# “WHERE DO THEY FIT? CATEGORIZING ENTREPRENEURIAL VENTURES IN THE AGE OF GENERATIVE ARTIFICIAL INTELLIGENCE”

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**Abstract:**

This paper investigates how generative artificial intelligence (GenAI) ventures can be systematically categorized within entrepreneurship theory. While many entrepreneurs currently seek to integrate GenAI in their business, the technology is often misunderstood and GenAI ventures are mischaracterized. Scholars have already identified taxonomies for digital ventures overall, yet none have accounted for the unique characteristics of GenAI-driven ventures such as their dependence on large foundational models providing intelligent results, massive upfront compute needs, blurry intellectual property and probabilistic user experience. On the contrary: Some researchers have miscategorized GenAI ventures through a lacking understanding of AI as well as its subcomponents machine learning and deep learning thus leading to confusion concerning the characteristics of corresponding ventures not just among entrepreneurs but also among venture capitalists and regulators. To address this issue, this study clarifies what GenAI is, challenges the existing theory on digital venture taxonomies as it relates to this new technology and develops a new taxonomy with four dimensions, categorizing GenAI ventures based on their general intelligence and pricing strategy. This provides entrepreneurs, venture capitalists and regulators with a strategic framework to position these ventures comparative to one another and thus helps achieve differentiation, optimized capital allocation and effective regulatory response.

**Keywords:** Generative Artificial Intelligence; Entrepreneurship; Venture; Taxonomy;

## 1. **Introduction:**

Entrepreneurship scholars increasingly examine the influence of generative artificial intelligence (GenAI) on ventures due to the technology's significant development and adoption in recent years (von Krogh et al., 2023; Kanbach et al., 2024). GenAI here refers to AI systems with the capacity to autonomously generate contextually relevant content, continuously learn from interactions, and refine outputs based on accumulated knowledge (Chowdhury et al., 2024). Specifically, von Krogh et al. identified that advancements in GenAI have sparked significant interest and investment from entrepreneurs seeking to start new innovative ventures (von Krogh et al., 2023). Furthermore, Kanbach et al. identified the potential of GenAI as a catalyst for transforming existing ventures, emphasizing the need for strategic alignment with business ecosystems to implement GenAI-driven innovation (Kanbach et al., 2024). These are the latest components of an ongoing scholarly discussion on the effects of digitalization and AI on entrepreneurship (Snihur & Zott, 2020; Davidsson & Sufyan, 2023). Taken together these studies indicate that GenAI fundamentally alters new ventures (Short & Short, 2023). Simultaneously, entrepreneurship researchers are increasingly categorizing digital ventures into taxonomies to identify patterns (Nambisan 2017, König et al., 2019; Bugl et al., 2022; Crawford et al., 2024). This has helped advance theory by clarifying the impact of various entrepreneurial activities (Trubnikov, 2021; Dey et al., 2022).

However, these theories on digital venture taxonomies do not yet account for the unique characteristics of GenAI such as dependence on large foundational deep learning models, extreme computing and data requirements at early stages, ambiguous intellectual property boundaries, and non-deterministic user experiences shaped by probabilistic outputs (Banh & Strobel, 2023; Sengar et al., 2024). As a result, existing digital venture taxonomies, such as the one by Nambisan (2017), risk misclassifying GenAI ventures, treating them as conventional software or platform ventures without recognizing their distinct technological constraints and strategic implications. This misclassification risks creating even more confusion around this novel technology and its definition – an example of which can be seen in the work of Davidsson's & Sufyan (2023) on the external enabler framework who confuse the field of GenAI with the field of Artificial Intelligence – GenAI being only a very small technology subsegment of this broad field of research that has been around for decades (Zhuhadar & Lytras, 2023).

The absence of a clear and detailed taxonomy on GenAI ventures also presents several practical challenges. First, venture capitalists (VCs) may misallocate funding to GenAI startups that lack technological sophistication and are vulnerable to displacement by large foundational model providers, thereby exposing investors to financial risk. Second, startup founders may mistakenly believe they have devised an advanced GenAI-driven venture with strong market potential, only to later realize that their use case is narrowly confined to a specific user segment, severely limiting revenue potential and increasing the likelihood of business failure (von Krogh et al., 2023). Third, the failure to properly categorize GenAI ventures contributes to regulatory uncertainty, as policymakers may introduce legal frameworks targeting sophisticated models, while inadvertently imposing burdensome compliance requirements on AI-tools with a far lower risk profile thus stifling innovation (Seidel et al., 2024).

