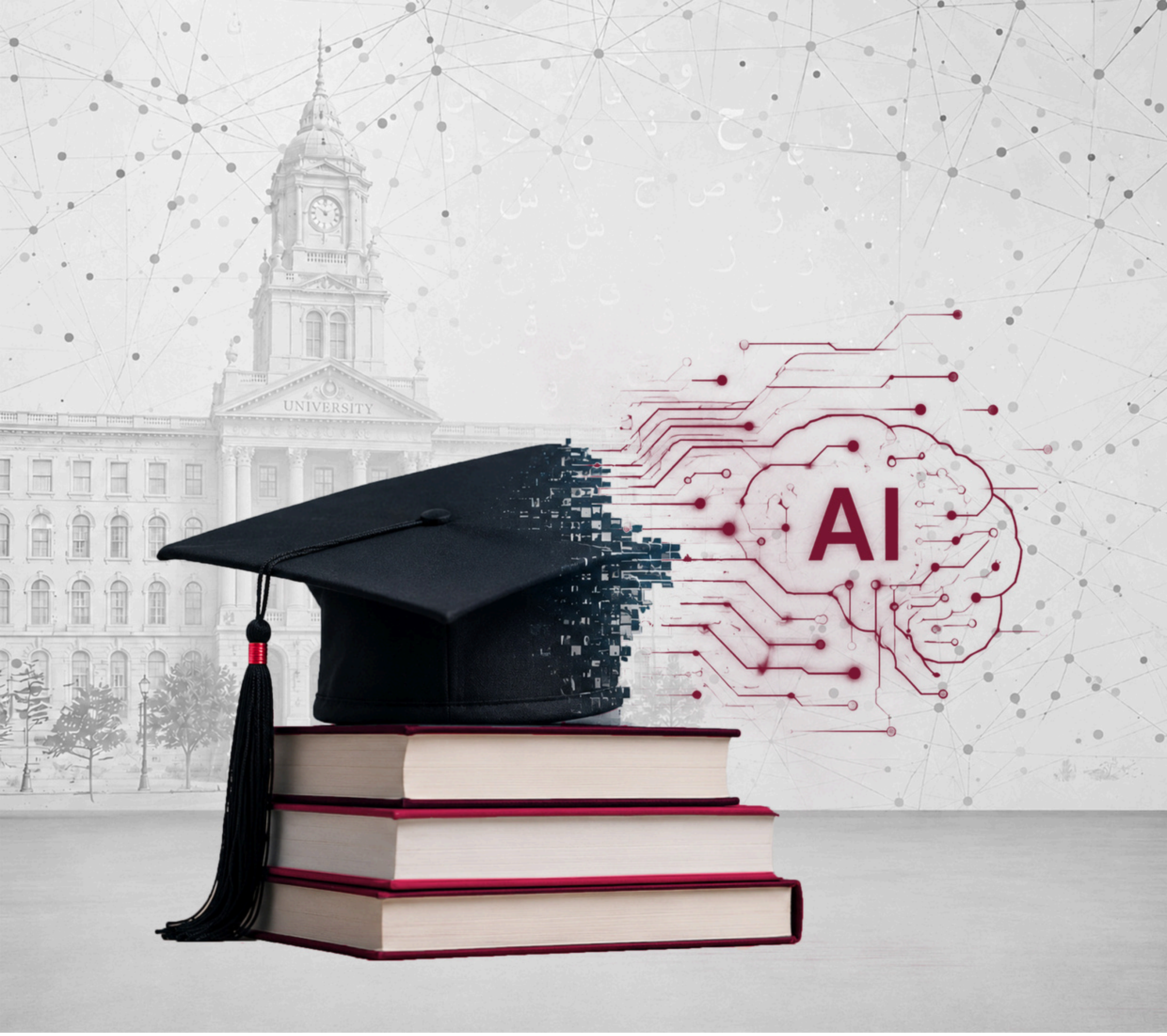

Assessing AI and Technological Readiness in Arab Universities Using an Intellectual Capital Framework

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Preface

This report forms part of a broader regional effort to strengthen digital transformation and advance knowledge economies across Arab states. The project provides a comparative, evidence-based assessment of Artificial Intelligence (AI) readiness in higher education, supporting mandates to enhance regional cooperation, inform policy design, and align university systems with the demands of future labor markets. Drawing on the Intellectual Capital (IC) framework—Human, Structural, and Relational Capital—the study evaluates how universities mobilize their people, infrastructure, and partnerships to navigate emerging technological transitions.

The report presents the results of the Arab University AI Readiness Assessment, which benchmarks 36 universities across 20 Arab member states and analyzes a purposive qualitative sub-sample. Using publicly available data, the study maps institutional strengths, identifies capacity gaps, and highlights systemic patterns in AI curriculum integration, research infrastructure, and external engagement. Findings are organized around the IC framework to ensure a structured and comparable analysis of readiness across institutions and countries.

Designed for policymakers, higher education leaders, international organizations, and industry partners, the report aims to support evidence-informed decision-making. It highlights promising practices, reveals institutional and systemic shortcomings, and offers targeted recommendations for strengthening AI capacity across the region's diverse higher education systems.

About the Author

Dr. Lina Khalil is an Assistant Professor at the American University of Beirut. Her research focuses on educational leadership and policy in crisis and fragile contexts, particularly in Lebanon. Her work examines how leadership shapes teaching and learning through organisational conditions and contributes to emerging theory on context-activated leadership. She has also examined technology integration and AI readiness in higher education systems.

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Executive Summary

This report assesses the readiness of universities across the Arab region to integrate Artificial Intelligence (AI) into teaching, research, and external engagement. Using the Intellectual Capital (IC) framework, the study evaluates Human, Structural, and Relational Capital across 36 universities in 20 countries, combining quantitative benchmarking with qualitative analysis of selected case studies.

The results reveal a three-tiered rather than binary landscape. Flagship institutions such as the American University of Beirut (AUB), Qatar University (QU), Khalifa University (KU), and King Saud University (KSU) demonstrate advanced readiness, with comprehensive AI curricula, high research productivity, and sustained global partnerships. A substantial middle tier—including Ain Shams – Egypt; Carnegie Mellon University–Qatar (CMU-Q), Mohammed VI Polytechnic University (UM6P), the University of Jordan (UJ), Birzeit University (BZU), Sultan Qaboos University (SQU), Kuwait University (KUW), and Prince Sultan University (PSU)—shows solid but uneven readiness. These institutions combine defined AI pathways, active laboratories, and structured collaborations, though their research depth and partnership maturity remain below those of regional leaders. At the lower end of the spectrum, smaller or resource-constrained universities such as Gulf University (GU), the University of Djibouti (UDJ), Sebha University (SEU), and the University of Nouakchott (UN) exhibit minimal curriculum integration, weak infrastructure, and largely transactional partnerships. This distribution confirms a three-tiered pattern with widening disparities in institutional capacity across the region.

The combined findings point to a three-tiered readiness pattern across the region: leaders positioned for global competitiveness, emerging universities building capacity, and lagging institutions at risk of exclusion. These disparities are not only academic but carry urgent policy implications. Curriculum gaps mean that graduates in many countries will lack essential AI-related skills, while low-income-state universities risk falling further behind without targeted support. If unaddressed, these divides will deepen regional inequalities and constrain the ability of higher education systems to contribute to innovation and economic transformation.

Within this overall pattern, several counterintuitive results also emerge. The data reveal that certain private universities in high-income Gulf states perform below expectations, while several public universities in middle-income countries achieve comparatively high readiness. This underscores that AI and digital transformation outcomes depend more on institutional strategy, governance, and policy alignment than on national wealth or ownership status.

The study therefore underscores the need for coordinated regional action. Policy responses must focus on updating curricula across disciplines, investing in shared research infrastructure, and building partnerships that extend opportunities to weaker institutions. Arab countries, in collaboration with national governments, universities, industry, and donors, has a critical role to play as a regional convener, ensuring that AI readiness becomes a collective regional priority rather than a privilege of a few well-resourced institutions.

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Introduction

The rapid evolution of AI and digital technologies is reshaping higher education institutions globally. In regions like the Arab world, the readiness of universities to respond to these shifts is vital for ensuring regional competitiveness, knowledge production, and educational equity.

The Intellectual Capital (IC) framework—originally formulated by Edvinsson and Malone (1997) to describe Human, Structural, and Customer/Relational Capital—has since been adapted extensively in higher education research (Bezhani, 2010; Ramírez et al., 2007; Secundo et al., 2016). In this study, the IC framework is used as a conceptual lens to evaluate how universities in Arab countries are responding to technological advances and the evolving demands of the AI-driven economy. The IC framework encompasses the tangible and intangible resources that institutions mobilize to create value—particularly in knowledge-intensive environments such as higher education. As widely applied in European and international studies, the framework organizes university capacities into three dimensions: Human Capital (skills, expertise, and faculty training), Structural Capital (infrastructure, data systems, and digital platforms), and Relational Capital (industry linkages, alumni networks, and international visibility). These dimensions align directly with how universities equip students and staff for AI-related roles, strengthen digital and research infrastructure, and engage externally to remain competitive.

By embedding this framework in a public data methodology, the study aims to offer a structured yet scalable approach to benchmarking AI readiness across universities in the region.

Research Question

The major question that guides the study is:

How are Arab universities meeting advances in technology and AI, based on publicly available data?

