This offers a new framework for examining competitively advantageous behavior in network-interdependent, knowledge-intensive enterprises that also lacks the direct ownership of resources but derives advantage based on superior orchestration capacity.

4.6.1.3 A Mid-Range Theory for DeepTech Entrepreneurship: From Fragmented Insights to an Integrated System

Most of the existing literature on DeepTech startups address challenges like long development cycle talent security and financing difficulties. But usually considered them in isolation rather than interconnected problems. This framework pulls these scattered insights together. It integrates what we know about constraints, the role of AI, and complex ecosystem dynamics into a unified, testable theory. Rather than just describing the landscape, we offer a clear explanation for how these companies can actually build a lasting capacity for innovation.

At its core, the model defines three key elements: Dynamic Human Capital, the External Ecosystem and AI as a Meta-Orchestrator. More importantly, it shows how they interact through specific processes, such as an internal "Augmentation Loop" and an external "Ecosystem Orchestration" process. By mapping these relationships, this study responds to an important in the literature, namely the absent of an integrated view of how AI enabled talent and resource strategies interact to support innovation under consideration of uncertainty and constraint. In doing so, it supports future research and theory development in technology entrepreneurship.

4.6.2 Practical Utility: A Blueprint for Action

For leaders and teams building DeepTech ventures, this model is designed to be practical. It isn't just theory; it’s meant to act as both a blueprint and a set of diagnostic tools. It gives founders, investors and managers a clear way to assess where they stand, make informed strategic choices and create initiatives that strengthen the very foundations of lasting innovation.

For Founders and Leadership Teams: A Strategic Audit, Operational Roadmap

The mindset gives founders a “mirror” to judge their ventures and an innovation engine for themselves. It acts as a ***strategic auditor***, causing management to question in very specific systemic terms: Are we simply using AI to automate the administrative routine? Or are we increasingly acting and operating at the level of a ***meta-orchestrator*** — optimizing what is learned, expected for R&D payoffs and external relationship capitalizations? How stable and diverse are the ***Ecosystem Links***—do we have food interaction with all four actor groups or perhaps we over-rely/only depend on one? What is the future of work? Are we executing on Our Real Goal which is the Development of ***Dynamic Human Capital*** in embedded learning systems or are we just hiring for credentials and hoping they will keep pace with the world?” By superimposing their operations onto the model, leaders can detect vital shortcomings — whether a neglected connection to academia that has left the talent pipeline parched or a myopic focus on AI for strategic foresight while pushing into it to gain a hiring edge. Hence, the model advocates for promoting ***“strategic orchestration”*** as an “explicit and core competency of leadership”, captured by the venture’s capability to handle (perform or organize) the coordinated flows that characterize it.

For Investors (VCs, CVCs, Angels): A Sophisticated Due Diligence and Value-Add Framework

For investors, the model offers a more nuanced due diligence lens that extends beyond the inherent promise of the core technology. It focuses on the organizational and strategic maturity of the project. That means that when doing due diligence, there are now key questions we can ask: How sophisticated is the start-up’s AI-Orchestration layer? Do they possess mechanisms for data-informed talent development and resource distribution? What are the strengths and quality of their Ecosystem Links? Have they signed key research labs deals? Do they understand regulatory landscapes? A business that actively works for this model becomes a de-risked, scalable opportunity. It shows not just a promising tech but also considerable resilience for finding one’s way through uncertainty, creating pull and tapping into adjacent resources. This indicates an increased likelihood of crossing the "valley of death" and making scalable impact. And the model helps investors understand how to add value beyond cash, whether that’s in facilitating focused introductions within an ecosystem or offering expertise about building AI-powered governance tools.

For Policymakers and Incubator/Accelerator Managers: A Guide for Systemic Intervention Design

The framework also highlights the importance of ecosystem architects by shifting support mechanisms from generic and systemic toward targeted. This finding suggests that optimal policies, not just the programs like them studied here, will focus on reinforcing the Ecosystem Orchestration Process itself. Beyond, for policymakers that means shaping interventions to remove certain points of friction in the model: providing regulatory sandboxes for experimentation with AI/HR tools safely; funding common AI and data infrastructure that talent analytic ecosystems can share among themselves (without creating prohibitive fixed costs for startups); structuring R&D grants in such a way as to make it necessary or incentivize academia-industry co-creation (thereby strengthening knowledge links). For managers of incubators and accelerators, the model calls for stepping here beyond generic business training to supplying specialized resources that build orchestration capacity: giving access to AI tools actually meaningful in portfolio management; being matchmakers with knowledgeable regulators who might aid with privacy or other law governed aspects; building mentor programs that explicitly focus on integrating human capital strategy with technical road mapping. The aim is to create ventures with an orchestration focus.

This down-to-earth analysis leads naturally to a collection of practical recommendations. The last section will extract the insights from this conceptual framework and previous task into concrete prescriptions for DeepTech founders, ecosystem enablers and policy makers, thus bridging the gap between diagnosis and theory on one side and implementation and impact on the other.

Conclusions and Recommendations

Conclusions

This study shows that for DeepTech ventures, long-term success depends on building organizations that can be innovative as their core technology. Using a mixed-methods approach—combining with literature review, concept analysis and expert surveys—this research explores how AI can strategically manage critical talent dynamics. The findings highlight both the possibilities AI brings and practical challenges of implementing it in a high shake resource constrained environment.

