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Benchmarking and Designing AI-Native Entrepreneurship Ecosystems: Switzerland and Jordan as a Case Study

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Abstract

AI is currently shaping how people are being entrepreneurial by allowing the establishment of AI-native ventures. The creation of these new types of businesses builds off an infrastructure of data, computing power, and research that typically accompany advanced economies. In contrast, most developing economies are still experiencing institutional and structural barriers that inhibit the formation of new ventures and their subsequent growth. Despite the existence of research that explores some of the ways in which successful ecosystems from developed economies could be applied to developing ecosystems, there is little guidance on how to systematically adapt these successful practices in resource-constrained environments. This research uses a comparative, document-based study design to assess how to benchmark and configure AI-native entrepreneurship ecosystems across heterogeneous institutional environments. Using Switzerland and Jordan as two contrasting analytical cases, we define twelve dimensions of an ecosystem and then create comparative ecosystem profiles using a standardized coding and scoring framework. We combine dimension-level data on talent development, applied research, infrastructure, financing, governance and market access with baseline socio-economic indicators. Our results demonstrate a high level of structural asymmetry between the two ecosystems. Switzerland has a balanced and highly coordinated configuration, whereas there is a strong university anchor and demand for talent in Jordan, but there are also significant weaknesses in terms of infrastructure, financing, and industry linkages. Building from these results, we present the parameter reweighting and the context-sensitive design model to encourage the emergence of AI-native entrepreneurship in Jordan through coordinated architecture, collaborative experimentation resources and internationalization at an early stage. This article advances both the fields of entrepreneurial ecosystems and digital entrepreneurship by framing AI-native entrepreneurship as a new form of knowledge-intensive venture creation and providing a context-sensitive approach for adapting entrepreneurial ecosystems. The results provide a document-informed basis for policymakers, academic institutions and other ecosystem actors seeking to develop AI-based innovation in resource-constrained economies.

Keywords: AI-native entrepreneurship; entrepreneurial ecosystems; comparative ecosystem analysis; emerging economies; innovation systems; context-sensitive design

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1. Introduction

Entrepreneurial activity is changing significantly as a result of artificial intelligence (AI) and the development of new AI-native ventures based on data-driven learning, algorithmic decision-making and sophisticated computer systems. Companies may use AI to a greater or lesser extent to accelerate or simplify their routine activities and/or may develop tools as part of a core product offering—a good example is the award-winning Swiss startup Yokoy, an AI-powered platform that automates company expense processes (https://www.top100startups.swiss/yokoy, accessed on 25 May 2026).

Although AI can provide economic advantages for startups by supporting business planning, they are exposed to a complex ecosystem of costs not typically incurred by startups in other domains. For example, the costs associated with acquiring data for training, validating, optimizing and deploying AI models are significant, as is adhering to compliance and ethics regulations, especially in areas such as healthcare, finance and security. The associated hardware and IT infrastructure and integration with other business software (e.g., CRM or ERP systems) is also expensive, and the speed with which AI and other technologies evolve means regular and often costly maintenance and upgrades must be made. Thus, the way in which AI-native ventures are created and grow is influenced not only by the ability of the individual entrepreneur but also by the structural configuration of the surrounding innovation ecosystem (Carayannis et al., 2018; OECD, 2021). There have been a number of recent systematic and bibliometric reviews that support the rapid growth of research into the convergence between AI and entrepreneurship and call for greater structured theorization on the areas of AI-enabled venture creation and ecosystem dynamics (Blanco-González-Tejero et al., 2023; Mumi et al., 2025; Obschonka et al., 2025).

During the past decade, a few advanced economies have built up fully developed and functioning AI-native entrepreneurship ecosystems consisting of multiple interconnected networks including universities and research organizations, private-sector firms, venture and angel investors and governmental organizations, all of which work together to accelerate and facilitate the transformation of scientific innovations into scalable entrepreneurial ventures. By contrast, entrepreneurship in many emerging economies is limited by fragmented governance systems, insufficient collaboration with industry and an underdeveloped financial backbone, as well as a lack of access to data and computational resources (Audretsch & Belitski, 2017). To date, research literature on entrepreneurship provides limited insight into how to systematically transfer or adapt elements of entrepreneurial ecosystems found in advanced AI economies to less developed countries and/or to regions where the underlying institutional and economic conditions are vastly different.

The OECD (2020) and others have suggested that there can be no straightforward replication of successful entrepreneurial ecosystems across contexts because the efficacy of the implementation is dependent on how the environments have evolved historically and how the constituent parts of the ecosystem complement each other (Huang et al., 2017; Nambisan, 2017; OECD, 2020). More recent research has called for more context-sensitive approaches to ecosystem design focusing on adaptive designs rather than relying on best-practice diffusion (Acs et al., 2017; Stam & Van de Ven, 2021). Although this literature has considered technology-based and knowledge-intensive entrepreneurship, AI-native entrepreneurship has not been extensively examined through this lens. There have not been many systematic frameworks that connect ecosystem insights from advanced artificial intelligence environments to develop actionable strategies for emerging economies. Foundational entrepreneurial ecosystem research emphasizes the interdependence of actors, institutions and resources (Brown & Mason, 2014; D. J. Isenberg, 2010; Spigel, 2017). However, these frameworks do not explicitly foreground the combined dependence of AI-native ventures on data, computational capacity, continuous model validation, responsible AI governance and sector-specific experimentation. These requirements distinguish AI-native entrepreneurship from digital and technology entrepreneurship more broadly.

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This paper fills this gap by proposing a context-sensitive design framework for AI-native entrepreneurship ecosystems based on a comparative benchmarking study and document-based empirical research. The goal is to provide a transparent, systematic means by which to compare ecosystems and identify significant structural differences between them. The framework assigns twelve specific ecosystem parameters which can then be treated as variables in a design process: each dimension can be re-weighted and reconfigured according to local limitations and opportunities. The methodology has been applied to the AI-native entrepreneurship ecosystems in Switzerland and Jordan. The Swiss innovation ecosystem is a highly evolved, research-intensive ecosystem of cooperation based on strong links between universities and industry. It has decentralized governance arrangements and regulations that adapt to meet evolving needs (https://www.ch.ch/en/political-system/, accessed on 25 May 2026). The Jordanian ecosystem, by contrast, is an emerging ecosystem with a significant amount of highly educated human capital and potential for entrepreneurship. However, Jordan's AI-native entrepreneurship ecosystem lacks significant industrial, R&D and venture inputs and infrastructure (Tullis, 2025).

Documents analyzed in the study include national policy documents, reports on the higher education system and on innovation agencies, and indicators of global benchmarking. Each of the twelve ecosystem dimensions is assessed using a standard coding and scoring procedure. The results of the comparisons are used to propose a layered, context-sensitive ecosystem design for AI-native entrepreneurship in Jordan. Accordingly, this study addresses two research questions: (1) How do AI-native entrepreneurship ecosystem configurations differ between a mature and a resource-constrained national context? (2) How can ecosystem functions be adapted and re-weighted to support AI-native venture development in an emerging economy?

This study makes four contributions:

1. Theoretical: it positions AI-native entrepreneurship as a distinct form of knowledge-intensive entrepreneurship shaped by data, computational capacity, model validation, and responsible AI governance.
2. Methodological: it develops a twelve-dimension framework for systematically comparing AI-native entrepreneurship ecosystems.
3. Empirical: it identifies structural differences between the Swiss and Jordanian ecosystems through a document-based comparative analysis.
4. Practical: it translates the twelve-dimension ecosystem assessment into a context-sensitive design model for identifying priorities, assigning responsibilities and sequencing interventions under the conditions of an emerging economy.

The paper is organized as follows: Section 2 provides a review of relevant materials and develops the framework of analysis; Section 3 describes the methodology and coding process used to collect data; Section 4 benchmarks Swiss AI-native entrepreneurship ecosystems; Section 5 evaluates AI-native entrepreneurship ecosystems in Jordan and compares it with the Swiss ecosystem; Section 6 discusses the comparative findings and develops the context-sensitive design model; and Section 7 summarizes the implications and limitations of the findings and recommends areas for further study.

2. Conceptual Foundations and Analytical Framework

2.1. AI-Native Entrepreneurship and Knowledge-Intensive Ventures

AI-native entrepreneurship refers to entrepreneurial activity in which AI constitutes a central technological and economic foundation of the venture (Rai et al., 2019). Often such ventures rely significantly on large data sets, machine learning models and complex computing environments to develop value, as well as having a high dependence on specialized human capital and extended development cycles, all of which lead to a high degree of uncertainty (Whittaker et al., 2018).

Unlike many traditional digital-startups that seek to develop quickly and incrementally, ventures using AI require a longer-term approach for experimentation and iteration of models (Stam & Van de Ven, 2021): their success relies on access to quality data, computing resources, a combination of different subject matter expertise and regulatory environments that allow for responsible experimentation. Thus, although AI-native entrepreneurship falls within the broader domain of technology entrepreneurship, AI-native ventures exhibit a distinctive combination of dependencies related to data access, computational resources, specialized talent and regulatory coordination (Uriarte et al., 2026).

Based on the analysis of Uriarte et al. (2026), this study combines the issues discussed in that article into five broader analytical areas. These areas represent an author-developed synthesis rather than a five-part framework directly proposed by Uriarte et al. (2026). First, data, including labeled and domain-specific datasets, is not only a market resource but a core production input for model training, testing and improvement. Second, computational infrastructure directly shapes experimentation speed, development cost and scalability. Third, AI-native ventures require continuous model validation, including testing for accuracy, bias, reliability, safety and domain suitability. Fourth, regulatory and ethical governance affects whether AI systems can be responsibly deployed, especially in sensitive sectors such as health, finance, education and public services. Fifth, market validation often depends on access to sector-specific partners who can provide real-world use cases, pilot environments and feedback loops. These characteristics justify the need for an AI-specific ecosystem benchmarking framework rather than a generic digital entrepreneurship model.

2.2. Entrepreneurial Ecosystems and Contextual Embeddedness

The view of the entrepreneurial ecosystem is that the creation and growth of businesses will depend upon various networks of stakeholders, institutions and resources interconnected within a geographical context (Feldman & Zoller, 2012). The ecosystem is made up of many interdependent entities including universities, businesses, investors, support organizations, policy frameworks and cultural norms. Successful entrepreneurial ecosystems do not derive from individual components but are dependent on the relationship between different components to create complementary and coordinated systems that facilitate the flow of knowledge and mobilization of resources (European Commission, 2020b).

Other studies have stressed how entrepreneurship ecosystems are contextually dependent and that they exist in a historical framework (Guerrero et al., 2016; Wright et al., 2017). Successful entrepreneurship ecosystems contain a history of institutional arrangements that cannot be duplicated mechanically from region to region. Thus, policies that try to impose "best practices" in leading entrepreneurship ecosystems do not generally yield similar results.

Given that AI-native entrepreneurs rely on globally dispersed, specialized resources, comparing ecosystems necessitates understanding how those resources are organized and governed across different institutional settings.