This is further explored using the sub-questions below:

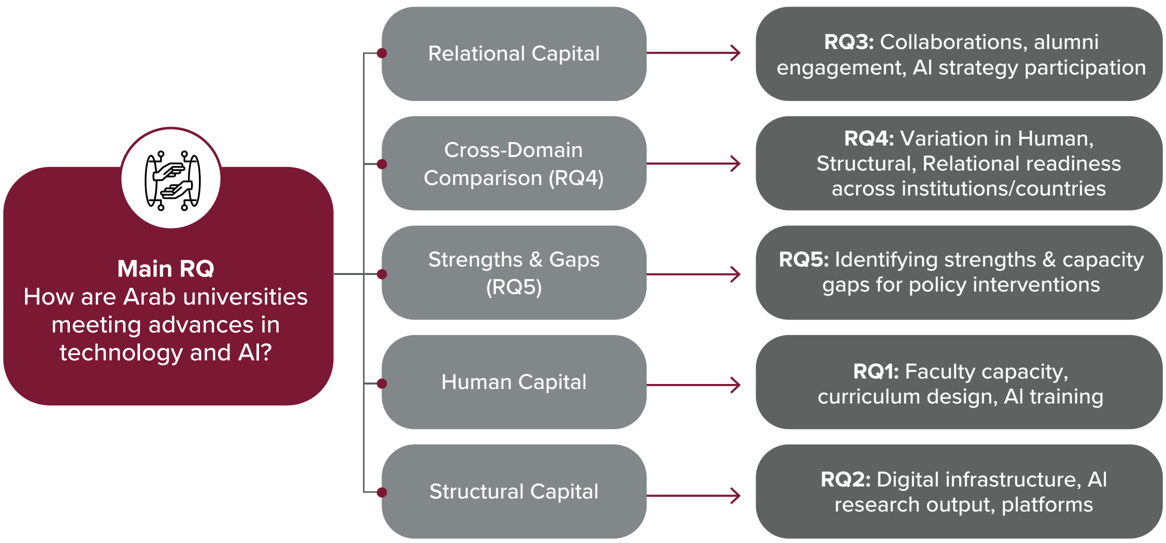
1. What indicators of **Human Capital** (faculty capacity, curriculum design, AI-related training) are evident across Arab universities?
2. How are universities investing in **Structural Capital** (digital infrastructure, AI research output, technological platforms)?
3. What forms of **Relational Capital** (industry collaboration, alumni engagement, participation in AI strategies) can be observed?
4. How do Human, Structural, and Relational Capital readiness scores vary across institutions and countries in the Arab region?
5. What strengths and capacity gaps across IC dimensions can be identified that may inform regional or national policy interventions?

Objectives

- To develop a set of AI and technology-readiness indicators, aligned with the IC framework.
- To benchmark the performance of selected Arab universities using publicly accessible data sources.
- To identify strengths and gaps in institutional capacity, curricula, partnerships, and strategic alignment.
- To inform regionally relevant, evidence-based policy recommendations.
- To document how ESCWA universities publicly present and adapt their curricula for AI and digital technologies—through the introduction of new programs, tracks, and modules—using evidence from program catalogs, strategic plans, and other online disclosures.

Figure 1 below illustrates the IC framework used in this study and shows how the three main dimensions—Human, Structural, and Relational Capital—directly align with the research sub-questions. Human Capital corresponds to RQ1, Structural Capital to RQ2, and Relational Capital to RQ3, while RQ4 and RQ5 examine cross-institutional variation and capacity gaps across all three IC dimensions.

Figure 1. Intellectual Capital (IC) framework and study sub-questions used to assess AI readiness in Arab universities.



Methodology

Research Design

This study adopts a comparative descriptive research design based exclusively on publicly available secondary data (Creswell & Creswell, 2018). Such a design is particularly appropriate for a benchmarking study that seeks to evaluate how universities in the Arab region are responding to the demands of AI and digital transformation. Comparative approaches allow for meaningful cross-institutional analysis, highlighting both convergences and divergences across higher education systems (Hanushek & Woesmann, 2020). Descriptive designs, meanwhile, enable the systematic mapping of institutional practices without intervening in university operations, which is critical in contexts where access to internal records may be restricted (Creswell & Creswell, 2018).

The choice of a secondary-data methodology ensures feasibility and scalability while also aligning with prior IC research in higher education, which has often relied on disclosure practices, strategic plans, and public reports to assess institutional capacities. Given the reliance on public data, the study used a stratified purposive sampling approach to ensure both regional representation and the inclusion of institutions with adequate online transparency to support IC-based benchmarking.

Data Sources

Data was collected from a range of public and verifiable sources, ensuring both breadth and transparency. The major sources of data included:

- University websites (program catalogs, research center pages, strategy documents, news updates).
- Global university rankings and databases: QS World University Rankings, Times Higher Education (THE), CSRankings.
- Research repositories: Scopus, Web of Science, Google Scholar for publication records.
- Intellectual property repositories: World Intellectual Property Organization (WIPO), national IP registries.
- Professional networking platforms: LinkedIn analytics for alumni employment trends.[1]
- Governmental and regional strategy portals: national AI strategies, reports, Arab Digital Economy Federation publications.
- AI-related curriculum was identified through publicly available program descriptions across all faculties. Evidence from non-ICT majors (e.g., medicine, business, design) was included when explicitly documented online; however, the study did not conduct a full audit of every course in the university catalog, in line with the exclusive reliance on publicly available data.

1 LinkedIn analytics were collected manually from publicly available alumni pages and institutional LinkedIn dashboards. These data are not provided by universities, nor were they scraped or downloaded using automated tools. Only aggregate, publicly visible information was used, in line with the study's reliance on open-access secondary data

The triangulation of these diverse sources mitigated the limitations associated with relying on a single database and enhanced the overall credibility of the analysis (Creswell & Creswell, 2018; Denzin, 2017; World Bank, 2022).

Conceptual Framework and Indicators

While the IC framework by Bezhani (2010) and Ramírez et al. (2007) was initially developed through studies of UK and Spanish universities, its core components—Human, Structural, and Relational Capital—are theoretically robust and adaptable across diverse higher education contexts (Secundo et al., 2020; Kianto et al., 2022). In this study, these dimensions were refined to better align with the structural and operational realities of Arab-region universities.

Key refinements accounted for linguistic diversity in instructional delivery, regional policy dependencies, and infrastructural disparities. For instance, Human Capital indicators were expanded to include bilingual AI instruction capability (Arabic–English), certifications from global platforms (e.g., Coursera, Google AI), and participation in national AI capacity-building initiatives supported by the Arab Digital Economy Federation. Structural Capital incorporated distinctions between donor-dependent and internally funded R&D activities, cloud-based laboratory access, and the use of open-access research dissemination platforms—factors particularly relevant for visibility in resource-constrained settings. Relational Capital was adapted to emphasize alignment with national AI strategies, partnerships with regional tech accelerators, and involvement in Arab League or digital policy forums.

These refinements ensured both theoretical fidelity and contextual relevance, enhancing the framework's diagnostic precision. Similar adaptations of IC frameworks to emerging economies have been validated in literature on intellectual capital in non-Western academic contexts (Cuozzo et al., 2017; Kianto et al., 2022; Secundo et al., 2021). To strengthen local relevance and validity, the study incorporated a regional expert validation step, involving stakeholders from ministries, regional AI researchers, and sectoral representatives, following best practices in context-sensitive evaluation design (World Bank, 2022).

To bridge the conceptual framework and the operational methodology, the following section presents the indicators used to assess Human, Structural, and Relational Capital across the sampled universities. The indicator set is categorized according to the three IC dimensions (see Table 1).

Table 1. Intellectual capital metrics and indicators used for Arab universities.

Type of Capital	Metric Category	Key Indicators	Courses score
Human Capital	Curriculum	AI-related degrees, interdisciplinary programs, bilingual AI instruction, faculty certifications (Coursera, Google), regional training	University websites, Arab Digital Economy Federation
Structural Capital	Research Output	AI publications, citations, patents, open access platforms, donor-based vs. internal R&D funding	Scopus, Web of Science, WIPO, university websites
Structural Capital	Infrastructure	Smart classrooms, HPC resources, LMS/digital systems, cloud-based lab access, research data portals	University websites, EDUCAUSE
Relational Capital	Partnerships	Tech company links, national AI strategy alignment, regional collaborations (Arabnet, Flat6Labs), forums	University websites, Arabnet, Flat6Labs
Relational Capital	Graduate Outcomes	Alumni engagement in AI-related sectors, talent exchange and co-tutelage programs	LinkedIn analytics, university career portals
Relational Capital	Visibility & Transparency	Global rankings, AI-focused centers, transparency in research, curricula, governance data	QS, THE, LinkedIn, national portals

The use of publicly accessible data—course catalogs, alumni employment records, strategic plans, and digital infrastructure—aligns with the data sources commonly used in IC research. Adapting the framework from disclosure assessment to readiness benchmarking enables it to capture dynamic institutional responses to AI and technology transitions, reinforcing its applicability in the Arab higher-education context (Secundo et al., 2020). International studies further validate this approach, confirming the IC framework's flexibility and relevance for managing innovation and transformation in higher education systems, including those in emerging regions.

IC-based assessments relying on public data cannot fully capture internal processes, governance mechanisms, or non-disclosed initiatives that universities may use to manage innovation. As with any disclosure-based methodology, some institutional capacities—particularly those recorded only in internal or offline documents—may not be visible online and therefore fall outside the scope of this analysis. Thus, while the IC framework provides conceptual clarity and methodological feasibility for evaluating AI readiness in the Arab context, findings should be interpreted with an understanding of these transparency-related constraints.

Sampling Procedure for Arab University AI Readiness Study

The study covered 36 universities across 20 Arab countries, with the aim of ensuring balanced regional representation and inclusion of both public and private institutions. A stratified purposive sampling strategy was adopted: stratification ensured geographic coverage across the 20 countries and, where possible, the inclusion of both a public and a private university in each. Purposive criteria further required that selected institutions maintain a functional website and provide sufficient publicly accessible documentation to allow IC-based benchmarking. Selection was guided by three main criteria:

1. Availability of a functional website in Arabic and/or English;
2. Evidence of AI or digital engagement (programs, centers, or initiatives); and
3. Accessible documents such as strategic plans, curricula, or alumni data.

Where possible, one public and one private university were included from each country to capture institutional diversity. In a few cases—notably Comoros and Mauritania—gaps in online presence limited the ability to include a private institution. To contextualize cross-country variation, each country in the sample was classified into High-, Middle-, or Low-GDP categories using the World Bank's 2024 income-based country classifications. These categories, commonly used as proxies for national economic capacity, help interpret readiness disparities across institutions operating in high-resource versus low-resource environments. High-GDP countries in the sample include Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the UAE; middle-GDP countries include Algeria, Egypt, Iraq, Jordan, Lebanon, Libya, Mauritania, Morocco, Palestine, Somalia, Sudan, Syria, Tunisia, and Yemen; and low-GDP countries include Comoros and Djibouti (World Bank, 2024). Additional details are provided in **Appendix A**.

