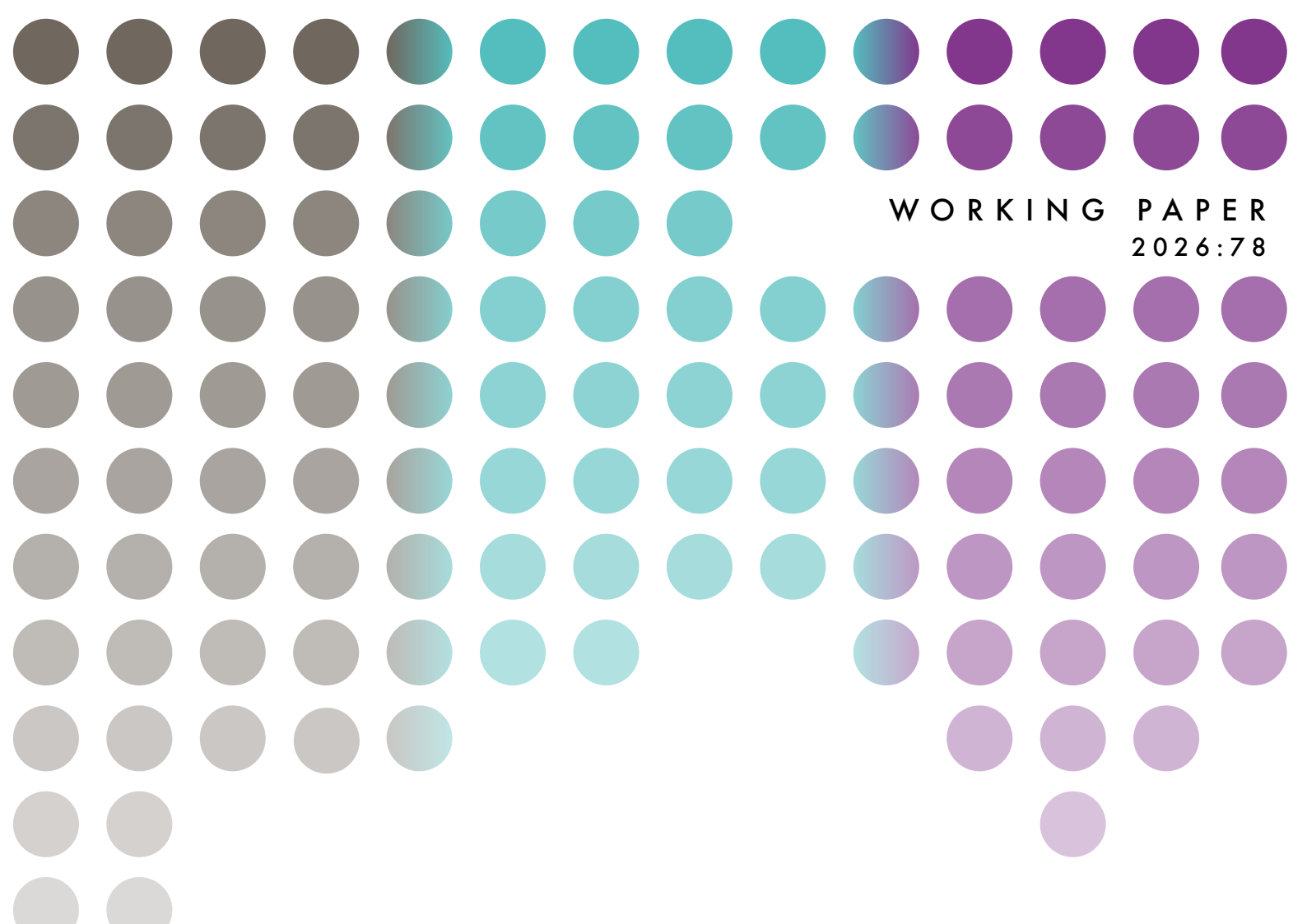




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Who Anticipates Needing Digital Competence?

An empirical Analysis of Firm-Level Heterogeneity in Perceived Digital Skill Needs among Swedish Firms

MARTIN ANDERSSON¹, TONY GORSCHKE² AND ANNA KUSETOGULLARI³

Abstract

This paper provides an empirical account of heterogeneity in firms' self-reported needs for digital competence. Using a 2020 Statistics Sweden survey of 2,479 firms, linked to register data and the Community Innovation Survey, we relate perceived needs to firms' existing digital competence profile, size, R&D activity, workforce education and industry. Firms that already hold a broad set of digital competences report anticipated needs more often, mainly for recruitment rather than internal development. The differences associated with AI and automation competence and with workforce education lie in decision-making rather than administrative roles. These are cross-sectional associations in self-reported data that are open to several interpretations. Together, they offer a set of stylized facts on the demand side of digital skills just before generative AI tools became widely available.

Keywords: digital competence of firms, AI, human capital, digital transformation, skill demand, firm heterogeneity, Sweden

JEL: O33, J24, L21, L25, M15, D22

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1. INTRODUCTION

The diffusion of artificial intelligence (AI) and related digital technologies across firms has been uneven. Survey evidence from several countries shows large differences between firms at the digital frontier and others in both technology adoption and skills (Ransbotham et al. 2017, Gal et al. 2019, Dahlke et al. 2024, OECD/BCG/INSEAD 2025), and firms' ability to make use of these technologies is widely held to depend on access to relevant competence (Brynjolfsson and McAfee 2014, Babina et al. 2024). Much of what is known about this heterogeneity concerns the supply-side of digital skills or realized adoption. Considerably less is known about how firms themselves perceive their need for digital competence: which firms report needing it, whether they expect to meet that need by training existing staff or by recruiting, and where in the organisation they locate it.