The first is that the constraints DeepTech startups confront — financial, human, technological and organizational — are unique and interdependent to determine the mode in which innovation can take place. Rather than allowing these constraints to be stumbling blocks, successful enterprises interpret them as drivers of entrepreneurial virtuosity. They employ AI not as a luxury, but as the cornerstone “force multiplier” and “meta-asset” that allows small teams to achieve sophistication in talent acquisition, development and retention which would otherwise be out of reach.

Second, the research confirms that AI's primary value extends far beyond automating administrative HR tasks. And its enduring contribution is that it enables continual and exponential innovation. By speeding up the R&D with predictive modelling and generative design, by integrating knowledge from outside their own discipline and creating data-driven decision-making, AI is placing an organization in location with its own learning loop. This turns innovation from something that sprays out of the nozzle into something that can be operated as a fine-tuned tool that moves startups to new sources of progress in technology under conditions like uncertainty and long development cycles.

Third, empirical research highlights an important but often underestimated aspect: the external innovation ecosystem is not merely a background feature, but an active co-creator of an AI-enabled talent strategy of start-ups. The feasibility, ethics, and trajectory of integrating AI and HR are deeply shaped by incubators, investors and policymakers. A lack of "coordination" was identified as the door, demonstrating that whether a startup succeeds or fails has more to do with orchestrating external relationships and resources than mastery over technical skills.

Fourth, the AI-Orchestrated Innovation Capacity Model is developed to combine these insights into an integrated theoretical model. AI-Orchestrated Innovation Capacity The model provides the link and extension between Human Capital Theory and Resource Orchestration. Theory by embedding AI as a transformational enabler, which connects continual nurturing of dynamic human capital with strategic coordination of a wide array of resources. It offers a compelling theoretical framework for how DeepTech ventures can develop a defensible competitive advantage based on the mutualism of human judgment and machine intelligence. These findings move the conversation from theoretical potential to actionable strategy. The following recommendations translate the core principles of the AI-Orchestrated Innovation Capacity Model into a practical agenda for the key actors who shape the DeepTech ecosystem.

Recommendations

Considering these findings the following focus recommendations are suggested to key actors in the ecosystem for DeepTech innovation:

For DeepTech Founders and Leadership Teams:

Adopt a Strategic, Phased Approach to AI Integration: Move beyond ad-hoc tool adoption with a deliberate “crawl-walk-run” strategy. Begins with high impact manageable use cases (e.g., AI-powered candidate screening) to demonstrate tangible value, build internal trust and create a foundation for scaling.

Invest in Building AI Literacy and Hybrid Skills: Focus on investment in lifelong learning platforms that enable personalized upskilling programs to develop technical AI skills. As well as the “soft” skills required for human-AI collaboration. Nurture T-shaped professionals who can connect to domains.

Proactively Manage the External Ecosystem: Be active in managing relationships with incubators, investors and academic partners. Leverage these networks not only for capital, but to tap into specialized knowledge, shared data infrastructure and mentorship around implementing ethical AI and strategic HR.

Institute Lightweight Ethical Governance: Set out clear and transparent guidelines for the application of AI in HR from day one. Even without a large team of compliance to build modest review for algorithms to decrease bias, meet privacy regulations (such as GDPR) and keep employees’ trust.

For HR Professionals within DeepTech Ventures:

Transition from Administrator to Strategic Orchestrator: Leverage AI to automate routine tasks and create space for managing higher-value projects such as culture creation, employee experience program design and internal talent maneuvering.
Develop Data Fluency: Proactively work to become skilled at reading HR analytics and AI-driven insights. Collaborate to be certain AI tools are configured to deliver and outputs are comprehended and ethically acted upon in a human centred context.
***Champion the Human-in-the-Loop Model**:* Advocate for and implement processes in which AI support human decision making in hiring, performance evaluation and development rather than replacing it. Communicate openly about how AI tools are applied.

For Investors (Venture Capital):

Incorporate Talent and AI Strategy into Due Diligence: Evaluate a startup not only on its technological promise but also on the sophistication of its human capital strategy and its planned use of AI for scaling. Assess the founders' competency in orchestrating key ecosystem relationships.
Provide Value-Added Support Beyond Capital: Make ensure that, teams can reach ethics advisors when needed ethical advisory and the AI talent networks and potential research partners. Support, as needed, portfolio companies on best practices as it relates to AI governance and scalable HR infrastructure.
Encourage Long-Term Investment in Human Capital: This is not overhead spending on AI-enabled learning platforms and ethical audits but a fundamental investment in the innovative capabilities and resiliency of your venture.

For Policymakers and Ecosystem Enablers (Incubators, Accelerators, Academia):

Foster Collaborative Platforms to Reduce Coordination Deficits: Create a fully structured forums and digital platforms that can link startups with advisors from academia, regulators and in the future civil society actors to co-develop solutions for ethical AI-HR integration.
Design Targeted Financial and Regulatory Support: Innovation grants should be developed specifically to support piloting AI in SME and startups. HR under safe regulatory conditions. Which provides a clear, accessible guidelines on compliance with regulations.
Co-create Talent Pipelines and Knowledge-Sharing Programs: Encourage strong collaboration among universities, DeepTech clusters and startups to develop interdisciplinary curricula that directly address existing skills gaps. Furthermore, establish a secure, privacy-

protected framework for sharing anonymized, aggregate industry data to help train more reliable and less biased AI models for sector wide benefit.