2.3. Universities, Applied Research, and Innovation Systems

Universities are central to entrepreneurship initiatives based on technology and intensive knowledge, as they provide specialized human capital, create scientific ideas and aid in the commercialization process. Essentially, they are an interface between scientific research and industry, facilitated by their technology transfer offices, incubation centers and joint research initiatives.

In developing economies, where there is frequently a limited amount of private-sector research and development capability, universities also frequently take on a broader role as innovation intermediaries (OECD, 2019). They provide education and research, as well as places to experiment and develop new businesses. This broad function supports the idea of the entrepreneurial university and its role in institutional participation in the economic and social development of the surrounding community (Perkmann et al., 2013).

From an innovation systems perspective, the successful commercialization of new ideas is contingent upon having research, business, financing and regulation entities aligned with an idea that is going to market (Arora et al., 2021). A major concern for entrepreneurs who want to develop revenue through AI technologies is finding a way to align technical experimentation with ethical governance and market validation. A growing body of empirical evidence supports the idea that AI technologies can improve the resilience and ability of an organization to adapt, affirming the critical need for coordination between multiple organizations or firms within an ecosystem in order to facilitate AI and machine learning initiatives (Lei et al., 2025).

2.4. From Ecosystem Replication to Context-Sensitive Adaptation

Traditional methods of developing ecosystems often prioritize discovering and passing on the most effective practices based on prior successes found in different locations (European Commission, 2020a). However, it has long been noted that replication-based strategies may not yield positive results when deployed in dissimilar institutional settings (Armbrust et al., 2010) and that design-based methodologies associated with creating new ecosystems should have a stronger emphasis on contextual adaptation and functional replacements for components of the ecosystem (Guerrero et al., 2015; Weiblen & Chesbrough, 2015).

Through this type of context-sensitive ecosystem analysis, components of institutional and support mechanisms can be viewed as adaptive (i.e., changeable) components instead of as set or permanent items. Accordingly, rather than asking how the leading ecosystem can be cloned, the context-sensitive approach systematically explores what basic functions (i.e., talent development, testing/experimentation, financing and accessing the market) may be accomplished within the constraints of the universe in which the ecosystem is to be constructed (Hochberg, 2016). Applied to AI-native entrepreneurship ecosystems, this approach can provide ways for early-stage ecosystems to move forward even when there is a lack of support and/or coordination.

These strands of literature suggest that AI-native entrepreneurship should not be analyzed solely through a generic startup lens. While entrepreneurial ecosystem theory explains the importance of interconnected local actors and institutions, innovation systems and university-based entrepreneurship literature help explain how research capabilities, applied experimentation, and knowledge transfer are organized. In the AI context, these ecosystem functions must also accommodate access to data, computing infrastructure, and governance arrangements for responsible experimentation. For this reason, the paper adapts rather than replaces existing ecosystem theory, specifying the dimensions that become particularly salient for AI-native ventures.

2.5. Benchmarking Dimensions for AI-Native Entrepreneurship Ecosystems

Based upon the theoretical framework discussed above, this study develops a conceptual framework for an AI-native entrepreneurship ecosystem, viewed as a multidimensional interdependent structural and institutional system. Some of these dimensions are shared with technology entrepreneurship more broadly, while others become especially critical in AI-native venture creation, particularly data access and governance, computational infrastructure, applied research linkages, and regulatory conditions for experimentation.

The AI-specific contribution therefore lies not in treating all twelve dimensions as new, but in reinterpreting established ecosystem functions around the distinct resource, validation, and governance requirements of AI-native ventures. The conceptual framework incorporates twelve analytical dimensions to facilitate the benchmarking of similar AI-native entrepreneurship ecosystems through systematic comparison and design-based adaptations to them, which are:

1. AI talent pipeline;
2. Applied research and knowledge transfer;
3. Data access and governance;
4. Computational infrastructure;
5. Universities as institutional anchors;
6. Industry-startup linkages;
7. Entrepreneurial support mechanisms;
8. Risk capital and funding pathways;
9. Regulatory and policy environment;
10. Market access and scaling pathways;
11. Ecosystem coordination and governance;
12. Entrepreneurial culture and risk orientation.

The twelve dimensions were developed by synthesizing the literature reviewed in Sections 2.1–2.4 on entrepreneurial ecosystems, innovation systems, university-based entrepreneurship, and the specific requirements of AI-native ventures. They therefore constitute an author-developed analytical framework grounded in existing theory rather than the direct adoption of a single prior model.

Table 1 provides a summary of the analytical dimensions and their operational definitions, and Figure 1 shows the associated analytical framework. The analytical weights of each dimension are equal at this stage, and thus all dimensions provide a neutral reference architecture for subsequent empirical benchmarking.

Table 1. AI-native entrepreneurship ecosystem benchmarking dimensions.

Dimension	Description	Relevance to AI-Native Entrepreneurship	Indicative Supporting Literature
AI Talent Pipeline	Availability and quality of AI-related human capital across education, research and industry	AI-native ventures depend on scarce, highly specialized talent; talent bottlenecks strongly constrain venture formation and scaling	Uriarte et al. (2026); Whittaker et al. (2018)
Applied Research and Knowledge Transfer	Strength of applied AI research, technology transfer mechanisms and industry-facing research interfaces	AI-native startups often emerge from applied research and require continuous knowledge exchange	Arora et al. (2021); Perkmann et al. (2013)
Data Access and Governance	Availability of high-quality data, data-sharing mechanisms and regulatory clarity	Data is a core production input for AI-native ventures; governance regimes directly affect feasibility and scalability	Rai et al. (2019); Uriarte et al. (2026)
Computational Infrastructure	Access to computing resources (cloud, HPC, GPUs) and supporting digital infrastructure	Computational capacity affects experimentation speed, model development and cost structures	Uriarte et al. (2026); Whittaker et al. (2018)
Universities as Institutional Anchors	Extent to which universities act as ecosystem anchors beyond education and research	Universities often substitute for missing ecosystem components in emerging contexts	OECD (2019); Perkmann et al. (2013)

Table 1. *Cont.*

Dimension	Description	Relevance to AI-Native Entrepreneurship	Indicative Supporting Literature
Industry–Startup Linkages	Depth of collaboration between AI startups, incumbents and sectoral partners	Early pilot customers and industrial use cases are critical for AI venture validation	Arora et al. (2021); Feldman and Zoller (2012)
Entrepreneurial Support Mechanisms	Availability of incubators, accelerators, mentorship and AI-specific venture support	Generic entrepreneurship support is often insufficient for AI-native ventures	Feldman and Zoller (2012); Stam and Van de Ven (2021)
Risk Capital and Funding Pathways	Access to early-stage and growth-stage financing aligned with AI venture timelines	AI-native ventures often face longer development cycles and higher upfront costs	Audretsch and Belitski (2017); Stam and Van de Ven (2021)
Regulatory and Policy Environment	Clarity, flexibility, and alignment of AI-related regulation and innovation policy	Regulatory uncertainty can either enable experimentation or suppress venture activity	Floridi et al. (2018); Uriarte et al. (2026)
Market Access and Scaling Pathways	Ability of AI-native ventures to access domestic and international markets	Small domestic markets require early internationalization strategies	Nambisan (2017); Stam and Van de Ven (2021)
Ecosystem Coordination and Governance	Degree of coordination among public, academic and private actors	Fragmented governance weakens ecosystem coherence and learning effects	European Commission (2020b); Lei et al. (2025)
Entrepreneurial Culture and Risk Orientation	Societal attitudes toward risk, failure and high-uncertainty ventures	Cultural acceptance of risk influences AI startup formation and persistence	Acs et al. (2017); Wright et al. (2017)

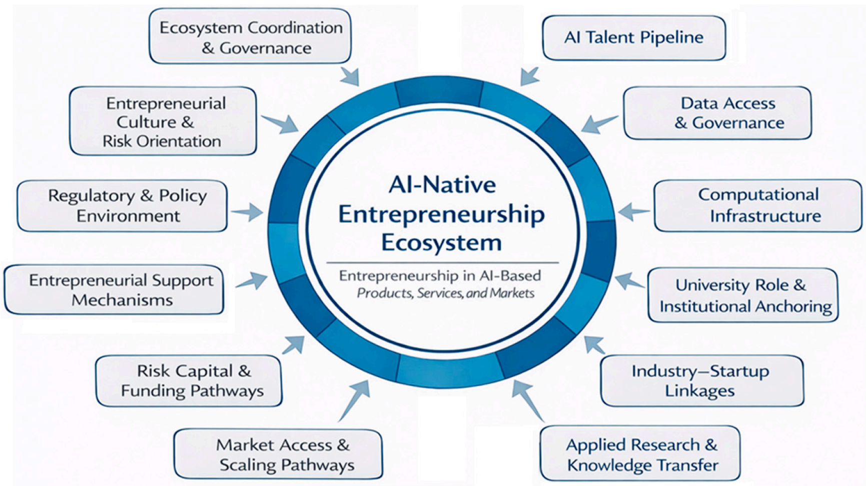

Figure 1. Conceptual framework diagram illustrating the multidimensional structure of AI-native entrepreneurship ecosystems and the analytical process linking ecosystem benchmarking, contextual parameter re-weighting and context-sensitive adaptation. The framework integrates institutional actors, resource infrastructures and governance mechanisms across twelve ecosystem dimensions.

2.6. Analytical Implications for Comparative Ecosystem Design

The benchmarking framework presented above provides the conceptual basis for comparative analysis in Sections 4 and 5 by adapting entrepreneurial ecosystem and innovation systems perspectives to the specific requirements of AI-native entrepreneurship. It enables systematic differentiation across national contexts by operationalizing both general ecosystem functions and AI-salient conditions in observable terms. This information is used to adjust the re-weighting parameters and the configuration of the context-sensitive design model proposed in Section 6.

3. Materials and Methods

3.1. Research Design

This research utilizes a comparative, document-based approach to explore the potential for benchmarking and contextualization of AI-native entrepreneurship ecosystems across different institutions. The combination of conceptualizing an ecosystem and analyzing systematic documentary data embeds the proposed design model in observable policy, organizational and infrastructure conditions. To enhance transparency and replicability, comparative document analysis is accompanied by an explicit coding protocol, indicator-level scoring rules, and appendix-based examples of how scores were assigned.

Document-based comparative methods have been used extensively in entrepreneurship and innovation research to understand the structure of ecosystems, especially when comparable datasets at the venture level are limited or non-existent (OECD, 2016; Tullis, 2025). Such methods are particularly suitable in emerging technology areas, given that institutions and governance systems shape entrepreneurial activity significantly (Schneegans et al., 2021).

