Cambridge Judge Business School
Entrepreneurship Centre

EnterpriseTECH Commercial Feasibility Report

Brainoid Technologies

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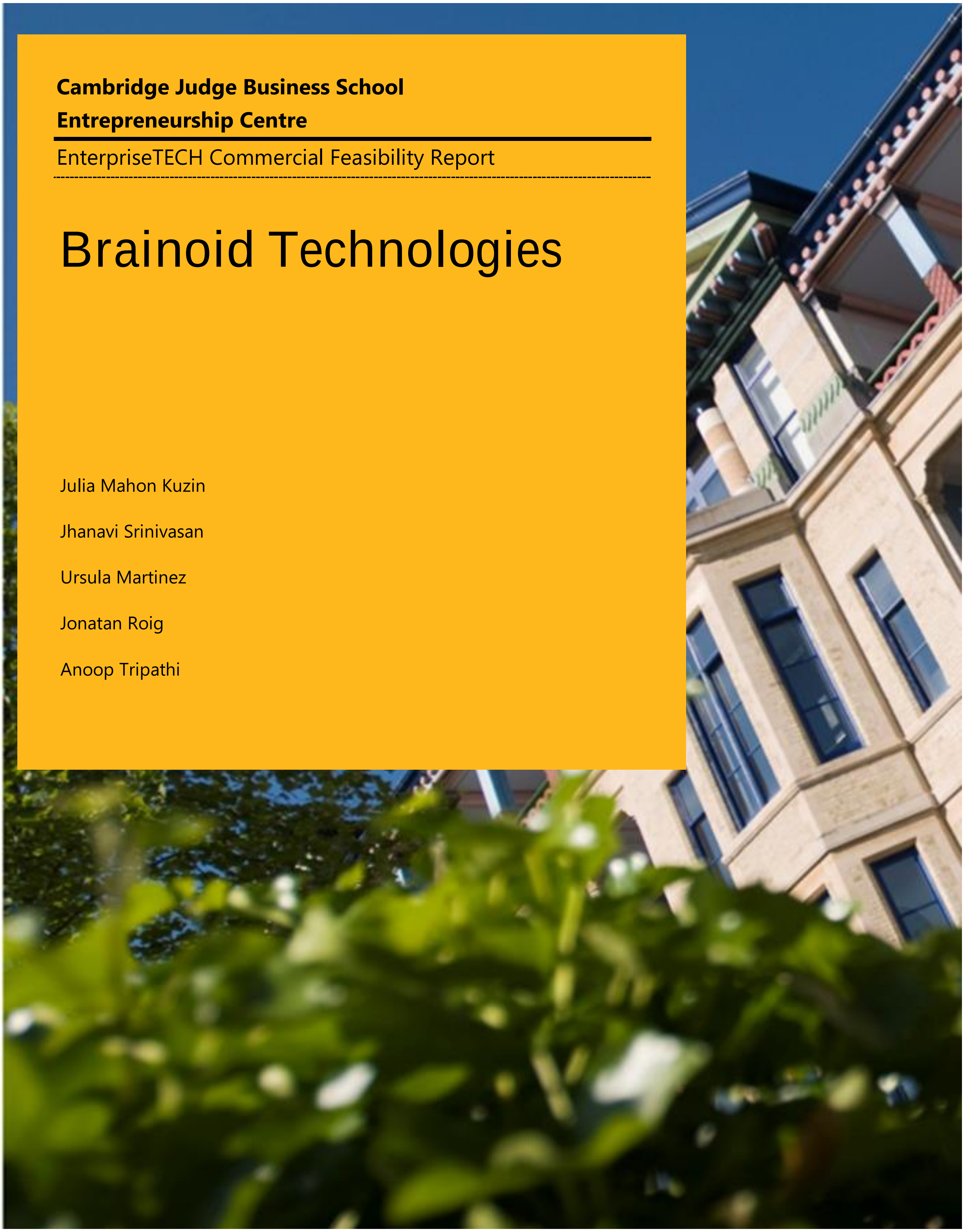

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1. Executive summary

World models are AI systems that understand, predict, and reason within physical environments. They are critical infrastructure within autonomous vehicles and robotics, yet the companies building them face exponentially rising training costs and persistent robustness failures.

Brainoid Technologies addresses this by fundamentally re-designing the training architectures themselves, offering an AI development infrastructure platform grounded in peer-reviewed research with proprietary data efficiency research. The approach currently demonstrates 2-5x efficiency gains under controlled conditions, with the foundations in place to scale toward improvements of 100x by year 5, while also providing increased robustness in unforeseen environments.

Brainoid has a partner engagement with LOXO, the first company in Europe to achieve Level 4 autonomous driving. Brainoid's planned market expansion approach is driven by continuous customer feedback and progressive product releases as the deep-tech matures.

This report examines market opportunity, execution risk, and return on assets, to validate the proposed phased pathway and concludes that Brainoid's proposed three stage expansion as commercially feasible.

2. Introduction to the Technology

2.1 Problem overview

Brainoid Technologies wants to create a step change in the robustness and efficiency of AI world models. These models learn from experience to model the environment, and they are very useful for robotics, autonomous systems, and simulations.

The approach used nowadays to train these models is by scaling data and computational power, creating an exponential growth of costs for incremental performance gains with significant issues to generalize their knowledge to novel situations.

These training strategies are significantly behind biological intelligence in terms of sample efficiency (i.e., rate of learning per experience), so the bottleneck is not a physical constraint but a limitation in the AI training architectures used.

In the figure below there is a representation of the different layers that exist between the hardware used to train an AI model and the application that makes the model available to end users.

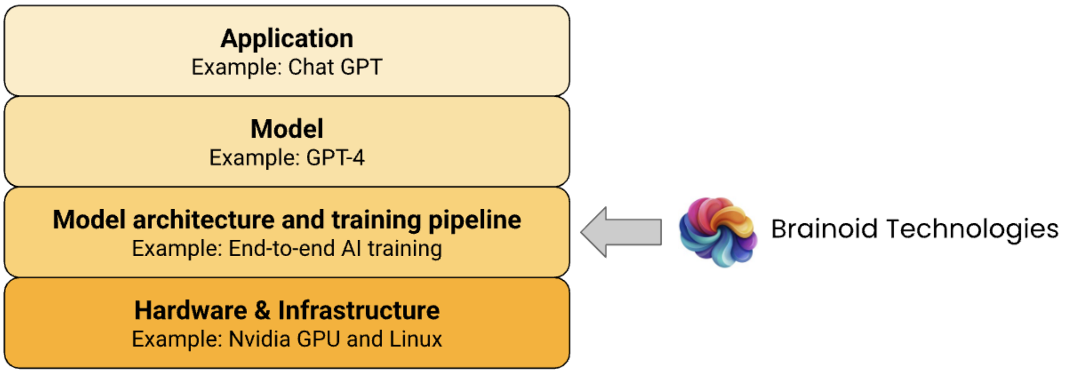

Figure 1. Brainoid positioning

2.2 Solution proposed

Brainoid Technologies wants to work in two workstreams that converge together.

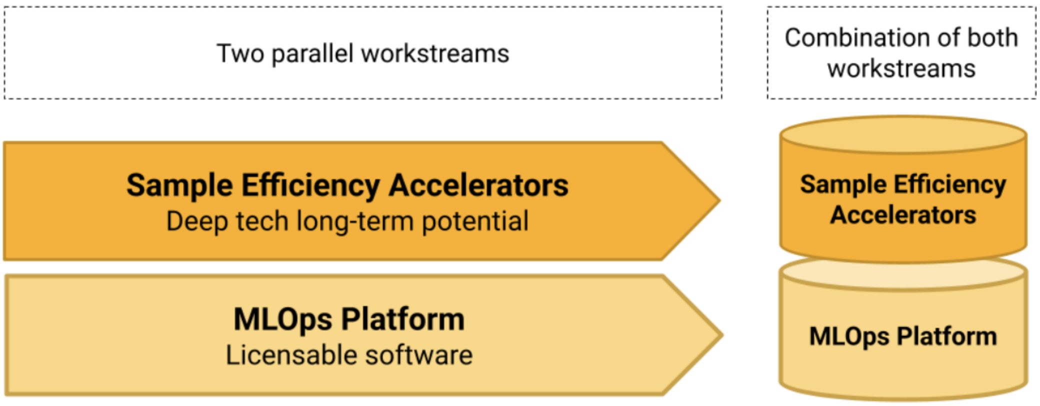

Figure 2. Brainoid workstreams

2.2.1 Product Development: MLOps Platform

An MLOps platform (Machine Learning Operations) for AI world model development that will bring tools to simplify and reduce development times with no need of specialized teams.

Brainoid's MLOps platform differentiates itself from others by having a narrower focus on new non-generative (predictive) AI architecture. It is especially beneficial for companies that cannot afford large technical teams to explore non-generative alternatives who compete against very large competitors. The MLOps platform is also the software infrastructure needed to embed the core technology.

2.2.2 R&D towards a competitive advantage: Sample Efficiency Accelerators

In parallel, there will be a deep-tech development of AI sample efficiency accelerators, which are essentially a new architectural approach to the way AI world models are trained, achieving better robustness with significantly less data which ultimately means less cost and better environmental impact.

2.3 Roadmap

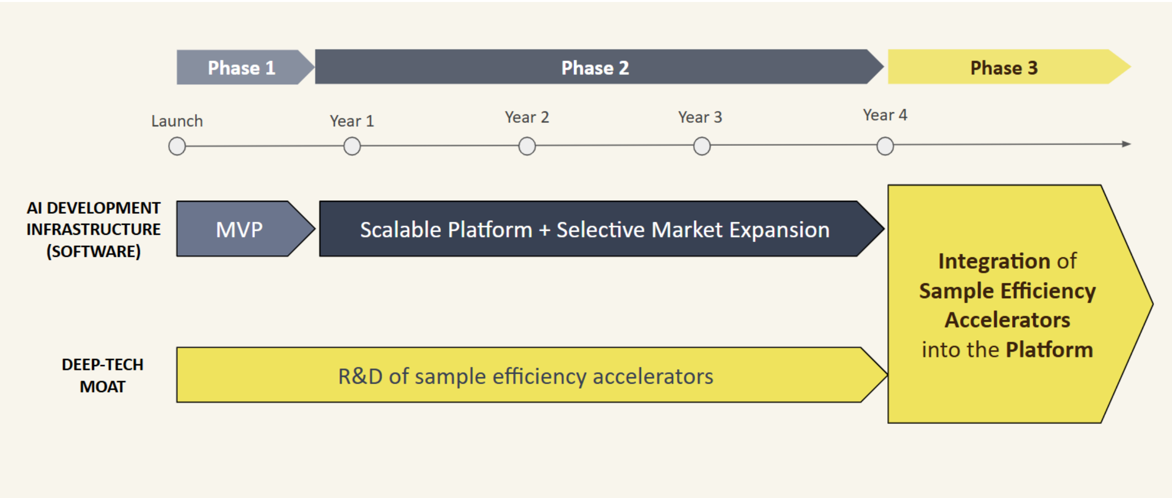

Figure 3. Roadmap for Brainoid product development

2.3.1 Phase 1 (2026-2027): Minimum Viable Product (MVP) & Pre-Product Market Fit

The goal of this first stage is validation of market demand by designing scalable solutions to critical model robustness problems alongside a handful of end-user companies that are facing challenges with scaling their AI training and model robustness, to ensure the product design responds to the intricate needs of the end-users.

2.3.2 Phase 2 (2027-2030): MLOps Platform Release

This second phase will give birth to the first version of a scalable MLOps platform for world models. The goal is to provide a software platform that delivers development toolkits and training architectures to R&D teams offering 10x reduction of costs for model improvements. During this phase, the sample efficiency R&D is not mature enough to be embedded into the product.

2.3.3 Phase 3 (2030): Sample Efficient Accelerators Maturity and Integration into the Platform

This third and final stage will integrate the sample efficiency accelerators into the MLOps development platform. This innovation will transform the value of the product and establish a competitive advantage by introducing a 100x+ sample efficiency increase for world models, it realises the technological value of the IP.

3. Technology and Product Readiness

3.1 Gap analysis towards minimum viable product

The three staged plan has a clear direction towards an MVP that can ultimately validate the ideas of Brainoid Technologies and deliver the first revenues. To get to a fully functional licensable MVP product, the first stage of the plan is to focus on the development of MLOps for JEPA (Joint Embedding Predictive Architecture) pipelines with Brainoid's partner LOXO (an autonomous driving startup) located in Switzerland.

JEPA is a new approach that uses abstract high-level representations that can be generalized well across many tasks. Notably, the focus on architectures like JEPA (which use latent representation, rather than end-to-end mapping) is in-line with the end goal of Brainoid Technologies for integrating its sample efficiency stack into its training pipelines. A pre-requisite of realising the value of sample efficiency accelerators in Phase 3 is to have a compatible infrastructure (training architecture) to enable models to learn with significantly less data by using more abstract patterns.

3.2 Technology readiness level

3.2.1 MLOps platform

This platform will be focused on using JEPA architectures which is based on existing open-source and publicly available peer-reviewed research. Currently the JEPA architecture behind this MLOps platform is TRL 6 (DoD OSEA, 2025) for the industries of robotics and autonomous driving and a bit higher for physics and simulations.

3.2.2 Sample efficiency accelerators

This technology will be proprietary based on the inventor's research and is currently offering between 2-5x efficiency gains under strictly controlled environments. More validation is still needed to evaluate how the technology would behave within a machine learning environment.

We can consider this product to be in a very early stage, with TRL 2-3 since the examples are using limited synthetic data and applications are still speculative (DoD OSEA, 2025). There is still not sufficient analysis to consider TRL3.

3.3 Intellectual Property Strategy

Table 1. Brainoid’s intellectual property strategy will evolve across different stages of development.