In conclusion, pioneering DeepTech means building organizations that are as intelligently architected as the technologies they create. This research suggests that by positioning AI as a strategic orchestrator of talent and external networks, startups can convert their most pressing limitations into foundations for scalable, long-term advantage—turning constraint into a catalyst and inherent constraints into a durable, scalable competitive advantage.

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Declaration on The Use of Artificial Intelligence

Artificial intelligence tools (Specially ChatGPT by OpenAI) were employed as an auxiliary resource during the preparation of this Final Master's Thesis to assist with language refinement, clarity of academic writing and structural consistency.

The AI tool was not used to generate original research ideas, develop the research design, create data collection instruments, construct data analysis, or interpretation of empirical results. All statistical analyses, findings, interpretations and conclusions presented in this thesis are solely the responsibility of the authors.

The use of artificial intelligence adhered to Vilnius University guidelines on the responsible and ethical use of AI tools in academic work.

Annexes

Annex 1

Questionnaire

Topic: AI and Talent in Deep-Tech Startups: How Emerging Ventures Build the Workforce of the Future

Purpose: This questionnaire aims to explore how external ecosystem actors (incubators, investors and policymakers) influence the integration of Artificial Intelligence (AI) into human resource (HR) management and its impact on innovation sustainability within deep-tech ventures.

All responses will remain confidential and used for academic purposes only.

SECTION 1: Respondent Background

1. What is your primary role in the deep-tech ecosystem?

☐ Startup founder / executive

☐ Investor / venture capitalist

☐ Incubator / accelerator representative

☐ Policymaker / government official

☐ Researcher / academic expert

☐ Other (please specify): ___________

2. How many years of experience do you have in the deep-tech or AI sector?

☐ Less than 2 years

☐ 2–5 years

☐ 6–10 years

☐ More than 10 years

3. What is the size of the organization you represent?

☐ Fewer than 10 employees

☐ 10–50 employees

☐ 51–200 employees

☐ More than 200 employees

4. Country of operation:

(Short answer)

SECTION 2: AI–HR Integration Practices

5. Please indicate how much you agree with the following statements:

(Scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree)

Statement	1 2 3 4 5
a. Our organization uses AI-based tools for recruitment and talent acquisition.	☐☐☐☐☐
b. AI is applied to analyse employee performance or engagement data.	☐☐☐☐☐
c. The HR department leverages data-driven insights from AI for strategic decisions.	☐☐☐☐☐
d. Employees receive training to effectively use AI-enabled HR systems.	☐☐☐☐☐
e. The adoption of AI in HR has enhanced fairness, efficiency, and transparency.	☐☐☐☐☐
f. AI adoption aligns closely with our organization's innovation strategy.	☐☐☐☐☐

6. What are the key barriers your organization faces when integrating AI in HR processes?
(Paragraph answer)

SECTION 3: Role of Ecosystem Actors

7. Please indicate your level of agreement with the following statements:
(Scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree

Statement	1 2 3 4 5
a. Incubators/accelerators provide strategic HR or AI adoption guidance.	☐☐☐☐☐
b. Investors actively support startups in building AI-driven HR capabilities.	☐☐☐☐☐
c. Policymakers encourage responsible and ethical AI use in HR.	☐☐☐☐☐
d. Collaboration among ecosystem actors enhances startups' ability to integrate AI and manage talent.	☐☐☐☐☐

e. The lack of coordination among ecosystem players creates barriers to AI–HR integration.	□□□□□
f. Public funding or regulatory frameworks significantly affect AI–HR integration decisions.	□□□□□

8. In your view, how can ecosystem actors (e.g., investors, incubators, policymakers) better enable AI–HR integration in deep-tech ventures?
(Paragraph answer)

SECTION 4: Innovation Sustainability

9. Please indicate how much you agree with the following statements:
(Scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree)

Statement	**1 2 3 4 5**
a. AI–HR integration strengthens our organization's capacity for continuous innovation.	□□□□□
b. AI-driven HR systems help us attract and retain innovative talent.	□□□□□
c. The combination of human creativity and AI tools enhances organizational adaptability.	□□□□□
d. Over-dependence on AI can limit creativity and critical thinking among employees.	□□□□□
e. External ecosystem support contributes to long-term innovation sustainability.	□□□□□

10. From your perspective, what practices can ensure the sustainable coexistence of AI systems and human talent in deep-tech startups?
(Paragraph answer)

Annex 2

Table 1

Comprehensive Metrics for Assessing AI's Impact on Innovation Capacity

Category	**Metric**	**How it Demonstrates Sustained Innovation**
Quantitative Metrics	R&D Velocity (experiments/week)	Increased output with same resources, demonstrating enhanced efficiency in knowledge generation
	Idea Throughput (viable concepts/quarter)	Enhanced creativity and screening capabilities, showing improved innovation pipeline health
	Reduction in Cost per Prototype	Direct efficiency gain from AI simulations and generative design
	Patent Citations & Technological Breadth	Quality and influence of innovation output, reflecting knowledge creation and reuse (Feng et al., 2025)
	AI driven Innovation Efficiency Ratio	Patents or publications per R&D dollar, measuring resource optimization
Qualitative Metrics	Cross-Functional Collaboration Score	Improved knowledge integration and breaking down of disciplinary silos
	Strategic Pivot Speed	Enhanced dynamic capability and organizational responsiveness to change
	Employee Skill Diversification Index	Growth of internal human capital and adaptive learning capabilities
	Failure-to-Learning Conversion Rate	Effectiveness in institutionalizing lessons from setbacks
	Ecosystem Connectivity Index	Strength and diversity of external knowledge networks and partnerships