Switzerland and Jordan were selected through a most-different systems comparative logic as discussed by Anckar (2008) and Meckstroth (1975). This logic is used here to examine how the same ecosystem functions are configured under substantially different institutional and resource conditions, rather than to identify a single causal factor. The two cases combine a clear contrast in ecosystem maturity with sufficient higher education and entrepreneurial capacity in both settings to allow meaningful comparison of how ecosystem functions are configured and adapted. Switzerland represents a mature, research-intensive and highly ranked innovation ecosystem with strong university–industry linkages, advanced research infrastructure and developed funding pathways. Jordan, by contrast, represents an emerging, resource-constrained ecosystem with a comparatively strong higher education base but weaker industrial R&D capacity, limited venture financing and fragmented ecosystem coordination. Other advanced and emerging economies could also provide useful comparisons; however, Switzerland and Jordan were selected because they offer both a pronounced contrast in ecosystem maturity and sufficient common ground in higher education and entrepreneurial capacity for applying the same twelve dimensions. Descriptive statistics for the two countries are presented in Table 2. The comparison is therefore not intended to claim broad statistical generalizability, but to generate analytical insight into how AI-native entrepreneurship ecosystem functions may be configured differently under contrasting institutional and resource conditions. In this study, benchmarking refers to a structured comparison across common dimensions rather than a comprehensive multi-country ranking exercise.

This pairing was selected based on the contrasting structural characteristics summarized in Table 2, rather than on the results produced by the benchmarking framework. The cases expose the design problem at the center of this study: how AI-native entrepreneurship ecosystem functions can be adapted when a resource-constrained country possesses some enabling conditions, such as higher education capacity and entrepreneurial potential, but lacks several complementary ecosystem components. The comparison allows the study to examine which ecosystem functions are context-specific, which may be functionally substituted, and which require long-term institutional development. The two-country design is therefore intended to support in-depth framework development rather than representative country selection, and further research should apply the framework to additional advanced and emerging economies.

Table 2. Descriptive statistics for Jordan and Switzerland.

Key Economic Criteria	Switzerland	Jordan	Description
Population, 2024	9.0 M	11.7 M	Market and workforce size
Area (km^2)	41,285	89,213	Geographic clustering
GDP per capita, 2023	~$90,000	~$4500	Investment and purchasing power
Higher Education Institutions	38	30+	Institutional capacity
University Students	276,000	~480,000	Talent pipeline
R&D Expenditure (% GDP)	3.3%	0.4%	Innovation intensity
National AI Strategy	No centralized AI strategy; adaptive governance approach	Emerging draft	Policy focus
Venture Capital as % GDP	High (~0.5%+)	Low (<0.1%)	Funding availability
Global Innovation Index, 2024	#1	~80+	Ecosystem maturity
Government AI Readiness, 2024	High	Medium	AI ecosystem readiness
Tech Startup Density	High	Medium	Entrepreneurial vibrancy
English Proficiency for Tech	Very High	High	Talent pipeline signal

3.2. Data Sources

Open-source data were gathered from multiple sources in order to create a reliable and cross-validated set of information. The five main categories were (full references are given in Appendix B):

1. National policy and strategy documents detailing Artificial Intelligence, Digital Transformation, and Innovation;
2. Statistical reports issued by swissuniversities, the Swiss Federal Statistical Office and the Jordanian Ministry of Higher Education looking at the higher education system;
3. Documentation on Innovation and Entrepreneurship programs from national agencies, tech transfer offices and incubators;
4. International benchmarking reports produced by organizations such as WIPO, OECD and Oxford Insights; and
5. Industry and venture finance reports published by international development institutions and industry research companies.

Documents were selected if they met three criteria: first, they were publicly accessible and verifiable at the time of analysis; second, they were published by official public bodies, universities, innovation agencies, international organizations, recognized benchmarking institutions or credible industry sources; and third, they contained direct evidence relevant to at least one of the twelve AI-native entrepreneurship ecosystem dimensions. Documents were excluded if they were promotional in nature, inaccessible, unverifiable, outdated without contextual relevance, or not directly related to AI, digital entrepreneurship, innovation systems, higher education, infrastructure, finance or ecosystem governance.

The document search was conducted between January and March 2026. Searches were performed through official institutional websites, national statistical portals, international benchmarking databases, university and innovation agency websites, and targeted keyword searches combining country names (Switzerland and Jordan) with terms such as artificial intelligence, digital transformation, innovation strategy, entrepreneurship, venture capital, research and development, higher education, data governance, computational infrastructure, incubators, accelerators and AI startups. The search aimed to identify the most recent publicly available and verifiable sources for each ecosystem dimension, while older sources were retained where they provided authoritative baseline or longitudinal evidence. The search produced a broader pool of potentially relevant sources, although an exact initial count was not recorded. After applying the inclusion and exclusion criteria, 37 documents were retained. Based on their primary category, these comprised nine policy and strategy documents, eight statistical and higher education reports, eight innovation and entrepreneurship program documents, six international benchmarking reports, and six industry and venture finance reports.

3.3. Analytical Framework

Drawing on the empirical examination of AI-native entrepreneurship presented above, an analytical framework was constructed in which ecosystems are defined by multiple dimensions, with institutions, governance systems and resource infrastructures interacting to support entrepreneurial endeavors.

Similar to innovation systems research and ecosystem research, the framework focuses on functional interdependencies rather than isolated elements. Accordingly, twelve different dimensional functional classifications were created: AI talent pipeline, applied research and knowledge transfer, data access and governance, computational infrastructure, universities as institutional anchors, industry-startup linkages, entrepreneurial support mechanisms, risk capital and funding pathways, regulatory and policy environment, market access and scaling pathways, ecosystem coordination and governance and entrepreneurial culture and risk orientation.

3.4. Coding Scheme and Scoring Procedure

To capture the way each individual ecosystem dimension functions in conjunction with the other dimensions, three complementary indicators were defined. These correspond to institutional, resource-based and outcome-oriented dimensions, which together form the analytical framework.

Thus, each ecosystem dimension is assessed using three indicators. An indicator may reflect:

- Institutional structure, referring to the presence of formal policies, organizational structures and the supporting mechanisms necessary to implement them;
- Operational resources, referring to both the availability of resources and the capacity to deploy them effectively; or
- Outcomes, referring to observable performance results, events, or metrics emerging from the relevant marketplace.

This structure enables individual ecosystems to be assessed by classifying each indicator according to which of these three dimensions it represents.

The structure of indicators was designed to ensure analytical validity whilst mitigating against reliance upon single-source assessment. The indicators within each of the twelve ecosystem dimensions are further described in Appendix A, which also provides scoring anchors to illustrate how documentary evidence was translated into 0–1–2 scores.

Each indicator was coded using a three-point ordinal scale. A score of 0 indicates that the indicator was absent, undocumented, or supported only by weak and inconclusive evidence. A score of 1 indicates that the indicator was partially present, emerging, fragmented, or documented without clear evidence of operational maturity. A score of 2 indicates that the indicator was clearly present, operationally established, and supported by authoritative or multiple convergent sources. Scores were assigned at the indicator level before being averaged into dimension-level scores, thereby reducing the risk of broad impressionistic judgments at the ecosystem level. The three-point scale was selected because it distinguishes clearly between absent or limited, emerging or partial, and established or operational conditions. A finer scale would imply a level of precision that could not be applied consistently across the documentary sources. As an illustrative example, official higher education evidence identified AI-related degree programs in Jordan, but provision remained concentrated in a limited number of institutions (Jordanian Ministry of Higher Education and Scientific Research, 2026). This evidence was assigned to the "availability of AI-related degree programs" indicator within the AI Talent Pipeline dimension. Because provision was present but not widespread nationally, it matched the score-1 anchor for partial or limited provision, resulting in an indicator score of 1.

Each indicator was coded separately for Switzerland and Jordan using the same criteria and triangulated documentary evidence, where multiple sources were available. Indicator data were validated primarily through convergence across documents. Where initial coding interpretations differed, the authors reviewed the underlying documents jointly and reached a final score through discussion based on the predefined indicator criteria.

Scores were assigned using a rule-based interpretation of documentary evidence. A score of 0 was used where evidence was absent or showed very limited development; a score of 1 where evidence indicated partial, emerging, or fragmented provision; and a score of 2 where evidence showed established, functioning, and clearly documented provision. Coding decisions were made by matching documentary evidence against these criteria at indicator level rather than through overall subjective judgment. Where multiple sources were available, coding relied on triangulation across sources, with greater weight given to official statistical publications, government documents, and institutional reports that provided direct evidence relevant to the indicator.

Ecosystem dimension scores were derived using the arithmetic mean value of the individual ecosystem indicators. As a next step, the aggregate scores of all twelve dimensions were combined to produce the aggregated country-level ecosystem profile (Mazzucato, 2018). This approach was adopted because all indicators were treated as analytically important at this stage and the aim was to produce a transparent, comparable, and non-hierarchical summary measure for each ecosystem dimension rather than to impose ex ante weighting assumptions. The 0–1–2 scale is ordinal; therefore, the intervals between categories are not assumed to be equal. Values such as 1.33 and 1.67 are analytical summary measures derived from the three indicator ratings and should not be interpreted as statistical estimates or as implying statistical precision. The scale is not intended to quantify the full complexity of a national ecosystem, but to provide a consistent classification across the 36 indicators, interpreted alongside the documentary evidence and qualitative case analysis.

As an ordinal robustness check, the median of the three indicator scores was also calculated for each ecosystem dimension. The institutional structure, operational resources and outcome scores were ordered from lowest to highest, and the middle value was retained as the dimension median. Unlike the arithmetic mean, this procedure does not assume equal intervals between the categories 0, 1 and 2.

Where evidence for an indicator was missing, unavailable, weak, or contradictory, the indicator was not automatically treated as absent. Instead, the authors reviewed whether the lack of evidence reflected a genuine ecosystem gap, a documentation limitation, or inconsistency across sources. When evidence was unavailable but related sources suggested partial activity, a conservative score of 1 was assigned only if there was credible documentary support. When no reliable evidence of operational presence could be identified across the selected source categories, a score of 0 was assigned. When sources contradicted one another, greater weight was given to official statistical publications, government documents, institutional reports, and recent international benchmarking sources. All indicator scores, including conservatively assigned scores, were retained in the arithmetic mean used to calculate dimension-level scores, rather than being excluded from aggregation.

3.5. Reliability and Validity Considerations

A number of strategies were used to improve the accuracy and consistency of document analysis, in particular:

- Triangulation using national datasets, governmental policy documents, international reports and institutional publications;
- Transparent coding processes in case analyses;
- Collaborative approach to coding choices, in which the authors worked together to verify the coding choices to improve the consistency of the interpretations of what was being coded;
- Comparison of the scores from the aggregation of the dimensions with international benchmarks, such as innovation indicators and digital readiness indicators, to assess the integrity of the results.