Phase	Phase 1: MVP and Pre-Product Market Fit	Phase 2: Release of MLOps Software Platform	Phase 3: Sample Efficiency Platform & Deep-Tech IP
Timeframe	Year 1	Year 2	Year 3+
IP Focus / What to Protect	• Core algorithms • System design • Early prototypes	• World Model development tools • New training architectures and improvements on existing ones • Cost-efficient solutions, technical know-how	• World Model development tools • Sample-efficient accelerators • AI training architectures • Breakthrough world models
Action / How	• Trade secrets • Enforce NDAs with early clients (AI labs, robotics companies) • Enforce well-designed employee agreements for IP protection	• Use copyrights and software licenses for platform • Maintain trade secrets for internal optimizations • Internal IP protection policies for employees	• Selective patent filings • License IP to AI companies and research institutions • Align IP filings with R&D team progress
Purpose / Why	• Protect foundational IP before public engagement • Enable early client validation	• Build defensible portfolio • Enable licensing and partnerships • Secure commercialization	• Establish industry standard • Create barriers to entry • Generate revenue via licensing • Defend competitive advantage

4. Market Opportunity

4.1 Industry Classification & Definition

AI world models simulate and predict physical environments to support decision-making in real-world machines like robots, drones, and autonomous vehicles (Ding et al., 2025; Gartner, 2025). Recognised as a top strategic technology trend for 2026 (Gartner, 2025) and potentially essential for human-level machine intelligence (LeCun, 2022). While general-purpose generative foundational models offer a starting point, they lack the persistent state needed for these physical applications (Ding et al., 2025). Developing world models today is highly resource-intensive, costing tens of millions of dollars and demanding exponential increases in computational resources and massive datasets (Maslej et al., 2025). Established MLOps tooling exists for traditional machine learning (Kreuzberger et al., 2023), however world models require fundamentally different data pipelines, integrating lidar, vision, and sensor data (Ding et al., 2025), especially for non-generative world models. No existing MLOps platform exists for these unique data streams pipelines, so there is a significant gap between the growing demand for AI world models and the industry's capacity to build them effectively.

Table 2. Industry segments for AI world models.

ROBOTICS	
• Humanoid robots • Healthcare / surgical robots • Manufacturing robots	• Logistics robots • Warehouse robots • Defence robots / drones
AUTONOMOUS DRIVING	
• Consumer cars	• Cargo trucks / freight
SCIENTIFIC & INDUSTRIAL SIMULATIONS	
• Drug discovery • Physics simulations	• Materials science • Climate & environmental modelling
VIRTUAL ENVIRONMENTS	
• Gaming intelligence	• Societal modelling

4.2 Commercial advantage of Brainoid

Porter's Generic Competitive Strategies (Porter, 1980) map positioning along two axes: competitive advantage (cost vs. differentiation) and market scope (broad vs. narrow). Brainoid targets a narrow segment of AI development teams building world models for physical AI, with a focus on differentiating itself in non-generative world models (for example JEPA). The competition targets both cost and differentiation, as shown in Figure 4.

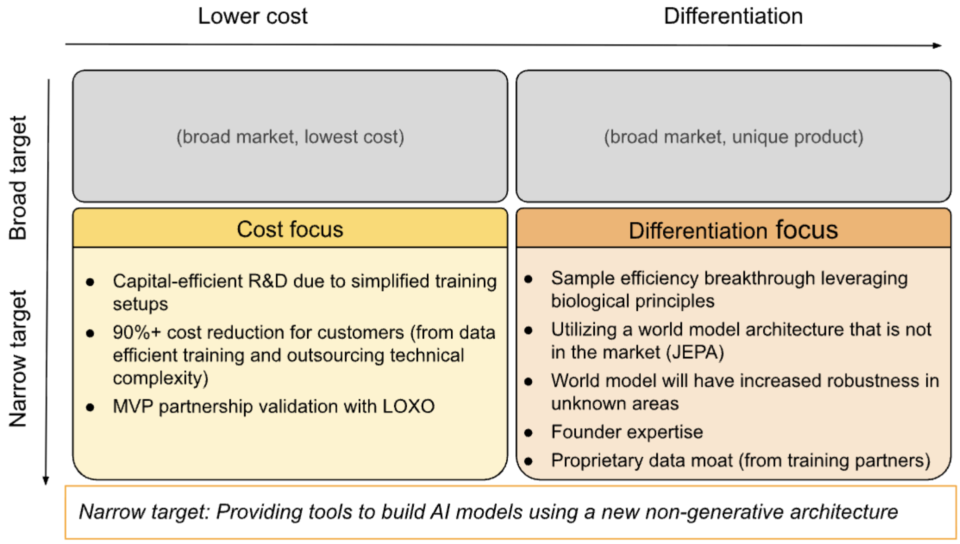

Figure 4. Brainoid's commercial advantages, using Porter's Generic Competitive Strategies.

(Data provided by inventor; Porter, 1980)

4.3 Market research and pricing analysis

The AI world model market is expanding rapidly, with investments reaching $6.9 billion in 2025 (CB Insights, 2026). While major tech firms spend billions to overcome training data bottlenecks (CB Insights, 2026), Brainoid's sample efficiency technology aims to minimize data requirements through efficient model architectures. Its MLOps pipeline aims to significantly reduce the costs of model improvements.

In the broader machine learning sector, dedicated tooling is crucial. 70% of organizations invest in some form of conventional ML workflow platforms (Zarour et al., 2025) to achieve significantly higher financial returns (McKinsey & Company, 2022). Brainoid fills a current void in tooling for world models within ML. Brainoid will adopt a software licensing model comparable to enterprise platforms. For this see the pricing breakdown in "Pricing Models" tables.

The market size within each major global region (North America, Asia-Pacific, Europe, and Latin America) is expected to increase 10-fold between 2025 and 2034. Brainoid is initially targeting customers in Europe due to proximity and current partnership with LOXO, based in Switzerland. See Appendix Table 1 for further regional breakdown.

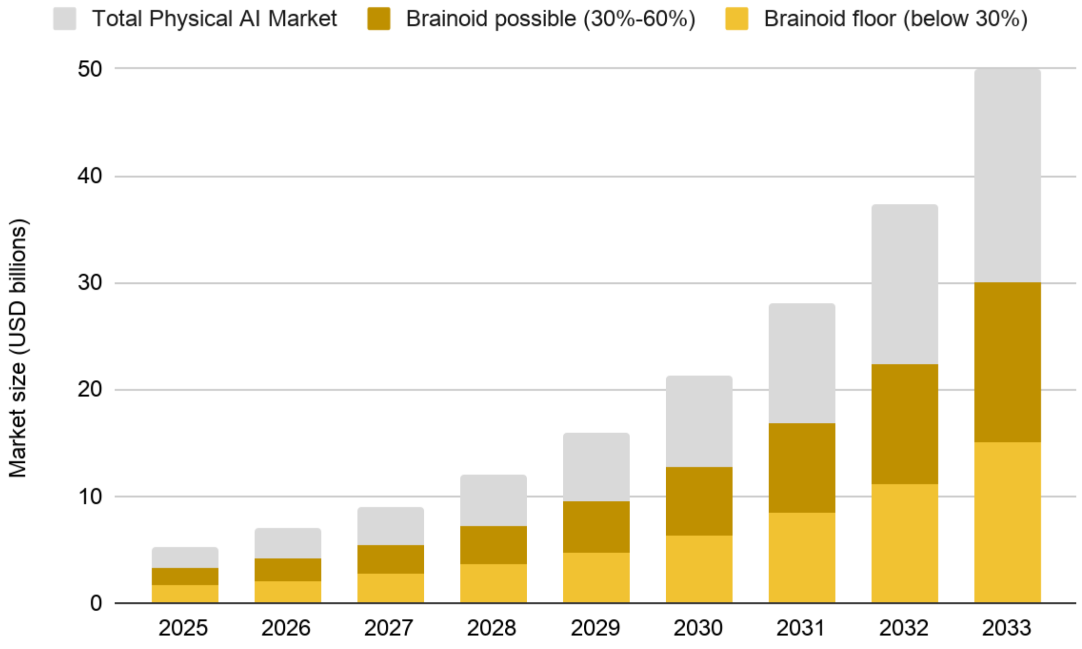

Figure 5. Brainoid within the global physical AI market growth
The global physical AI world model development market is predicted to grow from $6.9B in 2026 to $50B in 2033 (SNS Insider, 2025). Brainoid's target shows variance in the cost that different companies put into R&D of world models. Brainoid targets R&D costs (30-60% of the market) of model improvement (SNS Insider, 2025; Codiant, 2026, March; Grand View Research, 2023)

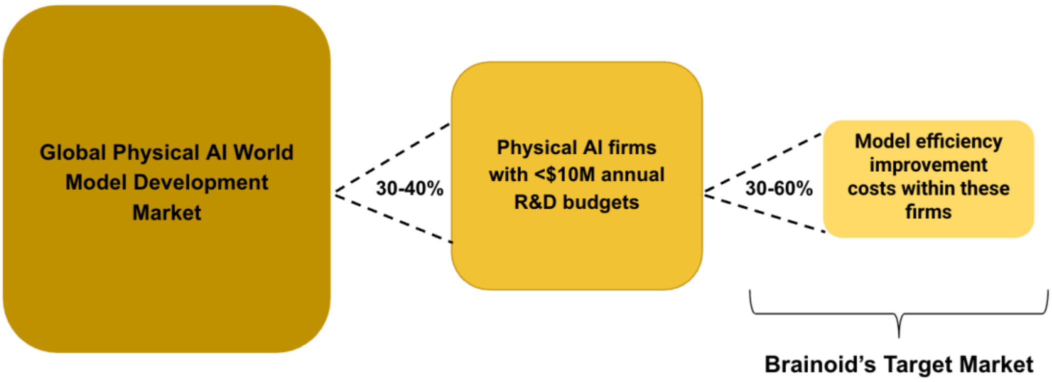

Figure 6. Market Overview
30-40% of the global physical AI world development market comprises firms with less than $10M in annual R&D budgets. Brainoid targets the 30-60% of model efficiency improvement R&D costs in physical AI firms (Codiant, 2025, Grand View Research, 2023).

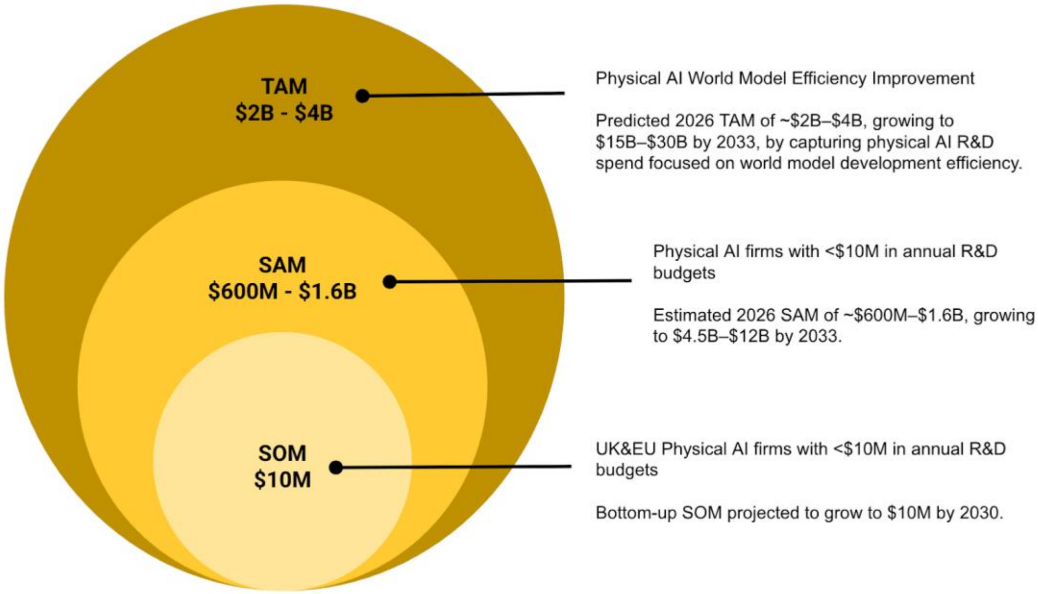

Figure 7. Brainoid TAM/SAM/SOM

(SNS Insider, 2025, Codiant, 2025, Grand View Research, 2023).

4.4 Brainoid's Customers

Brainoid is selling a tooling platform to those building AI world models.

