What Knowledge-Intensive Entrepreneurs Still Need to Learn: Skill Gaps in the Age of AI

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Abstract

Founders in an advanced Croatian technology incubator rate sales and marketing as the gaps that most limit their growth, while close to half call technical and artificial-intelligence skills irrelevant, and most access AI through shared platform interfaces rather than building it in-house. We ask whether the skill gaps that constrain knowledge-intensive entrepreneurial firms shift with the firm's AI strategy, and what the answer means for the future of business education. From a survey of 56 startups at the Zagreb Innovation Centre, we group firms by their digital and AI strategy and relate skill-gap severity to how deeply firms engage AI. Commercial gaps dominate every profile and, far from narrowing as firms commit to AI, they deepen with it: the firms that build their own AI report the largest business-development gap, and the more a firm prioritises AI the larger its own data and AI gap. AI does not close these gaps; engaging it more deeply raises the demand for the commercial and business-model skills they describe. Because advantage in the age of AI accrues to firms whose business models and processes are organised around knowledge, the competence these founders most lack is the design of a knowledge-centric business model that uses cheap, widely available AI. Teaching that competence, in degree programmes and in the continuing education of working founders, is the direction in which business education must develop.

Keywords: *knowledge-intensive entrepreneurship, skill gaps, artificial intelligence strategy, latent class analysis, business education, incubator.*

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1. Introduction

Knowledge-intensive entrepreneurial firms turn advanced scientific and technical knowledge into new products and markets, and the economies that climb the technology ladder build ecosystems to grow them [1], [2]. What limits these firms is a first-order policy question, and access to skills, competence and knowledge sits at its centre [3]. For one advanced population the answer is direct. Inside a leading incubator the technical foundation is already strong and cheaply available, so the binding constraint is commercial competence, and a new general-purpose technology is sharpening that constraint rather than dissolving it.

Artificial intelligence is spreading through entrepreneurship the way earlier general-purpose technologies spread through the wider economy: cheap to access, improving fast, and shared across competitors [4], [5], [6]. When the same capability is cheap and available to every firm, owning the technology ceases to confer advantage, and the business model that puts it to work becomes the differentiator. Whether AI closes the competence gaps founders face or opens new ones remains unsettled, and it is an active question for research [7].

We study 56 knowledge-intensive startups hosted by the Zagreb Innovation Centre (ZICER), a Croatian incubator, and ask a question with two parts: do the skill gaps that most limit growth shift with the firm's AI strategy, and what does the resulting pattern mean for the future of business education? The contribution is to cross two dimensions the descriptive evidence has so far kept apart. We group firms by their AI strategy, test how skill-gap severity differs across those groups, and read the result as a question of what business education must teach. The competence the data single out is the design of a knowledge-centric business model on commodity AI, which falls within the established remit of business education.

2. Knowledge-intensive entrepreneurship and the skill-gap question

2.1 Knowledge-intensive entrepreneurial firms

Knowledge-intensive entrepreneurship denotes new ventures that draw on, and add to, advanced bodies of knowledge, joining Schumpeterian novelty with the cumulative learning that evolutionary economics and innovation-systems research describe [1]. These firms matter beyond their own balance sheets: they diffuse knowledge, attract complementary investment, and pull regional ecosystems toward higher-value activity [8]. In Central and Eastern Europe the orientation of such firms shapes how fast economies catch up technologically [2]. Incubators concentrate this population, which makes them a useful site for studying the constraints that bind it. University entrepreneurial ecosystems, in particular, depend on the presence and growth of knowledge-intensive firms [9].

Knowledge intensity describes how a firm competes, not the sector it sits in. A knowledge-centric venture builds its advantage on what it knows and on how its model and processes turn that knowledge into value, rather than on cost, scale, or a protected market [1], [3]. The assets that carry the advantage are intangible: skills, routines, data and relationships that are hard to buy and hard to copy [10]. The policy interest follows. Economies that want to move up the value chain need more firms that compete on knowledge, and they need the institutions that build the human capital behind them [2], [11]. Which part of that human capital is now scarce, and who can supply it, is the question this study pursues.

2.2 Where the gaps sit: commercial, not only technical

The competence a knowledge-intensive firm lacks is rarely a single thing. Performance in these firms depends on a bundle of capabilities, and managerial and commercial competences gate growth at least as tightly as technical depth [3]. There is more than one route to high performance, and firms reach it through different combinations of capability, which is why the gaps a firm reports are heterogeneous rather than uniform [12]. The composition of the founding team explains part of that heterogeneity: variety in founder experience shapes which functions a firm can staff from within and which it must learn [13]. A firm's existing knowledge base also sets the ceiling on what new competence it can absorb, so a technically strong team does not automatically become commercially capable [10].