This paper offers an empirical analysis of that question. We use a survey of 2,479 Swedish firms conducted by Statistics Sweden in 2020 in which firms were asked whether they currently need to develop or recruit digital competence, whether they expect to need to do so within three years, and whether anticipated needs concern technical specialists or more general digital competence in administrative versus decision-making roles. Because the survey can be linked to register data and to the Community Innovation Survey, we can relate these self-reported needs to firms' existing digital competence profile (including whether they report having AI and automation competence), as well as to size, R&D activity, workforce education, international engagement and industry.

Our aim is making an empirical contribution. We do not test competing theories of why firms perceive competence needs, nor do we claim to identify causal effects. Instead, we try to establish a set of stylized facts about a measure that is rarely observed at the firm level and that is distinct from, and complementary to, measures of realised adoption or of objective skill shortages. The questions we ask are descriptive: Which types of firms report perceived needs for digital competence? Do the needs reported by firms with an advanced digital competence profile differ in kind from those reported by other firms, for instance in the balance between internal development and recruitment, or between administrative and decision-making roles? And how much of the raw differences across firms remains once sector and basic firm characteristics are held constant?

There are two reasons why an analysis of this kind is useful. First, perceived need is an intermediate step between the state of a firm's competence and its subsequent investment in training and hiring. Documenting how it is distributed across firms is a precondition for understanding the demand-side of digital skills, and for designing skills policies that target the right firms. Second, the timing of the survey has some value in itself. The data were collected in 2020, with a three-year horizon for anticipated needs, which places them immediately before generative AI tools became widely available from late 2022. The patterns we describe therefore characterise the state of firms' perceived digital competence needs before that shift. We make no claims about what has happened since; but a reference point from this period may be useful for studies that later observe comparable measures.

Three patterns emerge from the analysis. First, firms that already hold a broad set of digital competences, including AI and automation competence, report anticipated needs more often than other firms, and this difference is considerably larger for recruitment than for internal competence development. Firms with AI and automation competence are somewhat less likely than others to report a current need to develop the competence of existing staff. Second, the difference between firms with and without AI and automation competence is concentrated in decision-making roles, and is small and statistically indistinguishable from zero for administrative roles once other competences are held constant. Third, the share of employees with higher education is positively associated with anticipated needs in decision-making roles but not in administrative roles, where the association is weak or negative. R&D activity, by contrast, is associated with higher reported needs across all role categories.

We are careful in how we read these patterns. A firm's reported need for digital competence may be high because it undertakes many digital activities and expects to expand them, because its business model requires such competence, or because it is better placed to recognise what it lacks. Conversely, a low reported need may reflect limited requirements as well as limited recognition. The data do not allow us to distinguish between these interpretations, and we treat them as open. The contribution is to document the patterns themselves, with enough detail about the form and location of perceived needs that subsequent work, ideally with longitudinal data and direct measures of the relevant mechanisms, can build on them.

The remainder of the paper is structured as follows. Section 2 briefly reviews related work and sets out the conceptual considerations that inform how we organise and interpret the description. Section 3 describes the data and the measures. Section 4 presents descriptive patterns in the raw data. Section 5 reports conditional associations from multinomial and binary logit models, which we use as descriptive devices for summarising differences across firms while holding sector and basic characteristics constant. Section 6 discusses interpretations, limitations and implications, and Section 7 concludes.

2. BACKGROUND AND CONCEPTUAL CONSIDERATIONS

2.1 Perceived competence needs as an object of study

The literature on digital technology and firm performance has established that digital technologies and human capital are complements: returns to technology investment depend on the availability of appropriate skills and on organisational adaptation (Bresnahan et al. 2002, Brynjolfsson and Hitt 2000). This holds for automation technologies and AI as well (Brynjolfsson and McAfee 2014, Tambe et al. 2019). Skill shortages are correspondingly reported as a leading obstacle to AI adoption, including among firms that are otherwise well resourced (OECD/BCG/INSEAD 2025). Firm-level studies of adoption consistently find that larger, R&D-active and skill-rich firms adopt digital technologies and AI at higher rates (Andersson et al. 2023, Brey and van der Marel 2024, Eurostat 2025).

Against this background, the firm's own perception of its competence needs is an intermediate variable that has received comparatively little attention. It can be assumed to be located between the firm's current competence stock and its subsequent investments in training and hiring, and it is observed here from the firm's own point of view rather than inferred from job postings or realised adoption. Perceived need is not the same thing as an objective skill gap, nor the same thing as managerial awareness of such a gap. A firm may report high needs because it is expanding digital activities, because its products or processes require them, or because it recognises deficiencies; it may report low needs because it has few such activities, because it has already met its requirements, or because it does not recognise what it lacks. We return to these distinctions when interpreting the results.

2.2 Interpretive lenses

Several strands of theory offer reasons to expect perceived competence needs to vary systematically across firms. We use them here to organise the description and to frame alternative readings of the patterns, not as hypotheses to be tested; the mechanisms they emphasise are not measured in our data.

A first set of arguments suggests that firms with a richer existing digital competence base will report more extensive needs. The absorptive capacity perspective holds that prior related knowledge is a precondition for recognising the value of new external knowledge and for identifying what further knowledge is required (Cohen and Levinthal 1990, Zahra and George 2002). The dynamic capabilities perspective similarly emphasises routines for sensing opportunities and reconfiguring the competence base in response (Teece et al. 1997). Task-based models of automation add a further reason: automation of some tasks tends to create new tasks, often more knowledge-intensive and decision-oriented than those displaced, so that firms that deploy AI and automation may generate new competence demands rather than converge toward self-sufficiency (Acemoglu and Restrepo 2018, 2019). Agrawal et al. (2024) argue, relatedly, that adopting AI

in a core decision process affects interrelated decisions throughout the firm and raises demands for coordination and managerial oversight. On these views, one would expect firms with a broad digital competence profile to report more needs, and to locate a larger share of those needs in decision-making functions.