Data Collection and Analysis

Data collection relied exclusively on publicly available sources, including university websites, international rankings, research repositories, and national or regional strategy portals. These materials were reviewed using a standardized template aligned with the IC framework.

Each sub-index—Human Capital, Structural Capital, and Relational Capital—was scored on a normalized 0–3 scale using a predefined rubric (see **Appendix A**). Indicators within each dimension (e.g., curriculum, research, infrastructure) were assessed according to explicit qualitative evidence drawn from institutional sources. The Composite Readiness Score (CRS) was then computed as the arithmetic mean of the three sub-indices, each equally weighted to ensure balanced representation across the intellectual capital dimensions. Because all dimensions were pre-normalized to the same 0–3 range, no additional statistical normalization or weighting was applied.

To complement the benchmarking, a purposive sub-sample of six universities was examined qualitatively using high-value documents such as strategic plans and program catalogs. The qualitative component served to contextualize the quantitative results by providing deeper insight into how institutions articulate their strategies and capacities. The sub-sample was selected to reflect variation in CRS (high, medium, and low performers) as well as regional diversity, as outlined in Table A1 and summarized in Table B in **Appendix A** and **B** respectively. High-value documents—including strategic plans, program catalogs, descriptions of AI labs or centers, and partnership announcements—were analyzed using deductive thematic coding aligned with the IC framework. This approach enabled systematic comparison across Human, Structural, and Relational Capital dimensions while linking qualitative evidence to the underlying scoring rationale. A full list of publicly available documents used for qualitative coding is provided in **Appendix C**.

Findings were synthesized into CRS, supported by comparative visualizations (clustered bar charts, heatmaps) to highlight institutional strengths, gaps, and regional patterns.

Data Visualization

To effectively communicate the findings of the AI Readiness Benchmarking Study across 36 Arab universities, three key visualizations have been selected based on their analytical value, visual clarity, and feasibility within a single-researcher, time-constrained context. These charts represent the most meaningful synthesis of quantitative benchmarking outcomes aligned with the IC framework.

- Clustered Bar Chart: This chart allows for side-by-side comparison of HC, SC, and RC scores across each university. It enables readers to observe domain-specific strengths and gaps in institutional capacity.
- Heatmap Table: This matrix-style chart uses conditional color formatting to visualize HC, SC, RC, and CRS. It facilitates pattern detection across universities and highlights performance clusters, making it especially useful for policymakers.

Qualitative Coding

To complement the benchmarking results, a qualitative component was incorporated to contextualize differences in university readiness and to explain patterns observed in the composite scores. A purposive sub-sample (Polkinghorne, 2005) of six universities was selected to ensure variation across high-, medium-, and low-performing institutions, as well as representation from different subregions of the Arab region (**Appendix A**). This qualitative strand was designed from the outset as an explanatory element within the mixed-methods design.

Qualitative evidence consisted solely of publicly available, high-value documents, including program catalogs, strategic plans, research center descriptions, partnership announcements, and other official webpages. Document identification followed a structured table created for the study, which served as the document checklist. The table captured the key fields reported in **Appendix C2**—university name, IC dimension, indicator, source type, and URL—ensuring traceability and consistency in data extraction. Because the dataset was limited and consisted of clear, verifiable institutional documents, no additional metadata (e.g., date accessed, verification codes, relevance scoring) was required. **Appendix C2** therefore functions as the complete evidence inventory for the qualitative component.

The coding process was deductive, based on a codebook developed prior to analysis. The codebook was structured around the three domains of the IC framework—Human, Structural, and Relational Capital—with indicators adapted from the EDUCAUSE Digital Capacity Framework (Nowell et al., 2017). Human Capital codes captured curriculum breadth, AI-related modules and degrees, faculty development signals, and bilingual instruction; Structural Capital codes captured infrastructure, research centers, digital platforms, and research visibility; and Relational Capital codes captured industry engagement, regional and international partnerships, and alumni visibility. These indicators align with the thematic coding chart presented in **Appendix C3**.

Given the limited volume and highly structured format of the qualitative evidence, all coding was conducted manually by the Principal Investigator (PI). Manual coding allowed for close interpretation of institutional narratives and for mapping excerpts directly onto IC indicators without the need for software such as NVivo or Atlas.ti. As coding was performed by a single researcher and involved structured documentary content rather than narrative interview data, inter-coder reliability procedures were not applicable.

For each of the six universities, two to three illustrative excerpts were extracted for each IC dimension to ensure comparability across cases while keeping the dataset analytically manageable. These excerpts were entered into an integration matrix linking: (1) the document source, (2) the IC code, and (3) short interpretive notes. This ensured a consistent connection between the qualitative evidence, the IC indicators, and the IC-based benchmarking framework. The synthesized qualitative summaries produced through this process are presented in **Appendix C1**, while the complete indicator mapping appears in **Appendix C3**.

To deepen the Human Capital analysis, a complementary curriculum-governance scan was conducted. This targeted scan reviewed publicly available curriculum-governance documents, including program catalogs, strategic plans, quality-assurance policies, and academic governance handbooks where available. The purpose was to identify publicly visible signals of curriculum adaptation—such as newly introduced AI programs, minors, or tracks—and any references to curriculum-review processes or program-modification procedures. Because internal approval mechanisms, bureaucratic pathways, and formal review cycles are seldom disclosed online, this analysis is limited to what universities publicly report. The scan therefore provides insight into curriculum transparency and adaptation capacity, rather than a full account of internal governance processes. Curriculum evidence was reviewed across all faculties where publicly documented—including non-ICT majors such as medicine, business, design, and education. However, only programs with explicit online evidence of AI-related modules or competencies were included.

In this way, the qualitative analysis illuminates how institutions narrate their readiness, how they describe investments in curriculum and infrastructure, and how they frame partnerships and external engagement. These insights are subsequently triangulated with the quantitative findings to clarify both consistencies and divergences between institutional discourse and measured capacity.

Data Integration and Analysis

Quantitative and qualitative results were triangulated to provide a richer account of institutional AI readiness. The analysis generated domain-specific scores, composite readiness scores, cross-country comparisons, and thematic insights. Visualizations—including clustered bar charts and heatmaps—are presented to communicate these findings.

Ethical Considerations

The study was based exclusively on publicly available data, with no direct involvement of human participants (BERA, 2018). Consequently, approval from an institutional ethics board was not required. Ethical measures were adhered to throughout the research process, including accurate citation of all sources, avoiding any misrepresentation of institutions, and clearly acknowledging the inherent limitations associated with relying on online transparency.

With these ethical parameters addressed, the following section presents the main limitations encountered during the study.

Limitations

The study has the following limitations:

Data Scope Constraints

The study relies solely on publicly available data, which may omit internal documents, offline strategies, or non-disclosed AI initiatives—particularly in universities where online transparency is limited.

Language Accessibility

While language barriers were initially expected to limit the analysis of Arabic-only university websites, the inclusion of a bilingual researcher (English–Arabic) mitigated this challenge and allowed for broader access to institutional materials. However, the exclusion of French-language websites—particularly relevant in countries such as Lebanon, Tunisia, and Morocco—represents a minor limitation, as it may have omitted additional evidence from francophone institutions where key strategic or research content is not reflected in Arabic or English.

Digital Transparency Variance

Institutional differences in the structure, clarity, and availability of online materials—ranging from outdated websites to incomplete course catalogs—may introduce inconsistencies in the benchmarking process as well as the final outcomes.

Sampling Trade-offs

The stratified purposive sampling approach—designed to ensure broad representation across Arab countries and, where possible, across public and private sectors—limited the sample to 30–36 universities due to time and data-access constraints. While this ensured feasibility, it may not capture the full spectrum of institutional readiness in each country.

In some countries—most notably Libya and Qatar—private universities could not be included because their online presence did not provide the minimum level of publicly accessible documentation required for IC-based benchmarking (e.g., program catalogs, research activities, or partnership details). As a result, certain American-affiliated universities appear in the sample not out of preferential selection, but because they were among the few private institutions with sufficiently transparent and functional websites to allow systematic scoring.

Scoring of Human, Structural, and Relational Capital indicators was conducted by a single trained research assistant due to project time constraints and the volume of institutions assessed. A predefined scoring rubric (**Appendix A**) guided all decisions, and cases of uncertainty were escalated to the lead researcher to ensure consistent interpretation of indicators across universities. While inter-rater reliability could not be established, the structured rubric and internal review process helped mitigate subjective bias.

Lack of Validation from Institutions

As the study does not involve direct institutional participation (e.g., interviews or surveys), some contextual nuances may not be fully captured or validated through internal stakeholders.

Finally, while curriculum content and AI-related offerings were benchmarked using public sources, the study could not systematically capture internal curriculum-governance processes—such as the exact frequency of program reviews, formal approval timelines, or the degree of bureaucratic rigidity—because these details are rarely disclosed on university websites or in public policy documents.

Significance and Contribution

This study introduces a replicable IC-based framework for tracking AI readiness in higher education. It builds on prior European frameworks to offer Arab universities and policymakers a tool for benchmarking and strategic planning in line with emerging labor market demands.

Findings

The findings of this study are structured around the major question in general and the five research sub-questions in particular, drawing on Human, Structural, and Relational Capital indicators. To illustrate the results, examples of both high-performing and low-performing universities are provided. Visualizations are included to highlight cross-institutional comparisons.

Faculty Capacity, Curriculum, and AI-related Training

Human Capital indicators reveal significant differences in curriculum integration and faculty capacity across institutions. High-readiness universities such as the American University of Beirut (3.0) and the University of Petra (3.0) demonstrate structured AI pathways supported by faculty certifications, bilingual instruction, and research-active staff. Carnegie Mellon University–Qatar (2.25) also performs strongly as a private institution with a rigorous computing curriculum adapted from its U.S. counterpart, though at a smaller institutional scale. By contrast, Gulf University (0.0), the University of Djibouti (0.5), and the University of Nouakchott (1.0) show limited or no evidence of AI-related programs or systematic faculty development. In this study, faculty development is treated as a core mechanism through which overall faculty capacity is built, consistent with the Human Capital dimension of the IC framework.