Two kinds of competence sit behind these gaps, and they are not symmetric. Technical competence, meaning engineering, product and data skills, is what founders in a technology incubator usually bring with them, because it is the reason the venture exists. Commercial competence is learned later, if at all. It covers the work of finding customers, pricing, positioning, financing, and assembling the business model that connects them, and it is the competence that converts a working technology into a growing firm [3], [12]. In a population selected for technical strength, the commercial side is where the binding constraint is most likely to sit. The AI literature gives a reason to expect that constraint to tighten rather than ease.

2.3 AI as a general-purpose technology: closing gaps or opening them

General-purpose technologies create value only when user firms invent the complementary practices that put them to work [4]. AI fits this pattern, and recent work treats it as a method of invention whose returns depend on recombination inside the adopting firm rather than on the technology itself [5]. The economics of AI sharpen the point: as machine prediction becomes cheap, the scarce and valuable inputs become judgement, problem framing, and business-model design [6]. For small and medium firms, the depth of AI adoption interacts with the firm's knowledge base to determine which constraints actually bind [14]. Startups already reach for generative AI inside commercial functions such as growth and marketing, not only inside engineering [15]. The mechanism predicts a shift rather than a closure. AI lowers the technical and data barrier and raises the value of the commercial competence around it.

A second consequence concerns the distribution of advantage. When a general-purpose technology becomes cheap and shared, the firms that gain the most are those whose business model and processes are organised around knowledge, because the technology rewards knowledge-centric designs more than knowledge-light ones [4], [5]. Cheap prediction adds the most value where a firm understands the problem deeply, holds a distinctive view of its data, and has a clear account of how the prediction creates value [6]. The returns to AI are therefore uneven. They accrue to firms organised around knowledge and widen the distance between them and firms that add AI to a knowledge-light operation [14].

The scarce competence shifts accordingly. Operating the technology is inexpensive and becoming more so; the demanding task is the design of a knowledge-centric business, a business model and set of processes that create, capture and compound knowledge with AI built into them, so that the firm's advantage grows rather than erodes. This competence is commercial and strategic, and it becomes scarcer and more valuable as AI spreads.

2.4 Research question

This logic is testable in a population that has already adopted AI to varying degrees. If AI mainly lowers technical barriers, then firms with deeper AI strategies should report smaller technical and data gaps. If the commercial gap is the binding one, it should persist across AI strategies, including among the most technically advanced firms. We test both expectations and then ask what the answer means for the future of business education. Behind both lies a larger question: if AI rewards knowledge-centric firms, what should business education teach founders to build?

3. Data and methods

We use survey evidence from 56 startups hosted by ZICER. The survey covers seven strategic dimensions of the firm. These are young, technology-oriented ventures, which makes the sample an advanced rather than a representative cross-section of small firms.

Skill gaps. Founders rated how much a gap in each of eight functions limits the firm's growth, on a four-point scale from 0 (not relevant) to 3 (severely limiting growth): technical or engineering, sales and business development, marketing and communications, finance and accounting, operations and logistics, leadership and management, product development, and data analysis or AI.

AI strategy. The survey records each firm's digital and AI strategy through four blocks: digital-transformation initiatives, the form of cooperation with AI providers, the AI hardware and infrastructure in use, and the rated importance of seven AI application areas. We summarise these into profiles using latent class analysis, an unsupervised model that assigns each firm to the strategy class it most resembles (estimated with the R package poLCA). A three-class solution

gave the clearest and most interpretable profiles; class-assignment certainty was high (entropy $R^2 = 0.99$). The model used 56 firms with complete strategy data.

Three AI-strategy profiles. We order the three classes by their AI build-depth: dedicated hardware, proprietary models, and strategic or licensing relationships with providers. The deepest profile is **AI-Native** (n = 10); the shallowest is **Minimal-AI** (n = 26); the middle profile, which reaches AI through interfaces and the cloud, is **Adopters** (n = 20). The labels follow the class profiles, not arbitrary numbering.