Formal inter-coder reliability testing, such as Cohen's kappa or Krippendorff's alpha, was not conducted because the coding was developed through a collaborative consensus process rather than independent parallel coding. A retrospective reliability coefficient would therefore not provide a valid independent measure of agreement. We acknowledge that this remains a limitation of the study and that the consensus process may retain shared interpretive bias. To reduce this risk, coding decisions were based on predefined indicator criteria, the scoring anchors presented in Appendix A, triangulation across multiple source types, indicator-level rather than ecosystem-level scoring, and joint review of ambiguous cases against the original documentary evidence. Future applications of the framework should use independent parallel coding and report formal inter-coder reliability statistics.

3.6. Data Analysis and Synthesis

The data collected was examined in three phases. The first phase involved collecting baseline data about socio-economic and innovation indicators to develop a contextual understanding of the data being analyzed (see Table 2).

In the second phase, profiles of each country were created, and ecosystem dimensions were scored using the above coding scheme.

In the third phase, patterns of comparison were interpreted through the lens of the re-weighted contextual parameters.

The aim of this analysis was not to test for causal relationships between factors; rather, it was to identify the structural divergences, compensation mechanisms and sequencing requirements that could subsequently be used to develop a model for ecosystem design.

3.7. Methodological Limitations

There are limitations associated with a document-based methodology. First, the documents that are officially available may represent formal strategies but do not necessarily reflect how those strategies were actually implemented by an organization. Second, there can be substantial variation in the quality of reporting performed by institutions and countries when it comes to their practices and the level of detail in their documentation. Informal networks and tacit coordination—which can be highly effective in practice—are difficult to identify through documentary sources alone. The documentary analysis therefore assesses the formal and publicly observable architecture of the ecosystem; it does not measure how consistently these arrangements are implemented, accessed or experienced by individual entrepreneurs and organizations. In an attempt to mitigate the effect of these limitations, several data sources were triangulated, and a conservative scoring methodology was used. The approach gives significant insight into the broad structural conditions of the ecosystems and lays the ground for further empirical studies, for example, incorporating longitudinal data about startups or interviewing experts. Such studies could also incorporate direct input from entrepreneurs, investors, policymakers, and other ecosystem actors to examine how the documented structures operate in practice. Accordingly, the proposed model should be interpreted as a document-informed design heuristic that identifies plausible structural options, rather than as a validated representation of how ecosystem actors coordinate in practice.

The model has been developed from two contrasting country cases and has not yet been tested in other national contexts. Future research should apply the framework to additional advanced and emerging economies to assess its wider applicability.

4. Benchmarking the Swiss AI-Native Entrepreneurship Ecosystem

4.1. Contextual Overview

Switzerland serves as a valid reference to evaluate how mature entrepreneurial ecosystems support the development of AI-based businesses because it is characterized by strong innovation levels, multinational R&D investment and good institutional collaboration. Indicators of socio-economic and innovation systems in Switzerland in comparison to Jordan are shown in Table 2, with major differences identified concerning market size, income level, ability to produce university-level graduates and research intensity. Switzerland has consistently been one of the top nations in terms of its ability to generate new innovations and develop digital economies through the use of public- and private-sector investments in R&D, high-quality higher education institutions and developed financial systems (Dutta et al., 2024; OECD, 2023; Oxford Insights, 2024).

Switzerland, with a population of approximately 9 million, has a high GDP per capita (Table 2) and a small domestic market, although it is internationally well integrated (World Bank, 2024). This underpins the structural conditions which encourage technology-oriented enterprises to pursue early international markets, and emphasizes the need for worldwide export markets to be included in entrepreneurial strategies. The higher education system consists of a concentrated number of research-oriented universities, universities of applied sciences and independent research institutes that educate over 270,000 students each year (Table 2) (Swissuniversities, 2026).

In addition, national strategies directed at promoting innovation and digitalization lend additional support to Switzerland's competitiveness as a coordinated and research-oriented ecosystem. Public agencies, universities and private enterprises work together in a structured fashion through the use of collaborative funding mechanisms, shared research facilities and applied innovation platforms (OECD, 2021). Importantly, it invests over CHF 25 billion in R&D annually, which makes it one of the largest R&D investors in the world. Two-thirds of all R&D is funded by the private sector. (https://www.aboutswitzerland.eda.admin.ch/en/research-and-development, accessed on 25 May 2026).

4.2. Dimension-Level Analysis

4.2.1. AI Talent Pipeline

Switzerland's advanced skill level is attributed to a robust talent development system with a strong foundation in Science, Technology, Engineering and Mathematics (STEM) education and the free movement of professionals and researchers from outside Switzerland (OECD, 2019). Higher-level education (universities and applied scientific schools) focuses on data science, machine learning and computational engineering, and businesses are able to maintain constantly updated skill sets via partnerships with education institutions.

English language skills and global collaboration in research projects are an additional competitive advantage in the AI field.

Switzerland's commitment to AI is clearly stated by the State Secretariat for Education, Research and Innovation (SERI): "Switzerland must use the potential of AI as effectively as possible. Education, research and innovation play a central role". SERI also provides a list of support mechanisms to enable opportunities, whilst not being blind to the challenges (State Secretariat for Education, Research and Innovation [SERI], 2025).

All of these factors provide evidence of the considerable advantages that Swiss talent enjoys when compared to other countries, as can be seen in the relatively high ratings of all of the variables used to track talent across the globe (see Table 3).

Table 3. Swiss AI-native entrepreneurship ecosystem: dimension scores.

Dimension	Institutional Structure	Operational Resources	Outcomes	Mean Score
AI Talent Pipeline	2	2	2	2.00
Applied Research and Knowledge Transfer	2	2	2	2.00
Data Access and Governance	2	2	1	1.67
Computational Infrastructure	2	2	2	2.00
Universities as Institutional Anchors	2	2	2	2.00
Industry–Startup Linkages	2	2	1	1.67
Entrepreneurial Support Mechanisms	2	2	2	2.00
Risk Capital and Funding Pathways	2	2	2	2.00
Regulatory and Policy Environment	2	1	2	1.67
Market Access and Scaling Pathways	2	2	2	2.00
Ecosystem Coordination and Governance	2	2	1	1.67
Entrepreneurial Culture and Risk Orientation	2	2	2	2.00

4.2.2. Applied Research and Knowledge Transfer

Applied research serves as a key foundation of the entrepreneurship ecosystem for AI in Switzerland. National researchers, along with university researchers, industry-sponsored research centers/universities and industry labs also conduct applied research with the goal of solving practical problems that can result in a commercially viable product, for example, through the Swiss National Science Foundation (www.snf.ch). Many parties also collaborate with one another on these projects through the use of technology transfer offices, research consortia and public–private partnerships to enable researchers to better use results from research applications to create marketable products/services, for example, through the Swiss Technology Transfer Association (www.switt.ch). In addition, existing mechanisms for industry-sponsored research and for creating spin-off companies have existed for a long time and are now extending their reach to support the ongoing creation of ventures involved in AI technologies. Good examples are Innosuisse, which offers financial and non-financial support for science innovation projects (www.innosuisse.admin.ch) and the Swiss Innovation Agency's Venturelab, which already supports 90% of Swiss startups and has expanded its offering to include Microsoft's AI Tech Accelerator (www.venturelab.swiss; https://news.microsoft.com/de-ch/microsoft-for-startups-ai-tech-accelerator/, accessed on 25 May 2026).

4.2.3. Data Access and Governance

In Switzerland, there are strong data governance frameworks that provide a balance between the goals of innovation and privacy and security (European Commission, 2020a). A number of national open data platforms exist that share data by sector (in particular health, mobility and finance) and that can be used for controlled experimentation under strict regulatory guidance. Even though the regulatory stringency may slow down the aggregation of large datasets, the overall governance environment provides enough legal clarity for responsible AI entrepreneurs to operate.

4.2.4. Computational Infrastructure

There are significant advantages to the Swiss ecosystem because of the availability of cloud computing resources, research-oriented digital platforms and high-performance computing (HPC) facilities, including the Swiss HPC Service Provider Community (www.hpc-ch.org). National supercomputing centers operated by public research institutes provide entrepreneurs access to substantial supercomputing facilities, as do commercial cloud providers that offer scalable resources to startup companies and research teams. In addition, access to computational resources for early-stage businesses is also subsidized by targeted funding programs, further reducing barriers to entry for new companies in computationally intensive fields (Martens, 2024).

4.2.5. Universities as Institutional Anchors

The Swiss system relies heavily on higher education institutions to serve as key players in coordinating the various aspects of an innovation environment. Higher education institutions provide education and research, but they are also home to incubators, accelerators and innovation hubs that support entrepreneurs in developing their businesses, such as, for example, the FHNW's ImpactLab (https://impactlab.fhnw.ch/). The formal collaboration of the university community with various local authorities and industry actors supports the sharing of resources and strategic collaborative efforts.

The role of these institutions as "anchors" provides stability to the ecosystem and reduces failures associated with lack of coordination.

4.2.6. Industry–Startup Linkages

Swiss AI startups are able to leverage extensive networking opportunities with established companies in manufacturing, finance, healthcare and logistics, often through programs initiated and supported directly by industry, such as Roche's involvement with Basel's biotech incubator BaseLaunch (BaseLaunch Press Release, 2020). These companies offer pilot project opportunities, joint development agreements and corporate venture funding, thus providing early validation of market demand in domain-specific applications.

Other forms of support for Swiss AI startups include public procurement and partnerships through innovation, which enable experimentation in heavily regulated industries. Publicly funded foundations also have many programs to help accelerate the adoption of AI by Swiss SMEs in addition to fostering diffusion of knowledge. National support bodies include Innosuisse (www.innosuisse.ch) and Venturelab (www.venturelab.swiss), among others.

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4.2.7. Entrepreneurial Support and Venture Capital

As noted above, there are various types of support mechanisms available to entrepreneurs in Switzerland, such as AI-specific accelerators, mentorship networks and technical validation programs. Additionally, there is also a well-established venture capital market that has a large amount of involvement by institutional and corporate investors.

Swiss government data show that venture capital investment in SMEs comprises around 0.26% of GDP—a staggering CHF2.2 bn ($2.83 bn) (Federal Statistical Office, 2025; SME Portal, 2024).

4.2.8. Regulatory and Policy Environment

Switzerland decided against creating new legislation dedicated to AI, in contrast with its European neighbors and the European Union AI Act (European Commission, 2025; European Data Protection Supervisor, 2025). Instead, Swiss authorities have chosen to build on existing legal and sectoral regulations, whilst requiring companies working with or exporting to the EU to respect the EU AI Act. Nonetheless, AI remains a priority of the Federal Council, which is tasked with considering calls for further clarification of the regulatory situation surrounding AI as part of their 2023–2027 legislative plan (OFCOM Report, 2025). This type of regulatory mechanism reflects Switzerland's larger institutional model for innovation-driven governance versus prescriptive governance through legislation (European Commission, 2025). This balanced approach reduces uncertainty around regulation while at the same time creating and preserving public trust.