Digital Infrastructure, Research Output, and Platforms

Structural Capital results highlight strong research ecosystems in institutions such as AUB (3.0), Khalifa University (3.0), and King Saud University (2.67), which maintain advanced laboratories, research centers, and high publication visibility. Carnegie Mellon University–Qatar (2.33) and Sultan Qaboos University (2.33) occupy an intermediate position with active but moderately scaled infrastructure. At the other end, Gulf University (0.67), the University of Djibouti (0.33), and Sebha University (1.33) lack specialized AI research facilities, reflecting foundational structural deficits across lower-income systems.

Having considered internal capacities, the analysis now turns to external engagement through industry collaborations and partnerships.

Industry Collaborations and External Engagement

Relational Capital results remain uneven across the region. Universities in high-income Gulf states—such as Kuwait University (3.0), Sultan Qaboos University (3.0), Khalifa University (3.0), and Qatar University (3.0)—demonstrate deep and recurring collaborations with global technology firms, national innovation agencies, and regional industry actors. Carnegie Mellon University–Qatar (2.43) also exhibits strong relational engagement, outperforming many private institutions in the Gulf, particularly through industry-aligned training and applied research initiatives.

By contrast, institutions in lower-income contexts—such as the University of Djibouti (0.17), Gulf University (0.33), and the University of Damascus (0.33)—show shallow, ad hoc partnerships with limited evidence of industry integration. These findings confirm that relational capacity is a decisive differentiator in AI readiness.

Prince Sultan University (2.33) illustrates a middle-tier pattern: active partnerships exist, including VMware and SDAIA initiatives, but remain narrower and less institutionalized than those of regional leaders. Similarly, South Mediterranean University (1.67) in Tunisia reflects limited but emerging engagement with industry and regional networks.

Variation Across Institutions and Countries

CRS range from nearly 3.0 at AUB to below 0.5 at Gulf University, illustrating strong institutional stratification across the region. High-income public universities—such as Qatar University, Khalifa University, and King Saud University—consistently achieve top-tier scores, whereas private institutions vary widely: Ajman University (2.56) and Carnegie Mellon University-Qatar (2.35) perform strongly, while Gulf University (0.33) remains among the lowest performers. Middle-income public universities such as Birzeit (2.22), the University of Jordan (2.61), and Mohammed VI Polytechnic University (2.50) demonstrate notable readiness despite fiscal constraints. In contrast, universities in fragile or low-income contexts—including the University of Djibouti (0.33), Sebha University (1.33), and the University of Nouakchott (1.22)—face compounded human, structural, and relational deficits.

Figure 2. Heatmap of Composite Readiness Scores (CRS) across 40 Arab universities, grouped by region.

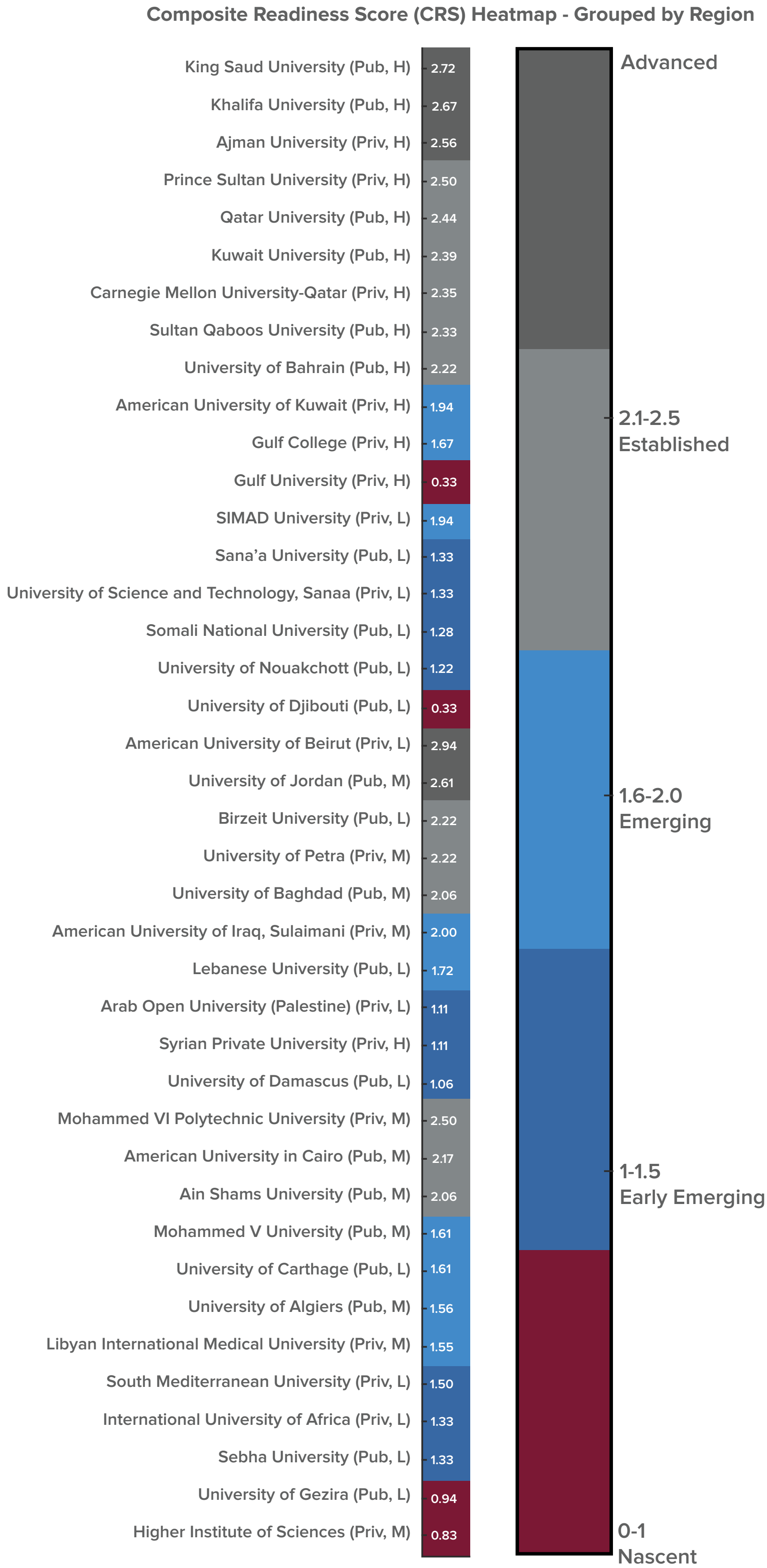
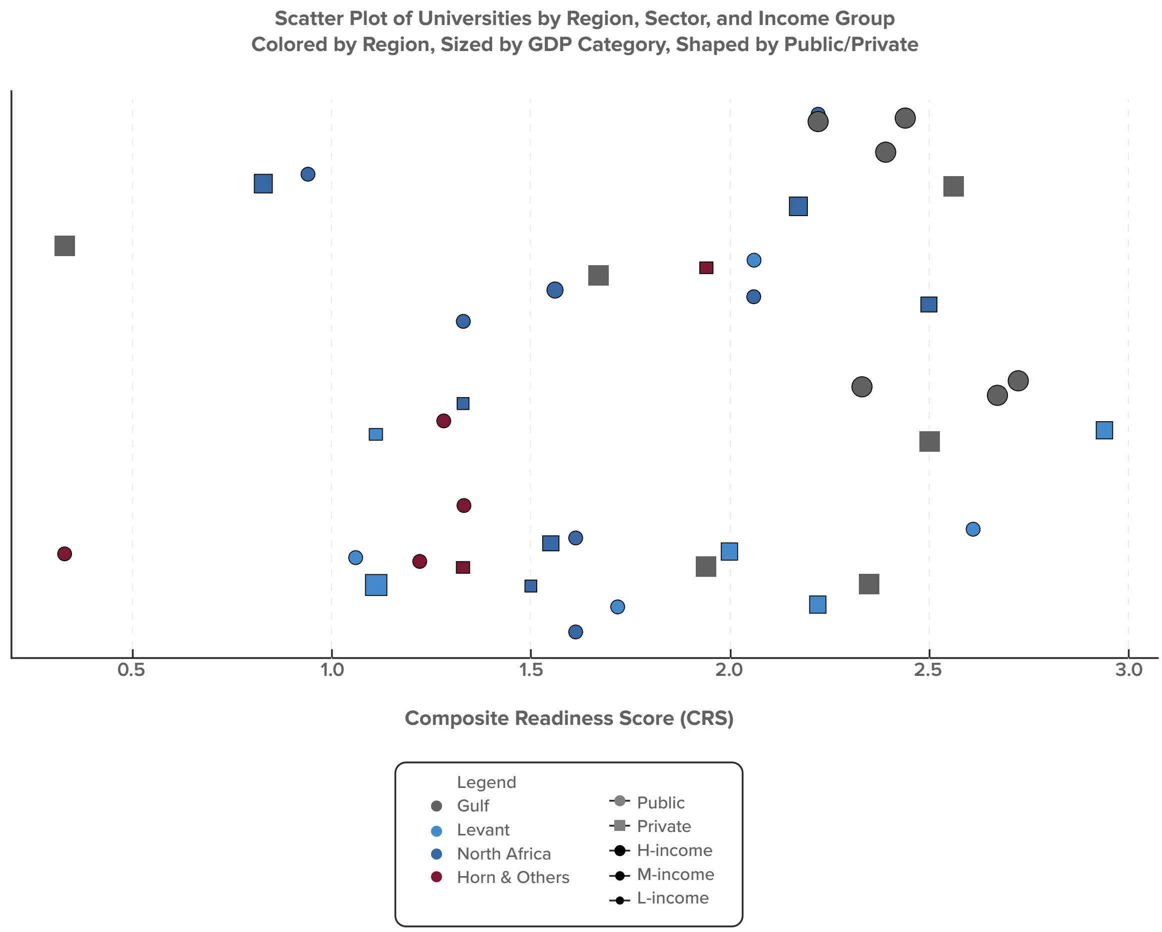


Figure 2 uses a five-level color scale (nascent to advanced) to visualize CRS variation. Institutions are organized by region (Gulf, Levant, North Africa, Horn & Others), with labels indicating public/private status and national income group. The heatmap highlights pronounced regional clustering and wide intra-regional variation.