Annex 3

Figure 1

Primary role in the deep-tech ecosystem

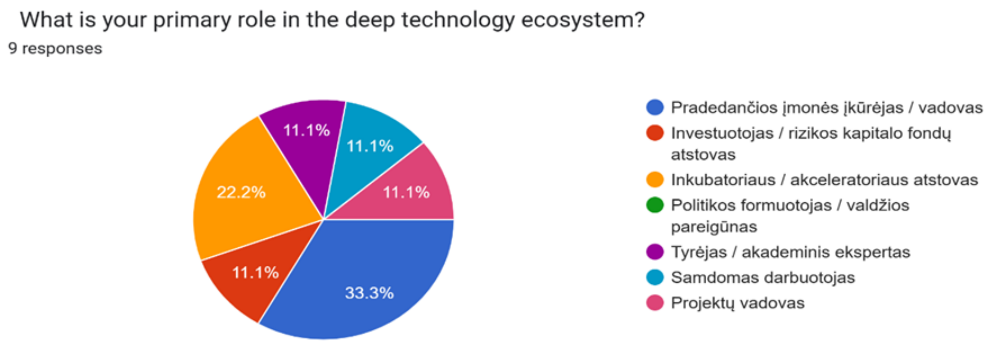

Figure 2

Working Experience in DeepTech and AI Sector

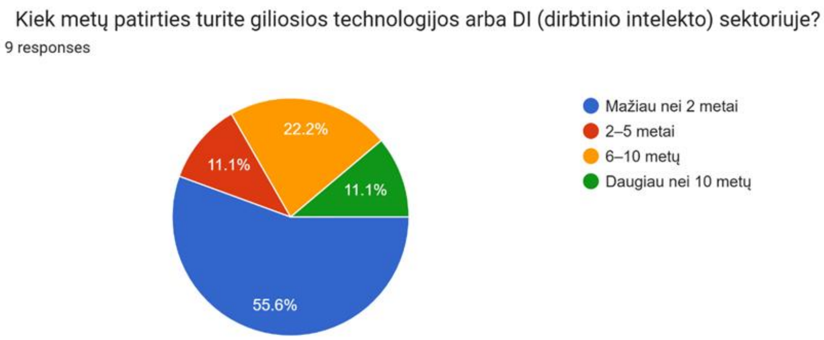

Figure 3

Size of the organization

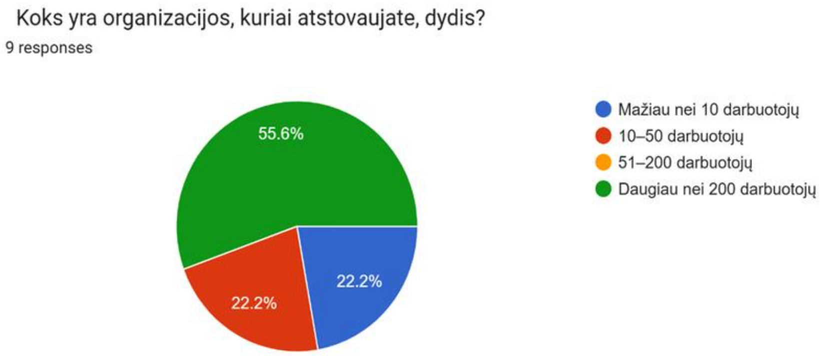

Figure 4

Organization uses AI-based tools for employee selection and talent acquisition

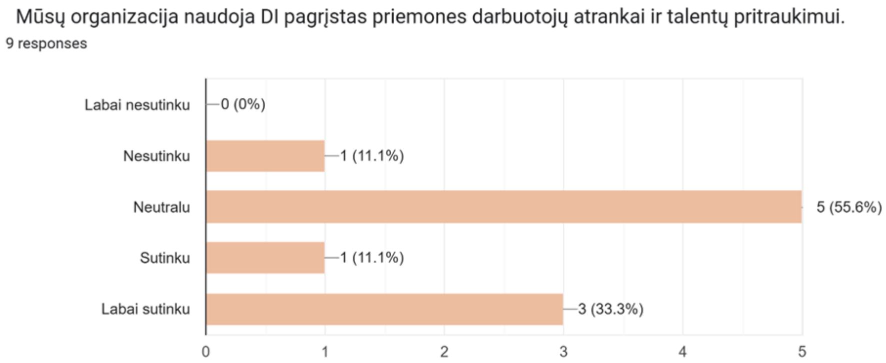

Figure 5

AI is used to analyse employee performance or engagement data