4.2.9. Market Access and Scaling Pathways

As noted above, Swiss AI startups tend to have an internationalization strategy from the outset because of the small size of the domestic market. Export activities are supported by export promotion organizations, cross-border research projects and support from interested multinational corporations. Switzerland's largest trading partner is the US, followed by Germany and Slovenia. Its neutral status in the current world political and economic situation gives its exporters the freedom to trade with most countries (SECO, 2025).

A strong global perspective and language skills, combined with welcoming intellectual property legislation and international collaboration in R&D, also help facilitate growth opportunities outside of Switzerland.

4.2.10. Ecosystem Coordination and Entrepreneurial Culture

Although culturally risk-averse with a preference for caution, the benefits of entrepreneur culture are recognized and supported. Switzerland's entrepreneurship ecosystem provides significant input for startups based on cooperation between agencies, research centers and private companies, including support for business planning and strategy.

4.3. Ecosystem Profile Summary

This synthesis of the document-based analysis scores the different dimensional aspects using the coding procedures outlined in Section 3 above (Table 3 summarizes both individual and aggregated dimension scores for Switzerland).

As seen from both Table 3 (scores) and Figure 2 (visualization), Switzerland has a well-balanced profile across Talent Formation, Applied Research and Infrastructure/Digital Infrastructure, with consistently high scores in each. There are minor differences with regard to Data Governance, Regulatory Coordination, and Industry Linkage that reflect selective institutional conservatism rather than systematic structural weakness.

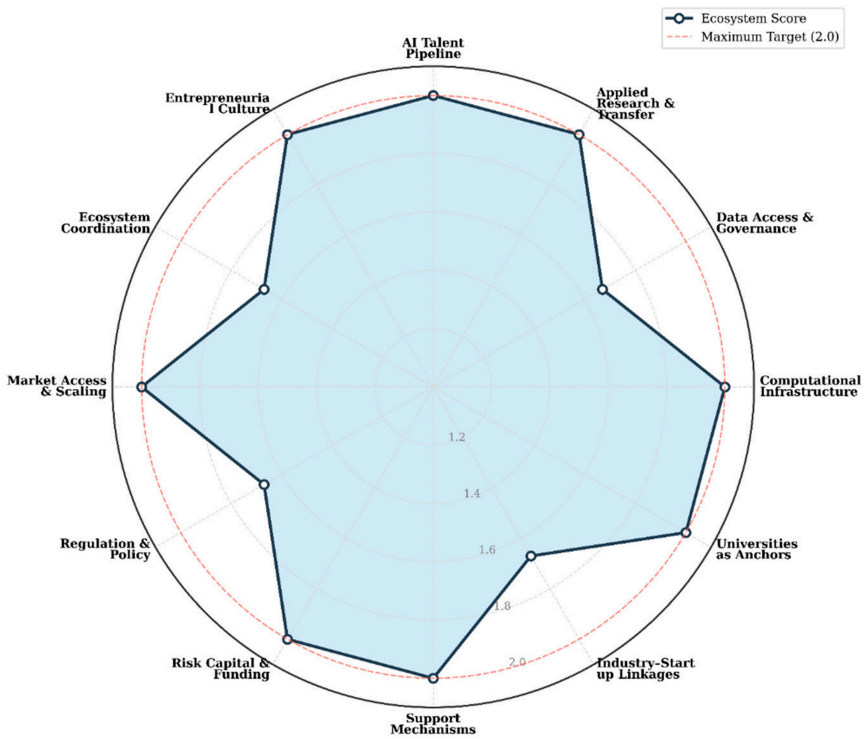

Figure 2. Radar chart of Switzerland's twelve AI-native entrepreneurship ecosystem dimension scores.

5. The Jordanian Context and Comparative Ecosystem Results

5.1. Contextual Overview

Jordan is developing an AI-style entrepreneurship ecosystem, with a high-skilled workforce and a growing level of digital infrastructure. Nevertheless, the country lacks industrial R&D capabilities, has a fragmented governance framework and has limited access to venture funding resources. The socio-economic (including Innovation) baseline characteristics for the Kingdom of Jordan are provided in Table 2. It is characterized by relatively low research spending, a moderately sized market, and a low level of GDP/capita. Jordan's national research expenditures are lower than those of other high-income economies (Schneegans et al., 2021; World Bank, 2024). With a population of over 11 million and a highly fragmented and dispersed economy, it has a difficult time generating concentrated innovation and obtaining economies of scale (Jordanian Department of Statistics [DOS], 2024). Nonetheless, the government has invested heavily in higher education, with approximately 480,000 students enrolled in public and private universities in Jordan (Jordanian Ministry of Higher Education and Scientific Research, 2026), and the significant number of Jordanian graduates is expected to be an important advantage in developing knowledge-based entrepreneurial companies including digital and AI-based businesses.

Jordan has introduced new national regulations to increase entrepreneurship through national digital transformation and innovation policies that encourage developing skills and using technology. These new policies reflect part of the many reforms taking place in Jordan to help SMEs and promote entrepreneurship (OECD, 2018). Nevertheless, the systemic impact of these initiatives is limited due to poor capacity for implementation across sectors and geographic regions.

5.2. Dimension-Level Constraints and Opportunities

5.2.1. AI Talent Pipeline

There is a considerable amount of support for the creation of a good talent pipeline in Jordan, based on a significant uptake of higher education amongst the population and its status as a State priority (Jordanian Ministry of Higher Education and Scientific Research, 2026). Education is deeply rooted in culture and society, and it is underpinned, for example, by Royal initiatives such as the Madrasati Initiative (https://www.madrasati.jo/), which aims to bring together public, private and civil society sectors to promote quality education from a very early age. It encourages science and engineering through initiatives such as the Jordan Young Scientist initiative (www.jordanys.com).

Many young people enter STEM careers, and their fluency in communication in English enables them to readily interact with colleagues, business contacts and research partners globally. It also facilitates the exodus of highly qualified graduates to foreign employers abroad, which is less desirable for the country.

5.2.2. Applied Research and Knowledge Transfer

Many universities have set up innovation and entrepreneurship (I/E) centers to encourage and support entrepreneurship. Strong links to industry are still under development, and in December 2025 the Higher Council for Science and Technology (HCST) announced fifteen priority sectors for academia-industry collaboration underpinned by the Scientific Research and Innovation Fund (Jordan Times, 2025). AI-native entrepreneurship and commercialization of AI output are not well established.

5.2.3. Data Access and Governance

There are two key structural constraints that impede AI entrepreneurs in Jordan: data availability and governance. Data-sharing frameworks used by the public sector have been limited thus far; legal uncertainty combined with institutional fragmentation also severely limits data access to those working in the private sector (UNDP, 2025). Recent government initiatives to develop and implement digital governance and open data policies, however, are promising. It is developing a significant digital presence, for example, with the SANAD digital ID application, which has 1.8 m users, and digitizing over 80% of government services (Al Naimi, 2025). This openness to digital technologies puts Jordan in a good position to encourage and benefit from home-grown AI-native entrepreneurship.

5.2.4. Computational Infrastructure

Jordanian AI-native ventures face a major challenge due to limited access to advanced computer infrastructure. According to ITU (2020), there are few high-performance computing (HPC) facilities and limited access to subsidized cloud services. Moreover, commercial cloud services generally create high costs for initial-stage companies, who therefore have less opportunity to conduct experiments and are more dependent on outside suppliers of infrastructure.

5.2.5. Universities as Institutional Anchors

Universities are well-positioned to anchor the entrepreneurial ecosystem in Jordan. As noted above, there are many public universities with incubators, innovation hubs and entrepreneurship programs to make up for the weak support structures provided by the private sector. Dedicated hubs also exist, such as the Innovation Resource Centre of Jordan (https://irc-jordan.com/).

The role of the universities as institutional anchors partially supplements the ecosystems' infrastructure gaps but may place a large burden on the academic institutions for coordination efforts.

5.2.6. Industry–Startup Linkages

In Jordan, the connections between industries and startups are not strong, especially in AI-heavy industries. Very few companies carry out corporate R&D, making it difficult to find opportunities to run pilot programs or conduct early market testing. Nonetheless, many of the AI-native ventures in Jordan have found opportunities to build relationships with foreign companies or provide services under contract. Although there is a way to go to commercialization "at home", it is at least a starting point for the entrepreneurs and their products.

5.2.7. Entrepreneurial Support and Risk Capital

Jordan has an entrepreneurial support ecosystem consisting of incubators, accelerators, and donor-funded programs that provide mentorship and assistance to startups (e.g., the IRC https://irc-jordan.com/). However, many programs focus on "general" entrepreneurship rather than validating AI entities in a specific domain. Private equity sources are reluctant to invest, and sources of seed capital in particular are lacking (Ahmad et al., 2018). While some public co-funding schemes exist to help offset the gap in funding available for startups, they are not sufficient or scalable enough to fill the gap being left by banks and venture capitalists. Access to finance remains one of the main considerations for Jordanian entrepreneurs (Alshwawra et al., 2025).

5.2.8. Regulatory and Policy Environment

The government of Jordan has introduced major digital changes recently and is keen to encourage digital innovation and entrepreneurship. ICT strategies, legislation regulating startups and initiatives for digitizing the public sector demonstrate the government's commitment. Several gaps still need to be addressed, however, including the absence of an enforcement system and poor coordination, which leads to a fragmentation of policy and regulatory efforts.

Additionally, regulatory sandboxes and experimental governance mechanisms are lacking, resulting in limited opportunities for innovation within this rapidly expanding data-heavy landscape.

5.2.9. Market Access and Scaling Pathways

Because of the small size of Jordan's home market, many AI-native ventures in Jordan target international markets when they get started. Diaspora networks, outsourcing contracts and regional partnerships are all important ways to help these companies grow quickly. However, poor demand for advanced digital solutions domestically limits the potential for continued learning about the local market.

5.2.10. Ecosystem Coordination and Entrepreneurial Culture

Ecosystem coordination within Jordan is disjointed: various government ministries, educational institutions, private entities and international aid agencies all have roles, but often overlapping programs and short-term funding cycles mean there is little opportunity for institutional continuity.

Nonetheless, there is a high degree of entrepreneurial opportunity orientation and social acceptance for creating new businesses amongst youth cohorts. Alshwawra et al. (2025) report that early-stage entrepreneurial activity increased in Jordan by 34% between

2023 and 2024. This dynamism within the culture represents a critical enabling factor for the overall development of the ecosystem.

5.3. Ecosystem Profile Summary

Table 4 and Figure 3 summarize Jordan's dimension scores. Universities as institutional anchors received the highest score (1.67), while risk capital and funding received the lowest score (0.33). Talent, support mechanisms, market access and entrepreneurial culture each scored 1.33, whereas data governance, computational infrastructure, industry–startup linkages and ecosystem coordination each scored 0.67. These findings are compared with the Swiss profile in Section 5.4.

Table 4. Jordan AI-native entrepreneurship ecosystem: dimension scores.