A second set of arguments points in the opposite direction. The behavioural theory of the firm holds that performance shortfalls relative to aspirations trigger search aimed at addressing perceived deficiencies (Cyert and March 1963, Greve 2003), and the literature on latecomer firms treats the recognition of competence deficits as a first step in deliberate catch-up (Bell and Figueiredo 2012). If digital laggards experience competitive pressure from more digitalised rivals, they might report particularly large needs for digital competence. There is a well-known tension between these two sets of arguments, since the absorptive capacity view implies that firms with little prior digital knowledge may be unable to recognise the gaps that would, on the behavioural view, drive their search.

A third consideration, which cuts across both, is that perceived needs may simply scale with digital activity. Firms that do more with digital technologies will, other things equal, have more occasions to need digital competence, irrespective of how well they sense gaps or how strongly they feel competitive pressure. This is not a theory of awareness or of catch-up, but it is an important benchmark against which the other interpretations must be read.

We do not attempt to adjudicate between these lenses. What they suggest is that a useful description should distinguish not only whether firms report needs, but also the form of those needs (internal development versus recruitment, current versus anticipated) and their organisational location (administrative versus decision-making roles, technical specialists versus general competence). These distinctions are available in our data and organise the analysis that follows.

3. DATA AND MEASURES

3.1 Survey and linked data

The empirical analysis draws on a survey conducted by Statistics Sweden in collaboration with Swedsoft in 2020. The survey targets firm-level digitalisation and was designed to capture firms' current digital competence, their use of key digital technologies (including AI and automation), and their anticipated competence needs over the following three years. The survey covers 2,479 firms with ten or more employees.

A main benefit of the survey is that participating firms can be identified in Swedish register-based microdata from Statistics Sweden and in the 2020 Community Innovation Survey (CIS). In addition to firms' survey answers, we therefore have register information on sector classification, size, ownership structure and the educational composition of employees, and CIS information on R&D activity. The merged dataset allows us to describe perceived competence needs alongside both the firm's existing digital competence profile and its structural characteristics.

3.2 Indicators of current digital competence

The survey asks firms whether they currently have employees with competence in each of several digital areas. One question asks whether the firm possesses AI and automation competence. Only 16% of firms in the sample report having this competence, which indicates that in 2020 AI remained a frontier capability held by a relatively small subset of firms. Further questions ask whether firms have employees skilled in business systems (databases), social media, cybersecurity, data analytics, IT infrastructure (hardware and software), and websites and e-commerce. We use firms' answers to these seven questions as binary indicators of their current digital competence profile.

We refer throughout to a firm's "digital competence profile" rather than to its "digital maturity". The seven indicators are not a validated maturity scale of the kind used in parts of the information systems literature (see, for example, Orero-Blat et al. 2025), and they capture distinct, if related, competences rather than a single underlying construct. In the descriptive analysis we accordingly treat them separately, and the regression tables report each indicator's association with perceived needs conditional on the others. Where we speak of firms with a "broad" or "advanced" digital competence profile, we mean firms reporting competence in many of these areas, with AI and automation competence as the least common and, in that sense, most advanced indicator.

3.3 Measures of perceived competence need

Firms were asked about their current and anticipated needs for digital competence, yielding four outcome variables:

- (i) a need to develop digital competence today (that is, to train existing employees);
- (ii) a need to recruit digital competence today;
- (iii) an expected need to develop digital competence within three years;
- (iv) an expected need to recruit digital competence within three years.

In addition, the survey asks about anticipated needs for technical specialists and for general digital competence, each broken down by whether the need applies to administrative positions or to decision-making positions. Administrative positions cover customer support, administrative tasks, production of goods or services, purchasing, sales, and logistics and transportation; decision-making positions cover product development and design, testing, evaluation and certification, marketing and communication, business analysis and development of decision support, decision making, and research and development. This yields four further binary outcomes: the expected need for technical specialists in administrative roles, technical specialists in decision-making roles, general digital competence in administrative roles, and general digital competence in decision-making roles.

These eight variables are the firm's own statements about its needs. They do not measure realised investment in training or hiring, and, as discussed in Section 2, they should not be read as direct measures of awareness of competence gaps.

3.4 Firm characteristics

From the register and CIS data we construct firm size categories (small, 10–49 employees; medium, 50–249; large, 250 or more), a dummy for whether the firm reports R&D activity, the share of employees with tertiary education, an exporter dummy, a dummy for membership in a multinational enterprise group, and two-digit NACE sector codes. Box 1 in the Appendix summarizes the main variables.

4. DESCRIPTIVE STATISTICS

4.1 Current digital competence across industries and firm sizes

Table 1 shows how firms with and without AI and automation competence are distributed across two-digit NACE industries. Firms reporting AI and automation competence are over-represented in knowledge- and data-intensive sectors. IT services and telecommunications account for 11.9% of firms with AI and automation competence but 4.5% of other firms; technical engineering and R&D services for 7.9% versus 5.7%; financial intermediation for 7.1% versus 3.8%; and law and management consultancy for 6.6% versus 3.9%. Within manufacturing, wood and paper (5.1% versus 2.9%) and vehicles (3.5% versus 1.8%) are

over-represented among firms with AI and automation competence. By contrast, construction (2.3% versus 6.9%), accommodation (0% versus 3.1%), arts and entertainment (0.5% versus 4.0%) and food, beverages and tobacco (0.8% versus 2.7%) are markedly under-represented.

Table 1. Distribution of firms across industries by AI and automation competence (%).