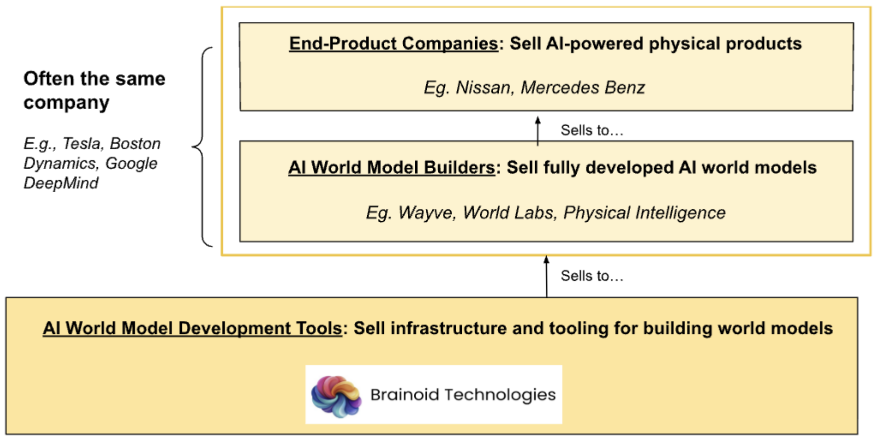

Figure 8. AI world model vertical market

Table 3. Brainoid industry customer pain points
(Sathyam and Li, 2025; Yoo et al., 2025; Nvidia, 2025)

Segment	Pain Points
Autonomous Driving	• Models fail to generalise beyond training data, leading to misrepresentation of physical surroundings and safety-critical errors

	• High computational cost of ensuring reliability
Robotics	• Deployment environments vary widely (warehouses, sidewalks, surgical theatres) and retraining for each is costly and slow • Data collection for every new environment is costly and slow
Simulation & Research	• Simulated environments must accurately capture real-world dynamics • Generated synthetic data is only useful if the underlying model is faithful to physics

Table 4. Customer segmentation

Co-development customer (The "Evangelists")		**Cloud platform customer**
They need a robust and cost-effective way to build a world model. They have time and developers to co-develop with Brainoid Need to outsource the technical complexity	**Who they are**	They need a robust and cost-effective way to build a world model. They have developers that can integrate with the product's middleware Prefer to outsource technical complexity
Firms with less than $10 million	**Size**	Mainly firms with less than $10 million
Fine-tuning existing foundational models or building world models from scratch	**Status quo**	Fine-tuning existing foundational models or building world models from scratch
Need a technical edge to stay alive in the market	**Motivation**	Cost-effective scaling and outsourcing complexity
Active co-builder. Brainoid provides the valuable world-model-native infrastructure and tooling	**Brainoid's role**	Platform operator. Brainoid handles infrastructure, MLOps, and maintenance

4.5 Industry Dynamics & Competitive Landscape

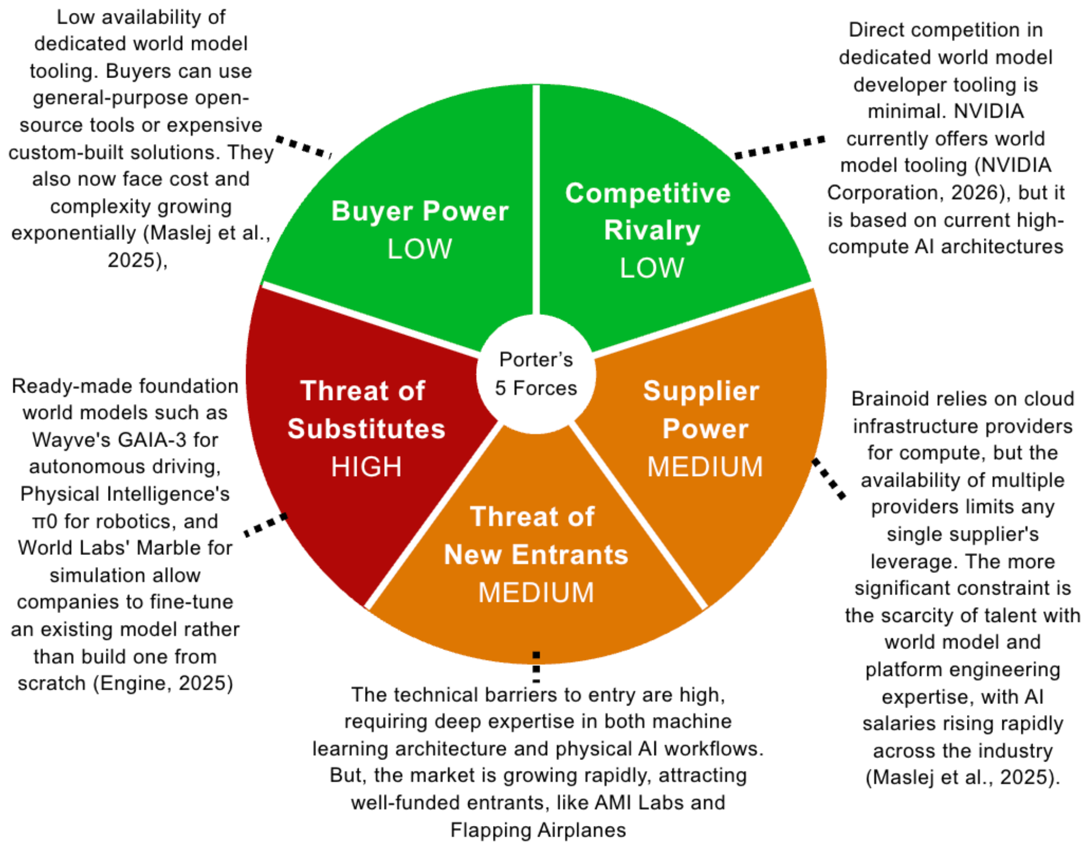

Figure 9. Porter's 5 Forces in Physical AI Market

(Porter, 1980)

Table 5. Descriptions of Brainoid's competitors

(1. Flapping Airplanes, n.d.; 2. Chen, C., 2026; 3. AMI Labs (n.d.); 4. NVIDIA Corporation, 2026; 5. NVIDIA 2025; 6. Google DeepMind, 2025; 7. World Labs, 2026; 8. Physical Intelligence, 2026; 9. Pearce et al., 2024; 10. Hugging Face, n.d.; 11. Linux Foundation, 2022)

Company	Approach	Brainoid's Similarities and Distinctions
RESEARCH-FOCUSED STARTUPS		
Flapping Airplanes (1)	Well-funded research lab exploring sample-efficiency in AI training. No announced product, platform, or commercial timeline.	Both focus on sample efficiency. Flapping Airplanes pursues open-ended research with no commercial timeline. Brainoid commercialises the architecture using market feedback to guide

		development.
Advanced Machine Intelligence (2, 3)	Research lab building foundational world models based on JEPA. Led by Yann LeCun, who introduced JEPA. Explicit intention to publish open-source stacks to encourage adoption.	Both build on JEPA architecture, but Brainoid focuses on the tooling layer to enable commercial adoption. AMI could be a direct competitor if they build a tooling platform, an acquirer of Brainoid, or provide support to Brainoid with their open-source offering.
ESTABLISHED FULL-STACK GIANTS		
NVIDIA (4, 5)	Provides developer tooling to accelerate adoption across Physical AI, focused on existing architectures reliant on high computational resources.	Brainoid is betting on future adoption of innovative AI architectures, like JEPA, positioning for integration of sample efficiency breakthroughs.
END-TO-END WORLD MODEL BUILDERS		
Google DeepMind (6) World Labs (7) Physical Intelligence (8)	Building AI models using existing architectures for specific applications. Need for high data and computational resources (9).	Brainoid builds cross-domain tooling to enable specialized development of AI world models, without heavy resource requirements.
OPEN-SOURCE TOOLS		
Open Source Tooling (10, 11)	Often requires significant engineering talent to use, plus judgement to select from an endlessly large set of tools.	Provides a commercial-grade platform with innovative AI architectures that are not currently used in open source. Also improves deployment complexity.

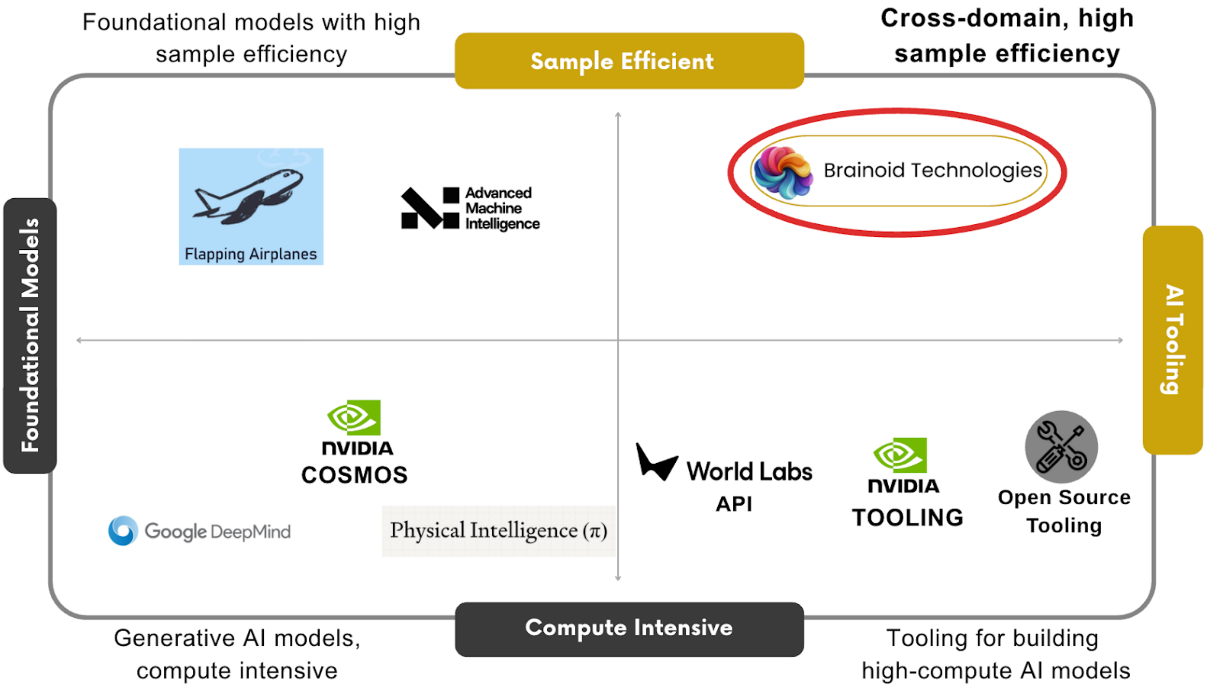

Figure 10. Competitor matrix

Competition for predictive AI world-model developer tooling remains limited. The main long-term threats come from large research startups, for example, AMI Labs and Flapping Airplanes, but neither has a market-ready product. The threat also comes with the possibility of acquisition.

Improvements in robustness for generative foundational models (Physical Intelligence, World Labs) can reduce the need for Brainoid's solutions, potentially shrinking Brainoid's addressable market (Engine, 2025). While generative models are versatile, they require enormous data and can introduce predictive uncertainty in safety-critical settings (Hussain et al, 2026). Brainoid counters with tooling built on underutilised efficient models (ex. JEPA), betting on sample-efficient architectures.

5. Business Strategy

5.1 Potential business models

Brainoid is a deep-tech company that is pre-product-market-fit. Research shows that scaling revenue or formalizing licensing too early can reduce learning opportunities and long-term advantage (Weber et al., 2022; Lei et al., 2025). In Brainoid's case, its value proposition is its training platform, which enables major cost reductions through improved sample efficiency. Because of Brainoid's technology and research based activities a business model should be structured in three phases: exploration (research based and developing the technology), validation (proving with partnerships that the tech works), and exploitation (scaling once the tech is mature) (Weber et al., 2022; Lei et al., 2025; Halecker & Dotzel, 2023).

Table 6. Business Model Canvas.

Brainoid's value capture strategy focuses on building an MLOps platform and data efficiency accelerator to reduce data needs, enabling faster, cheaper, and more energy-efficient AI training. Strategic end-user partnerships will help validate the technology and support expansion into sectors like autonomous driving and robotics. The company will sustain growth through dedicated customer support and continued investment in R&D, though executing this strategy will require substantial human, operational, and infrastructure resources. More information in Appendix Section 4.

Key Partnerships	**Key activities**	**Value Proposition**	**Customer relationships**	**Customer segments**
Autonomous driving companies (LOXO) Robotics Research institutions and AI research collaborators	R&D of MLOps platform accomplishing energy and cost reductions Validating the platform in suitable environments Continuous support and platform maintenance	Brainoid creates a sustainable and efficient AI training platform that will enable saving cost of training, less data usage and a 1000x energy reduction.	Sales meetings Support team and customer service	Robotics firms Autonomous driving Scientific and Industrial simulation Virtual Environments
Cost structure	**Key resources**	**Channels**		**Revenue streams**
R&D, engineering salaries, hardware, cloud infrastructure, testing and certification, business development, customer support, and operational costs.	Core AI capability and architecture Data and infrastructure Human capital: engineers and staff Organizational and software assets	Direct B2B sales, website, technical demos, conferences, secure software portal, email support, documentation portal, and account management.		Software licensing

5.2 Scalability analysis

Brainoid's long-term success depends on its ability to scale efficiently by increasing revenue without matching rises in cost or complexity (Chakraborty et al., 2025). However, deep-tech AI startups often face challenges such as high integration costs, customised solutions, and reliance on human expertise, meaning growth requires substantial human, financial, and technological resources (Chakraborty et al., 2025). As a result, Brainoid's scalability can be evaluated using seven key scale drivers for technology startup growth (Chakraborty et al., 2025).