Dimension	Institutional Structure	Operational Resources	Outcomes	Mean Score
AI Talent Pipeline	1	1	2	1.33
Applied Research and Knowledge Transfer	1	1	1	1.00
Data Access and Governance	1	1	0	0.67
Computational Infrastructure	0	1	1	0.67
Universities as Institutional Anchors	2	2	1	1.67
Industry–Startup Linkages	1	1	0	0.67
Entrepreneurial Support Mechanisms	1	2	1	1.33
Risk Capital and Funding Pathways	0	1	0	0.33
Regulatory and Policy Environment	1	1	1	1.00
Market Access and Scaling Pathways	1	2	1	1.33
Ecosystem Coordination and Governance	1	1	0	0.67
Entrepreneurial Culture and Risk Orientation	1	2	1	1.33

Figure 3. Radar chart of Jordan's twelve AI-native entrepreneurship ecosystem dimension scores.

5.4. Comparative Ecosystem Results

Table 5 and Figure 4 show that the largest differences between the two cases concern risk capital and funding, computational infrastructure, applied research, data governance, industry–startup linkages and ecosystem coordination. The smallest difference concerns universities as institutional anchors, indicating that higher education represents Jordan's strongest relative institutional foundation. These differences provide the empirical basis for the re-weighting logic presented in Table 6.

Table 5. Comparative ecosystem scores: Switzerland and Jordan.

Dimension	Switzerland	Jordan	Difference
AI Talent Pipeline	2.00	1.33	+0.67
Applied Research and Knowledge Transfer	2.00	1.00	+1.00
Data Access and Governance	1.67	0.67	+1.00
Computational Infrastructure	2.00	0.67	+1.33
Universities as Institutional Anchors	2.00	1.67	+0.33
Industry–Startup Linkages	1.67	0.67	+1.00
Entrepreneurial Support Mechanisms	2.00	1.33	+0.67
Risk Capital and Funding Pathways	2.00	0.33	+1.67
Regulatory and Policy Environment	1.67	1.00	+0.67
Market Access and Scaling Pathways	2.00	1.33	+0.67
Ecosystem Coordination and Governance	1.67	0.67	+1.00
Entrepreneurial Culture and Risk Orientation	2.00	1.33	+0.67

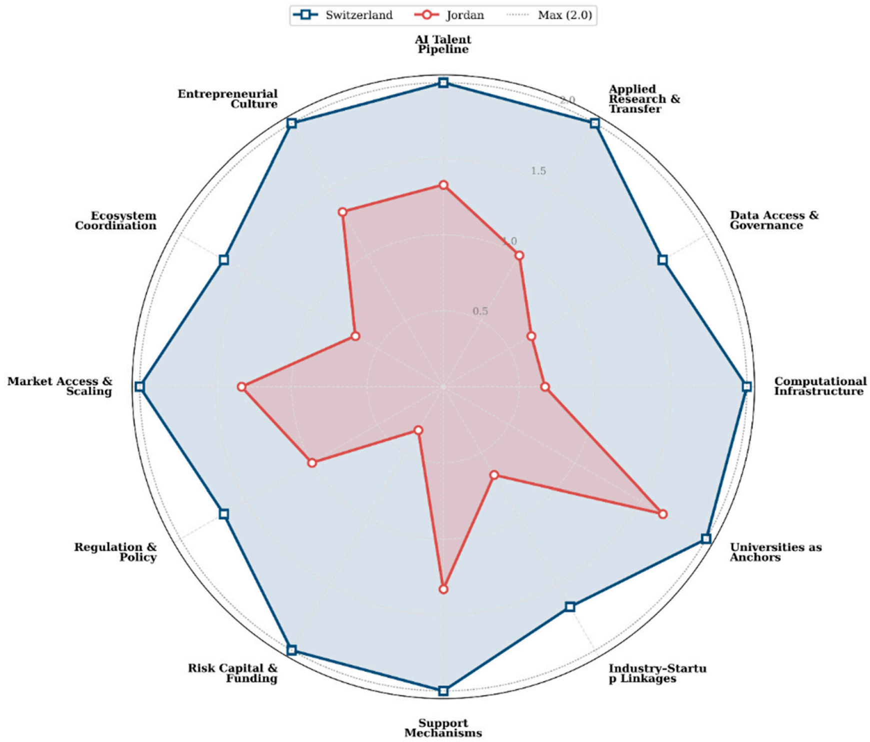

Figure 4. Radar chart comparing the twelve AI-native entrepreneurship ecosystem dimension scores of Switzerland and Jordan.

As an ordinal robustness check, the median of the three indicator scores was calculated for each dimension. Switzerland retained a median score of 2 across all twelve dimensions. Jordan retained a median score of 2 for universities as institutional anchors, 0 for risk capital and funding pathways, and 1 for the remaining ten dimensions. This reproduces the principal pattern obtained from the mean scores: a broadly established Swiss ecosystem profile, a strong university anchor in Jordan and a particularly weak financing function. The main interpretation therefore does not depend solely on arithmetic averaging of the ordinal categories.

Table 6. Illustrative parameter re-weighting logic for Jordan.

Weak Dimension	Comparative Finding	Compensating Mechanism	Lead Actor(s)	Time Horizon
Computational infrastructure	Jordan scores substantially below Switzerland	Shared national or university-linked compute access; public support for cloud/HPC access	Public agencies, universities, applied research centers	Short to medium term
Risk capital and funding pathways	Weakest relative score in Jordan	Public co-funding, blended finance, and international investor partnerships	Government, development finance actors, private investors	Medium term
Industry–startup linkages	Limited pilot and partnership structures	Universities and applied labs act as intermediaries for pilots and validation	Universities, corporates, sector agencies	Short to medium term
Data access and governance	Fragmented data access and limited sharing frameworks	Public-sector data governance reform and controlled data-sharing mechanisms	Government, regulators, public institutions	Medium to long term
Ecosystem coordination and governance	Weak alignment across actors	National coordination platform or cross-sector council	Government, universities, ecosystem intermediaries	Short term

6. Discussion: A Context-Sensitive AI-Native Entrepreneurship Design Model for Jordan

6.1. Design Logic and Conceptual Foundations

This section builds on the comparative benchmarking results found in Sections 4 and 5 and proposes a design model that takes into consideration local context to strengthen AI-native entrepreneurship within Jordan. Instead of focusing on replicating mature ecosystems, this model focuses on reconfiguring the way in which ecosystem functions are performed to make them consistent with local circumstances, capabilities and developmental priorities. Developing ecosystems should emphasize the functional adequacy of the ecosystem—as opposed to structural imitation—where entrepreneurial functions are able to be performed by entrepreneurs despite the absence of conventional institutional forms. This creates a dynamic that will allow for the successful achievement of the objective, namely creating entrepreneurial opportunities.

These differences in the ecosystem profile inform the re-weighting of system parameters in Jordan rather than the replication of Swiss arrangements. In particular, dimensions that are presently weak are linked to compensatory functions delivered by actors already showing relative strength or institutional capacity. This means, for example, that universities and applied research entities are assigned a stronger interim role in talent development, experimentation, and industry mediation, while public entities assume greater responsibility for data governance, infrastructure access, coordination, and international partnership formation. The purpose of this re-weighting is not to treat these substitutions as permanent equivalents, but to identify feasible pathways through which missing ecosystem functions can be progressively built.

Before these priorities are used for policy or implementation, the document-based ecosystem profile should be reviewed by a multi-stakeholder group including entrepreneurs, investors, universities, industry partners and relevant public agencies. This review should confirm or challenge the documentary scores, identify informal practices that are not visible in published sources, and adjust the proposed priorities, institutional responsibilities and sequencing. Stakeholder validation was not conducted in the present study and is therefore specified as a required application stage rather than claimed as completed empirical validation.

This re-weighting provides the empirical basis for the context-sensitive ecosystem design model developed below.

For example, Jordan's low score in computational infrastructure does not necessarily imply that every startup or university should independently build advanced computing capacity. A context-sensitive design response would re-weight this function toward shared access mechanisms, such as university-linked cloud credits, national GPU/HPC access schemes, or public–private agreements with cloud providers. In this configuration, universities and public agencies temporarily compensate for weak private infrastructure markets while AI-native ventures gain lower-cost experimentation capacity.

A second example concerns risk capital. Because AI-native ventures often require longer development cycles and higher upfront experimentation costs, Jordan's weak risk capital score suggests the need for blended finance rather than reliance on conventional venture capital alone. Public seed funding, donor-backed innovation grants, university proof-of-concept funds and international investor partnerships could jointly perform the early-stage financing function until a more mature private investment market develops.

More broadly, because Jordan operates within a resource-constrained environment, entrepreneurially resilient ecosystems require resource-sharing and coordination-oriented architectures for overcoming limited market depth and limited capacity for private investments. In addition, the design of an entrepreneurially resilient ecosystem should be adaptive and sequenced, allowing for gradual evolution and the upgrading of institutional and infrastructural components. The asymmetrical scores that emerge from the analysis underline these three principles.

6.2. Structural Architecture of the Design Model

The structure of the proposed design model is outlined below (Figure 5). It contains four interconnected layers: knowledge generation, experimental infrastructure, venture development and international scaling. The relationships among these layers reflect the progression from knowledge creation to experimentation, venture formation and market scaling discussed in the entrepreneurship and innovation literature (Arora et al., 2021; Perkmann et al., 2013; Stam & Van de Ven, 2021; Uriarte et al., 2026).

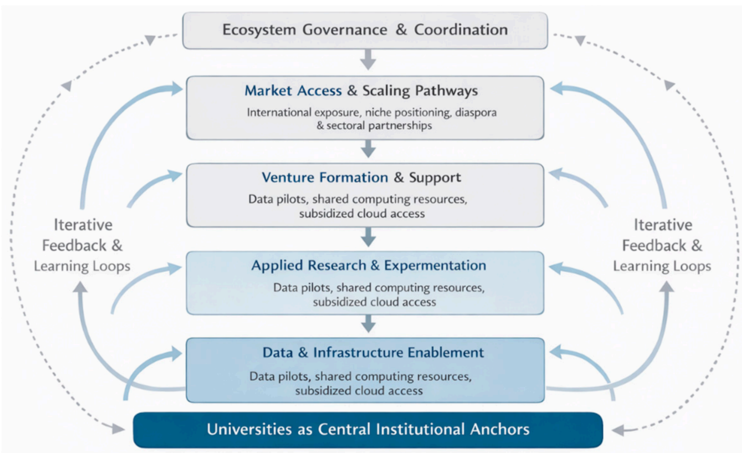

Figure 5. Four-layer context-sensitive AI-native entrepreneurship ecosystem design model for Jordan, comprising knowledge generation, experimentation and infrastructure, venture development and support, and international scaling.

6.2.1. Knowledge Generation Layer

The knowledge creation layer primarily establishes itself within universities and also includes public research institutions. The knowledge creation layer combines formal education with applied research as well as interdisciplinary training in Data Science, Machine Learning and domain-specific applications of AI.