Figure 3. Scatter plot of universities by region, income group, and sector, plotted against Composite Readiness Scores (CRS).



In Figure 3, each point represents a university: colors denote region, marker shape indicates sector (public/private), and point size reflects national income level. The distribution spans the 0–3 CRS range and illustrates how regional location, income level, and sector align with readiness differences.

The scatter plot reveals several structural patterns. Gulf-region universities generally cluster toward the higher end of the readiness distribution, although notable exceptions exist—such as Gulf University and several private institutions that score below regional averages. Public universities in middle-income countries—such as the University of Jordan, Birzeit University, and the University of Bahrain—perform strongly despite limited national resources, suggesting that institutional strategy and governance often outweigh macro-economic context. Low-income-state universities are concentrated in the lower readiness bands, reflecting structural constraints including weaker digital infrastructure and limited industry engagement. The figure also demonstrates that private status alone does not guarantee high readiness: some private Gulf institutions fall below the median, while several public universities in middle-income settings outperform them.

While formal statistical testing (e.g., ANOVA) was not conducted due to the descriptive and benchmarking nature of the study, the scatter plot provides clear visual evidence of group-level differences. High-income Gulf universities cluster in the upper band, while institutions in fragile or low-income states appear in the lower band. Similarly, several middle-income public universities fall in the upper half of the distribution, whereas some private institutions in high-income countries are positioned below the median. Given the small and uneven group sizes across income and sector categories, visual inspection offers a more appropriate interpretive basis than inferential testing.

Across the region, performance varies not only by income but also by institutional type. Public universities in high-income states—such as Qatar University, Khalifa University, and King Saud University—consistently outperform many private counterparts, despite access to similar national resources. For example, Gulf University (Bahrain) records one of the lowest composite scores (0.28), while Prince Sultan University (Saudi Arabia) reaches an intermediate level (2.5). This underscores that national wealth and private status do not automatically translate into institutional readiness; governance structures, mission orientation, and public investment in faculty and research appear to be stronger determinants of performance (Altbach & Salmi, 2022; ESCWA, 2023). Similarly, middle-income public universities—such as Birzeit University and the University of Jordan—demonstrate notable capacity despite fiscal limitations, benefiting from strong academic traditions, donor partnerships, and alignment with national innovation systems.

Strengths and Capacity Gaps

The results reveal clear strengths and gaps across Arab universities. Strengths are concentrated in flagship institutions with robust Human and Structural Capital, often tied to international visibility, bilingual instruction, and integration into global research networks. However, many universities remain constrained by weak Relational Capital, limited industry engagement, and underdeveloped infrastructure. These gaps underline the importance of system-level policies that can support institutions beyond individual excellence.

While the benchmarking results highlight structural strengths and persistent gaps across institutions, these patterns require deeper contextual interpretation. To address this, a qualitative sub-sample of universities was analyzed, focusing on high-value documents such as curricula, strategic plans, and partnership agreements. The following section synthesizes these qualitative insights, which provide a richer understanding of how institutions frame and enact their readiness strategies.

Qualitative Findings

The qualitative analysis examined six universities representing high, medium, and low levels of AI readiness: the American University of Beirut (AUB, Lebanon), Birzeit University (BZU, Palestine), Khalifa University (KU, UAE), Sebha University (SEU, Libya), the University of Djibouti (UDJ, Djibouti), and the University of Nouakchott (UN, Mauritania). Evidence was drawn from high-value documents such as program catalogs, strategic plans, research center descriptions, and partnership announcements, coded against Human, Structural, and Relational Capital indicators. The qualitative findings are organized around the three domains of the IC framework—Human, Structural, and Relational Capital—providing a structured interpretation of how each institution articulates and signals its AI readiness.

Human Capital

Curriculum evidence reveals sharp contrasts in Human Capital across the six institutions. AUB and KU demonstrate comprehensive and structured AI pathways, offering degrees or concentrations in AI, data science, or related computing fields. Both institutions publicly document faculty development initiatives, bilingual instruction, and the existence of specialized computing or data science schools. BZU shows moderate but visible engagement, offering programs in computer science and engineering with emerging AI-related courses and departmental research interests. AUB and BZU also document bilingual or English-medium instruction in their computing and STEM programs, consistent with the HC3 indicator in the coding framework.

SEU presents partial evidence of computing-related teaching capacity, but with limited AI-specific content or visible faculty training. In low-readiness institutions such as the UDJ and UN, available documents indicate only general science or engineering programs, with minimal reference to AI, data science, or related pedagogical initiatives. Program pages are sparse, with no evidence of recently introduced AI courses or training.

Overall, institutions with higher Human Capital readiness signal curriculum innovation and faculty development more transparently, while lower-readiness institutions maintain static or minimally described offerings. While Human Capital reflects the composition and direction of academic programs and faculty capacity, Structural Capital sheds light on the institutional infrastructure and research environment underpinning these efforts.

Structural Capital

KU exhibits the strongest structural capacity among the six cases, with public documentation of advanced laboratories, AI research groups, Scopus-indexed output, and digital research platforms. AUB also demonstrates high structural readiness, maintaining HPC resources, institutional repositories, and multiple research centers with active publication profiles.

BU offers modest yet functional infrastructure, including computing facilities and research groups, but lacks large-scale AI laboratories or advanced digital systems found in higher performers. SEU provides partial evidence of basic laboratories and digital services but does not demonstrate specialized AI infrastructure or consistent research visibility.

The weakest structural capacity appears in UDJ and UN, both of which reveal only generic laboratories, limited research output, and minimal digital infrastructure. These patterns mirror their low quantitative Structural Capital scores and highlight infrastructure as a major constraint. Structural readiness, however, does not fully explain institutional positioning. A third dimension—Relational Capital—captures the partnerships, collaborations, and external engagements that shape universities' visibility and integration in broader innovation ecosystems.

Relational Capital

Relational Capital varies significantly across the sample. KU and AUB demonstrate the strongest external engagement, with documented collaborations involving global technology firms, national innovation agencies, and active alumni networks. Their visibility is reinforced by international rankings, participation in regional and global forums, and in AUB's case, strong alumni visibility through publicly accessible LinkedIn profiles and international employment signals (RC3).

BU shows emerging relational capacity, with documented partnerships, community engagement initiatives, and moderate alumni visibility. SEU presents limited but identifiable engagement through local partnerships and publicly shared collaboration announcements.

In contrast, UDJ and UN show weak relational capacity. Their partnership references are sporadic, often lacking detail, and appear largely transactional. Alumni visibility is minimal, and there is no evidence of alignment with national or regional AI strategies. These gaps correspond directly with their low relational scores and reinforce the structural disadvantage faced by universities in fragile or low-resource contexts. Across the six universities, readiness appears less determined by national wealth than by institutional governance, curriculum strategy, and the strength of external partnerships.

Interpretation

The quantitative and qualitative components of this study draw on related but analytically distinct forms of publicly available evidence. The quantitative benchmarking applies a structured rubric to 36 universities, scoring predefined indicators of Human, Structural, and Relational Capital (e.g., program offerings, research visibility, partnerships) in a comparable and replicable manner (Creswell & Creswell, 2018). The qualitative analysis, in contrast, examines a smaller purposive sub-sample of six universities through deeper textual evidence—including strategic plans, program catalogs, and descriptions of research or partnership initiatives—using deductive thematic coding aligned with the IC framework (Nowell et al., 2017; Polkinghorne, 2005). While both strands rely on publicly accessible documents due to the study design, they serve different methodological purposes: the quantitative provides breadth and standardization, whereas the qualitative provides depth, interpretation, and contextual meaning. This distinction mitigates risks of Common Method Bias (Podsakoff et al., 2003) by ensuring that each strand contributes unique analytical value before integration.

Taken together, the two strands reveal a coherent three-tiered readiness structure across the region. Quantitatively, universities such as AUB, QU, and KU consistently score at the top of the 0–3 scale across intellectual capital dimensions. Middle-performing institutions—including CMU-Q, UM6P, PSU, BZU, and SQU—demonstrate structured but variably scaled AI-related programs, laboratories, and partnerships. Low-readiness institutions such as the UDJ and UN cluster at the bottom end, with minimal curriculum integration, limited research infrastructure, and shallow partnership networks.

The qualitative findings help explain the mechanisms behind these quantitative differences. High-readiness institutions articulate deliberate strategies for expanding AI and digital capacities, including the introduction of new degree programs, establishment of advanced laboratories, and cultivation of multi-layered partnerships with national innovation bodies and global technology firms. Middle-tier institutions exhibit emerging trajectories: for example, PSU's AIDA and RIOTU labs or CMU-Q's high-quality but small-scale computing offerings reflect strategic priorities that are visible but not yet institution-wide. Low-readiness universities (UDJ, UN) display generic program descriptions, minimal research presence, and largely transactional or undeclared partnerships—patterns consistent with their low structural and relational scores. These qualitative insights therefore clarify ***why*** quantitative variation exists by revealing institutional behaviors, strategic orientations, and transparency practices.

Across both sets of evidence, several cross-cutting interpretations emerge. Although high-income contexts often correlate with stronger readiness, the results show that macro-level wealth is not determinative. Institutional governance, strategic alignment, and integration into national innovation systems matter more than country income levels (Altbach & Salmi, 2022; Marginson, 2022). Limited online disclosure may also contribute to lower scores for some institutions, since the public-data methodology can only capture what universities make visible. This helps explain why certain private institutions in wealthy states—such as GU—appear weak, while public universities in middle-income settings—such as the UJ or BU—perform comparatively well due to stronger academic traditions, donor engagement, and policy alignment. These findings are consistent with global IC research showing that structural and relational investments, rather than resource availability alone, drive institutional capacity (Secundo et al., 2020; Kianto et al., 2022).