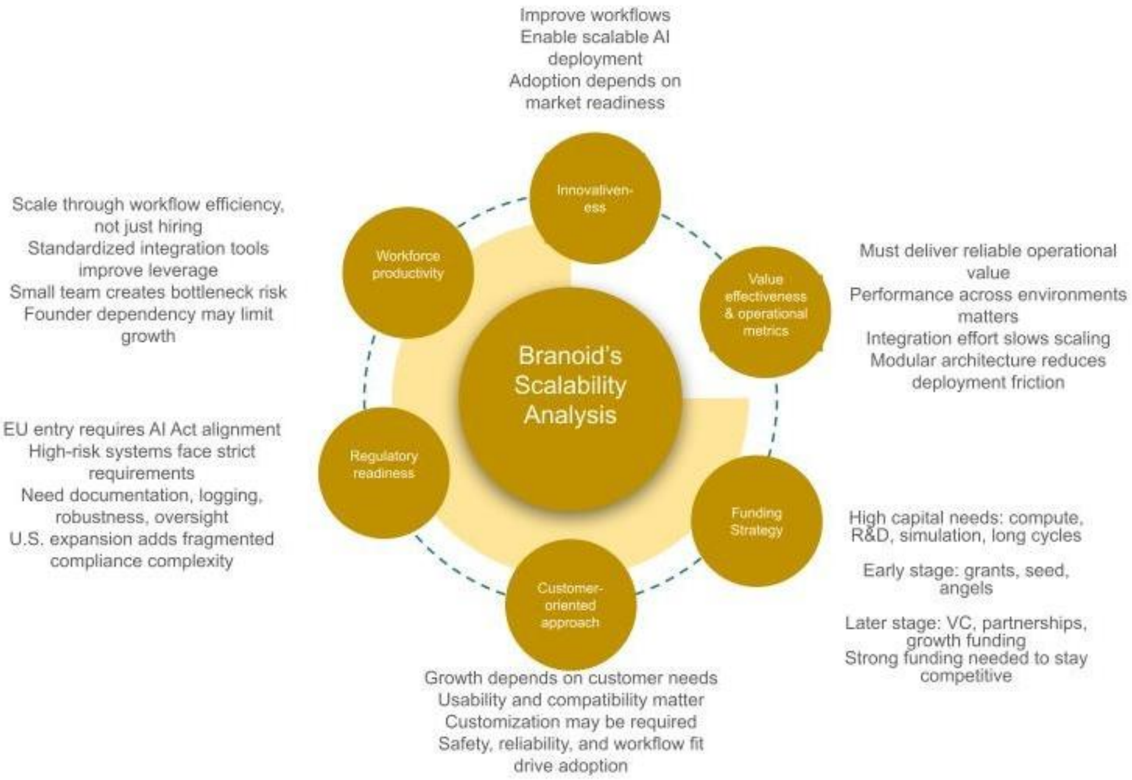

Figure 11. Scalability Analysis.

Brainoid's growth depends on balancing innovation, efficiency, funding, and regulatory readiness. Rather than focusing only on new technology, the company must improve real-world performance and integrate smoothly into customer workflows while keeping operations efficient despite a small team and reliance on the founder. Scaling will require strong funding, customer-focused solutions that are easy to adopt, and compliance with regulations such as the EU AI Act, with additional challenges likely in the more fragmented U.S. market. More about the scalability analysis can be found in the Appendix section 4.

5.3 Stakeholder analysis

Stakeholder analysis for Brainoid identifies key actors ranging from customers and investors to research partners and the AI community, to map the influence, dependencies, opportunities, and risks across all stages of the development.

Table 7. Brainoid Stakeholder Mapping: Influence, Interest, and Engagement Strategy.
This table identifies key stakeholders shaping Brainoid's development, categorising them by influence and interest to clarify their roles in technology validation, funding, and market adoption. It reflects established stakeholder management frameworks where aligning engagement strategies with stakeholder power and interest is critical for innovation success (Freeman, 1984; Mitchell et al., 1997).

Stakeholder Group	Interest Level	Influence Level	Role in Brainoid	Engagement Strategy
Founder & Core Team	High	High	Technology development, vision	Direct control and execution
Early Clients & Research Partners	High	Medium–High	Validation, co-development	Close collaboration
AI Developers & Industrial Users	High	High	Primary customers	Product-market alignment
Investors & VC Firms	Medium–High	High	Funding, strategic direction	Regular reporting and alignment
Infrastructure Providers	Medium	High	Compute resources, platforms	Strategic partnerships
AI Research Community	Medium	Medium	Validation, credibility, diffusion	Open engagement and publication

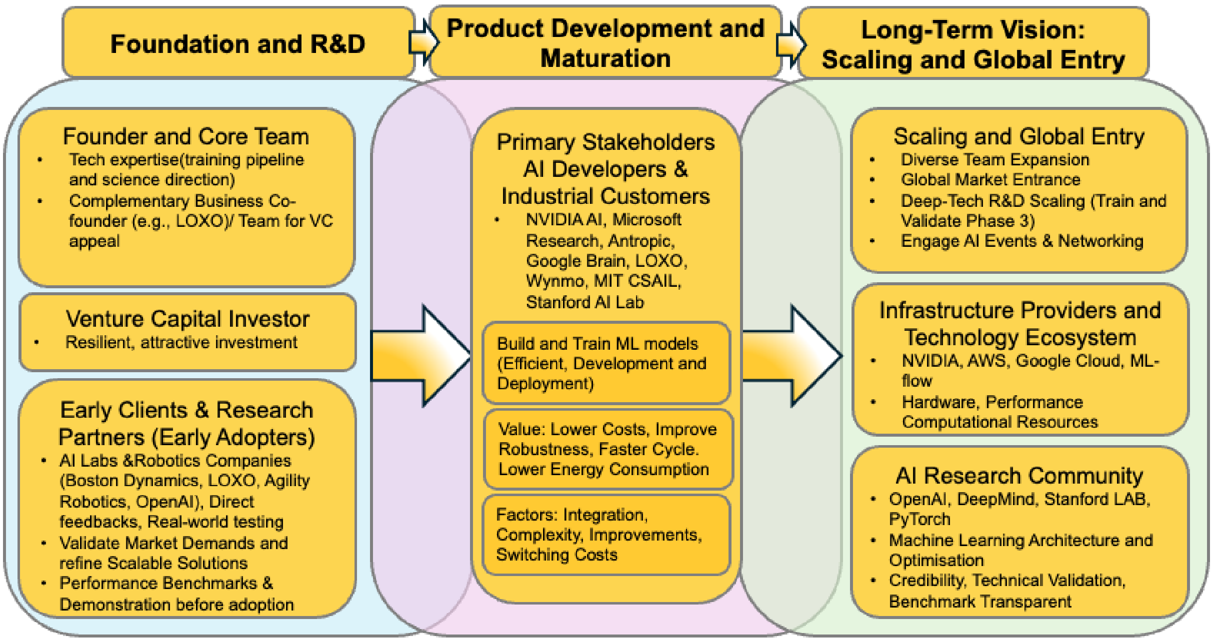

Figure 12: Brainoid's Three-Phase Development and Stakeholder Engagement Model
This figure illustrates the progression from Foundation & R&D to Product Development and Global Scaling, showing how key stakeholders, founders, investors, early adopters, AI developers, infrastructure providers, and the research community contribute to technology validation, product maturation, and large-scale deployment. Stakeholder roles, influence, and engagement strategies evolve across phases to support cost reduction, performance optimisation, and eventual positioning as AI infrastructure; detailed stakeholder mapping is provided in Appendix section 8.

6. Financial Overview

6.1 Revenue streams and pricing models

Our approach for Brainoid's revenue model is to test multiple revenue streams. While all revenue pathways monetize the MLOps platform, each caters to specific customer segments. Given the early-stage nature of the technology, this approach will ensure product-market-fit and multiple revenue paths. It allows for long-term sustainability of the business model while allowing room for changes based on market and economic conditions. The reasonable course of action would be to test each revenue stream incrementally: start on a small-scale basis with preliminary customers/partners, obtain feedback, and monitor revenue growth, and based on how each revenue stream is performing, increase the customer base accordingly. Potential revenue streams are shown in Figure 13.

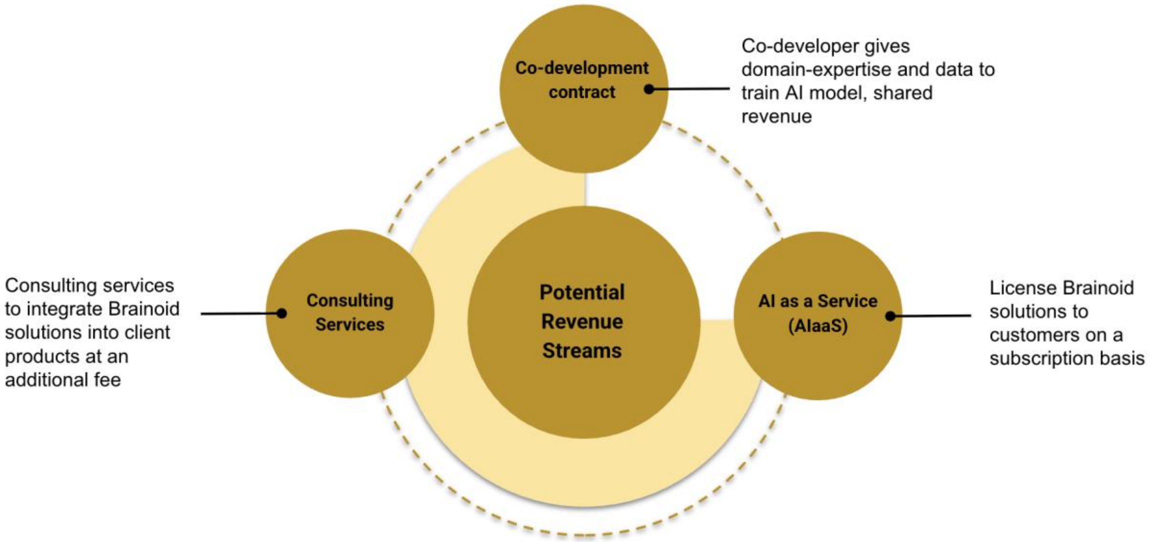

Figure 13. Potential Brainoid Revenue Streams

Co-development contract

One way to monetise Brainoid's MLOps platform is to develop world models for robotics, autonomous driving, and other customer segments. However, one of the major limiting factors for development of AI world models is availability of infrastructure, large datasets to train and optimise models, and domain expertise. The use of co-development contracts addresses this limiting factor for Brainoid (Mahendra et al., 2023, Jorzik et al., 2025). A common revenue stream used by AI startups is a unit-based model, where the AI is part of a product (e.g., LOXO's autonomous delivery vans) and revenue is generated by product sales (Mahendra et al., 2023). Using a co-development contract, Brainoid can enter a revenue share contract with an upfront deployment/integration fee with its pilot customers.

Pricing models should be based on the value provided to the customer (Nagle, 2024). Brainoid's current objective is to provide custom solutions to initial partner(s) (for example LOXO) since the MLOps platform offers substantial value in current/prospective partner growth. The most common royalty rate in licensing agreements is 5%, with royalty rates in the software industry averaging at 7-13% (Parr, 2018). Recent licensing industry statistics indicate software licensing royalty rates average 7-12% of revenue, with SaaS deals typically ranging from 5-10% (Zipdo, 2026). However, unpatented and early-stage technologies (e.g., knowhow and trade secrets) often have up to 50% reduced royalty rates (Parr, 2018). This is relevant to Brainoid and based on these statistics, a revenue share model with a 5-7% royalty rate (or an equivalent fixed fee) seems feasible for co-development contracts.

License Subscription Model: AI as a Service (AIaaS)

Package the MLOps technology in a subscription-based software licensing model (AIaaS) using annual developer, deployment, and enterprise licenses (Syed et al., 2025). Brainoid can build additional Cloud infrastructure (based on customer need) to make it easier for users to deploy Brainoid's AI training without having to manage their own infrastructure.

Additional revenue streams

The milestone for financial growth would be to have Brainoid's technology at a software-stage and reach a stable revenue stream using a subscription model (Licensing, AIaaS). The initial revenue streams can allow an iterative testing of any additional revenue streams such as consulting services (Syed et al., 2025).

Figure 14 highlights the timeline for commercialising Brainoid's MLOps platform using the revenue streams discussed above.

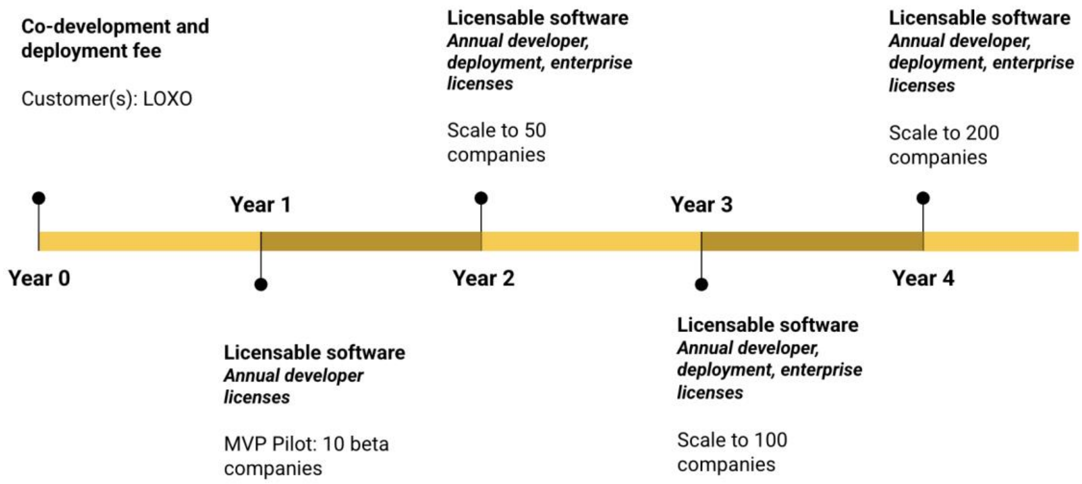

Figure 14. Brainoid timeline for adopting revenue streams

An overview of pricing models for technologies like Brainoid's MLOps platform is shown in Table 8 to understand Brainoid's pricing strategies shown in Table 9.