Industry classification	No AI and automation competence	AI and automation competence	Total
Food/Beverages/Tobacco	2.71	0.76	2.38
Textiles/Clothing	1.10	1.01	1.09
Wood/Paper	2.86	5.06	3.22
Chemicals/Pharmaceutics	1.80	2.78	1.97
Rubber/Plastics	2.20	2.28	2.22
Glass/Ceramics/Concrete	1.55	1.27	1.51
Metals	6.11	4.81	5.90
Machinery/Equipment	3.96	4.56	4.06
Electronics/Electrical Equipment	3.51	4.30	3.64
Vehicles	1.80	3.54	2.09
Furniture/Other Manufacturing	1.85	3.04	2.05
Water Supply/Waste/Recycle	3.11	3.29	3.14
Energy/Oil	2.00	3.04	2.17
Wholesale Trade	4.36	3.54	4.22
Transportation/Postal Services	7.97	5.57	7.57
Printing/Publishing/Media	4.36	3.29	4.18
IT Services/Telecommunications	4.51	11.90	5.73
Financial Intermediation	3.81	7.09	4.35
Consulting/Advertising	1.60	0.76	1.46
Technical Engineering/R&D	5.71	7.85	6.06
Other Producer Services	8.22	5.82	7.82
Law and Management Consultancy	3.91	6.58	4.35
Construction	6.91	2.28	6.15
Retail	4.21	3.29	4.06
Accommodation	3.11	0.00	2.59
Health	2.81	1.77	2.63
Arts/Entertainment	3.96	0.51	3.39
Total	100	100	100

Note: Based on NACE Rev. 2 two-digit classification.

These differences are consistent with the view that sectors with more structured data and more routine processes are better suited to AI and automation (Brynjolfsson and McElheran 2016), while industries that depend on unstructured physical work or interpersonal services face higher barriers (OECD 2024). They also serve as a reminder that sector composition must be held constant when comparing firms with different digital competence profiles, which motivates the inclusion of sector fixed effects in Section 5.

Figure 1 shows the distribution of AI and automation competence across firm size categories. Large firms (250 or more employees) make up 20.7% of firms with AI and automation competence, compared with 6.3% of firms without it. Small firms (10–49 employees) account for 37% of firms with AI and automation competence and 63% of other firms. AI and automation competence is thus considerably more common among larger firms, which is in line with the size gradient documented in adoption studies (Eurostat 2025) and with the general finding that scale is associated with technology adoption (Shefer and Frenkel 2005, Rogers 2004, Vaona and Pianta 2008).

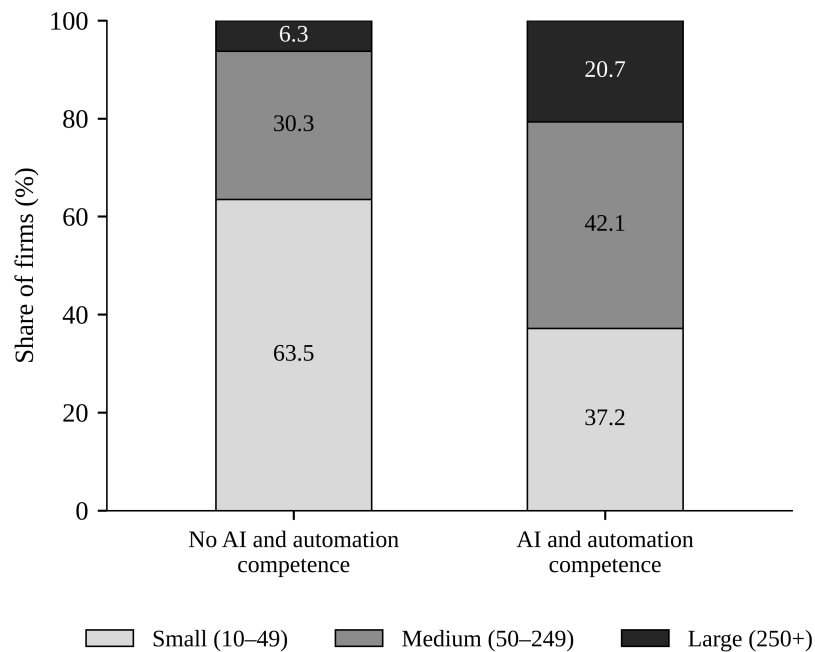


Figure 1. Distribution of firms with and without AI and automation competence across size categories.

Note: Each column shows the size distribution (number of employees) of firms without and with AI and automation competence, in per cent. Each column sums to 100.

4.2 Co-occurrence of digital competences

The seven competence indicators are far from independent. Table 2 reports sample means for all firms and for the subset reporting AI and automation competence. Among the latter, 86% report competence in IT infrastructure (compared with 65% of all firms), 75% in cybersecurity (45%), 74% in business systems (57%), 70% in websites and e-commerce (50%), 65% in social media (47%) and 62% in data analytics (32%).

Table 2. Summary statistics, all firms and firms reporting AI and automation competence (“AI firms”).