Overall, by analyzing quantitative scores and qualitative narratives separately and then integrating them, the study provides a more robust interpretation of the strategic, structural, and contextual factors shaping AI readiness in Arab universities. This mixed-methods structure enhances validity and mitigates risks of Common Method Bias by ensuring that the qualitative component does not merely replicate the quantitative scoring, but instead provides interpretive depth and explanatory insight into institutional trajectories across the region.

Discussion

The findings of this study align with international research showing that universities with stronger governance coherence, strategic investment, and visibility tend to exhibit higher readiness across Intellectual Capital dimensions (Secundo et al., 2020; Kianto et al., 2022). In the Arab region, this was evident in institutions such as QU and AUB, where the qualitative data revealed integrated curriculum pipelines, dedicated research centers, and sustained industry partnerships. These patterns reflect well-established global trends in which strategic IC investments enhance institutional competitiveness (Bezhani, 2010; Cuozzo et al., 2017).

The results also reinforce international literature on curriculum reform. As seen in ***Human Capital subsection of the Qualitative Findings***, universities with systematic AI curricular integration—such as AUB, QU, and CMU-Q—demonstrate clearer alignment with emerging workforce demands, echoing Abbasi's (2024) findings on the relationship between curriculum design and graduate preparedness. In contrast, lower-performing institutions offered generic or outdated curriculum information, and their limited faculty development opportunities align with Hadi and AlShaikh-Hasan's (2025) argument that curriculum reform requires parallel investment in pedagogy and professional learning.

Structural and relational gaps identified in the findings further mirror global concerns about the uneven distribution of digital capacity (UNESCO, 2017; ESCWA, 2023). The study's Relational Industry Scores presented in the ***Industry Collaborations and External Engagement*** section and summarized in ***Appendix C,*** show that lower-performing institutions tend to engage in transactional rather than strategic partnerships, limiting their access to innovation networks. This echoes Marginson's (2022) view that resource concentration in elite institutions perpetuates systemic inequalities.

The qualitative evidence also revealed instances of symbolic signaling—the strategic use of visibility through rankings, new program announcements, and partnership publicity. While such practices strengthen relational positioning, the findings suggest that signaling does not always correspond to deeper structural capacity, particularly among emerging universities. This aligns with Bourdieu's (1991) conceptualization of symbolic capital and highlights the risk of over-relying on public visibility as a proxy for readiness.

Concerns about graduate competencies also emerged indirectly. Only a subset of universities showed evidence of interdisciplinary, ethics-focused, or applied AI learning opportunities reported in the ***Faculty Capacity, Curriculum, and AI-related Training*** section, aligning with global calls for education systems to move beyond rote learning (George, 2023). Without such competencies, graduates—particularly in lower-income settings—risk further exclusion from rapidly evolving labor markets (World Bank, 2022; WEF, 2023).

Equity considerations surface indirectly through the Structural and Relational Capital results. Universities with low readiness scores showed limited curriculum transparency, minimal alumni visibility, and weak engagement in regional AI ecosystems, as reflected in the ***Faculty Capacity, Curriculum, and AI-related Training, Industry***

Collaborations and External Engagement, and ***Relational Capital*** findings. Although the study did not directly measure gender, language, or socioeconomic inequities, international evidence indicates that such structural gaps disproportionately affect underrepresented groups (UNESCO, 2017; ESCWA, 2023). This raises concerns that uneven AI readiness may exacerbate existing inequalities unless inclusive strategies are prioritized.

Taken together, the findings point to differentiated pathways for strengthening AI readiness. High-performing institutions can act as anchors in regional ecosystems, supporting middle-tier universities through resource sharing and mentorship. Meanwhile, targeted national and regional policies are needed to support low-readiness institutions, where structural and relational deficits limit progress. These interpretations expand beyond the descriptive results presented earlier, explaining ***why*** readiness varies and ***how*** these variations are likely to shape institutional trajectories across the region.

Policy Implications

The results point to urgent policy considerations for higher education systems in the Arab region. The benchmarking and qualitative evidence confirm that a three-tiered structure has emerged, with a small group of flagship universities consolidating global competitiveness, a limited number of institutions showing emerging capacity, and many universities in fragile or resource-constrained contexts remaining at nascent levels.

This polarization has several implications. First, without coordinated regional action, the gap between leaders and lagging institutions will widen, leaving entire countries at risk of exclusion from the digital and knowledge economy. Second, curriculum gaps highlight the urgent need for national ministries to align accreditation and quality assurance systems with labor market needs by mandating AI and data science content across multiple disciplines. Third, the limited infrastructure in weaker institutions underscores the importance of pooled investment in regional laboratories and research centers that can serve multiple countries, particularly those affected by fragility. Finally, the uneven distribution of relational capital shows that international partnerships alone cannot drive readiness; governments and Arab countries must take a more active role in creating regional platforms for collaboration, resource sharing, and policy coordination. Unless inclusivity is built into these reforms, existing divides—by gender, language, or socioeconomic status—are likely to deepen.

Priority 1 – Update University Curricula

Universities should expand teaching programs to embed AI and Data Science across disciplines, not only within computer science. All programs could integrate AI into decision-making, while social sciences could emphasize AI ethics and governance. Engineering programs should strengthen applications in design and automation. Ministries of education have a central role in ensuring accreditation frameworks reflect labor market needs, while universities are responsible for developing and delivering courses. Leading institutions such as AUB, HBKU, and QU can share resources and course templates with emerging and smaller institutions. Arab countries can facilitate regional curriculum guidelines to ensure consistency and quality. Abbasi (2024) underscores that embedding AI across disciplines is essential for graduate employability, while George (2023) emphasizes including ethics and interdisciplinarity to prepare students for societal impacts of AI.

Priority 2 – Build and Share Research Facilities

Governments and donors should prioritize investment in laboratories, digital platforms, and collaborative research centers that can be shared across multiple universities. This is particularly urgent in low-income states, where infrastructure is minimal. Regional best practices already illustrate the transformative impact of shared facilities. For example, the Qatar Computing Research Institute (QCRI) and the Huawei–Qatar University AI Lab operate as national hubs whose resources—high-performance computing, AI labs, and sectoral research platforms—are accessed by multiple universities and government agencies.

Similarly, KU's joint AI and clean-energy labs with Alibaba Cloud, and the EPFL–UM6P "Excellence in Africa" partnership in Morocco, demonstrate how shared regional facilities accelerate curriculum development, faculty training, and applied research. These models show how smaller institutions benefit when anchor universities host centralized research infrastructure that is open to regional partners. Establishing comparable Arab-region centers of excellence, equipped with advanced computing and training facilities, would allow universities in fragile or low-income contexts—such as Djibouti, Yemen, and Mauritania—to access resources they cannot afford to build individually.

Regional centers of excellence—equipped with advanced computing, AI laboratories, and high-performance systems—would allow smaller institutions to benefit from shared resources. Universities must take responsibility for maintaining facilities and ensuring open access, while Arab countries can coordinate cross-border collaboration and resource sharing. Building such facilities also ensures students and faculty gain practical exposure that enhances employability and innovation potential (World Bank, 2022; World Economic Forum, 2023).

Priority 3 – Grow University Partnerships

Universities should strengthen cooperation with industry, international organizations, and alumni networks to ensure that teaching and research remain relevant to technological change. Technology companies such as Huawei, Microsoft, and Omdena can contribute expertise, internships, and technology transfer. Several universities in the region already demonstrate how these partnerships work in practice.

For example, QU and HBKU host Huawei-supported AI and ICT labs, while KU collaborates with Alibaba Cloud and Siemens on applied AI research and talent development. PSU partners with Omdena through applied AI challenges, and AUC and Ain Shams University work with Microsoft on digital skills training and cybersecurity initiatives. Alumni networks also provide mentorship and employment pathways, as seen in AUB's active alumni groups and ACM-affiliated networking events, which link students with industry professionals.

Governments can encourage these partnerships through policy incentives, while Arab countries can facilitate cross-border cooperation and joint projects. Importantly, these partnerships should not only be transactional but should contribute to inclusive workforce pipelines that benefit both elite and low-income-state universities.

Priority 4 – Support Weaker Universities

Smaller universities, particularly in low-income states such as Djibouti, Yemen, and Mauritania, need targeted support so they are not left behind. Donors and governments should provide dedicated funding for integrating AI related skills in their curricula and laboratories, while Arab countries can coordinate regional mentorship programs

Flagship universities—including AUB and KU—should serve as mentors by offering technical assistance, training, and joint initiatives. Examples from within the qualitative sample illustrate how such knowledge-exchange mechanisms already operate in practice. KU's model of structured AI laboratories and interdisciplinary research groups demonstrates how advanced institutions can support others through co-designed projects, shared training materials, and access to research infrastructure. AUB's engagement with partners such as EBRD and ALI, combined with its active alumni networks, shows how universities can leverage external expertise to strengthen curriculum development, professional training, and applied research in neighboring institutions.

Faculty and student mobility programs—already evident in SEU's participation in Erasmus+ exchanges—provide a concrete template for scalable knowledge transfer. Extending similar short-term exchanges, joint workshops, and co-taught modules between high-performing institutions (AUB, KU) and lower-capacity universities (UD, UN, SEU) would accelerate capacity-building. These practices represent feasible, regionally grounded models for university partnerships and cross-institutional knowledge exchange.

Faculty and student exchanges—funded by donors and facilitated by Arab countries—can help transfer knowledge and build capacity. These efforts must deliberately target inclusion, ensuring women and underrepresented groups benefit from new opportunities (UNESCO, 2017; ESCWA, 2023).

Priority 5 – Align Policies with Education Goals

Ministries of education and higher education should align national policies and accreditation frameworks with the development of AI in higher education. Governments should include AI readiness indicators in national quality assurance systems, requiring universities to report annually on progress. At the regional level, Arab countries should oversee a monitoring framework that tracks progress, promotes accountability, and highlights best practices.