Table 8. Market pricing overview

Company / Product	Product Type	Use Case	Target Customers	Pricing Model	Price Range
NVIDIA (DGX Systems)	Hardware (AI compute infrastructure)	AI training, HPC workloads in data centres	AI labs, enterprises, research institutions	Hardware sales, cloud subscription	\$300,000–\$500,000 per system OR ~\$30,000/month
NVIDIA (Omniverse & Cosmos)	Simulation software	Synthetic data generation, robotics simulation, validation	Enterprises, robotics companies, autonomy developers	Annual enterprise software licensing (per GPU)	~\$4,500 per GPU/year
NVIDIA (DRIVE AGX)	Embedded hardware + software	Real-time sensor processing in autonomous vehicles	OEMs, AV companies, Tier 1 suppliers	Custom enterprise licensing and integration, hardware sales	Not public (NDA-based quotes)

Applied Intuition	Simulation software platform	Virtual testing for autonomous systems	OEMs, Tier 1 suppliers, autonomy programs	Multi-year software subscription (seat + compute)	~$740,000 (3–5 year contracts)
BlackBerry QNX	Embedded OS/ middleware	Autonomous driving, robotics, defence, medical devices	OEMs, industrials, defence contractors	Developer licenses, Enterprise licenses	Not public
IBM ILOG CPLEX *(software benchmark for Brainoid)*	Optimisation software	Mathematical optimisation for AI, logistics, planning	Enterprises, analytics teams, industrial firms	Developer licenses, Enterprise licenses	Single-user: ~$5,000–$9,000+; Enterprise: >$100,000/year
Gurobi Optimizer	Optimisation software	Mathematical optimisation for AI, logistics, planning (benchmark for Brainoid)	Enterprises, AI/ML teams, operations research teams	Developer licenses, Deployment licenses, Enterprise licenses,	Single-user: ~$10,000–$16,000; Enterprise: up to ~$200,000+/year

Table 9. Brainoid pricing strategy based on market pricing and revenue streams.

Revenue stream	**Features**	**Price**	**Target customer(s)**
Customisation and deployment fee	Upfront customisation and deployment fee to develop and integrate Brainoid's solution in customer products.	$150k-$300k	Co-development partner(s) i.e., LOXO
Annual Developer license	Develop/train models.	$5000/user	All Brainoid clients
Annual Deployment license	Deploy the technology in products. Required when you run the software inside a production system. Licensed based on compute infrastructure. Licensing agreement	$10k-$50k	Mid-size companies with market-ready products and limited compute infrastructure.

	would cover the number of servers.		
Annual Enterprise license	Custom licenses covering development and deployment. These licenses scale based on number of use cases and/or servers.	$50k-$200k	Enterprise clients

6.2 Revenue Projection

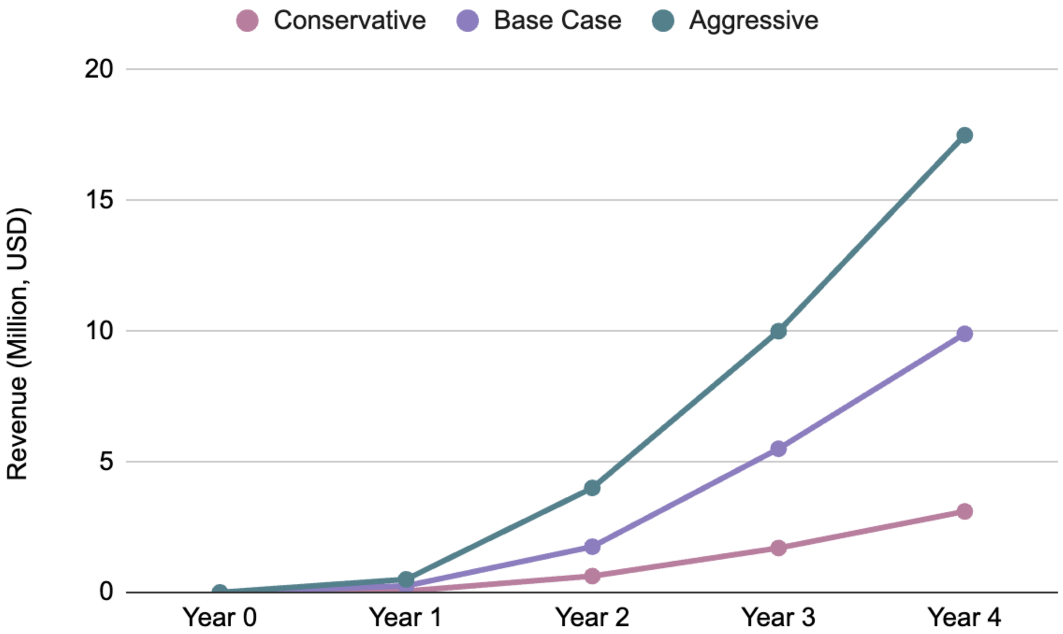

Figure 15. Brainoid revenue projections (Million, USD) based on pricing strategies shown in Table 9. Conservative, base case, and aggressive refer to minimum, average, and maximum adoption, respectively, by target customers. See Appendix Table 3 for raw data points and calculations.

6.3 Financing and fundraising strategies

Brainoid's financing strategy should follow a staged, hybrid approach, combining public funding, venture capital, and strategic partnerships, reflecting the high capital intensity of deep-tech AI development (Figure 16). It is critical that the project secures significant funding, especially for Phase 3, where a dedicated R&D team must be hired to advance the development of the new sample-efficient training architecture.

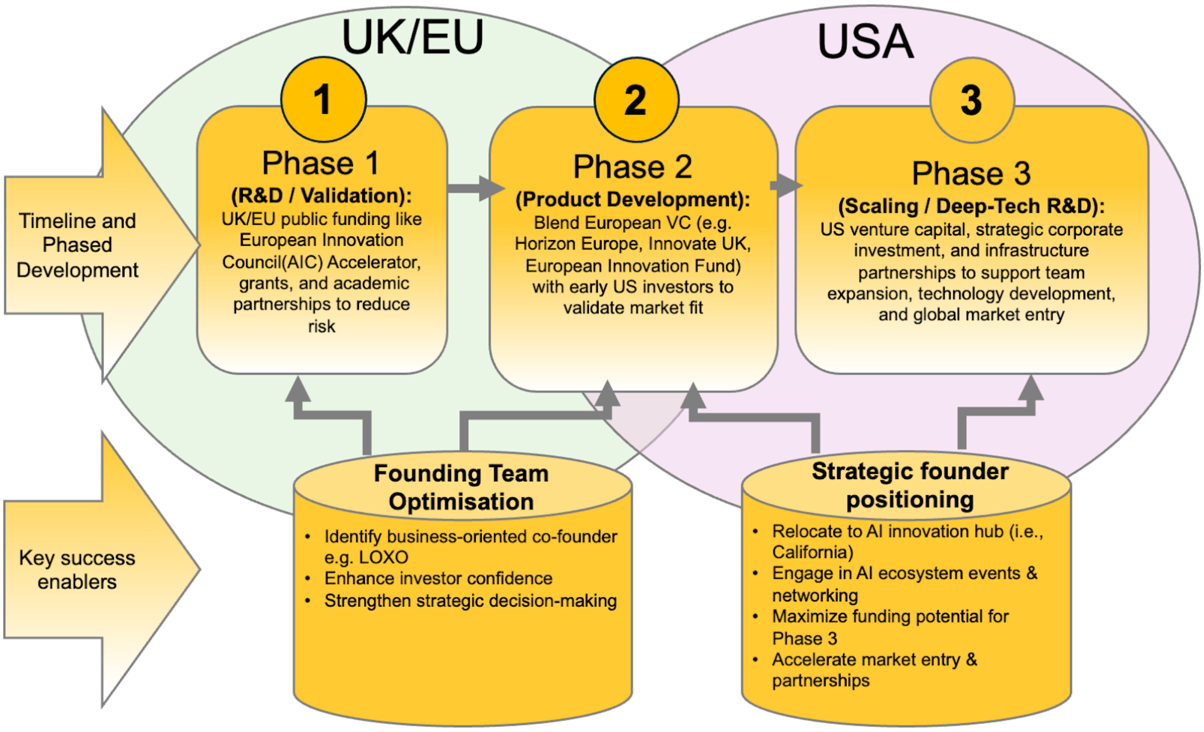

Figure 16. Brainoid's Staged Hybrid Financing Strategy and Global Scaling Pathway
This figure illustrates a phased financing approach combining UK/EU public funding and early-stage VC with US-based venture capital and strategic partnerships to support deep-tech AI scaling. It highlights the importance of geographic positioning and a complementary founding team in securing large-scale investment and accelerating market entry (Kerr & Nanda, 2015; Janeway et al., 2021). For details see Appendix section 9.

Table 10. Brainoid's Three-Phase Technology, Market and Commercial Scaling Framework.
This framework outlines Brainoid's evolution from experimental validation to industry-standard AI infrastructure, highlighting shifts in technology maturity, customer segments, and revenue potential across three phases. It reflects established deep-tech scaling patterns where early public-funded validation transitions into venture-backed growth and platform-level market leadership (Kerr & Nanda, 2015; Janeway et al., 2021).

Development Phase	Investor Type / Example Firms	Region	Indicative Funding Range (USD)	Purpose
Phase 1 – R&D / Proof of Concept	Innovate UK, EIC Accelerator, Horizon Europe Grants	UK/EU	$200k – $2.5M	Early validation, proof-of-concept, prototype development

Phase 1 – Seed / Angel	Local angel investors, AI-focused seed funds	UK/EU	$100k – $500k	Complement grants, fund initial team expansion and technical development
Phase 2 – Product Development / Series A	Andreessen Horowitz, Sequoia Capital, Lightspeed, True Ventures	US/UK	$3M – $10M	Scale R&D team, platform integration, market validation
Phase 2 – Strategic Corporate VC	NVIDIA Inception Fund, Google Ventures, Microsoft M12	US	$1M – $5M	Strategic partnerships, infrastructure access, co-development
Phase 3 – Scaling / Series B & Beyond	Khosla Ventures, Scale Venture Partners, DCM Ventures	US	$10M – $50M+	Team expansion, sample-efficient training architecture, global rollout
Phase 3 – Infrastructure & Partnerships	AWS Activate, Google Cloud Credits, NVIDIA GPU grants	US/EU	$0.5M – $5M (credits & grants)	Cloud compute resources, GPUs, AI infrastructure support

This staged approach ensures Brainoid can navigate the high costs, long timelines, and technical risks of deep-tech AI while building credibility with investors and strategic partners.

6.4 Go-to-market strategy

Commercialising deep-technology innovations typically requires a phased strategy that aligns technological maturity with market adoption and funding availability. Research on innovation financing suggests that deep-tech ventures often require long development cycles and staged validation before reaching scalable commercial markets (Kerr & Nanda, 2015; Janeway et al., 2021).

Brainoid's commercialisation strategy is structured as a three-phase progression, with each phase reflecting a distinct stage of technological maturity and market engagement. As the company evolves, there is a corresponding shift in product form, customer segment, and revenue logic from potential collaboration to scalable platform delivery and, ultimately, infrastructure-level positioning. Table 11 summarises this transition and Tables 12-14 highlight key features of each phase.

Table 11: Summary of Phase Transition

Phase	Objective	Brainoid Offering	Target Users	Example Collaborators / Industry Analogues	Revenue Model
Phase 1 Pre-Product Market Fit	Validate demand & refine MVP	Custom training optimisation prototypes (robustness and sample efficiency modules)	AI labs, robotics teams	University ML labs (Oxford/Cambridge), robotics startups, autonomy teams (e.g., LOXO, Waymo, Nuro, Oxbotica-type organisations)	Limited consulting / pilot funding
Phase 2 Platform	Scale validated solution	Brainoid training optimisation platform (APIs and integration tools)	AI R&D teams, infrastructure startups	Applied AI teams in industry, robotics firms, autonomous driving companies (e.g., LOXO, Waymo, Aurora, NVIDIA DRIVE ecosystem users)	Licensing / subscription / usage-based
Phase 3 Infrastructure	Establish ecosystem position	Sample efficient training architecture and platform layer	AI infrastructure providers, cloud platforms	Large AI labs, cloud ecosystems (e.g., AWS, Google Cloud, NVIDIA AI platform ecosystem)	Platform + IP licensing

Table 12: Phase 1: Pre-Product Market Fit.

Phase 1 focuses on early validation through close collaboration with technically advanced users, emphasising learning, optimisation, and initial proof of value.

Component	Brainoid-Specific Detail
Core Problem	High compute cost (e.g., £50k–£500k per training cycle), unstable training, poor sample efficiency
Solution (Prototype)	Modules improving training stability and reducing sample requirements
Pilot Use Cases	Robotics simulation, reinforcement learning, early world-model experiments
Example Collaborators	Academic ML labs; robotics startups; autonomy-focused teams (similar to LOXO, Waymo, Nuro, Oxbotica)
Engagement Model	Pilot partnerships (3–6 months), co-development with integration into existing pipelines
Data Context	Simulation environments and partner-provided datasets (e.g., control data, perception data)
IP Strategy	Brainoid retains core algorithms; partners receive limited usage rights
Outputs	Benchmark reports, pilot case studies, prototype validation
Success Metrics (KPI)	15–30% reduction in training time or compute; ≥2 repeat collaborations

Table 13: Phase 2: Scalable Licensable Software Platform

Following validation, Phase 2 shifts toward productisation and scale, introducing a licensable platform designed to deliver measurable efficiency and cost benefits.

Component	Brainoid-Specific Detail
Core Product	API-based optimisation layer compatible with PyTorch/JEPA pipelines
Key Features	Training efficiency optimisation, robustness tuning, sample-efficient learning modules
Integration	Plug-in layer for ML pipelines used in autonomy, and simulation systems
Target Customers	AI startups (£100k–£5M compute spend), robotics firms, autonomy

	developers
Example Use Case	Reducing training cost of models in autonomous systems (e.g., pipelines used by LOXO, Waymo) by ~20–30%
Customer Value	Reduced cloud spend and faster iteration cycles for ML teams
Marketing Proof Points	Case studies, benchmarks vs baseline training pipelines
Adoption Strategy	Expand from pilot partners to similar companies in autonomy & robotics ecosystems
KPIs	≥20% cost reduction, 5–10 paying customers, strong retention

Table 14: Phase 3: Sample Efficiency Platform and Deep-Tech IP.
Phase 3 represents the long-term vision, where Brainoid positions itself as a foundational infrastructure and IP provider within the evolving AI ecosystem.