Tests. We join skill gaps and AI-strategy class firm by firm (n = 56). Our primary measure of AI engagement is continuous. The AI-build index counts a firm's own-AI commitments across hardware, infrastructure and provider relationships, from dedicated processors and in-house infrastructure to proprietary models and strategic or licensing partnerships (range 0–6); the AI-ambition index is the mean rated importance of the seven AI applications (0–3). We relate each of the eight gap scores to these two indices with Spearman rank correlations. As a class-level check we also compare each gap across the three AI-strategy classes with a one-way Welch analysis of variance, which does not assume equal variances across the unequal-sized classes, and a Kruskal–Wallis test confirms the same conclusion. We treat the four-point gap items as interval scores, a common simplification, and read all results as descriptive patterns: with 10 firms in the smallest class the class comparisons have little power, so we report relationships and effect sizes rather than leaning on significance, and report p-values uncorrected with the caveat that an isolated significant result would warrant caution. The sample is one incubator at one time, so the numbers are local.

4. Results

Sales and marketing are the gaps that most often limit growth (Figure 1). 61% of founders rate sales and business development as moderately or severely limiting, and 54% say the same of marketing. Technical and data skills run the other way: 34% call the technical gap not relevant and 46% call the data/AI gap not relevant. The most limiting function on average is sales / business development. The pattern matches the composition of the population: strong engineering foundations alongside limited commercial capability.

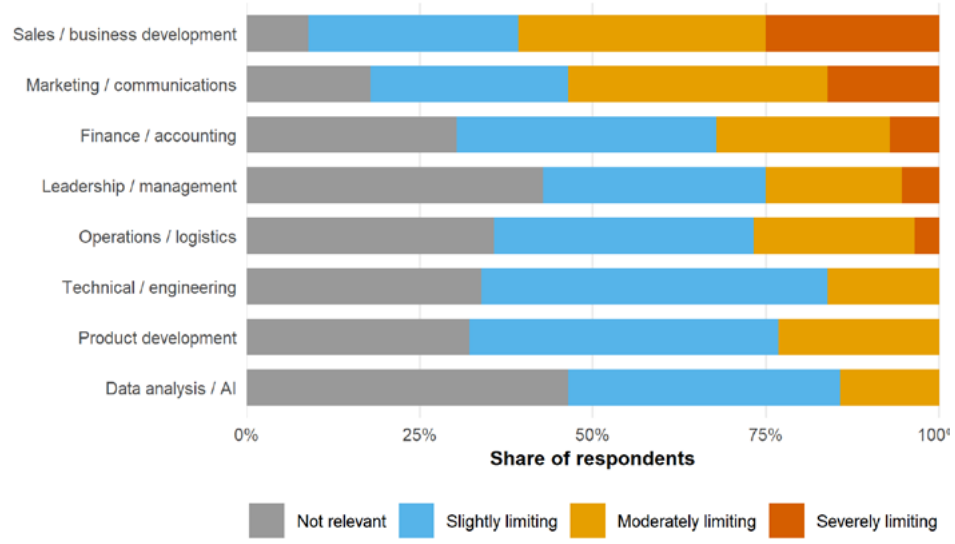


Figure 1. Impact of skill gaps on firm growth across the sample. Bars show the share of respondents at each level; commercial functions carry the most weight on the right.

Firms differ sharply in how they approach AI (Figure 2). Most reach AI through external providers: 64% via platform interfaces and 32% by buying software or services, while 46% use no specialised hardware. A minority builds in-house: the AI-Native tier concentrates the firms with their own infrastructure, proprietary models, and strategic provider relationships.

Each bar in Figure 2 shows one strategy indicator as a share of its maximum, so a longer bar means the class scores higher on that indicator, and the three shades run from Minimal-AI (light) to AI-Native (dark). Reading down the panel, the classes separate on the build items — own hardware, in-house infrastructure, proprietary models — and differ far less on whether AI matters to them. What distinguishes the classes is build depth, not enthusiasm.