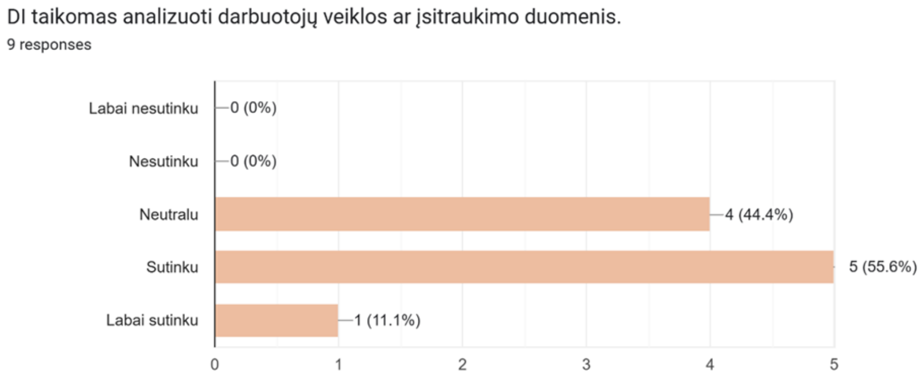

Figure 6

The Human Resources (HR) department is leveraging AI-based data insights to make strategic decisions

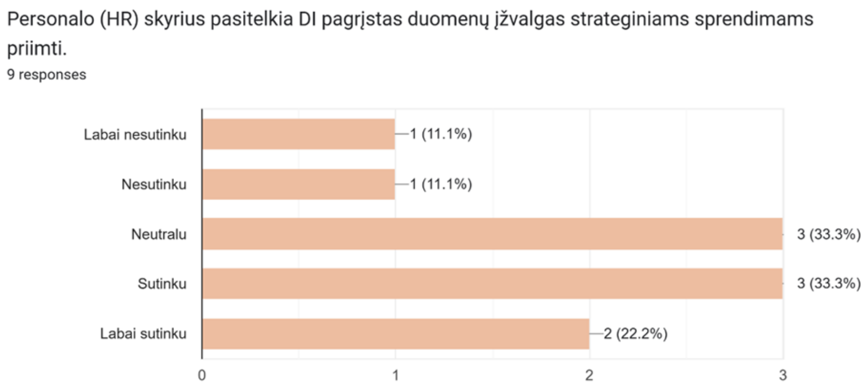

Figure 7

Employees receive training on how to effectively use AI-enabled human resources systems

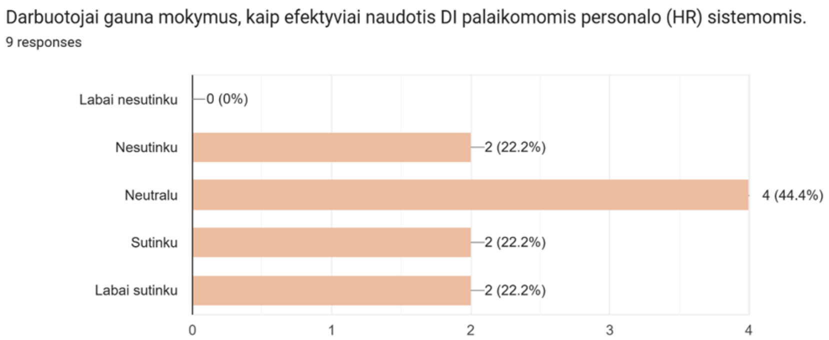

Figure 8

Employees receive training on how to effectively use AI-enabled human resources systems