Component	Brainoid-Specific Detail
Core Innovation	Proprietary architectures enabling significant sample-efficiency gains
Platform Role	Foundational layer for training next-generation AI systems
Target Partners	Cloud providers, large AI labs, infrastructure startups
Example Ecosystem Fit	Integration within cloud ML stacks (e.g., AWS SageMaker, Google Vertex AI, NVIDIA AI platforms) used by companies like Waymo or large robotics teams
Revenue Streams	Platform licensing, cloud partnerships, IP licensing
Strategic Advantage	Reduced reliance on large-scale compute and datasets
Ecosystem Role	Enabling smaller players to compete with compute-heavy leaders
KPIs	Step-change efficiency (e.g., 5–10x in specific domains), strategic partnerships

Progression of Strategy Through Phases

In the final phase, Brainoid aims to establish itself as a core technology provider within the AI ecosystem. Building on earlier platform development, the company leverages advances in sample-efficient training to offer infrastructure-level solutions and proprietary architectures. This stage emphasises long-term strategic positioning, ecosystem integration, and technological leadership.

Table 15: Brainoid's Three-Phase Evolution: From Experimental Prototypes to AI Infrastructure. This table captures the progression of Brainoid across technology maturity, customer segments, and market positioning, illustrating a typical deep-tech transition from validation to platform dominance. It reflects how innovation-driven ventures build competitive advantage through evolving IP strategy, performance differentiation, and scaling customer impact (Kerr & Nanda, 2015).

Dimension	Phase 1	Phase 2	Phase 3
Technology	Experimental prototypes	Stable platform	Advanced architectures
Customers	Early adopters (labs e.g. Cambridge/Oxford, robotics startups like LOXO)	Scaling AI teams (incl. autonomy companies like LOXO, Waymo-type organisations)	Infrastructure providers & large AI labs (e.g., Waymo, NVIDIA, AWS)
Compute Impact	Initial savings demonstrated	20–30% cost reduction	Transformational efficiency gains
Differentiation	Technical insight	Cost-performance advantage	Architectural leadership
IP Role	Protection	Competitive moat	Core monetisation layer
Market Position	Experimental partner	Trusted optimisation layer	Industry-standard infrastructure

6.5 Risk assessment and mitigation

Table 16. Risk assessment and mitigation

Risk Category	Description	Implications	Mitigation Strategies
Technology Risk (1,2,3)	Possibility that the technology does not work when scaled for commercial use.	Failure to transition from prototype to scalable product; delays in commercialisation; increased R&D costs.	Iterative testing following the TRL framework; Reassessment at each stage to ensure milestones are achieved; Talent acquisition to ensure Brainoid meets KPIs.

Product–Market Fit Risk (1,4,5)	Difficulty in balancing technology development and identifying relevant market sectors, generating revenue, and scaling, especially given long time-to-market in deep-tech ventures.	Delayed revenue generation	Create an "option space" where Brainoid products address a broad set of well-defined problems (preserving optionality) using multiple solution pathways (generating optionality); Identify problem/market fit by defining problems first, then mapping to market sectors; Use the option space to select optimal solution pathways as the venture evolves.
Financial Risk: Underinvestment due to Information Asymmetry (1,3,6,7)	Deep-tech ventures often face the "Valley of Death" at TRL 2–3 due to confidential IP, long development cycles, and lack of scaling capital, relying heavily on public grants	Difficulty securing private investment	Build strategic partnerships and secure non-dilutive funding (e.g., grants tailored to deep-tech); Develop innovation environments suited to deep-tech financing; Invest in intellectual capital (commercial and legal expertise) to improve communication with investors and reduce information asymmetry.
Competitive Risk	Competition from industry giants with established client bases and supply chain networks.	Difficulty gaining market share; pricing pressure; barriers to entry	Implement feasible pricing strategies; Establish long-term client relationships to demonstrate traction and credibility; Diversify partners after MVP stage to reduce dependency and expand market reach.
General Commercialisation Risk (1)	Uncertainty across different stages of the commercialisation process in deep-tech ventures.	Increased overall venture risk; delayed or failed market entry;	Adopt dynamic learning to continuously de-risk across stages of commercialisation; Focus on a Minimum Viable Pathway (MVP pathway) to market to incrementally build value and reduce uncertainty before full-scale launch.

6.6 Exit strategies

Mergers/Acquisition: Building strategic partnerships is one of the most important de-risking strategies for deep-tech ventures such as Brainoid. It allows technology validation, establishment of long-term clients, recurring revenue contributing to financial growth, and essentially forms the foundation for the go-to-market strategy. Importantly, it also provides a rational exit for developers through acquisition by partner or competitor companies, which are already established in the market, with the infrastructure and budget to adopt Brainoid technology into their products. Potential companies include LOXO, NVIDIA, IBM, Google, Flapping Airplanes, AMI Labs. NVIDIA and IBM are in the top strategic buyers acquiring software companies (Hammer, 2026). There are three potential exit strategies for Brainoid in the product development timeline, as highlighted in Figure 17. Tables 17 and 18 highlight the valuation potential for Brainoid if acquired at exit path 2 or 3.

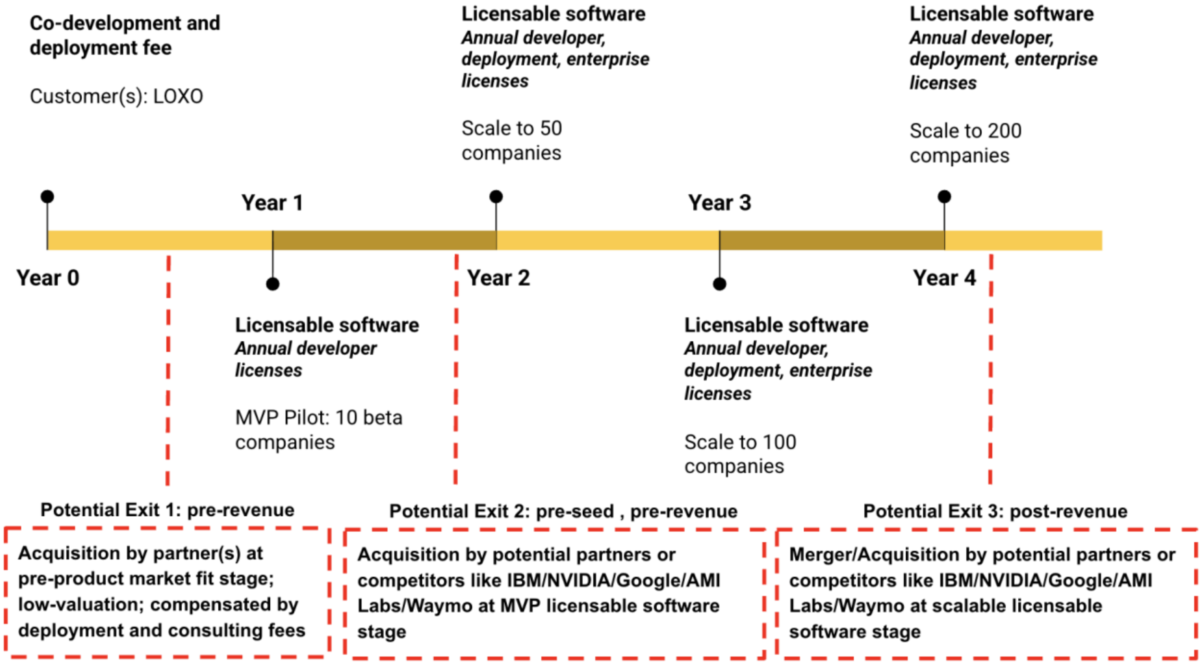

Figure 17. Potential exit strategies for Brainoid.

Table 17. Typical pre-seed pre-money valuation for AI deep tech startups as of 2025. (ICanPitch, 2024, Ansari, 2025)

Region	Pre-seed pre-money valuation
USA	$2-$8M
Europe	$1.6-$5.4M
Globally	Median = $3.6M

NB. First-time technical founders usually value at market baseline

Table 18. 2026 pre-money valuation of Brainoid's 'near-term threat' competitors. (Heim, 2026, Lourdes 2026)

Company	Pre-money valuation
AMI Labs	$3.1B
Flapping Airplanes	$1.3B

7. Sustainability and Ethics

7.1 Sustainability considerations

AI's rapid growth is driving major environmental impacts, with energy use rising sharply (e.g., Llama-3.1-405B) and emissions exceeding 5,000 tons for GPT-4 (Stanford Institute for Human-Centered Artificial Intelligence, 2025). Data centres now use ~2.1% of global electricity (International Telecommunication Union, 2025). Brainoid should set science-based targets: cut emissions 20–30% by 2028, use 100% renewable energy by 2030, reduce compute emissions, and reach net-zero by 2045.

7.2 Non-financial and ethical review

Brainoid must embed safeguards to protect human rights, privacy, and society, ensuring AI systems remain aligned and safe (Cath et al., 2018; Gabriel & Manzini, 2024; Google DeepMind). It should adopt governance aligned with the EU AI Act, ensuring high-risk systems meet requirements for risk mitigation, data governance, transparency, oversight, and robustness (European Commission, n.d.).

Broader Societal Effects

AI can boost productivity and reduce costs (Brynjolfsson & McElheran, 2016; Yee et al., 2025), but benefits may concentrate among large firms and skilled workers, increasing inequality (OECD, 2020). Automation of routine tasks may also displace jobs, widen the skills gap, and increase the need for retraining (Brynjolfsson & McElheran, 2016).

8. Conclusion

The market gap for dedicated AI world-model tooling is real and growing rapidly. It is recommended for Brainoid to first formalise its market entrypoint by co-developing the JEPA MLOps platform with companies that require a technical edge, funded primarily by grants. The engagements should generate hard performance metrics of training efficiency gains, data requirements, and cost savings. Next, scale the JEPA MLOps platform starting with smart-driving vehicle companies across Europe. This expansion should be enabled by venture capital funding, supported by a clear path towards revenue growth. To abide by regulatory standards, Brainoid should implement EU AI Act risk management, data governance, and a concrete sustainability program to accelerate European entry and investor confidence.

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10. Appendix

1. Industry breakdown / description

AI world models, the systems that learn to simulate and predict the dynamics of physical environments, are emerging as a distinct and rapidly growing segment within the broader artificial intelligence industry.

The purpose of world models is to understand the dynamics of the physical world and then support downstream decision-making and planning in applications ranging from robotics to autonomous driving (Ding et al, 2025). Like other frontier AI systems, world models are subject to the scaling laws that govern model development (Pearce et al., 2024). These laws describe a relationship where each successive improvement in model performance requires exponentially more training data, model size, and computational resources (Kaplan et al., 2020; Maslej et al., 2025). It costs tens of millions of dollars to train the leading AI models (Maslej et al., 2025). However, research into scaling behavior in world models has shown that the choices made while designing a model's architecture can significantly influence scaling efficiency, where different model designs yield substantially different outcomes for the same investment in computational resources (Pearce et al., 2024).

Many industry experts see improvements in physical AI, which is the category encompassing AI world models, as the next frontier of AI development. Gartner identified it as a top strategic technology trend for 2026 (Gartner, 2025). Some researchers believe world models are necessary to achieve a human level of machine intelligence (LeCun, 2022).

The main industry segments developing world models span embodied agents, societal modeling, urban systems, and game intelligence (Ding et al, 2025), with practical applications in any machines that sense, decide, and act in the real world, including robots, drones, and smart equipment (Gartner, 2025).

Training AI world model systems today requires massive datasets (video, sensor, and spatial data), petabytes of information, and thousands of hours of human effort in preparation (NVIDIA, 2025). While general-purpose foundational models (huge pre-trained AI models that can be adapted or fine-tuned to specific applications) offer an accessible starting point for building AI world model applications, they generally lack the persistent state required for high-impact use cases such as autonomous driving and robotics (Ding et al., 2025).

In established areas of machine learning, such as image recognition and text analysis, operational platforms (known as MLOps) exist to help teams build AI systems effectively (Kreuzberger et al., 2023). No equivalent tooling exists for world model development, where training data comprises streams of video, radar, and sensor data, rather than labelled images (NVIDIA, 2025; Ding et al., 2025). This presents a gap between the growing demand for world models and the ability to build them effectively.

2. Competitor descriptions

Nvidia

Nvidia dominates AI development through full stack integration, controlling GPU hardware, the CUDA software layer, and acceleration libraries (CUDA-X), which are optimized to extract the highest performance given their hardware designs (NVIDIA Corporation, 2026). Developer lock-in is a key strength. The Nvidia Developer Program and the Inception program both provide free access and guidance to the Nvidia platform. They have hundreds of partnerships with universities and support tens of thousands of startups (NVIDIA Corporation, 2026). These initiatives encourage developer lock-in as they build their AI workflows around Nvidia's ecosystem.

However, their dominance depends on existing AI training infrastructure, not JEPA architecture. They have tight coupling between their hardware and software, where CUDA only runs on Nvidia hardware. This can become a weakness as competitors, like Brainoid, offer tools that work across multiple types of hardware (OpenAI, 2021). The most significant external threat comes from U.S. export controls. Under current rules, Nvidia cannot deliver a "competitive product for China's data center market" (NVIDIA Corporation, 2026). This could push international buyers to reduce their reliance on the Nvidia ecosystem and invest in other tools, like Brainoid.

Google

Google is investing heavily into world models & embodied AI with their two main foundational world models, Gemini Robotics and Genie. For gemini robotics, it can be used with robots of various shapes and sizes to interact with the world and it can solve a wide range of complex real-world tasks (Gemini Robotics, n.d.)

Flapping Airplanes

Investigating the same possible architectural breakthroughs as proposed by Brainoid, Flapping Airplanes is researching how to produce paradigm-shifting AI models. Their strengths lie in being heavily funded, $180 million, with a lot of famous industry backers like Google Ventures, Sequoia Capital, and Index Ventures (Flapping Airplanes, n.d.), which provide credibility to their product.