Hence, the purpose of this study is to develop a taxonomy of GenAI ventures thus answering the question: *"How can GenAI ventures be categorized effectively?"*.

To address this research question, this study uses a taxonomy development method as outlined by Nickerson et al. (2013) to systematically classify GenAI ventures. This iterative conceptual-to-empirical approach is based on a comprehensive and theoretically grounded classification framework.

Addressing this research question contributes to academia by first clarifying what GenAI is compared to AI and then expanding upon Nambisan's (2017) theory of digital entrepreneurship by illustrating that his taxonomy of ventures does not account for the unique characteristics of GenAI. This paper then introduces a new taxonomy specifically for GenAI ventures which helps startup founders, VCs and regulators address the risks outlined above.

## 2. **Theoretical Background:**

The transformative impact of generative artificial intelligence ventures has emerged as a focal point in recent scholarly discussions (Grimes et al., 2023). Within this field GenAI ventures can be seen as a subsegment of digital ventures and furthermore as subsegments of AI ventures, Machine Learning Ventures and Deep Learning Ventures as illustrated by Figure 1.

**<< Insert Figure 1 about here >>**

Digital ventures are defined as entrepreneurial entities that identify, evaluate, and exploit digital market opportunities by creatively mobilizing resources and establishing innovative organizational forms (Huang et al., 2017). Scholars such as Shane (2003) argue that digital ventures are fundamentally about recognizing and seizing opportunities through innovation and risk-taking, a perspective that emphasizes dynamic market responsiveness and strategic resource configuration. Nambisan (2017) expanded on this view by categorizing different forms of digital ventures into three types: Those based on digital artifacts, digital platforms, and digital infrastructure. Digital artifacts refer to stand-alone digital components, applications, or media content that provide a distinct functionality or service. These can either be independent software products or integrated into broader systems (Nambisan, 2017, p. 3). Digital platforms serve as foundational architectures that facilitate complementary digital products and services, such as app ecosystems in mobile operating systems (Nambisan, 2017, p. 4). Lastly, digital infrastructure comprises technological tools and systems – such as cloud computing, data analytics, and online communities – that support communication, collaboration, and business scaling (Nambisan, 2017, p. 4). This classification highlights how digital ventures leverage different technological enablers to shape their entrepreneurial processes and market strategies. Despite these contributions, neither Shane (2003) nor Nambisan (2017) offer a granular taxonomy of ventures within specific digital technology domains, such as Generative AI (GenAI) ventures. Nambisan’s classification focuses broadly on digital technology enablers but does not systematically distinguish how different digital entrepreneurial models emerge within the AI space, nor does it consider the unique scaling dynamics and innovation mechanisms of GenAI-driven startups. GenAI ventures differ from traditional digital ventures as defined by Nambisan (2017) in that they rely on large-scale foundational models and probabilistic AI systems that mimic human intelligence as core components of their value creation logic (Kanbach et al. 2024). Specifically, GenAI ventures do not fit Nambisan's definition for digital artifacts outlined above as GenAI ventures embody dynamic, adaptive, and co-creative systems whose value emerges from continuous human-AI interaction, learning, and customization, transcending the fixed-functionality scope of digital artifacts. They also do not fit into the category of digital platforms: While GenAI ventures may incorporate platform-like features, their core innovation lies in generative capabilities and emergent intelligence rather than in orchestrating multi-sided interactions or hosting third-party complements (Banh & Strobel, 2023; Sengar et al., 2024). Lastly GenAI ventures can also not solely be seen as digital infrastructure: While they are built upon and leverage such infrastructure, GenAI ventures integrate these tools into intelligent, generative systems that actively shape and co-create value with users, positioning them as novel socio-technical assemblages rather than passive enabling layers (Sengar et al., 2024). In summary, the emergence of GenAI's fundamentally reshapes how value is created, delivered, and captured within the digital ventures (Banh & Strobel, 2023; Sengar et al., 2024).

Nambisan's digital venture taxonomy does not capture this nuance thus creating a gap in literature that is illustrated further by other researchers who have assessed the impact of GenAI on business ventures such as Chalmers et al. (2021). They state that such technologies fundamentally influence the design, development, and scaling of ventures and argue that these ventures "can grow rapidly without encountering many of the constraints or challenges new ventures traditionally face" (Chalmers et al., 2021, p. 13). Yet here again the existing literature does not categorize GenAI ventures in an exhaustive and mutually exclusive manner, leaving a gap in our understanding of how different strategic approaches and organizational structures manifest in the evolving GenAI ecosystem.