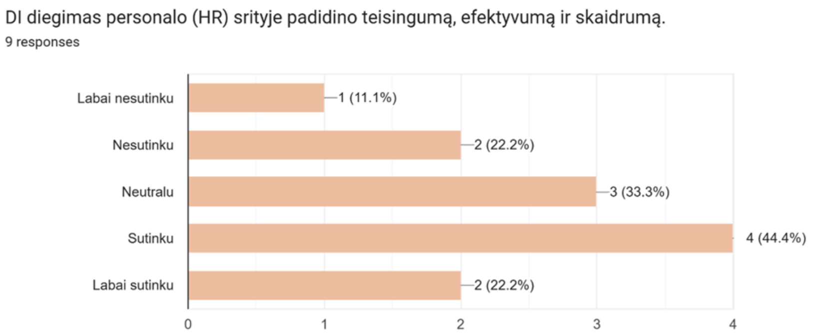

Figure 9

The implementation of AI closely aligns with our organization's innovation

Figure 10

Incubators/accelerators provide strategic guidance on HR or AI implementation

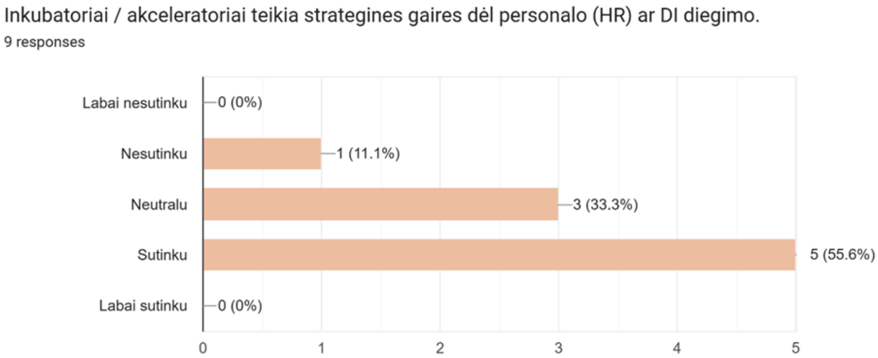

Figure 11

Investors are actively backing startups in developing AI-based HR capabilities

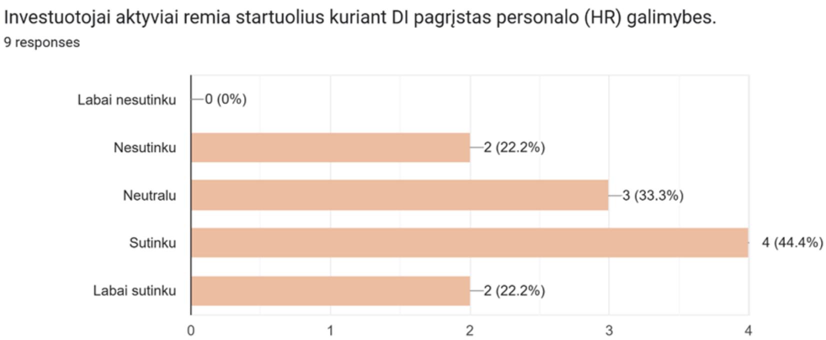

Figure 12

Policymakers are promoting the responsible and ethical use of AI in human

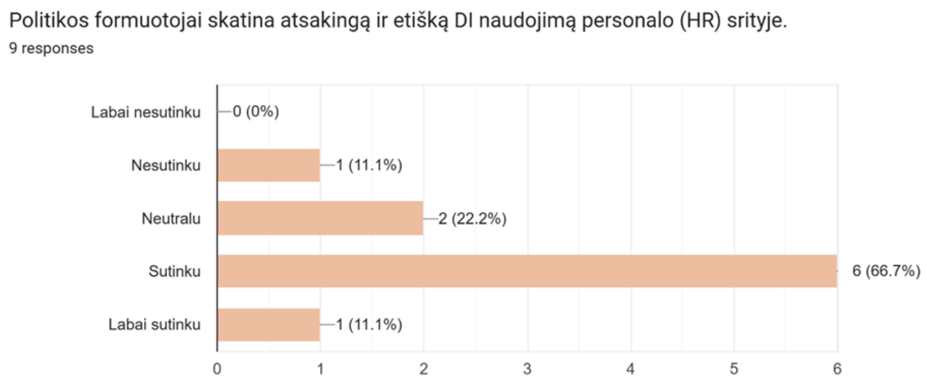

Figure 13

Collaboration between ecosystem players increases startups' ability to integrate AI and manage talent’

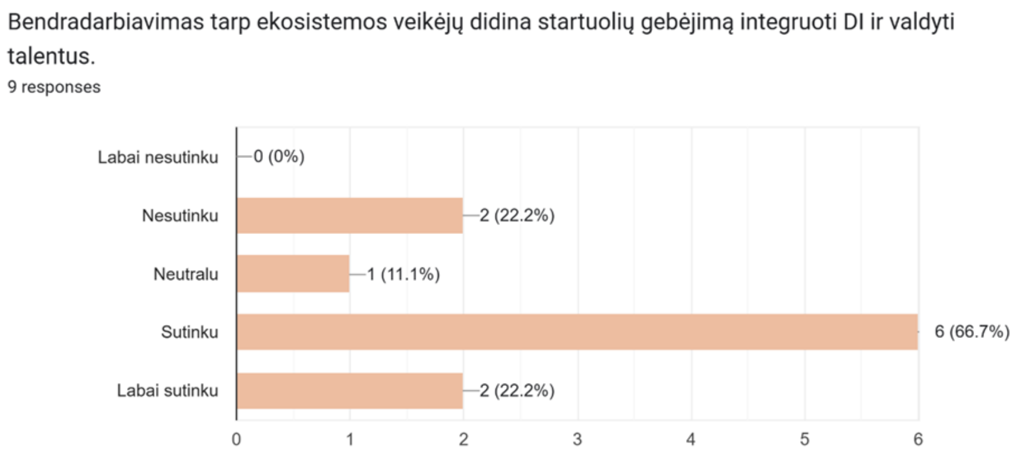

Figure 14

Lack of coordination among ecosystem participants creates obstacles to the integration of AI and human resources

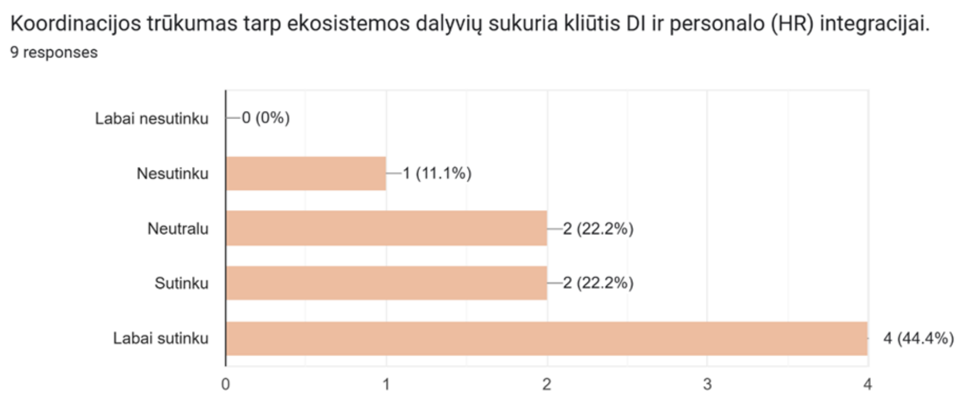

Figure 15

Public funding or the regulatory framework significantly influences decisions regarding AI and human resources integration