Alignment with workforce development strategies will ensure that reforms are not siloed in education policy but contribute directly to employability and innovation goals. For instance, KU's integration of AI laboratories and applied research groups with national technology priorities in the UAE provides a practical illustration of how linking curriculum and research to workforce needs strengthens graduate pathways into AI, energy, and digital sectors. Similarly, AUB's partnerships with organizations such as EBRD and ALI, which focus on upskilling and industry-aligned training, show how universities can connect academic reform to labor-market demand in ways that improve employability outcomes.

Priority 6 – Ensure Inclusion and Responsibility

Universities should ensure that AI education reflects values of fairness, responsibility, and sustainability. As George (2023) argues, preparing students for an AI-driven world requires integrating ethics, equity, and interdisciplinary learning into curricula. Without such measures, existing inequalities may be exacerbated, leaving under-resourced institutions and vulnerable groups at a greater disadvantage.

Governments can support this effort by creating scholarship programs and national inclusion targets. Arab countries can develop regional guidelines for gender equality and the ethical use of AI. Donors can provide funding for programs that expand access to excluded groups and link AI education to the Sustainable Development Goals (SDGs). To ensure that public universities can keep pace with better-resourced private institutions, ministries of education should also introduce targeted measures such as dedicated funding lines for digital infrastructure, national faculty development schemes, and incentives for curriculum modernization. Public universities—especially in low-income or fragile contexts—require predictable public investment to upgrade laboratories, strengthen digital systems, and support faculty training. Ministries of education can further propel this effort by embedding AI-readiness indicators into accreditation and quality assurance standards, ensuring that all institutions—regardless of ownership—are accountable for progress in curriculum, skills development, and inclusion.

Conclusion

This study provides the first regional benchmarking of AI readiness in higher education institutions across the Arab region. By combining quantitative and qualitative evidence, it identifies a clear three-tiered structure: leaders such as AUB, HBKU, and QU that demonstrate comprehensive readiness; emerging institutions like PSU that are building capacity; and low-income universities such as GU and UDJ that remain constrained.

The findings highlight both opportunities and risks. Flagship institutions can act as anchors of innovation and regional collaboration, but unless support is urgently extended to weaker universities, polarization will deepen and limit the region's collective potential. The recommendations presented in this report offer a pathway forward by focusing on curriculum reform, research investment, partnerships, equity, policy alignment, and inclusivity.

As Arab countries and their partners consider next steps, the evidence suggests that sustained collaboration, resource sharing, and strategic policy design are essential for ensuring that all universities — regardless of size or location — are equipped to prepare students and societies for the age of Artificial Intelligence.

Appendix A

Appendix A presents the universities included in both the quantitative and qualitative components of the study, along with the rationale for their inclusion.

Table A1. Quantitative sample of universities

Country	University	Type	Website	Justification for Inclusion	Year Founded	GDP2 (H/M/L)
Algeria	University of Algiers	Public	http://www.univ-alger.dz/	Oldest and largest public university with strong national relevance	1909	M
Algeria	Higher Institute of Sciences	Private	https://his.edu.dz/	First accredited private multidisciplinary university	N/A	M
Bahrain	University of Bahrain	Public	http://www.uob.edu.bh/	Main national university with STEM programs	1986	H
Bahrain	Gulf University	Private	http://www.gulfuniversity.edu.bh/	Private university offering IT/engineering degrees	N/A	H
Comoros	University of the Comoros	Public	http://www.univ-comores.km/	Website often down	2003	L
Comoros	*Private institution*	Private	N/A	No major private institutions found with an active online presence	N/A	N/A
Djibouti	University of Djibouti	Public	http://www.univ-djibouti.dj/	National university with online data available	2006	L
Djibouti	*Private institution*	Private	N/A	No private institutions identified online	N/A	L
Egypt	Ain Shams University	Public	https://www.asu.edu.eg/ar	Fully functional bilingual website with strong programs in computer science and AI	1950	M
Egypt	American University in Cairo	Private	http://www.aucegypt.edu/	Highly ranked private university with AI programs	1919	M
Iraq	University of Baghdad	Public	http://www.uobaghdad.edu.iq/	Largest and most prominent public university	1957	M
Iraq	American University of Iraq, Sulaimani	Private	http://www.auis.edu.krd/	Private university with international affiliations	2006	M
Jordan	University of Jordan	Public	http://www.ju.edu.jo/	Flagship public university with strong tech faculty	1962	M
Jordan	University of Petra	Private	http://www.uop.edu.jo/	Private university with IT and AI-related programs	1991	M
Kuwait	Kuwait University	Public	http://www.ku.edu.kw/	Primary public university with accessible online data	1966	H

Income thresholds (World Bank, 2024):

- High-income: ≥ USD 14,005 GNI per capita
- Upper-middle-income: USD 4,466–14,005
- Lower-middle-income: USD 1,146–4,465
- Low-income: ≤ USD 1,145

Kuwait	American University of Kuwait	Private	http://www.auk.edu.kw/	Accredited private university with tech curriculum	2003	H
Lebanon	Lebanese University	Public	http://www.lu.edu.lb/	National public university with wide coverage	1951	Lower middle
Lebanon	American University of Beirut	Private	http://www.aub.edu.lb/	Regionally prominent university with AI initiatives	1866	Lower middle
Libya	Libyan International Medical University	Private	https://limu.edu.ly/	It is the only Libyan private university with a fully functional and regularly updated online presence that provides sufficient publicly available evidence	2007	Upper middle
Libya	Sebha University	Public	http://www.sbu.edu.ly/	Representative public university in southern Libya	1976	Upper middle
Mauritania	University of Nouakchott	Public	http://www.univ-nkc.mr/	Primary public university with online visibility	1981	Lower middle
Mauritania	*Private institution*	Private	N/A	No private institutions with adequate web presence	N/A	N/A
Morocco	Mohammed V University	Public	http://www.um5.ac.ma/	Historic public university with research output	1957	M
Morocco	Mohammed VI Polytechnic University	Private	http://www.um6p.ma/	Private university with AI/ digital research	2013	M
Oman	Sultan Qaboos University	Public	http://www.squ.edu.om/	National public university with STEM programs	1986	H
Oman	Gulf College	Private	http://www.gulfcollege.edu.om/	Private college with business and IT programs	1990	H
Palestine	Birzeit University	Public	http://www.birzeit.edu/	Well-ranked Palestinian public university	1972	Lower middle
Palestine	Arab Open University (Palestine)	Private	http://www.aou.edu.ps/	Accessible online programs and regional reach	2002	Lower middle
Qatar	Qatar University	Public	http://www.qu.edu.qa/	Main national public university	1973	H
Qatar	Carnegie Mellon University Qatar	Private	https://www.qatar.cmu.edu/	Has a recognized parent institution, offering rigorous U.S.-accredited undergraduate programs and publicly available data across enrollment, programs, and institutional standing	2010	H
Saudi Arabia	King Saud University	Public	http://www.ksu.edu.sa/	Top public university with advanced research centers	1957	H
Saudi Arabia	Prince Sultan University	Private	http://www.psu.edu.sa/	Well-ranked private university with tech focus	1999	H
Somalia	Somali National University	Public	http://www.snu.edu.so/	Flagship national public university	1954	Lower middle
Somalia	SIMAD University	Private	http://www.simad.edu.so/	Private university offering business and IT degrees	1999	Lower middle
Sudan	University of Gezira	Public	https://uofg.edu.sd	Established institution; broad range of faculties, strong research relevance	1975	Lower middle

Sudan	International University of Africa	Private	http://www.iua.edu.sd/	Private Islamic-focused university with tech streams	1977	Lower middle
Syria	University of Damascus	Public	http://www.univ-damascus.sy/	Oldest public university in Syria	1923	Lower middle
Syria	Syrian Private University	Private	http://www.spu.edu.sy/	Private university with accessible web content	2005	Lower middle
Tunisia	South Mediterranean University	Private	www.smu.tn	Private English-medium institution in Tunis with active AI and tech programs	2002	Lower middle
Tunisia	University of Carthage	Public	http://www.ucar.rnu.tn/	Public university with technical programs	1988	Lower middle
UAE	Khalifa University	Public	http://www.ku.ac.ae/	Top-ranked public university for AI and STEM	2007	H
UAE	Ajman University	Private	http://www.ajman.ac.ae/	Private university with accredited programs	1988	H
Yemen	Sana'a University	Public	http://www.sanauniv.edu.ye/	Primary public university in Yemen	1970	Lower middle
Yemen	University of Science and Technology, Sanaa	Private	http://www.usst.edu.ye/	Private institution with tech offerings	1994	Lower middle

Table A2. Qualitative sub-sample of six universities and rationale for selection.

University	Country	Rationale for Selection
American University of Beirut	Lebanon	High performer (CRS 2.94)
Birzeit University	Palestine	Medium performer (CRS 2.22)
University of Djibouti	Djibouti	Low performer (CRS 0.33)
Khalifa University	UAE	High performer (CRS 2.66)
Sebha University	Libya	Medium performer (CRS 1.33)
University of Nouakchott	Mauritania	Low performer (CRS 1.22)

Figure 2 uses a five-level color scale (nascent to advanced) to visualize CRS variation. Institutions are organized by region (Gulf, Levant, North Africa, Horn & Others), with labels indicating public/private status and national income group. The heatmap highlights pronounced regional clustering and wide intra-regional variation.

Appendix B: Composite readiness scores (CRS) across universities

Table B summarizes composite readiness scores, providing a cross-institutional snapshot of capacity levels across the region

Note. Composite Readiness Scores (CRS) represent the arithmetic mean of Human, Structural, and Relational Capital sub-scores. Each dimension was pre-scored on a normalized 0–3 scale and equally weighted (1/3) in the composite calculation.