If unaddressed this lack of understanding on how to categorize GenAI ventures will lead to more works such as the one by Davidsson & Sufyan's (2023) who correctly acknowledge AI's impact on the field of entrepreneurship however only discuss one very specific generative artificial intelligence tool (ChatGPT) that cannot be seen as synonymous for the entire field. They do not address that AI is a broad field of computer science that has been around for decades and consists of various subsegments with GenAI models such as ChatGPT being only one. If GenAI ventures are analyzed yet not placed into context compared to one another or the broader field of AI, we will increasingly see wrong categorizations of AI, Machine Learning, Deep Learning and GenAI-based organizations thus leading to incoherent research on technology progress and impact.

This study addresses these issues by introducing a new GenAI venture taxonomy. This taxonomy clarifies how GenAI drives entrepreneurship at a venture-level and maps GenAI's enabling mechanisms across venture types, offering a precise and actionable framework.

## 3. **Methodology:**

This study follows an iterative taxonomy development process as outlined by Nickerson et al. (2013) in the figure below. The first step in this methodology is determining the meta-characteristic of the taxonomy, which serves as the guiding principle for classification. This ensures that the taxonomy captures the diversity of GenAI ventures while maintaining a coherent classification framework.

**<< Insert Figure 2 about here>>**

Following the identification of the meta-characteristic, the study establishes ending conditions – both objective and subjective – to determine when the taxonomy is complete. Objective criteria require that each dimension exhibits mutually exclusive and collectively exhaustive characteristics, no new dimensions or characteristics emerge in later iterations, and all sampled GenAI ventures are classifiable within the framework, ensuring final stability. Subjective conditions demand that the taxonomy remains concise for manageability, robust in differentiating ventures, comprehensive in capturing all relevant aspects, extendible to accommodate future developments, and explanatory in clarifying how GenAI supports various venture types. The taxonomy is finalized only when all these conditions are met (Nickerson et al., 2013).

The research proceeds through an iterative conceptual-to-empirical approach – chosen over the empirical-to-conceptual approach given the need to discuss existing theories on digital ventures first. The study begins by conceptualizing new dimensions based on prior research in digital entrepreneurship and artificial intelligence. These proposed dimensions are then tested against real-world GenAI ventures, ensuring that they accurately reflect the distinguishing features of these ventures. Any inconsistencies or missing elements are addressed through iterative refinements, leading to the revision of the taxonomy. Employing this taxonomy development method by Nickerson et al. (2013) ensures that the resulting framework is robust and comprehensive thereby accommodating future shifts in the digital economy (Nambisan, 2017; Grimes et al., 2023; Kanbach et al., 2024).

## 4. **Results:**

### 4.1. **Determining the meta-characteristic:**

The guiding meta-characteristic selected for this research effort, termed “Strategic Success”, encapsulates the way a GenAI venture aligns its innovative technology advancements with its overall objectives to grow its revenue and customer base. This single, overarching attribute was chosen as it provides a clear lens for understanding a venture's competitive positioning within the broader digital entrepreneurship landscape. By emphasizing the coherent integration of GenAI into a venture’s core business model, the taxonomy framework derived through this meta-characteristic offers valuable insights for investors, entrepreneurs, and regulators alike.

### 4.2. **Determining Ending Conditions:**

In line with Nickerson et al. (2013) as well as with Doty and Glick’s (1994) framework for taxonomy design, the taxonomy for GenAI ventures must meet both objective and subjective ending conditions to conclude its iterative development. Objectively, the taxonomy must consist of clear dimensions, be collectively exhaustive, and mutually exclusive: every category and dimension must be precisely defined, the framework must encompass all viable types of GenAI ventures, and no category should overlap with another, ensuring unambiguous placement of ventures (Nickerson et al, 2013, p. 343). Subjectively, the taxonomy must also be concise, robust, comprehensive, extendible and explanatory – offering a concise yet robust structure that not only simplifies complex organizational forms but also enhances our understanding of strategic outcomes such as organizational effectiveness (Nickerson et al, 2013, p. 343). Once these objective conditions (clear dimensions, exhaustiveness, mutual exclusivity) and subjective criteria (conciseness, robustness, comprehensiveness, extendibility and explainability) are fully satisfied, the iterative process of taxonomy creation is deemed complete.