	N	Mean (all)	SD (all)	Min	Max	Mean, AI firms	SD, AI firms
Need to develop digital competence today	2479	0.10	0.30	0	1	0.042	0.20
Need to recruit digital competence today	2479	0.056	0.23	0	1	0.094	0.29
Expected need to develop digital competence within three years	2479	0.24	0.43	0	1	0.22	0.42
Expected need to recruit digital competence within three years	2479	0.30	0.46	0	1	0.54	0.50
Need for technical specialists (administrative positions)	2479	0.56	0.50	0	1	0.67	0.47
Need for technical specialists (decision- making positions)	2479	0.52	0.50	0	1	0.75	0.43
Need for general digital competence (administrative positions)	2479	0.68	0.47	0	1	0.81	0.39
Need for general digital competence (decision-making positions)	2479	0.51	0.50	0	1	0.72	0.45
AI and automation competence	2479	0.16	0.37	0	1	1	0
Business systems (database)	2479	0.57	0.50	0	1	0.74	0.44
Social media	2479	0.47	0.50	0	1	0.65	0.48
Cybersecurity	2479	0.45	0.50	0	1	0.75	0.43
Data analytics	2479	0.32	0.47	0	1	0.62	0.49
IT infrastructure (hardware and software)	2479	0.65	0.48	0	1	0.86	0.34
Websites and e-commerce	2479	0.50	0.50	0	1	0.70	0.46
Small (10–49)	2479	0.59	0.48	0	1	0.51	0.50
Medium (50–249)	2479	0.32	0.47	0	1	0.42	0.49
Large (250+)	2479	0.086	0.28	0	1	0.21	0.41
R&D dummy	2479	0.50	0.50	0	1	0.60	0.49
Workers with higher education (share)	2479	0.23	0.25	0	1	0.31	0.26
Export dummy	2479	0.41	0.49	0	1	0.57	0.50
MNE	2479	0.33	0.47	0	1	0.54	0.50
Manufacturing firms	2479	0.41	0.49	0	1	0.41	0.49

Figure 2 presents the complementary view: the share of firms with AI and automation competence is highest among firms that also report data analytics competence (31.7%) and cybersecurity competence (27.7%), against 16% in the sample.

This clustering is consistent with the view that digital competences accumulate in bundles and build on one another (Bughin et al. 2018), and that AI depends on complementary competences in data, infrastructure and security (Tambe et al. 2019). For the present purposes, it has a methodological implication: the raw difference between firms with and without AI and automation competence will partly reflect differences in the other competences. The regressions in Section 5 therefore include all seven indicators jointly, so that the

AI and automation coefficient describes the difference between firms that are otherwise similar in their digital competence profile.

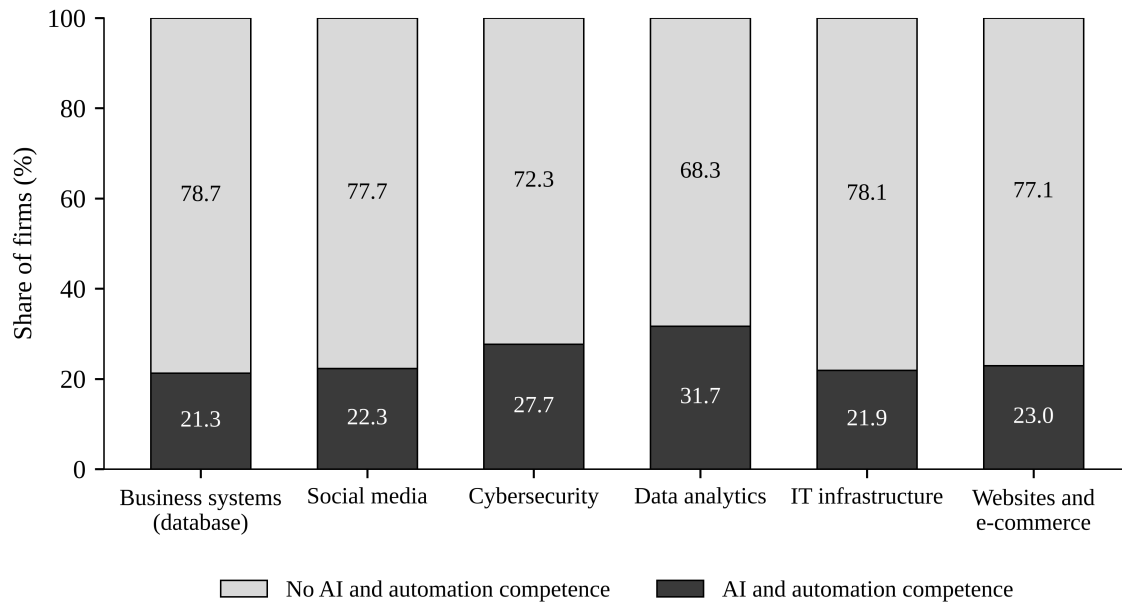


Figure 2. Share of firms with AI and automation competence among firms reporting each other digital competence.

Note: Each column shows, for firms reporting the given digital competence, the percentage that also report AI and automation competence and the percentage that do not. Each column sums to 100.

4.3 Perceived competence needs by digital competence profile

Table 2 also provides a first view of how perceived needs differ between firms with and without AI and automation competence. Two features are worth noting.

The first concerns the form and timing of needs. Among all firms, 10% report a current need to develop digital competence among existing employees and 5.6% a current need to recruit it; 24% expect to need to develop and 30% expect to need to recruit digital competence within three years. Among firms with AI and automation competence, the corresponding shares are 4.2%, 9.4%, 22% and 54%. Firms with AI and automation competence are thus not uniformly more likely to report needs. They are much more likely to anticipate recruiting (54% versus 30%), somewhat more likely to report a current recruitment need (9.4% versus 5.6%), about as likely to anticipate developing competence internally (22% versus 24%), and less likely to report a current need for internal development (4.2% versus 10%). The difference between the two groups is, in other words, largely a difference in anticipated recruitment.

The second concerns organisational location. Firms with AI and automation competence report anticipated needs more often in all four role categories, but the gap is larger for decision-making roles. For technical specialists, 75% of firms with AI and automation competence report an anticipated need in decision-making positions, against 52% of all firms (a difference of 23 percentage points), while the corresponding figures for administrative positions are 67% and 56% (11 percentage points). For general digital competence, the

figures are 72% versus 51% for decision-making positions (21 percentage points) and 81% versus 68% for administrative positions (13 percentage points). In the sample as a whole, anticipated needs for general digital competence are more common in administrative than in decision-making roles (68% versus 51%), whereas among firms with AI and automation competence the two are closer (81% versus 72%).