Because of Jordan's relatively robust capacity for higher education, universities will operate as both the main coordinators of the ecosystem and the entities responsible for aligning curriculum, research and entrepreneurial activities. Within this layer, the central mechanisms for collaboration will include joint doctoral programs, industry-specific projects and open innovation platforms (Arora et al., 2021; Perkmann et al., 2013).

6.2.2. Experimentation and Infrastructure Layer

Shared experimentation and infrastructure resources, such as cloud computing services, data-sharing platforms, regulatory sandboxes, model-testing environments and responsible AI validation protocols, enable early-stage AI-native ventures to train, test, audit and refine models before market deployment.

To reduce the infrastructural constraints identified in Section 5, additional mechanisms to pool access and create co-investment between private and public sectors are emphasized in this layer. National research networks, platforms that are supported by international donors and regional data hubs can be created to substitute for large-scale private infrastructure.

This layer will lower the barriers of entry for computation-intensive businesses and allow for iterative model development (Stam & Van de Ven, 2021; Uriarte et al., 2026).

6.2.3. Venture Development and Support Layer

This is where startups are formed, validated and begin to grow. This includes incubators, accelerators, mentoring networks, intellectual property services and seed funding.

This layer differs from other entrepreneurship resources because it focuses on domain-specific validation processes for AI-native ventures, which include technical audits, data compliance assessments and pilot deployment partnerships.

Universities and applied research centers, alongside business incubators and such entities, act as intermediaries by connecting startups with sectoral partners. Public co-funding programs and blended finance instruments can complement sourcing and mitigate risk at this early stage (Arora et al., 2021; Stam & Van de Ven, 2021).

6.2.4. Internationalization and Scaling Layer

The top layer of the model provides both international market access as well as the ability to scale over time. It unites export promotion agencies, diaspora networks, multinational corporate partnerships and international research and innovation program participation. After exhausting opportunities domestically, businesses are set up for internationalization early because they need to be able to grow before they can become successful: standardized compliance frameworks, cross-border accelerator programs and strategic partnerships enable companies to more easily integrate on a global level. The top layer will ensure that if a startup has local innovations, it will have an economic impact that will be sustainable (Nambisan, 2017; Stam & Van de Ven, 2021).

6.3. Governance and Coordination Mechanisms

A coordinated system of governance is required to ensure that the design model is implemented effectively across different organizations. Therefore, there are three complementary coordination mechanisms within the model:

One coordination mechanism is establishing a National AI-native Entrepreneurship Coordination Platform, coordinated by the government and the private sector, which provides overall strategic coherence for national government, regional and municipal authorities, universities, and private-sector actors.

A second coordination mechanism involves the establishment of a number of "mission-oriented funding instruments" to support cross-sectoral initiatives in each of a number of strategic priority domains. Examples include health and wellness, energy, and smart cities/infrastructure.

A third coordination mechanism is to implement monitoring and evaluation systems that measure ecosystem performance against each of the twelve benchmark dimensions, provide an evidence-based approach to adjust policies and promote institutional learning.

Together, these three coordination mechanisms will improve the systematic coherence of the system and reduce the fragmentation of the system.

6.4. Dynamic Adaptation and Sequencing Strategy

The proposed design model is intended to be dynamic and evolutionary rather than prescribing a static institutional configuration; it will specify a number of development pathways by which the elements of the system may be systematically strengthened.

In the short term, emphasis will be given to the establishment of universities as coordinators, the development of access to shared infrastructure and the establishment of international partnerships. In the medium term, priority will be given to the expansion of private industry participation in R&D, the creation of specialized venture capital funds and the establishment of sector-specific data platforms. In the long term, the model anticipates a gradual movement toward market-driven coordination and diverse funding structures.

This sequencing logic follows the parameter weighting relationships described in Section 5 and reduces the risk of premature institutional growth.

6.5. Theoretical Implications and Empirical Validation

This study extends entrepreneurial ecosystem research in two ways. First, it shows that established ecosystem functions must be reinterpreted for AI-native entrepreneurship, particularly in relation to data access, computational infrastructure, continuous model validation and responsible AI governance. Second, it treats ecosystem components as configurable functions rather than fixed institutional forms. This suggests that actors may temporarily perform compensating roles when conventional ecosystem components are weak, while the configuration evolves toward more specialized and market-based arrangements.

The benchmarking approach also differs from conventional ecosystem rankings or descriptive mappings. Its purpose is not simply to identify which ecosystem performs better, but to use structured comparison to identify functional gaps, possible substitutions and development priorities. The framework therefore connects ecosystem diagnosis with context-sensitive design. Future research should validate these relationships through additional country comparisons, longitudinal analysis, interviews with ecosystem actors and venture-level data examining whether the proposed configurations improve AI-native venture formation and scaling.

6.6. Transferability and Broader Applicability

While the model was designed for use in Jordan, its underlying design principles may also apply to other developing or middle-income countries seeking to build AI-native entrepreneurship capacity. The model is most transferable to contexts that share three conditions: a relatively strong higher education base, an emerging digital entrepreneurship culture, and gaps in private-sector R&D, risk capital, computational infrastructure or ecosystem coordination. In such settings, universities, public agencies and ecosystem intermediaries may temporarily perform compensating functions while more mature market-based ecosystem components develop.

The model is less directly applicable to contexts where the higher education sector is weak, where basic digital infrastructure is absent, or where public institutions lack the capacity to coordinate cross-sectoral initiatives. It is also less relevant to mature ecosystems in which private capital, corporate R&D, data infrastructure and market validation mechanisms are already well developed. Accordingly, the framework should be understood as an analytical model demonstrated through two contrasting national cases, rather than as a universally validated design framework. Its broader applicability should be tested across additional countries and through empirical studies incorporating longitudinal, stakeholder-level, and venture-level evidence.

Several implementation risks should also be recognized. Over-reliance on universities may place excessive coordination burdens on academic institutions. Donor-backed or public funding mechanisms may become unsustainable if they do not gradually attract private-sector participation. Shared data and computing platforms may raise governance, privacy, access and accountability concerns if not accompanied by clear rules. Finally, public coordination platforms may reproduce fragmentation if mandates overlap or if monitoring mechanisms are weak. For these reasons, the model requires phased implementation, clear institutional responsibilities, periodic evaluation and gradual transition toward more sustainable market-based coordination.

7. Conclusions, Limitations and Future Research

This research investigated how AI-native entrepreneurship ecosystems can be systematically compared and qualitatively adapted across varying institutional contexts. Using a combination of comparative analysis based on documentary evidence, a context-sensitive approach, and comparative ecosystem mapping, this paper proposes preliminary design principles for configuring entrepreneurial ecosystems.

The comparison of Switzerland and Jordan indicates that successful AI-native entrepreneurship is not based solely on replicating existing institutions but on strategically reconfiguring the functions of the ecosystem using local opportunities and constraints as guides.

The study contributes theoretically to entrepreneurial ecosystem and digital entrepreneurship research by conceptualizing AI-native entrepreneurship as a distinct form of knowledge-intensive venture creation requiring specific infrastructural, governance, and coordination adaptations.

The re-weighting of parameters proposed in this study builds upon the characteristics of existing ecosystems and considers institutional components to be configurable design variables rather than fixed structural elements. This viewpoint results in a broader understanding of the evolutionary path of ecosystems in developing and transitional economies.

In addition to the theoretical implications described above, the study has several practical implications. For policymakers, the results reveal the importance of the university sector as the principal coordinating body for resources in resource-constrained environments and the value of common experimentation infrastructures and blended financial instruments. For support organizations and intermediaries in the ecosystem, the study provides insight into the need for domain-specific validations and early stages of international activity for AI-native ventures. Finally, for academia, the study proposes a model that demonstrates how educational, research and entrepreneurial missions may be integrated strategically to build innovation capacity. However, these implications should be interpreted within the boundary conditions identified in Section 6.6, particularly the need for sufficient institutional capacity, sustainable funding mechanisms and safeguards against overburdening universities or creating donor-dependent ecosystem structures.

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There are three key limitations that should be recognized in this study. First, the document-based methodological approach relies on publicly available data to obtain information that may not include informal coordination methods and actual operational practices. Second, although the scoring procedure was structured through predefined indicators, ordinal scoring anchors and source triangulation, some degree of interpretive judgment remains inherent in document-based ecosystem assessment. The study therefore treats the scores as comparative analytical indicators rather than precise measurements of ecosystem performance. Third, because the research is based on only two examples, direct generalization to other cases is limited.

There are many avenues for future research to extend and build upon this work. Longitudinal studies examining how ecosystem configurations change with policy interventions or market dynamics would provide significant insight into the development of local AI ecosystems. Venture-based datasets, as well as qualitative interviews with company executives, may provide further understanding of company- and market-specific adaptation processes. Additional comparisons of emerging and developed economies can be used to develop and expand the re-weighting parameter framework and broaden the generalizability of results.

Ultimately, this research suggests that context-sensitive design approaches may offer a more appropriate alternative to institutional replication when developing AI-native entrepreneurship ecosystems. By highlighting a context-sensitive process of comparative benchmarking, the study provides a document-informed basis for translating ecosystem practices into locally adapted strategies. Following further stakeholder-level, cross-country and reliability validation, the framework has the potential to contribute to policymaking related to AI-driven entrepreneurship development.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence

Appendix A

This appendix sets out the indicator structure and scoring logic used in the analysis. Dimension 1 is included as an illustrative worked example of how the 0–1–2 scoring criteria were operationalized. The same logic was applied across the other dimensions.

The appendix also presents the three indicators used for each ecosystem dimension and explains how they were scored.

Table A1. Scoring anchors for ecosystem indicator assessment.

Indicator Type	Score 0	Score 1	Score 2
Institutional structure	No formal policy, program, unit, strategy, regulation, or coordination mechanism is documented.	A policy, program, unit, strategy, regulation, or mechanism exists but is emerging, fragmented, limited in scope, or not clearly operational.	A formal and operational policy, program, unit, strategy, regulation, or mechanism is clearly documented and supported by authoritative sources.
Operational resources	No reliable evidence of relevant resources, infrastructure, funding, staff, facilities, platforms, or support capacity.	Some resources exist, but access is partial, fragmented, small-scale, costly, or dependent on temporary projects or external support.	Resources are clearly available, operational, accessible to relevant actors, and supported by sustained institutional or market capacity.
Outcomes	No documented outputs, activities, users, startups, pilots, partnerships, investments, or measurable results.	Some outputs or activities are documented, but they are limited, irregular, early-stage, or not clearly linked to AI-native entrepreneurship.	Clear and repeated outputs are documented, such as active programs, startups, pilots, partnerships, investments, graduates, or measurable ecosystem results.

Where numerical evidence was available, it was used to support scoring decisions. For example, an AI talent pipeline score of two would require evidence of multiple programs related to AI from both students and graduates, as well as documented national/institutional capacity for the education of AI. To have a risk capital score of two, evidence of active and accessible ways and means for funding, including venture capital, seed funds, public co-funding, and investor networks that have documented startup financing, will be required. In cases where no numerical evidence exists, the scoring will be based on documentary evidence from official, institutional, international, or industry sources that have been triangulated.