### 4.3. **Conceptualizing new characteristics and dimensions of objective:**

Following the logic outlined above several dimensions were identified throughout the research process via which GenAI organizations can be categorized:

**<< Insert Table 1 about here >>**

Out of all these assessed dimensions two are especially fitting for the purposes of a GenAI taxonomy under the constraints of the previously defined objective and subjective ending conditions:

1. General Intelligence: This dimension captures the evolving intelligence levels of GenAI models that set the underlying companies apart from other digital ventures. The corresponding axis ranges from low (organizations that typically build foundational models with only a few parameters and score low on standardized AI tests) to high (organizations that invest in extremely sophisticated self-trained foundational models that have reasoning capabilities and score highly in corresponding tests).

2. Pricing Strategy: This dimension captures that ventures are varying the price per million tokens that are generated by their respective model based on aspects such as the model’s area of applications, size, processing power needs and customer base. The corresponding axis also ranges from low (models that cost few cents per million tokes) to high (models that cost more than 40$ per million tokens).

All GenAI entrepreneurship ventures can be categorized into a two-dimensional matrix as illustrated below. Within this taxonomy-matrix the ventures can furthermore be categorized into four quadrants based on where they lie on the abovementioned axis:

**<< Insert Figure 3 about here >>**

The quadrants are defined as follows:

Quadrant 1 – High-Intelligence – Low-Cost Ventures: Organizations in this quadrant build sophisticated models for general-purpose use cases while minimizing costs for customers and hence become competitive across a wide range of use cases. As a result, this quadrant typically displays the highest density of ventures and is thus highly competitive and lucrative.

Quadrant 2 – High-Intelligence – High-Cost Ventures: Organizations in this quadrant deprioritize offer extremely intelligent models that can be used for highly specialized use cases such as the analysis of vast amounts of data or reasoning over several iterations of inference. To achieve this technological advancement the costs of the model training & development as well as datacenter processing costs are deprioritized thus making it only attractive to wealthy customers with tasks that require extreme levels of intelligence for their purposes.

Quadrant 3 – Low-Intelligence – Low-Cost Ventures: Organizations in this quadrant typically offer less advanced GenAI models that are either older (from a technology-development perspective) or can be used for niche use cases that do not require highly intelligent models such as specific translation services with no need for several inference cycles. This – in connection with the low datacenter processing needs – leads to the comparative low costs of the venture.

Quadrant 4 – Low-Intelligence – High-Cost Ventures: These ventures are typically quickly displaced from the market as they are unable to compete against other ventures that offer lower costs or more sophisticated models. Hence organizations typically try to refrain from entering this quadrant.

The resulting matrix not only visually categorizes GenAI startups along two key dimensions but also offers a clear framework to analyze strategic positioning within the GenAI landscape.

## 4.4. Examining objects for these characteristics and dimensions

An exemplary analysis of 12 ventures which deploy GenAI within their core business model was conducted to test the taxonomy. The ventures were chosen as they operate some of the currently most used GenAI models worldwide (Artificial Analysis, 2025). The analysis concluded in the following categorization:

**<< Insert Figure 4 about here >>**

Details on the ventures in question and their scores are available in the following table:

**<< Insert Table 2 about here >>**

The metrics chosen for determining the respective positioning of the organizations are as follows: The General Intelligence Score is a consolidation of seven common GenAI Model Metrics: MMLU-Pro evaluates understanding across 30 academic and professional subjects, while GPQA Diamond challenges deep factual and conceptual reasoning with graduate-level questions. Humanity's Last Exam pushes models to tackle complex philosophical, legal, and ethical dilemmas. LiveCodeBench assesses real-time coding capabilities, and SciCode focuses on scientific reasoning and code generation in STEM fields. For mathematical aptitude, AIME uses problems from the American Invitational Mathematics Examination, and MATH-500 presents 500 rigorously curated math challenges to test high-level problem-solving skills. The corresponding definitions and scores were taken from a consolidated report by the AI Market Analysis Organization “Artificial Analysis” (2025). Furthermore, the pricing of the individual models can be found via the respective company websites.