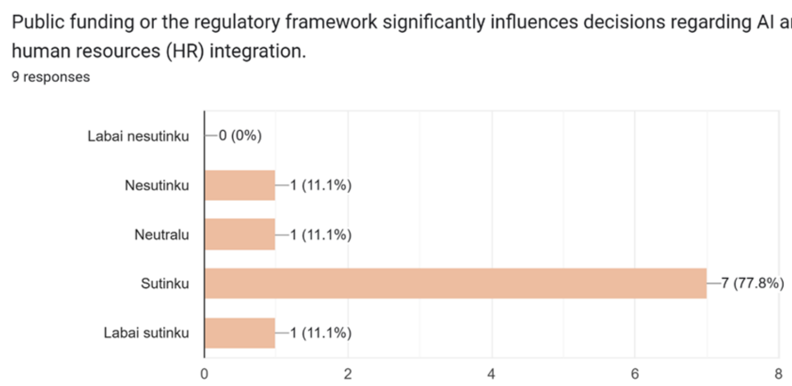

Figure 16

The integration of AI and human resources (HR) strengthens our organization's ability to continuously innovate

Figure 17

AI-based human resources (HR) systems help us attract and retain innovative

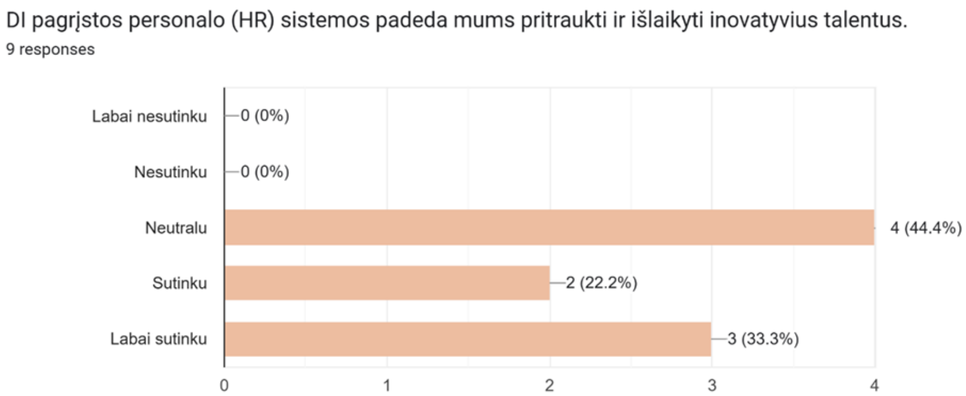

Figure 18

The combination of human creativity and AI tools increases an organization's ability to adapt'

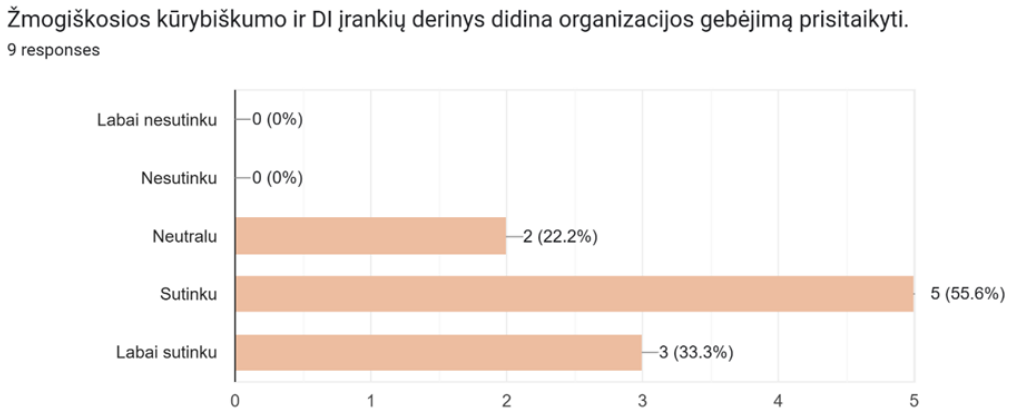

Figure 19

Overreliance on AI can limit employees' creativity and critical thinking

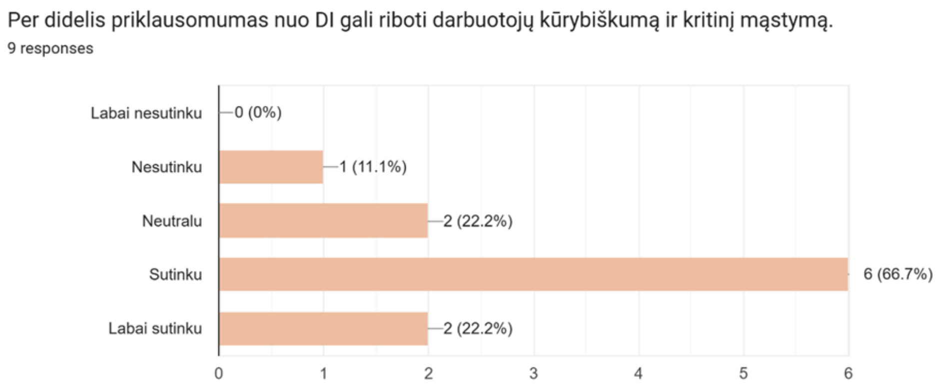

Figure 20

External ecosystem support contributes to the long-term sustainability of innovation