Even though they are operating in stealth mode, the hundreds of millions that they have raised suggests that Flapping Airplanes is focused on building foundational models instead of academically focusing on the root architectural problems of data efficiency within AI training.

World Labs

Their product Marble generates highly realistic 3D worlds, and robotics companies identified as one of the biggest potential beneficiaries (Fast Company, 2026). They provide development tools via their World API, to allow customers to generate world models from Marble (World Labs, 2026).

AMI Labs

Advanced Machine Intelligence (AMI) Labs is a research-focused company building world models using the JEPA architecture developed by Yann LeCun (LeBrun, A,. 2026; Chen, C., 2026). The JEPA architecture is the same fundamental research that Brainoid is basing its MLOps platform on. His platform will be open-source which is in contrast to the secrecy he sees as a "strategic mistake" among the U.S. AI companies (Murgia, M. 2026). AMI Labs has signalled healthcare as a primary focus, as its CEO was the cofounder of a health tech startup called Nabla, and AMI Labs' first partnership is with that same company (Feldman, 2026).

Two structural limitations limit AMI Labs as a competitor. First, technology spillovers tend to be geographically located through local interaction (Felten, E. et al. 2021), so its European base may hinder progress relative to Silicon Valley. Additionally, the CEO anticipates "at least a year of fundamental research before deploying first real-world applications" (LeBrun, A., 2026). This timeline creates a window for Brainoid to establish market presence before AMI Labs reaches commercialisation.

Physical Intelligence (π)

They are developing general-purpose foundation models for robots and have raised over $1 billion in total funding (The Robot Report, 2025). Its recent research includes focus on precise manipulation and enabling long-term execution of complex tasks (Physical Intelligence, 2026).

Wayve

Wayve builds their own world model for autonomous driving called GAIA-3 and licenses its AI Driver software directly to automakers (Wayve, 2025; Wayve, 2026). They plan to launch commercial robotaxi trials with Uber in 2026 and deploy supervised autonomy software in consumer vehicles from 2027 (Wayve, 2026)

Open-source tooling (Hugging Face / PyTorch)

Hugging Face is a leading open-source platform for machine learning. It allows developers to access pre-trained models, fine-tune them, and deploy them (Hugging Face, n.d.). Critical for the physical AI space, their LeRobot library provides models and tools for real-world robotics using Pytorch (Hugging Face, n.d.). And PyTorch is one of the most widely used deep learning frameworks (Linux Foundation, 2022).

However, because these tools are free and available to everyone, they cannot form the basis of a competitive advantage on their own. When any competitor can access the same open-source stack, startups must build an advantage through domain expertise and proprietary data (Vaidya, 2024).

Appendix Table 1. Market Research. Physical AI regional market growth with status

Region	Status	2025 Market size (USD)	2025 Market share	2034 Market size (USD)	2034 Market share
North America	Market leader. The U.S. is home to major AI innovators and Canada is emerging as a significant player	$2.07 billion	40.4%	$26.37 billion	38.5%
Asia-Pacific	Rapid growth, especially in China (AI & robotics for smarter manufacturing and automation), Japan (humanoid robots), South Korea	$1.59 billion	31.1%	$23.94 billion	34.9%
Europe	High investments with strategic policy	$1.2 billion	23.4%	$15.69 billion	22.9%
Latin America	Increasing adoption in sectors like healthcare, agriculture, and manufacturing	$0.26 billion	5.1%	$2.5 billion	3.6%
Global		$5.12 billion	→	$68.5 billion	

Brainoid is targeting initial partnerships in Europe due to proximity and current partnerships (Cervicorn Consulting, 2025)

The market for AI world models is growing rapidly, with investment increasing by nearly 400% in a single year, from $1.4 billion in 2024 to $6.9 billion in 2025 (CB Insights, 2026). Training data is a central bottleneck, seen from Nvidia acquiring synthetic data provider Gretel for over $320M in March 2025 and Meta taking a $14.8B stake in a data infrastructure company (CB Insights, 2026). While the largest companies address performance improvements through increasing investment in data, Brainoid is focused on heavily reducing the data requirement through efficient model architectures.

In adjacent markets within machine learning, dedicated tooling has proven critical to capturing value from AI at scale. 70% of organizations now invest in platforms for conventional machine learning workflows (Zarour et al., 2025), and companies adopting these tools achieve significantly higher returns (McKinsey & Company, 2022). No equivalent tooling yet exists for world model development, despite the previously mentioned rapid growth in investment.

Further proof of the market need for Brainoid is the sign-on of a first co-development partner, LOXO, a Swiss autonomous vehicle startup. They currently experience compounding errors where their vehicles deviate from the desired paths. They need a technical edge to be competitive in the physical AI marketplace, which is why they signed on to work with Brainoid.

Brainoid's pricing strategy is informed by comparable enterprise software platforms in the physical AI space. A detailed pricing analysis benchmarked against products including NVIDIA Omniverse, Applied Intuition, and IBM ILOG CPLEX is provided in the section "7.1 Pricing Models", the market pricing overview table. Brainoid's co-development offering will be followed by a software licensing model, consistent with the pricing structures observed across comparable companies.

4. Business model

Brainoid's 3 phase business model approach:

Stage 1: Exploration (Capability formation)

The priority is strengthening the core technology rather than generating revenue, focusing on robustness, training efficiency, and developing the core technology (Lei et al., 2025). Funding should mainly come from research grants (Innovate UK, UKRI/EPSRC, Horizon Europe), while rigid commercial contracts should be avoided to preserve learning flexibility (Weber et al., 2022; Lei et al., 2025). The technology should function as a reusable building block for multiple future applications in autonomous driving or robotics (Halecker & Dotzel, 2023). Transition to Stage 2 occurs once performance is consistent in real environments and the architecture is stable enough for pilot integration.

Stage 2: Validation (Extension)

Commercialization is introduced carefully to support research without changing the core technological logic. Brainoid's technology iis tested across several application streams, with flexible partnerships as LOXO and pilot projects used to demonstrate transferability (Halecker & Dotzel, 2023; Lei et al., 2025). In this stage revenue can come from pilots, co-development contracts, and limited integration contracts. Transition to Stage 3 requires stable performance across partners, predictable behaviour, architectural maturity, and clear willingness to pay (Weber et al., 2022; Lei et al., 2025; Halecker & Dotzel, 2023).

Stage 3: Exploitation (Scalable value capture)

Once the technology is mature, Brainoid can sell its technology through a licensable software providing a learning and training optimization layer that reduces AI training cost and time, while partners manage industry-specific applications. At this stage, revenue generation can become scalable.

Key Partnerships

Strategic partnerships are essential for deep-tech AI companies because developing and deploying advanced AI systems requires collaboration with organizations that provide complementary technology, infrastructure, and market access (Chakraborty et al., 2025; Weber et al., 2022). Partnerships with OEMs and system integrators allow Branoid's AI software to be embedded into real-world applications such as robotics, drones, industrial automation, and autonomous vehicles, accelerating deployment and reducing adoption barriers. Potential partners include companies in autonomous driving, delivery robotics, and drone logistics.

Collaboration with research institutions and universities supports innovation, validation, and access to talent, while partnerships with cloud and compute providers supply the high-performance infrastructure needed to train and deploy large-scale AI models. These relationships are critical for scaling development and enabling real-world implementation (Kadioglu, 2025; Yee et al., 2025).

Key Activities

Branoid's key activities focus on developing, validating, and deploying its AI world model platform while supporting adoption by industrial partners. Core activities include research and optimization of the model architecture, simulation and synthetic scenario generation to improve robustness, and real-world testing through pilot deployments and integration with partner systems. The company also works on ecosystem development by collaborating with OEMs, cloud providers, and research partners to enable industry adoption. In addition, Branoid maintains its platform through continuous updates, integration tools, and technical support for partners and customers.

Value Proposition

MLOps platform with sample efficiency accelerator archiving 1000x energy use reduction, this will reduce training costs, improve model robustness, and accelerate development cycles.

Customer Relationships

Customer relationships combine high-touch technical support for enterprise clients with scalable self-service channels for developers. Communication and support are provided through documentation portals, ticket systems, email, video meetings, and dedicated account management for strategic partners.

Customer Segments

Autonomous vehicle companies, robotics and drone developers, research institutions, and enterprise operators using autonomous systems.

Cost Structure

Major costs include research and development of AI training pipeline and sample efficiency software, salaries for engineers and researchers, hardware and prototype testing, cloud and IT infrastructure, system validation and certification, business development activities, customer support, and general operational expenses.

Key Resources

Branoid's key resources include the technological infrastructure, human expertise, and intellectual property required to develop and deploy its AI world model platform. The most important resource is its core AI architecture and training platform, which enables the creation and optimization of models capable of operating in complex real-world environments. High-quality data, simulation environments, and scalable computing infrastructure, including GPU and AI accelerator hardware, are essential for training and validating the system.

In addition, Branoid depends on specialized human capital such as AI researchers, machine learning engineers, and integration specialists. Its intellectual property, modular software platform, and developer tools are also critical resources, allowing partners to integrate the technology and supporting the growth of an external ecosystem.

Channels

Channels include direct sales meetings, the company website, and participation in industry conferences to reach potential customers. Customers evaluate the product through demonstrations, trial licenses, and technical documentation.

After purchase, the licensable software is delivered via secure download portal, private repository, or cloud platform. Ongoing communication and support are provided through email, ticketing systems, video calls, and documentation portals, with dedicated technical support for enterprise clients.

Revenue Streams

Branoid generates revenue through software licensing of its AI world-model platform, usage-based pricing for training and simulation, and integration contracts with industrial partners.

5. Scalability analysis

Innovativeness

Innovation today goes beyond creating entirely new technologies and increasingly involves combining existing solutions, improving workflows, and scaling them effectively (Weber et al., 2022). For Branoid, innovation should focus on strengthening its ability to create value by improving real-world performance, enabling machines to operate in complex environments, and increasing operational efficiency. This innovation can be incremental or disruptive, but it should consistently support better workflows and scalable AI deployment (Weber et al., 2022).

In addition, scalability depends not only on technological novelty but also on whether the market is ready to adopt the innovation. If the platform represents a fundamental change in how autonomy systems are developed or deployed, customers may require time to adapt their processes, which can slow adoption even when the technology itself is capable of scaling.

Workforce productivity

Workforce productivity in a licensing-based autonomy platform depends more on efficient workflows and process integration than on increasing the number of engineers (Kadioglu, 2025). Successful AI deployment also requires alignment between talent, infrastructure, and operating processes, which can be achieved through standardized integration tools that enable one team to support multiple programs simultaneously (Kadioglu, 2025). However, the shortage of skilled software and data engineers remains a major constraint and may limit growth if productivity gains are not achieved (Yee et al., 2025).

Branoid currently has only its founder and plans to hire an engineer and an additional staff member in the coming years, which creates a potential organizational bottleneck. Scaling the platform may require not only technical capability but also managerial capacity, as the founder must be able to coordinate research, customer projects, and expansion into new use cases simultaneously. If the organization remains too dependent on a single individual, growth may be limited regardless of the technical scalability of the platform.

Funding strategy

Scaling the platform requires substantial funding due to high costs related to compute infrastructure, ongoing research, simulation environments, and the long development cycles typical of AI and autonomy systems (Weber et al., 2022). In the early research stage, funding usually comes from research grants, seed capital, and angel investors, such as UKRI or Horizon Europe programs, which support technology development before commercialization. As the technology matures, larger investments are required, making venture capital, corporate partnerships, and growth funding essential to support commercialization, infrastructure expansion, OEM adoption, and ecosystem growth (Weber et al., 2022). The high capital intensity of AI development is reflected in industry trends, where major technology companies invest tens of billions annually in AI infrastructure, highlighting the need for strong financial backing for startups to remain competitive (Yee et al., 2025).

Value effectiveness and operational metrics

Solutions must deliver clear and reliable value, meaning Branoid's technology should perform consistently, transfer across environments, and generate measurable operational impact while integrating smoothly into existing customer workflows (Weber et al., 2022). Integration effort is a major scalability bottleneck in autonomy and robotics systems, as complex deployments require significant engineering time and can slow adoption, even when only adding a software layer (Kadioglu, 2025). Industry benchmarks show that integration can require tens to hundreds of engineering hours, and full validation and certification may take months, especially in safety-critical systems (Kadioglu, 2025).

To reduce these constraints, Branoid should focus on modular architecture and standardized tools that allow partners to integrate the platform more independently, improving scalability and deployment speed.

Customer-oriented approach

AI adoption is currently in a scaling phase, with organizations expanding deployment as AI becomes essential for competitiveness, although concerns about data privacy, output quality, and ethics still limit full implementation and require governance and validation mechanisms (Yee et al., 2025). For Branoid, understanding the needs of OEMs and enterprise customers is critical for growth, since adoption depends on usability, system compatibility, and alignment with existing workflows. Successful deployment may require customization and careful consideration of integration processes, operational constraints, and safety and reliability requirements.

Regulatory readiness

Branoid is starting its operations in the EU because of its current partnerships with LOXO (based in Switzerland), and an academic relationship with the University of Stockholm in Sweden. Regulatory alignment is needed to enable scaling and to commercialise in the EU Branoid should follow the EU AI Act, that provides a legal framework for managing AI risks. AI systems used in autonomous driving or robotics may be classified as high-risk systems; therefore, they are subject to strict requirements because failures could affect safety and fundamental rights.

To comply with EU regulations, Branoid should implement a risk-management system, maintain technical documentation, keep usage logs, and demonstrate robustness, accuracy, cybersecurity, and human oversight throughout the system lifecycle (European Union, 2024). Compliance must be proven through documented procedures and, in many cases, certification-like conformity checks, after which the system must receive an EU declaration of conformity and CE marking before deployment (European Union, 2024).