These raw comparisons do not hold constant sector, size or the other digital competences, all of which differ between the two groups. The next section asks how much of the pattern remains when they are.

5. CONDITIONAL ASSOCIATIONS

5.1 Approach

To summarize differences in perceived needs across firms while holding sector and basic firm characteristics constant, we estimate two sets of models on the cross-section of 2,479 firms. The estimates are conditional associations, and we do not interpret them as causal effects. Reverse causality is plausible (firms that perceive greater needs may invest in digital competence), and unobserved factors such as digital strategy, management quality or prior technology investments may be related both to the current competence profile and to perceived needs. What the models add to the raw comparisons in Section 4 is a way of asking whether, for example, the difference between firms with and without AI and automation competence persists among firms in the same sector, of the same size, and with the same other competences.

For the four need categories in Section 3.3 (develop today, recruit today, develop within three years, recruit within three years), we estimate a multinomial logit model (Greene 2012, Wooldridge 2010) in which firms reporting no current or anticipated need form the reference category. Because a firm may report needs in more than one category, we assign each firm to a single category using a priority ordering: current needs take priority over anticipated needs, and recruitment takes priority over internal development within the same time horizon. This ordering treats a current and externally sourced need as the more specific signal; it is a convention, and the appendix tables and the binary models below provide checks that do not rely on it. The multinomial logit rests on the assumption of independence of irrelevant alternatives, which may not hold when outcome categories overlap. We conducted Hausman–McFadden tests (Hausman and McFadden 1984), and the binary models below, which do not rely on the assumption, provide an additional check.⁴

For the four role-specific outcomes (technical specialists and general digital competence, in administrative and decision-making positions), we estimate separate binary logit models. Here a firm may report needs in several categories simultaneously, and modelling each outcome separately is the natural choice.

All models include the same set of explanatory variables: the seven indicators of current digital competence, size dummies for medium and large firms (small firms as the baseline), the R&D dummy, the share of employees with tertiary education, the exporter dummy, the MNE dummy, and two-digit NACE sector fixed effects. We report average marginal effects throughout, so that coefficients can be read as differences in the probability of each outcome, in percentage points, between firms that differ in a given characteristic but are otherwise similar on the included variables.

⁴ Test results are available from the authors on request.

5.2 Overall need categories

Table 3 reports the multinomial logit estimates. The first thing to note is that the pattern from the raw comparison in Section 4.3 survives conditioning on sector, size and the other competence indicators. Firms with AI and automation competence are about 3.6 percentage points more likely than otherwise similar firms to report a current need to recruit digital competence, and about 10 percentage points more likely to anticipate recruiting within three years. They are about 5.5 percentage points less likely to report a current need to develop competence internally, and no more or less likely to anticipate internal development. Given that the sample share reporting a current recruitment need is 5.6%, the first of these differences is large in relative terms; the 10-point difference in anticipated recruitment is set against a sample mean of 30%.

Table 3. Multinomial logit: perceived competence need categories and firm characteristics (average marginal effects).

	Need to develop digital competence today (1)	Need to recruit digital competence today (2)	Expected need to develop digital competence within three years (3)	Expected need to recruit digital competence within three years (4)
<i>Current digital competence</i>				
AI and automation	−0.055** (0.024)	0.036*** (0.012)	−0.003 (0.026)	0.100*** (0.022)
Business systems (database)	0.001 (0.013)	−0.008 (0.010)	0.028 (0.019)	0.018 (0.020)
Social media	0.007 (0.013)	0.007 (0.010)	−0.001 (0.018)	0.046** (0.018)
Cybersecurity	0.002 (0.015)	−0.026** (0.011)	0.013 (0.021)	0.077*** (0.020)
Data analytics	−0.024 (0.016)	0.002 (0.010)	0.010 (0.020)	0.082*** (0.019)
IT infrastructure (hardware and software)	0.016 (0.014)	−0.005 (0.011)	0.035 (0.022)	0.029 (0.023)
Web (websites and e-commerce)	−0.043*** (0.014)	0.014 (0.010)	0.030 (0.019)	0.069*** (0.019)
<i>Other firm characteristics</i>				
Medium (50–249)	−0.000 (0.014)	0.026** (0.011)	0.044** (0.019)	0.028 (0.020)
Large (250+)	−0.032 (0.029)	0.038** (0.017)	−0.019 (0.037)	0.150*** (0.031)
R&D dummy	0.020* (0.012)	0.011 (0.009)	0.007 (0.017)	0.036** (0.017)
Workers with higher education (share)	−0.007 (0.029)	−0.001 (0.023)	0.072* (0.042)	0.107*** (0.041)
Export dummy	0.023 (0.017)	−0.001 (0.012)	0.029 (0.023)	0.020 (0.023)
MNE	0.006 (0.016)	0.014 (0.011)	−0.026 (0.021)	0.016 (0.020)
NACE Rev. 2 sectors	Yes	Yes	Yes	Yes
Observations	2,479	2,479	2,479	2,479

Note: Dependent variable: perceived competence need category, with no current or anticipated need as the reference category. Average marginal effects with standard errors in parentheses. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

The other competence indicators show a similar tilt toward anticipated recruitment. Cybersecurity, data analytics, websites and e-commerce, and social media competence are each associated with a 5–8 percentage point higher probability of anticipating recruitment within three years, while none of them is associated with a higher probability of anticipated internal development, and websites and e-commerce competence is associated with a lower probability of a current need for internal development. Across the board, then, the perceived needs that distinguish firms with a broad digital competence profile from other firms are needs to bring in new people rather than to train existing ones. One reading is that such firms regard their current workforce as adequate for present requirements and locate their needs in competences not yet present in the firm; another is simply that firms with more digital activity expand their digital workforce more. The data do not distinguish between these.