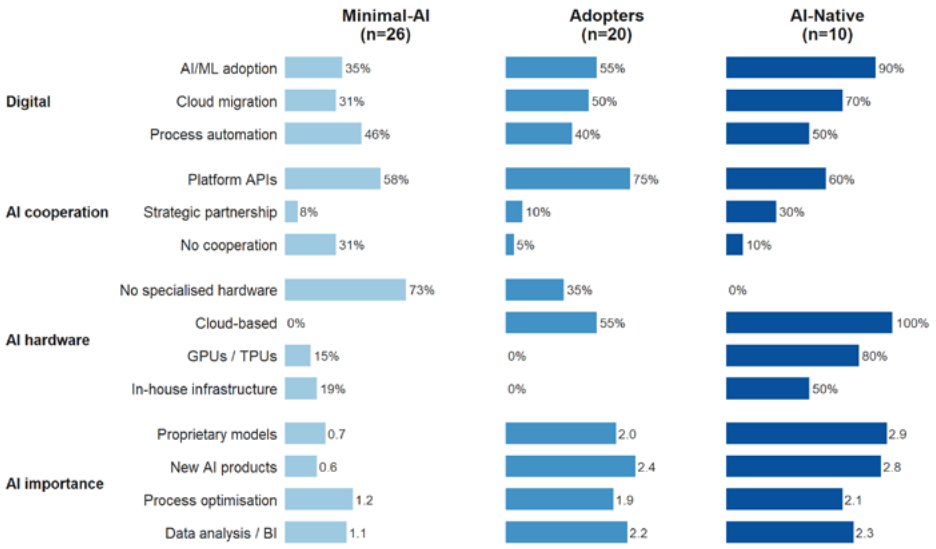


Figure 2. AI-strategy profiles from the three-class latent class model, ordered by build depth (light to dark: Minimal-AI to AI-Native). Bars show each indicator as a share of its maximum (firm share for adoption items; class mean on the 0–3 scale for AI-importance items), with the value printed at the bar end.

The deeper a firm goes into AI, the larger its business gap, not the smaller (Table 1). The AI-build index, which counts a firm's own-AI commitments from dedicated hardware to proprietary models and strategic provider partnerships, correlates positively with the sales and business-development gap (ρ = +0.28, p =.037). The firms that commit most to building AI report the greatest need for the competence to turn it into a business. AI ambition tracks the data and AI gap in the same direction: the more a firm rates AI as important across its applications, the larger its own data and AI skill gap (ρ = +0.24, p =.073). Engaging AI more deeply raises the demand for skills rather than removing it; the remaining gaps show no consistent relationship with either measure.

Table 1 reports rank correlations, so each entry asks whether firms that engage AI more deeply also report a larger gap in that function. A positive value means the gap grows with AI engagement; a negative value means it shrinks. Two entries stand out from zero, and both are positive: sales and business development against the build index, and data and AI against the ambition index.

The class view tells the same story and adds a second point: the gap is universal (Figure 3). Commercial functions carry the largest gaps in every AI-strategy class, and they are heaviest among the AI-Native builders, whose commercial-gap score (6.1 out of 12) runs above both the Adopters (4.6) and the Minimal-AI firms (5.4). No single class differs significantly on any gap (Welch ANOVA, all p >.05; a Kruskal–Wallis check agrees), which at 10 firms in the smallest class is what one expects. The commercial gap does not belong to one type of firm. It is the common condition of the population, and it is sharpest where AI commitment is deepest.

Figure 3 plots the mean severity of each gap within each AI-strategy class, on the same 0–3 scale founders used. Comparing the three bars within a row shows whether a gap belongs to one type of firm or to all of them; comparing rows shows which functions bind hardest. The commercial rows sit furthest right in all three classes, and the AI-Native bar leads them.

Skill gap	ρ with AI-build	ρ with AI-ambition
Sales / business development	+0.28*	-0.11
Marketing / communications	-0.05	-0.08
Finance / accounting	+0.04	+0.09
Leadership / management	+0.20	+0.18
Operations / logistics	-0.13	-0.02
Product development	-0.04	+0.03
Technical / engineering	-0.11	+0.03
Data analysis / AI	+0.15	+0.24†

Table 1. Spearman correlation of each skill gap with two continuous measures of AI engagement: the AI-build index (count of a firm's own-AI commitments, from dedicated hardware to proprietary models and strategic or licensing partnerships; 0–6) and the AI-ambition index (mean rated importance of seven AI applications; 0–3). A positive value means the gap is larger where AI engagement is deeper. Rows are ordered by overall severity. * p <.05, † p <.10; n = 56.