In later stages of commercialization, Branoid may consider expanding into the United States, where there is no single comprehensive AI regulation, and oversight is instead carried out by agencies such as the National Highway Traffic Safety Administration (NHTSA), which focuses on the safety and testing of automated driving systems. In the U.S., compliance requirements vary by state, increasing regulatory complexity (Kadioglu, 2025).

6. SWOT Analysis

Strengths

Brainoid's main strength is its potential to significantly reduce the computational cost of training AI models, a challenge that is becoming increasingly important as models grow larger and more complex (Kaplan et al., 2020).

The technology also has broad applicability across multiple industries, including robotics, scientific computing, and advanced AI research. Because Brainoid is designed as an infrastructure layer, it can potentially integrate with existing machine learning architectures without requiring major changes to current workflows.

If validated successfully, the platform could also demonstrate high scalability, allowing it to be deployed across different research environments and industrial AI systems.

Weaknesses

The main weakness of the project is that it remains at an early stage of technological development, meaning the system has not yet been validated in both small-scale and large-scale commercial environments.

Brainoid also depends on external adoption and integration by AI developers and research teams. Without strong evidence of performance improvements, organisations may be reluctant to incorporate a new training system into their existing pipelines.

Additionally, the value of training optimisation technologies can be difficult to demonstrate clearly, particularly when improvements vary across different models and computational environments.

Opportunities

Brainoid operates in a market where AI training costs are increasing rapidly, creating strong demand for solutions that improve computational efficiency (Patterson et al., 2021). Many AI research labs and smaller companies face budget constraints that limit access to large computing resources, making cost-reduction technologies highly attractive.

Furthermore, there is growing concern about the energy consumption and environmental impact of large-scale AI training, which increases interest in more efficient machine learning systems.

Threats

The most significant threat comes from large technology companies developing internal optimisation tools or proprietary infrastructure solutions. These organisations already dominate key areas of AI computing and may integrate efficiency improvements directly into their platforms.

Another potential threat is the expansion of open-source optimisation frameworks, which are widely adopted in the machine learning community and may reduce the demand for proprietary solutions.

In addition, Brainoid may face financial constraints typical of deep-tech startups, where high upfront R&D costs and delayed revenue generation can restrict growth and slow technological progress. Limited resources may also result in slower development cycles compared to well-funded competitors, reducing the speed at which the platform can reach market readiness. Intellectual property (IP) risks further compound these challenges, including difficulties in protecting novel algorithms, potential infringement issues, and the possibility that competitors replicate or bypass proprietary innovations. Collectively, these factors pose significant threats to Brainoid's ability to scale, compete effectively, and sustain a defensible market position. Finally, conservative adoption behaviour in research institutions could slow the adoption of new infrastructure technologies until they are thoroughly validated.

7. Porter's Five Forces Analysis

Porter's Five Forces framework helps evaluate the competitive environment in which Brainoid operates and the pressures that may influence its ability to capture value in the AI infrastructure market (Porter, 1979).

1. Threat of New Entrants-

The AI infrastructure sector is experiencing rapid growth, attracting startups, research groups, and large technology companies. The availability of open-source machine learning frameworks such as PyTorch and TensorFlow, along with publicly accessible research publications, lowers entry barriers and allows new teams to experiment with novel training methods (Paszke et al., 2019; Abadi et al., 2016). Venture capital investment in AI has also increased significantly, encouraging the creation of new deep-tech companies.

However, building systems that significantly improve training efficiency still requires advanced expertise in machine learning systems, distributed computing, and optimization. This technical complexity limits how easily new firms can enter the space. Brainoid can further strengthen its position by developing defensible intellectual property around its training architecture.

2. Bargaining Power of Buyers-

Brainoid's potential customers such as AI research teams, robotics laboratories, and autonomous systems developers are typically highly technical organizations with strong engineering capabilities. These groups often have the ability to build internal tools if external solutions do not offer sufficient value.

As a result, Brainoid will need to demonstrate clear benefits such as faster training, lower computational costs, or improved model robustness. The importance of training efficiency has increased as modern AI systems require extremely large computing resources to achieve incremental performance improvements (Kaplan et al., 2020). If Brainoid's technology becomes embedded within customers' development pipelines, switching costs may increase, which could reduce buyer power over time.

3. Competitive Rivalry-

Competition within the AI infrastructure market is intense. Large technology companies such as Nvidia and Google dominate key parts of the ecosystem, including hardware acceleration and large-scale machine learning infrastructure. Nvidia's GPU ecosystem, for example, has become the industry standard for training deep learning models (Jouppi et al., 2017).

At the same time, venture-backed startups are actively developing new AI architectures and training optimization methods. This combination of established technology companies and emerging startups creates a highly competitive environment.

Brainoid differentiates itself by focusing on improving the efficiency of the training pipeline rather than directly competing with companies developing large AI models. By positioning itself as an enabling technology layer, Brainoid can complement existing AI development systems rather than replace them.

4. Threat of Substitutes-

Several alternative approaches exist for improving AI training performance. Hardware improvements, such as more powerful GPUs and specialized AI accelerators, continue to increase computational efficiency (Jouppi et al., 2017). In addition, machine learning engineers frequently develop internal optimization tools to improve training workflows.

Open-source software ecosystems also represent a strong substitute threat, as new optimization techniques and model architectures are frequently shared within the research community. However, if Brainoid's architecture significantly improves sample efficiency and reduces compute requirements, it could offer advantages that hardware scaling alone cannot provide.

5.Bargaining Power of Suppliers-

The AI development ecosystem relies heavily on specialized hardware and large-scale computing infrastructure. A small number of companies dominate the GPU and cloud computing markets, which gives them considerable influence over pricing and access to computational resources.

Training modern AI systems often requires large GPU clusters and significant energy consumption, making compute availability a critical factor for AI development (Patterson et al., 2021). This concentration of infrastructure providers increases supplier power.

Brainoid may reduce this dependency by developing a hardware-agnostic training architecture that works efficiently across different computing environments, allowing organizations to optimize their training pipelines regardless of the underlying infrastructure.

8. Go-to-market strategy

Founder and Core Team

The founder and future research team represent the central stakeholders in the Brainoid project. The founder's technical expertise is essential for developing the proposed training architecture and for guiding the scientific direction of the technology. However, successful commercialization will likely require the addition of a business-oriented co-founder or management team capable of managing partnerships, fundraising, and market expansion. Venture capital investors often consider balanced founding teams with complementary technical and business expertise to be more resilient and attractive investment opportunities (Janeway et al., 2021).

Early Clients and Research Partners

During Phase 1, Brainoid will work closely with a small number of early clients/partners, such as AI research laboratories like LOXO, OpenAI's research partners, or robotics companies such as Boston Dynamics and Agility Robotics, to validate market demand and refine scalable solutions for model robustness. These organisations act as early adopters and co-development partners, providing real-world testing environments and direct feedback on the technology.

Early adopter stakeholders play a critical role in validating new technologies and shaping product development, particularly in highly technical fields where performance benchmarks and practical demonstrations are required before broader adoption can occur (Buenaflor et al.,2015). Their feedback will help Brainoid refine its platform and ensure that the final product addresses real industry needs.

AI Developers and Industrial Customers

As the platform matures in Phase 2, the primary stakeholders shift toward AI developers, industrial research teams, and technology companies that build and train machine learning models, such as Google Brain, Microsoft Research, NVIDIA AI, Anthropic, and Baidu Research, who rely on efficient, scalable platforms to accelerate model development and deployment. These organisations are increasingly affected by the growing computational cost of training modern AI systems, making efficiency improvements highly valuable (Kaplan et al., 2020).

For these stakeholders, Brainoid's value proposition lies in reducing training costs, improving model robustness, and accelerating development cycles. Their willingness to adopt the platform will depend on factors such as integration complexity, performance improvements, and switching costs from existing machine learning infrastructure.

Investors and Venture Capital Firms

Investors are another key stakeholder group, particularly because Brainoid's long-term technological vision requires significant research and development investment. Deep-technology startups often rely on venture capital funding to support early-stage research before sustainable commercial revenue is achieved (Kerr & Nanda, 2015).

Appendix Table 2. Infrastructure Providers and Technology Ecosystem

Stage	Pre-Seed / Seed	Series A / Product Scaling	Growth / Deep Tech / AI Infrastructure

Investors	True Ventures, Basis Set Ventures, Upfront Ventures	Andreessen Horowitz, Sequoia Capital, Lightspeed	Khosla, Scale Venture Partners, DCM Ventures

Brainoid's technology also depends on relationships with cloud computing providers (e.g., Amazon Web Services, Google Cloud, Microsoft Azure), hardware manufacturers (NVIDIA, AMD), and AI infrastructure platforms (Weights & Biases, MLflow). These stakeholders control access to the high-performance computational resources required to train large-scale machine learning models (Kell et al., 2020; Chen et al., 2021).

While these organisations can act as strategic partners, they may also represent potential competitors if they develop their own training optimisation technologies. Maintaining compatibility with multiple infrastructure environments may therefore help Brainoid reduce dependency on a single provider and strengthen its market position.

AI Research Community

The broader AI research community represents another influential stakeholder group. Researchers and developers from institutions such as OpenAI, DeepMind, MIT CSAIL, and Stanford AI Lab contribute to the development of new machine learning architectures and optimisation techniques, many of which are shared through open-source frameworks (TensorFlow, PyTorch, JAX) and peer-reviewed scientific publications (Silver et al., 2016; Vaswani et al., 2017).

The acceptance of Brainoid's technology within this community will depend on transparent benchmarking, technical validation, and demonstrated performance improvements. Recognition within the research ecosystem can significantly accelerate technology adoption and credibility.

Stakeholders impact:-

Stakeholders collectively shape the design, scalability, and commercial viability of Brainoid's business model. Early clients and AI developers define the value proposition by driving demand for cost reduction, efficiency, and robustness, while the founder team and research community guide the technological direction. Investors and early adopters influence revenue models and market entry strategies, including decisions around SaaS, licensing, or API-based approaches. Infrastructure providers impose cost and technical constraints that affect scalability and margins, while large AI firms act as both customers and competitors, shaping competitive positioning. Meanwhile, the AI research community plays a key role in establishing credibility and accelerating adoption. Overall, Brainoid's business model co-evolves with these stakeholders, whose incentives and constraints determine both its technical development and commercial success.

9. Financing and fundraising strategies

Brainoid's financing strategy should follow a staged, hybrid approach, combining public funding, venture capital, and strategic partnerships, reflecting the high capital intensity of deep-tech AI development. It is critical that the project secures significant funding, especially for Phase 3, where a dedicated R&D team must be hired to advance the development of the new sample-efficient training architecture.

UK & EU Strategy

In the UK and European ecosystem, Brainoid can leverage public funding and early-stage venture capital to de-risk initial development. Programmes such as the European Innovation Council (EIC) Accelerator provide substantial grants alongside equity investments for high-risk, high-impact technologies. Complementary initiatives like Horizon Europe, Innovate UK, and the European Investment Fund (EIF) provide grants, co-investment, and loan guarantees to support research-intensive projects (Kerr & Nanda, 2015). These sources are ideal for early validation and proof-of-concept work before the company seeks larger global funding.

US Strategy and Strategic Positioning

For Phase 3 and scaling, the US provides a more mature venture ecosystem, particularly in California, where a dense network of investors actively funds AI deep-tech startups (Janeway et al., 2021). To maximise funding potential, the founder should relocate closer to the evolving AI industry, engage in entrepreneurial events, and network to position Brainoid as an attractive investment opportunity. Strategic positioning in this ecosystem also facilitates access to corporate partnerships and infrastructure support, which can accelerate development and market entry.

Founding Team and Investor Confidence

Securing large-scale funding will also depend on the composition of the founding team. VCs consistently prefer ventures with complementary skill sets, so we recommend identifying a business-oriented co-founder to balance the founder's technical expertise. This enhances investor confidence, strengthens strategic decision-making, and increases the likelihood of attracting significant funding (Kerr & Nanda, 2015; Janeway et al., 2021).

10. Finances

Appendix Table 3. Data points for calculations of Brainoid revenue projections.

Revenue streams and Pricing	Conservative total	Base case total	Aggressive total	Year

1-10 users for 10 beta companies $5000 per user annual Developer licenses	$50k	$250k	$500K	2027
50 companies (30 small, 15 mid, 5 enterprise) $5000 per user annual Developer licenses 1-10 users per company for 30 small companies = ARR of $150k-$1.5M 1-10 users per company for 15 medium companies = ARR of $75k-$750k $10,000-$50,000 annual Deployment licenses 15 medium companies = ARR of $150k-$750k $50,000-$200,000 annual Enterprise licenses 5 companies = ARR of $250k-$1M	$625k	$1.75M	$4M	2028
100 companies (50 small, 30 mid, 20 enterprise) $5000 per user annual Developer licenses 1-10 users per company for 50 small companies = ARR of $250k-$2.5M 1-10 users per company for 30 medium companies = ARR of $150k-$1.5M	$1.7M	$5.5M	$10M	2029

$10,000-$50,000 annual Deployment licenses 30 medium companies = ARR of $300k-$1.5M $50,000-$200,000 annual Enterprise licenses 20 companies = ARR of $1M-$4M				
200 companies (100 small, 60 mid, 40 enterprise) $5000 per user annual Developer licenses 1-10 users per company for 100 small companies = ARR of $500k-$5M 1-10 users per company for 60 medium companies = ARR of $300k-$3M $10,000-$50,000 annual Deployment licenses 60 medium companies = ARR of $600k-$3M) $50,000-$200,000 annual Enterprise licenses 40 companies = ARR of $2M-$8M)	$3.1M	$9.9M	$17.5M	2030

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