Firm size is associated with perceived needs in the expected direction, and most strongly for anticipated recruitment. Large firms are about 15 percentage points more likely than small firms to anticipate recruiting digital competence within three years and about 4 points more likely to report a current recruitment need. Medium-sized firms are about 2.6 points more likely than small firms to report a current recruitment need and about 4.4 points more likely to anticipate internal development. The size gradient is consistent with adoption studies showing that large enterprises adopt AI at much higher rates than small ones (Eurostat 2025) and with the general association between scale and technology adoption (Gierden et al. 2021, Jibril and Roper 2025). It is also consistent with the mechanical point that larger firms, with more positions to fill, are more likely to anticipate recruiting in any given area.

Firms with R&D activity are somewhat more likely to anticipate recruiting digital competence (about 3.6 percentage points) and marginally more likely to report a current need for internal development. The share of employees with higher education is associated with anticipated needs, both for internal development (about 7 percentage points for a move from no to all employees with tertiary education, significant at the 10% level) and for recruitment (about 11 points), but not with current needs. Export status and MNE membership are not associated with the overall need categories once the other variables are held constant.

5.3 Needs by organisational role

Table 4 reports the binary logit estimates for the four role-specific outcomes. These models add detail on where within the organisation firms locate their anticipated needs, and they do not depend on the assignment rule or the IIA assumption of the multinomial model.

First, once the other six competence indicators, size, R&D, education, international engagement and sector are held constant, the difference between firms with and without AI and automation competence is confined to decision-making roles. Firms with AI and automation competence are about 5.6 percentage points more likely to anticipate needing technical specialists in decision-making positions and about 5.3 points more likely to anticipate needing general digital competence in such positions; the corresponding differences for administrative positions are 2.0 and 2.5 points and not statistically distinguishable from zero. The conditional differences are thus considerably smaller than the raw differences of 21–23 points in Section 4.3, which indicates that much of the raw gap is accounted for by the other competences and by sector and size. The part that remains is specific to decision-making roles.

Second, the other competence indicators are associated with anticipated needs across the board, and some of them more strongly than AI and automation competence. Data analytics competence is associated with 11–12 percentage point higher probabilities of anticipated needs in decision-making roles and 5–9 point higher probabilities in administrative roles. Business systems competence is associated with about 10 points in administrative roles and 4–5 points in decision-making roles. IT infrastructure competence is associated with 4–8 points across all four outcomes, and websites and e-commerce with 11 points for technical specialists in decision-making roles. Firms that hold one digital competence are, in short, more likely to anticipate needing others, which is in line with the co-occurrence patterns in Section 4.2 and with the view

that digital competences are complementary (Tambe et al. 2019). Whether this reflects accumulation of capabilities over time, a greater volume of digital activity, or both, cannot be settled with these data.

Table 4. Binary logit: anticipated need for technical specialists and general digital competence by organisational role (average marginal effects).

	Technical specialists, administrative positions [†] (1)	Technical specialists, decision-making positions [‡] (2)	General digital competence, administrative positions [†] (3)	General digital competence, decision-making positions [‡] (4)
<i>Current digital competence</i>				
AI and automation	0.020 (0.029)	0.056** (0.027)	0.025 (0.028)	0.053* (0.027)
Business systems (database)	0.099*** (0.021)	0.044** (0.020)	0.100*** (0.019)	0.045** (0.021)
Social media	0.045** (0.021)	0.042** (0.019)	0.048** (0.019)	0.096*** (0.019)
Cybersecurity	0.074*** (0.024)	0.022 (0.022)	0.087*** (0.022)	0.045** (0.023)
Data analytics	0.046* (0.024)	0.112*** (0.021)	0.085*** (0.022)	0.116*** (0.022)
IT infrastructure (hardware and software)	0.080*** (0.024)	0.073*** (0.022)	0.037* (0.021)	0.072*** (0.023)
Web (websites and e-commerce)	0.033 (0.022)	0.113*** (0.020)	0.039* (0.020)	0.056*** (0.021)
<i>Other firm characteristics</i>				
Medium (50–249)	0.003 (0.023)	0.020 (0.021)	0.067*** (0.021)	−0.000 (0.022)
Large (250+)	−0.048 (0.039)	0.081** (0.037)	0.049 (0.038)	0.094** (0.039)
R&D dummy	0.067*** (0.019)	0.092*** (0.018)	0.052*** (0.018)	0.062*** (0.019)
Workers with higher education (share)	−0.111** (0.047)	0.175*** (0.043)	−0.015 (0.043)	0.208*** (0.045)
Export dummy	0.060** (0.026)	0.077*** (0.024)	0.030 (0.024)	0.061** (0.025)
MNE	0.016 (0.024)	0.049** (0.022)	0.015 (0.023)	0.017 (0.023)
NACE Rev. 2 sectors	Yes	Yes	Yes	Yes
Observations	2,479	2,479	2,479	2,479

Note: Dependent variables: anticipated need for technical specialist expertise in (1) administrative and (2) decision-making positions, and for general digital competence in (3) administrative and (4) decision-making positions. Average marginal effects with standard errors in parentheses. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

[†] Customer support; administrative tasks; production of goods or services; purchasing; sales; logistics and transportation.

[‡] Product development and design; testing, evaluation and certification; marketing and communication; business analysis and development of decision support; decision making; research and development.

Third, firm characteristics other than the competence indicators relate to administrative and decision-making roles differently. The share of employees with higher education is associated with a markedly higher probability of anticipated needs in decision-making roles (about 18–21 percentage points for a move from no to all employees with tertiary education) but with a lower probability of anticipating technical specialists in administrative roles (about 11 points) and no difference for general digital competence in administrative roles. Large firms are 8–9 points more likely than small firms to anticipate needs in decision-making roles, with no significant difference for administrative roles; medium-sized firms differ from small firms only in general digital competence for administrative roles. R&D activity, by contrast, is associated with higher anticipated needs in all four categories (5–9 points), and exporters report higher anticipated needs in three of the four. MNE membership is associated only with technical specialists in decision-making roles.