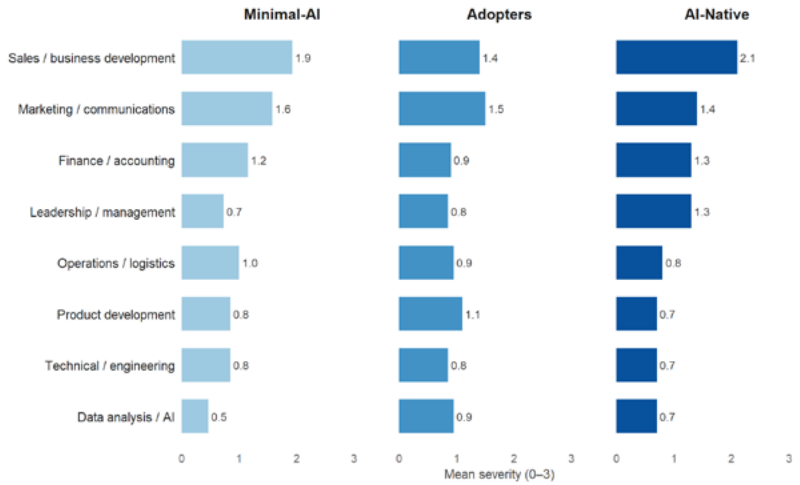


Figure 3. Mean severity of each skill gap by AI-strategy class (0 = not relevant, 3 = severely limiting). Gaps are ordered by overall severity.

The results converge on a single reading. The binding constraint in this population is commercial competence rather than technical capacity, and it binds hardest where AI runs deepest. As the technology grows cheaper and more capable, the scarce competence is the design of a competitive business, and the firms furthest into AI feel that scarcity most acutely.

5. Conclusion

The competence AI leaves scarce is the one business education exists to supply, and the firms that go furthest into AI need it most. In this sample the technical layer is inexpensive and shared: most firms reach AI through the same interfaces their competitors use, and the commercial functions carry the largest gaps in every AI-strategy class (Figure 3). The gap does not ease as firms commit to AI; it deepens. The firms that build their own AI report the largest business-development gap ($\rho = +0.28$), and the more a firm prioritises AI the larger its own data and AI gap ($\rho = +0.24$). Deeper AI engagement raises the demand for these competences rather than meeting it, which is what absorptive capacity [10] and the economics of cheap prediction [6] imply. Technical sophistication does not produce commercial sophistication.

The broader implication concerns the distribution of advantage. A cheap, shared technology does not raise every firm equally; it rewards businesses whose business models and processes are organised around knowledge and widens their lead over knowledge-light competitors [4], [5]. Advantage in the age of AI accrues to knowledge-centric firms, and it grows as more of the business comes to run on knowledge [6], [14]. The present data are consistent with this reading. The firms that engage AI most deeply report more skill needs rather than fewer, and the needs they report are commercial: how to design a business model and processes that create and compound knowledge, and how to build AI into them so the firm's advantage widens rather than erodes.

These findings set a direction for business education. If advantage flows to knowledge-centric firms, the skill worth teaching is how to make a business knowledge-centric: how to identify and build the proprietary knowledge, data and relationships that generic AI cannot supply, and how to design a business model that compounds them with AI. That curriculum is commercial and strategic, and it lies within the historical core of management and entrepreneurship education rather than alongside a technical course [16]. Three implications follow. The design of knowledge-centric, AI-empowered business models belongs in the required core of entrepreneurship and management programmes, taught as a concrete skill: how to price, position and defend a product whose visible capability is a commodity. The people who carry the gap are working founders rather than enrolled students, which places executive and continuing education at the centre of business education rather than at its margin. The incubator becomes a natural site of instruction, since the distinctive contribution of business education to firms adopting widely available AI is the business-model layer, a capability that recent work on AI and business-talent development places at the centre of its agenda [14], [17]. What these ventures most need is the competence to build a viable business on technology that is now cheap and shared [11].

The study has clear limits. It covers one Croatian incubator at one moment, with 56 firms and 10 in the smallest AI-strategy class, so the tests have low power, the effect-size intervals are wide, and a null result is uninformative rather than evidence of no difference. Latent class assignments are treated as fixed, which understates classification uncertainty. The findings are associations, not causal effects. What generalises beyond this sample is the mechanism rather than the magnitudes. Where AI is cheap and widely available, which the 64% reaching it through external interfaces here suggests is common, advantage shifts toward the knowledge a firm designs into its business, and supplying the competence to design it falls to business education.

The conclusion is straightforward. Founders in an advanced incubator are strong on technology and short on the commercial competence required to build a business with it, and AI does not remove this constraint; it raises the premium on it. The firms that advance will be the knowledge-centric ones, and their founders need to learn how to design a knowledge-centric business, which the technology itself does not teach. That competence is teachable, and teaching it is the task that now falls to business education. A natural next step is to test the pattern in other incubators and to follow founders over time, examining whether those trained to design knowledge-centric, AI-empowered business models grow faster than those who acquire the competence informally.

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