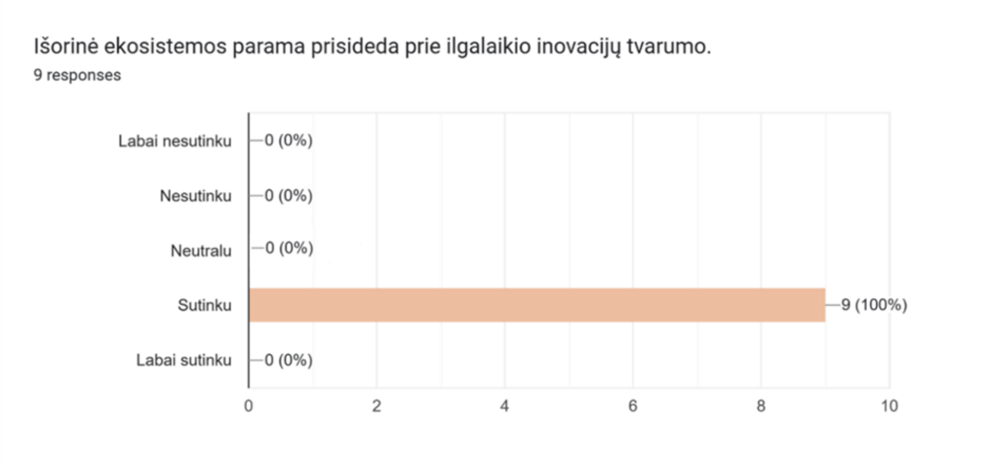

Figure 21

Bridging Human Capital; Theory and Resource Orchestration Theory in DeepTech: The Catalytic Role of AI

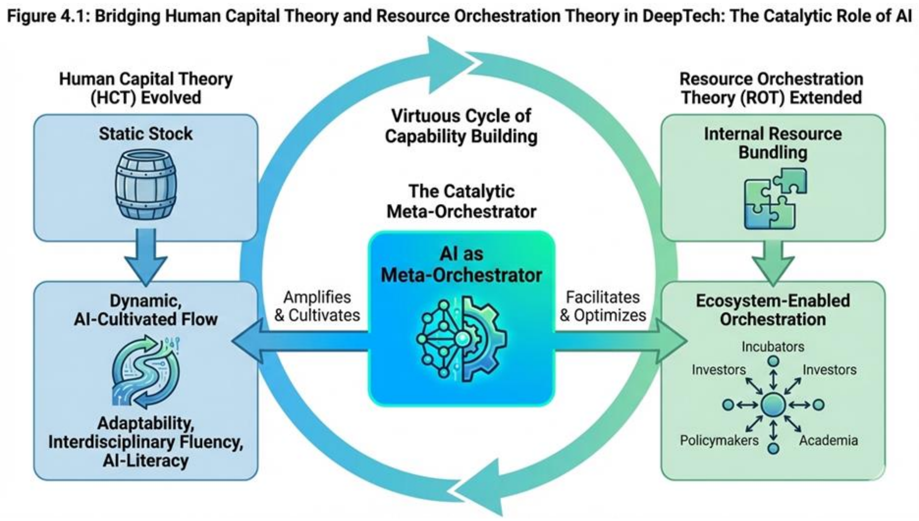

Figure 22

The AI Orchestrated Innovation Capacity Model

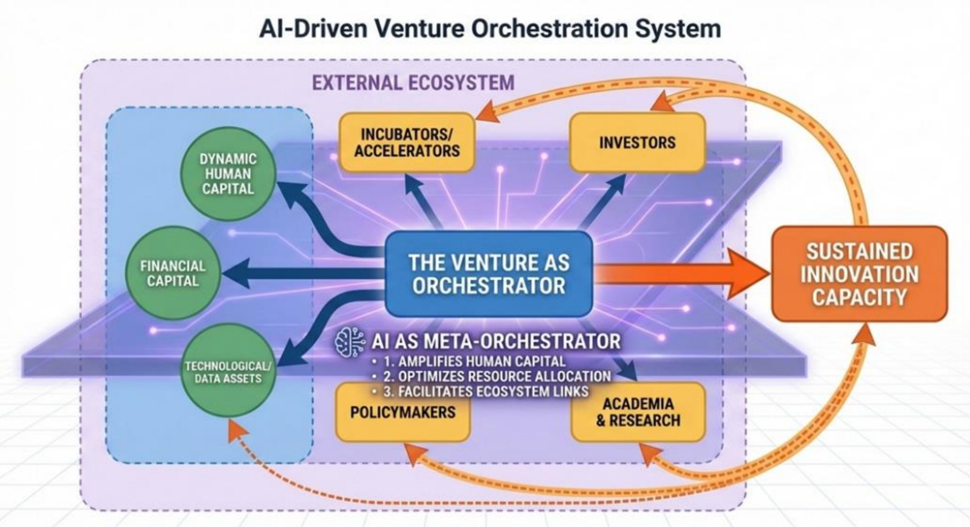

Figure 23

Core Component 4: AI as the Meta Orchestrator