## 4.5. Analysis of Ending Conditions and Limitations

This analysis concluded that the newly proposed venture taxonomy does fulfill the abovementioned objective ending conditions for a venture taxonomy as 1. There are clear definitions provided for each of the dimensions within the taxonomy. 2. The taxonomy manages to categorize all example GenAI ventures within the two dimensions thus indicating that it is collectively exhaustive. 3. There is no overlap or ambiguity between the categorized ventures across the dimensions thus illustrating that they are mutually exclusive. While most of the other assessed dimensions could also be clearly defined, they were often not mutually exclusive or collectively exhaustive. Furthermore, the subjective ending conditions were met as well: The taxonomy is concise, focusing on only two core dimensions that effectively capture the strategic variance among GenAI ventures. It is robust, as it allows for clear categorization even in a rapidly evolving technological landscape. The framework is also comprehensive, encompassing a wide range of GenAI business models and pricing strategies without oversimplifying the diversity in the ecosystem. It is extendible, meaning additional dimensions – such as regulatory compliance or domain specialization – can be incorporated in future iterations without disrupting the current structure. Also, it is explanatory, offering stakeholders such as investors, policymakers, and entrepreneurs a clear lens to understand the strategic positioning and competitive dynamics within the GenAI startup landscape. Lastly both dimensions “general intelligence” and “pricing strategy” can be seen as indicators for the overarching meta-characteristic “Strategic Success” of the venture, thus fulfilling this requirement as well.

While the proposed taxonomy offers a structured and insightful classification of GenAI ventures, several limitations must be acknowledged. First, the analysis focuses exclusively on ventures that develop foundational GenAI models, excluding those that build application-layer solutions or “wrappers” on top of such models. Second, the landscape of GenAI is evolving at an exceptionally rapid pace, and the strategic positioning of ventures may shift quickly in response to technological and market dynamics. Third, many companies operate multiple models simultaneously to target different segments along the pricing and intelligence dimensions, which must be acknowledged when the case arises. Lastly, the evaluation of general intelligence is based on text generation capabilities; multimodal models that generate images, audio, or video are not considered here.

## 5. **Concluding Discussion:**

The developed taxonomy above contributes to Nambisan's (2017) theory of digital entrepreneurship by expanding upon his three-tiered classification of digital ventures – comprising digital artifacts, digital platforms, and digital infrastructure – through the introduction of the new two-dimensional taxonomy specifically tailored to GenAI ventures. By systematically categorizing GenAI ventures into four distinct types, this taxonomy captures the diversity of emerging GenAI-driven ventures that would otherwise be miscategorized in existing digital venture taxonomies. This helps bring structure to an otherwise fragmented landscape and provides a solid theoretical foundation for future research on entrepreneurship in the field of Artificial Intelligence.

Practically, the exemplary assessment of 12 GenAI ventures currently on the market showed that there are varying levels of attractiveness among the four GenAI venture groups. Group 1 (High-Intelligence – Low-Cost Ventures) clearly shows the greatest density of ventures thus indicating a high degree of competition and potential revenue impact. Simultaneously, there are a few players among the largest GenAI model providers that fall into groups 2 (High-Intelligence – High-Cost) and 3 (Low-Intelligence – Low-Cost) thus indicating that there is some revenue potential here as well for more catered niche use cases. Lastly there are currently no ventures active in group 4 (Low-Intelligence – Low-Cost) as these players are likely quickly displaced by others. This identification could enable venture capitalists to more accurately assess the investment potential of future GenAI startups, thereby reducing the risk of misallocating funds. Additionally, it equips startup founders with a clearer understanding of their business model's positioning, helping to prevent overestimations of market potential and mitigating the risk of business failure. Furthermore, this nuanced classification aids regulators in designing targeted legal frameworks that are commensurate with the actual risk profiles of diverse GenAI model intelligence levels, ultimately fostering innovation while preventing unnecessary administrative burdens.

In conclusion, this research demonstrates that GenAI ventures warrant a distinct classification through the hereby introduced novel taxonomy that operates independently of Nambisan's (2017) digital entrepreneurship framework. By incorporating dimensions such as general intelligence and pricing strategy, this study establishes a theoretical foundation for distinguishing GenAI ventures from other digital enterprises, thereby enabling researchers to more accurately categorize these ventures and understand their strategic implications.

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## 7. Declaration of generative AI and AI-assisted technologies in the writing process:

During the preparation of this work the author used the tool “Google Gemini” to improve the readability and language of the manuscript. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

## 8. Figures:

As instructed, please refer to the separately submitted files containing figures 1-4 for details.