Table A2. Dimension 1: AI Talent Pipeline.

Indicator	Source	0	1	2	Coding Rule
AI Degree Programs	Jordanian Ministry of Higher Education and Scientific Research (2026); OECD (2019); Swissuniversities (2026)	None	Limited	Widespread	0 = no identifiable AI-related degree programs 1 = limited number of AI-related programs concentrated in few institutions 2 = AI-related programs offered across multiple nationally significant institutions
Advanced AI Training	OECD (2019); State Secretariat for Education, Research and Innovation (SERI, 2025); Tullis (2025)	Absent	Pilot	Institutionalized	0 = no formal advanced AI training provision identified 1 = pilot, short-course, or ad hoc provision identified 2 = institutionalized advanced training embedded in universities or national programs
Industry–Academia Mobility	Guerrero et al. (2016); OECD (2020); Perkmann et al. (2013)	Rare	Occasional	Systematic	0 = little or no evidence of staff, researcher, or student mobility between universities and industry 1 = occasional or project-based mobility through internships, joint projects, visiting roles, or short-term collaboration 2 = systematic and institutionalized mobility through recurring programs, formal partnerships, dual appointments, or structured placement pathways

Table A3. Dimension 2: Applied Research and Knowledge Transfer.

Indicator	Source	0	1	2
Applied AI Labs	OECD (2023); State Secretariat for Education, Research and Innovation (SERI, 2025);	None	Few	Multiple
Industry-Funded Research	Arora et al. (2021); OECD (2020); Tullis (2025)	Low	Moderate	High
Spin-off Mechanisms	Etzkowitz (2017); Perkmann et al. (2013); Wright et al. (2017)	Weak	Partial	Strong

Table A4. Dimension 3: Data Access and Governance.

Indicator	Source	0	1	2
Open Data Portals	OECD (2021); Tullis (2025); UNDP (2025);	None	Limited	Advanced
Data Sharing Frameworks	European Commission (2020a); European Data Protection Supervisor (2025); UNDP (2025)	Absent	Draft	Implemented
Sectoral Data Pilots	OECD (2020); Tullis (2025); UNDP (2025)	None	Few	Many

Table A5. Dimension 4: Computational Infrastructure.

Indicator	Source	0	1	2
National HPC Facilities	OECD (2023); State Secretariat for Education, Research and Innovation (SERI, 2025); Tullis (2025)	None	Limited	Extensive
Cloud Accessibility	Armbrust et al. (2010); ITU (2020); OECD (2021)	Low	Moderate	High
Subsidized Access	Mazzucato (2018); OECD (2020); Tullis (2025)	None	Pilot	Established

Table A6. Dimension 5: Universities as Anchors.

Indicator	Source	0	1	2
Entrepreneurship Units	Guerrero et al. (2016); Jordanian Ministry of Higher Education and Scientific Research (2026); Wright et al. (2017)	None	Partial	Integrated
AI Incubators	Hochberg (2016); OECD (2020); Weiblen and Chesbrough (2015)	None	Few	Multiple
Coordination Role	OECD (2020); Spigel (2017); Stam and Van de Ven (2021)	Weak	Moderate	Strong

Table A7. Dimension 6: Industry–Startup Linkages.

Indicator	Source	0	1	2
Pilot Programs	D. Isenberg and Onyemah (2016); OECD (2020); Tullis (2025)	None	Occasional	Systematic
Corporate Partnerships	OECD (2021); Perkmann et al. (2013); Weiblen and Chesbrough (2015)	Rare	Some	Common
Public Procurement	Mazzucato (2018); OECD (2020); Rodrik (2014)	Absent	Pilot	Established

Table A8. Dimension 7: Support Mechanisms.

Indicator	Source	0	1	2
AI-Focused Accelerators	Hochberg (2016); D. Isenberg and Onyemah (2016); OECD (2020)	None	Few	Many
Mentorship Networks	GEM Jordan Report (Alshwawra et al., 2025); OECD (2021)	Weak	Moderate	Strong
Technical Validation Support	OECD (2020); Tullis (2025); Wright et al. (2017)	None	Partial	Strong

Table A9. Dimension 8: Risk Capital.

Indicator	Source	0	1	2
AI-Focused VC Funds	Ahmad et al. (2018); GEM Jordan Report (Alshwawra et al., 2025); OECD (2020)	None	Few	Many
Public Co-Funding	OECD (2018); OECD (2020); Tullis (2025)	None	Limited	Extensive
Corporate Investment	Arora et al. (2021); OECD (2021); Weiblen and Chesbrough (2015)	Rare	Some	Common

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Table A10. Dimension 9: Regulation and Policy.

Indicator	Source	0	1	2
AI Strategy	European Commission (2025); State Secretariat for Education, Research and Innovation (SERI, 2025); Tullis (2025)	None	Draft	Implemented
Sandbox Frameworks	European Commission (2025); OECD (2021)	None	Pilot	Established
Ethical Guidelines	European Commission (2020b); Floridi et al. (2018); Whittaker et al. (2018)	Absent	Partial	Comprehensive

Table A11. Dimension 10: Market Access and Scaling.

Indicator	Source	0	1	2
Export Support	OECD (2020); SECO (2025); Tullis (2025)	Weak	Moderate	Strong
Global Partnerships	OECD (2021); Rodrik (2014); Tullis (2025)	Few	Some	Many
International Programs	European Commission (2020b); European Commission (2025); OECD (2021)	Rare	Some	Systematic

Table A12. Dimension 11: Ecosystem Coordination.

Indicator	Source	0	1	2
National Platforms	OECD (2020); Tullis (2025); UNDP (2025)	None	Fragmented	Unified
Cross-Sector Councils	OECD (2021); Stam and Van de Ven (2021)	None	Few	Strong
Strategy Alignment	OECD (2021); Rodrik (2014); Tullis (2025)	Low	Medium	High

Table A13. Dimension 12: Entrepreneurial Culture.

Indicator	Source	0	1	2
Risk Acceptance	GEM Jordan Report (Alshwawra et al., 2025); OECD (2021)	Low	Moderate	High
Failure Tolerance	GEM Jordan Report (Alshwawra et al., 2025); OECD (2021)	Low	Medium	High
Media Coverage	Jordan Times (2025); OECD (2021)	Rare	Occasional	Frequent

Appendix B

Table A14. Sources for Table 2's descriptive statistics of Jordan and Switzerland. Sources accessed between January and March 2026.

Key Economic Criteria	Jordanian Sources	Swiss Sources
Population (2024)	Jordanian Department of Statistics (DOS, 2024), available at: https://dosweb.dos.gov.jo/population/population-2/, accessed on 25 May 2026	Swiss Federal Statistical Office (2025a) https://www.bfs.admin.ch/bfs/en/home/statistics/population.html, accessed on 25 May 2026
Area, km^2	Jordanian Department of Statistics (DOS, 2024), available at: https://dosweb.dos.gov.jo/population/population-2/, accessed on 25 May 2026	Swiss Federal Statistical Office (2025b) https://www.bfs.admin.ch/bfs/en/home/statistics/territory-environment.html, accessed on 25 May 2026
GDP per capita (2024)	World Bank (2024), available at: https://data.worldbank.org, accessed on 25 May 2026	Swiss Federal Statistical Office (2024) https://www.bfs.admin.ch/bfs/en/home/statistics/national-economy.html, accessed on 25 May 2026
Higher education institutions	Jordanian Ministry of Higher Education and Scientific Research (2026), available at: https://mohe.gov.jo/EN/Pages/Higher_Education_in_Jordan, accessed on 25 May 2026	Swissuniversities (2026) https://www.swissuniversities.ch/en/topics/studying/accredited-swiss-higher-education-institutions, accessed on 25 May 2026

Table A14. *Cont.*

Key Economic Criteria	Jordanian Sources	Swiss Sources
Number of university students	Jordanian Ministry of Higher Education and Scientific Research (2026), available at: https://mohe.gov.jo/EN/Pages/Higher_Education_in_Jordan, accessed on 25 May 2026	Swiss Federal Statistical Office (2025c) https://www.bfs.admin.ch/bfs/en/home/statistics/education-science/pupils-students/tertiary-higher-education-institutions/universities.html, accessed on 25 May 2026
R&D expenditure (% GDP, 2024)	Schneegans et al. (2021), available at: https://unesdoc.unesco.org/ark:/48223/pf0000377433, accessed on 25 May 2026	Swiss Global Enterprise (2024) https://www.s-ge.com/en/article/news/20252-innovation-swiss-firms-forefront-research-spending?ct, accessed on 25 May 2026
National AI strategy	Tullis (2025), available at: https://doi.org/10.1596/42812 Jordan Times (2025), available at https://jordantimes.com/opinion/ahmad-al-naimi/jordans-path-to-digital-governance-advancements-in-gtmi, accessed on 25 May 2026	OFCOM Report (2025), Overview of Artificial Intelligence Regulation: Report to the Federal Council, 12 February 2025, accessed on 25 May 2026
Venture capital (% GDP, 2026)	GEM Jordan Report (Alshwawra et al., 2025), available at www.gemconsortium.org/report Ahmad et al. (2018), available at: https://hdl.handle.net/10986/31056, accessed on 25 May 2026	Swiss Confederation SME Portal (2026a), SME Financing: Venture Capital https://www.kmu.admin.ch/en/sme-financing-venture-capital?utm, accessed on 25 May 2026
Global Innovation Index (2024)	Dutta et al. (2024), available at: https://www.wipo.int/publications/en/details.jsp?id=4758, accessed on 25 May 2026	Swiss Confederation SME Portal (2026b), Switzerland remains the world's most innovative country https://www.kmu.admin.ch/en/news-en-2025?utm, accessed on 25 May 2026
Government AI Readiness (2024)	Oxford Insights (2024), pub. Oxford Insights https://oxfordinsights.com/wp-content/uploads/2025/06/2024-Government-AI-Readiness-Index.pdf?utm, accessed on 25 May 2026	Oxford Insights (2024), pub. Oxford Insights https://oxfordinsights.com/wp-content/uploads/2025/06/2024-Government-AI-Readiness-Index.pdf?utm, accessed on 25 May 2026
Technology startup density (2025) (number of startups per capita)	GEM Jordan Report (Alshwawra et al., 2025), available at www.gemconsortium.org/report, accessed on 25 May 2026	Venturelab (2025) https://www.venturelab.swiss/New-business-formations-in-Switzerland-2025 Swiss Federal Statistical Office (2024) https://www.bfs.admin.ch/bfs/en/home/statistics/national-economy.html, accessed on 25 May 2026
English proficiency (2025)	World Population Review (2025) https://worldpopulationreview.com/country-rankings/english-proficiency-by-country, accessed on 25 May 2026	World Population Review (2025) https://worldpopulationreview.com/country-rankings/english-proficiency-by-country, accessed on 25 May 2026

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