Table B. Composite Readiness Scores

University	Country	Type	GDP (L/M/H)	HC	SC	RC	CRS
Ain Shams University	Egypt	Public	M	2.0	2.0	2.17	2.06
Ajman University	UAE	Private	H	2.5	2.33	2.83	2.56
American University in Cairo	Egypt	Private	M	2.5	2.17	1.83	2.17
American University of Beirut	Lebanon	Private	Lower middle	3.0	3.0	2.83	2.94
American University of Iraq, Sulaimani	Iraq	Private	M	2.5	1.67	1.83	2.0
American University of Kuwait	Kuwait	Private	H	2.0	2.0	1.83	1.94
Arab Open University (Palestine)	Palestine	Private	Lower middle	1.5	1.0	0.83	1.11
Birzeit University	Palestine	Public	Lower middle	2.5	2.0	2.17	2.22
Gulf College	Oman	Private	H	1.5	2.0	1.5	1.67
Gulf University	Bahrain	Private	H	0.0	0.67	0.33	0.33
Carnegie Mellon University-Qatar	Qatar	Private	H	2.25	2.33	2.43	2.35
Higher Institute of Sciences	Algeria	Private	M	1.0	1.0	0.5	0.83
International University of Africa	Sudan	Private	Lower middle	2.0	1.67	0.33	1.33
Khalifa University	UAE	Public	H	2.0	3.0	3.0	2.67
King Saud University	Saudi Arabia	Public	H	2.5	2.67	3.0	2.72
Kuwait University	Kuwait	Public	H	2.5	2.33	2.33	2.39
Lebanese University	Lebanon	Public	Lower middle	2.0	1.33	1.83	1.72
Libyan International Medical University	Libya	Private	Upper middle	1.5	1.33	1.83	1.55
Mohammed V University	Morocco	Public	M	1.5	1.67	1.67	1.61
Mohammed VI Polytechnic University	Morocco	Private	M	2.5	2.67	2.33	2.5

Prince Sultan University	Saudi Arabia	Private	H	2.5	2.67	2.33	2.5
Qatar University	Qatar	Public	H	2.0	2.67	2.67	2.44
SIMAD University	Somalia	Private	Lower middle	2.0	2.0	1.83	1.94
Sana'a University	Yemen	Public	Lower middle	2.0	1.0	1.0	1.33
Sebha University	Libya	Public	Lower middle	1.5	1.33	1.17	1.33
Somali National University	Somalia	Public	Lower middle	1.0	1.67	1.17	1.28
South Mediterranean University	Tunisia	Private	Lower middle	1.5	1.33	1.67	1.5
Sultan Qaboos University	Oman	Public	H	2.0	2.33	2.67	2.33

Appendix C: Qualitative Findings

Appendix C presents the full qualitative evidence underlying the deductive thematic analysis described in Section 4.7. The appendix is organized into three tables that together provide a transparent account of how publicly available documents were identified, coded, and synthesized across the Human, Structural, and Relational Capital dimensions.

Table C1. Qualitative results by intellectual capital dimension

University	Country	Human Capital	Structural Capital	Relational Capital	Interpretation
American University of Beirut (AUB)	Lebanon	Structured AI curriculum: AI & Data Science diploma, AI program in ECE, new School of Computing & Data Sciences.	ScholarWorks repository, Scopus publications, HPC computing resources, Moodle LMS.	Partnerships with EBRD/ALI, ACM alumni events, LinkedIn employment evidence, QS ranking visibility.	Balanced strengths across all IC dimensions, with strong curriculum innovation and external linkages.
Birzeit University (BZU)	Palestine	Computer science & engineering programs with emerging AI content	Functional labs, moderate research presence	Community & academic partnerships; moderate alumni visibility	Medium readiness with emerging curriculum and partnerships
Khalifa University (KU)	UAE	Comprehensive engineering & computing degrees; faculty research profiles	Advanced labs, AI groups, Scopus output	Strong collaborations with national innovation bodies & global tech firms	High structural & relational capacity; regional leader
Sebha University (SEU)	Libya	Basic computing programs; limited AI-specific content	Basic labs; limited digital platforms	Limited partnerships; local engagement only	Medium–low readiness, constrained by resources
University of Djibouti (UDJ)	Djibouti	General science faculty; no AI programs	Basic laboratory infrastructure; low research output	Minimal partnerships; weak alumni visibility	Low readiness across all dimensions
University of Nouakchott (UN)	Mauritania	General science & engineering programs; no AI content	Basic laboratory infrastructure; low research visibility	Sparse partnerships; low transparency	Low–nascent readiness

Table C1 summarizes the qualitative findings for the six purposively selected universities. Each entry consolidates two to three high-value excerpts per Intellectual Capital dimension, capturing the main signals related to curriculum, infrastructure, and partnerships. These summaries reflect the interpreted qualitative patterns for each institution and support cross-case comparison.

Table C2. Public Sources by Capital Type and Indicator

University	Capital Type	Indicator	Source Type	URL
AUB	Human Capital	AI Curriculum / Programs	Program Catalogue	https://www.aub.edu.lb/Registrar/Pages/University-Catalogue.aspx
AUB	Human Capital	AI/DS Diploma	Program Page	https://www.aub.edu.lb/fas/cs/pages/aidiploma.aspx
AUB	Structural Capital	Strategic Plan / Infrastructure Priorities	Strategic Plan	https://www.aub.edu.lb/President/Documents/vital/VITAL-2030.pdf
AUB	Structural Capital	Research Centers / Digital Infrastructure	Press Release	https://www.aub.edu.lb/articles/Pages/school-of-computing-and-data-sciences.aspx
AUB	Relational Capital	Partnerships / MoUs	Partnership Map	https://www.aub.edu/oip/Documents/agreements-map.pdf
BZU	Human Capital	Curriculum / Programs Overview	Strategic Plan Summary	https://www.birzeit.edu/sites/default/files/upload/strategic_plan_summary_2022-2027.pdf
BZU	Structural Capital	Strategic Plan (Infrastructure/IT)	Strategic Plan	https://www.birzeit.edu/sites/default/files/strategic_plan_2017-2022.pdf
BZU	Relational Capital	Partnership Signals	OpenMed Roadmap	https://www.openmedproject.eu/wp-content/uploads/2017/10/OPENMED-ROADMAP-BIRZEIT.pdf
KU	Human Capital	Computer Science / AI Programs	Undergraduate Catalog	https://www.smartcatalogiq.com/en/catalogs/khalifa-university/2024-2025
KU	Structural Capital	Research Infrastructure	Research Page	https://www.ku.ac.ae/research
KU	Relational Capital	Strategic Partnerships	Partnership Page	https://www.ku.ac.ae/research/commercialization-and-enterprise/strategic-partnerships
SEU	Human Capital	Basic Program Offerings	Official Website	https://su.edu.ly/
SEU	Structural Capital	Institutional Profile / Research Visibility	Wikipedia Page	https://en.wikipedia.org/wiki/Sebha_University
SEU	Relational Capital	External Presence	QS Profile	https://www.topuniversities.com/universities/sebha-university
UDJ	Human Capital	Programs / Faculties	University Website	https://www.univ-djibouti.dj/
UDJ	Structural Capital	Research Center (CEALT)	Research Center Page	https://www.univ-djibouti.dj/recherche/cealt/
UDJ	Relational Capital	Collaborations / MoUs	CEALT News	https://www.univ-djibouti.dj/actualites/semaine-de-linnovation/
UN	Human Capital	Program Structures	Wikipedia	https://en.wikipedia.org/wiki/University_of_Nouakchott_Al_Aasriya
UN	Structural Capital	Research Units / Labs	Ministry of Higher Education	https://www.mesrs.gov.mr/recherche/structures_de_recherche
UN	Relational Capital	Partnerships	AUF Profile	https://www.auf.org/membres/?search_university=Nouakchott

Table C2 lists the publicly available documents used as evidence in the coding process. The table records the university, IC dimension, indicator, source type, and URL, mirroring the structured evidence checklist used during analysis. This table provides full traceability and shows the exact sources used in the qualitative coding.

Table C3. Thematic Coding Chart (Deductive Analysis)

Theme (IC Dimension)	Sub-theme / Indicator	Code	Example Evidence Extract	University
Human Capital (HC)	Curriculum breadth	HC1	Offers BS in Computer Science with AI and Data Science concentration	AUB, KU, CMU-Q
Human Capital (HC)	Faculty development / training	HC2	Faculty receive annual training in data science and digital pedagogy	AUB
Human Capital (HC)	Bilingual instruction	HC3	English is the primary medium of instruction across STEM programs	AUB, BZU
Human Capital (HC)	Absence of AI curriculum	HC4	No AI, data science, or computing specializations listed in program catalog	UDJ, UN
Human Capital (HC)	Basic/general programs only	HC5	General science programs only; no applied computing tracks visible	SEU, UN
Structural Capital (SC)	Research labs / centers	SC1	AI research groups listed under university research centers	KU, AUB
Structural Capital (SC)	Digital infrastructure	SC2	Institution hosts HPC clusters; digital learning platforms available	AUB
Structural Capital (SC)	Research visibility	SC3	Scopus-indexed research output through institutional repository	KU
Structural Capital (SC)	Basic infrastructure only	SC4	General labs listed; no specialized AI facilities described	SEU, UDJ
Structural Capital (SC)	Weak research transparency	SC5	No research lab listings or updated research pages	UN
Relational Capital (RC)	Industry partnerships	RC1	MoU with national innovation authority and IBM research center	KU, AUB
Relational Capital (RC)	International partnerships	RC2	Listed partnerships with European universities (OIP agreements)	AUB, BZU
Relational Capital (RC)	Alumni visibility	RC3	LinkedIn alumni profile shows international employment footprint	AUB
Relational Capital (RC)	Emerging partnerships	RC4	News article on collaboration with AUF or CEALT research center	UDJ
Relational Capital (RC)	Limited partnerships	RC5	No partnership announcements on institutional website	SEU, UN

Table C3 presents the deductive coding schema. It outlines the Intellectual Capital themes, sub-themes, and indicators; assigns each a code (e.g., HC1–HC5, SC1–SC5, RC1–RC5); and provides example evidence extracts. This chart illustrates how the codebook was operationalized and how specific types of qualitative evidence were mapped to IC indicators

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