9. **Tables:**

| **Taxonomy Options** | **Definitions** | **Sources** |
|---|---|---|
| Value Creation Mechanism | The approach a GenAI venture uses to generate value, often through the selection of model architecture - such as large language models (for text), diffusion models (for images) or multimodal models (combining the creation of text, images, videos & code) | McLees et al. (2024)<br>Berente et al. (2021)<br>IBM (2024) |
| Value Capture Mechanisms | The strategies a GenAI venture employs to generate revenue, such as subscription models (recurring fees for model access), token-based pricing (cost per API call), or licensing agreements. | Kanbach et al. (2024)<br>Remane et al. (2022) |
| Dataset Choice | The selection of datasets used to pre-train or fine-tune GenAI models, which may include open-source corpora (e.g., Common Crawl), proprietary data, or custom datasets tailored for specific tasks. | NeurIPS (2024)<br>Jiang et al. (2024) |
| Reinforcement Learning Algorithms | The design of reinforcement learning rules, including the use of Reinforcement Learning with Human Feedback (RLHF) to align GenAI behavior with ethical guidelines or other criteria. | Sutton et al. (2018) |
| Model Availability | How GenAI ventures make their models accessible, whether through APIs (hosted model endpoints), libraries (for developer integration), or downloadable models (for local use). | Gartner (2023) |
| Partnership and Ecosystem Strategy | The extent to which GenAI ventures form strategic partnerships - such as cloud providers, AI research labs, or platform ecosystems - to enhance their offerings and market reach. | Wang (2021) |
| Application Specificity | The degree to which the GenAI application is tailored for a particular domain, such as industry-specific models (e.g., healthcare), function-specific tools (e.g., legal document drafting), or agnostic productivity boosters. | Banh & Strobel (2023) |
| General Intelligence | The level of intelligence the underlying GenAI Models of the ventures portray across standardized tests such as the MMLU-Pro, GPQA Diamond, Humanity's Last Exam, LiveCodeBench, SciCode, AIME and MATH-500 | Schneider et al. (2024) |
| Pricing Strategy | The way in which the venture places its product (the GenAI model) on the market in terms of associated costs/price. This dimension can be quantified through cost per million tokens processed by the model underlying the venture. | Banh & Strobel (2023) |

*Table 1: GenAI Taxonomy Dimension Options, Definitions and Sources*

| Nr. | Venture Name | Underlying GenAI Model Name | General Intelligence based on the AAI Index incorporating 7 evaluations: MMLU-Pro, GPQA Diamond, Humanity's Last Exam, LiveCodeBench, SciCode, AIME and MATH-500 | Pricing Strategy based on the current price per million tokens to access the respective GenAI model via an API (Application Programming Interface) in USD |
|---|---|---|---|---|
| 1 | OpenAI | O3-Pro | 71 | 35,00 |
| 2 | DeepSeek | R1 | 68 | 0,96 |
| 3 | xAI | Grok 3 mini Reasoning | 67 | 0,35 |
| 4 | Google | Gemini 2.5 Flash | 65 | 0,99 |
| 5 | Anthropic | Claude 4 Opus Thinking | 64 | 30,00 |
| 6 | Alibaba | Qwen 235B | 62 | 2,63 |
| 7 | Nvidia | Llama Nemotron Ultra Reasoning | 60 | 0,9 |
| 8 | Meta | Llama 4 Maverick | 50 | 0,39 |
| 9 | Mistral | Medium 3 | 49 | 0,8 |
| 10 | AWS | Nova Premier | 42 | 5 |
| 11 | Perplexity | Sonar Pro | 42 | 6 |
| 12 | Cohere | Aya Expanse | 20 | 0,75 |

*Table 2: GenAI Venture Taxonomy Scores for General Intelligence and Pricing Strategy of twelve currently widely established GenAI model providers based on the current Artificial Analysis Index (AAI) available via [www.artificialanalysis.ai/models](www.artificialanalysis.ai/models) and last reviewed on 12.06.2025:*

Please note: The General Intelligence Score is a consolidation of a range of common GenAI Model Metrics that was gathered by the AI Market Analysis Organization "Artificial Analysis". The scoring changes continuously as the models evolve. Furthermore, the Pricing of the Individual Models can be found via "Artificial Analysis" as well as via the respective company websites. The selection of ventures was made based on an analysis of the most used GenAI Foundational Models across the world at the time of writing.