Taken together, Tables 3 and 4 indicate that perceived digital competence needs are not randomly distributed across firms, and that the variation is more structured than a simple “more or less” ordering would suggest. Firms with a broad digital competence profile, more highly educated workforces, R&D activity and larger size report anticipated needs more often; but the differences are concentrated in anticipated recruitment rather than internal development, and, for AI and automation competence, workforce education and size, in decision-making rather than administrative roles.

6. DISCUSSION

6.1 Summary of patterns

The analysis documents three stylized facts about Swedish firms’ perceived needs for digital competence in 2020.

First, firms with a broad existing digital competence profile report anticipated needs more often than other firms, and the difference lies almost entirely in anticipated recruitment. Firms with AI and automation competence, in particular, are about as likely as other firms to anticipate developing competence internally, less likely to report a current need to do so, and considerably more likely to anticipate recruiting.

Second, conditional on the other competences and on sector and size, the difference between firms with and without AI and automation competence is confined to decision-making roles. Other competences, notably data analytics and business systems, are associated with anticipated needs in both administrative and decision-making roles.

Third, workforce education and firm size are associated with anticipated needs in decision-making roles but not in administrative ones, while R&D activity is associated with anticipated needs in all role categories.

6.2 Interpretations

One reading, suggested by the absorptive capacity and dynamic capabilities perspectives, is that firms with a richer competence base are better placed to recognise what they still lack, and that firms deploying AI and automation generate new, more decision-oriented competence demands as routine tasks are automated (Acemoglu and Restrepo 2019, Agrawal et al. 2024). The concentration of the AI and automation difference in decision-making roles is consistent with this reading, as is the broader pattern that skill-rich and R&D-active firms anticipate needs more often. Ransbotham et al. (2017) report, from international survey data, that firms with more AI experience also express a fuller view of what AI requires, which has a similar flavour.

A second reading is that perceived needs scale with digital activity. Firms that already do more with digital technologies, and expect to do more, have more positions to fill in digital areas and more occasions to encounter competence gaps. On this reading the patterns in Tables 3 and 4 tell us about the distribution of digital activity across firms rather than about differences in how firms sense gaps. The fact that the

differences are concentrated in recruitment rather than internal development fits this reading at least as well as the first.

A third reading is that firms differ in their business models and in the technological requirements these entail. A firm in a sector or market where digital competence is not central may accurately report low needs. Sector fixed effects absorb part of this variation, but not differences within sectors.

The catch-up perspectives discussed in Section 2 would lead one to expect digital laggards to report particularly high needs. We do not observe this in the aggregate: firms with fewer digital competences, smaller size and less educated workforces report anticipated needs less often. But we would caution against reading this as evidence against catch-up pressure. The perceived-need measure cannot distinguish between a firm that faces no pressure and a firm that faces pressure but does not recognise it as a competence problem, and the survey does not measure performance shortfalls, aspiration levels or competitive pressure directly. The question of whether and how digital laggards perceive their position is, in our view, one of the more important ones that this description raises but cannot answer.

6.3 Relation to the period after 2022

The data were collected in 2020, with anticipated needs referring to the following three years. They therefore describe firms' perceptions in the period immediately before generative AI tools became widely available. We do not have observations from after that point and make no claims about how the patterns have evolved. Two remarks nonetheless seem warranted.

The first is that the patterns we document are not specific to generative AI, or indeed to AI. The competences that most strongly distinguish firms in Table 4 are data analytics, business systems and IT infrastructure, and the role-specific differences for workforce education and size do not depend on AI and automation competence at all. To the extent that uneven perceived needs are a general feature of digital transformation, they presumably predate and are likely to outlast any particular technology wave.

The second is that the evidence to date on the distribution of generative AI adoption is mixed. Experimental and quasi-experimental studies report that productivity gains from generative AI tools accrue disproportionately to less experienced workers (Brynjolfsson et al. 2025), which could in principle reduce competence gaps across firms. Cross-country adoption data, on the other hand, indicate that firms and countries with more prior AI adoption have continued to pull ahead (Kergroach and Héritier 2025, OECD/BCG/INSEAD 2025). Our data cannot speak to this question. What they offer is a reasonably detailed account of where firms stood before it arose, against which later observations of the same or similar measures could be compared.

6.4 Limitations

The limitations of the analysis follow from its design. The data are cross-sectional, so all estimates are associations at a single point in time, and we cannot say whether differences across firms were widening, narrowing or stable. The outcome measures are self-reported and reflect firms' own statements about their needs; they are not validated measures of competence gaps or of managerial awareness. The seven competence indicators are binary and describe the firm's competence profile rather than a validated digital maturity construct (Orero-Blat et al. 2025); they are best read individually, as we have done, rather than as a composite. The mechanisms emphasised by the theoretical perspectives in Section 2 (performance shortfalls, competitive pressure, sensing routines) are not measured. Reverse causality and unobserved heterogeneity in strategy and management are plausible and cannot be ruled out with the available data. Finally, the analysis covers Swedish firms with ten or more employees. Sweden is among the EU's more digitalised economies, with AI adoption rates in the upper range of the EU distribution (Kergroach and Héritier 2025), and the patterns may differ in countries with a larger gap between leading and lagging firms.

6.5 Implications

For research, the analyses suggest several lines of further work. Longitudinal data on perceived needs, ideally for the same firms before and after 2022, would allow one to examine whether the patterns documented here persisted and whether the gap between firms with broad and narrow competence profiles changed. Direct measures of firms' assessments of their competitive position and of their aspirations would allow the awareness and catch-up interpretations to be examined rather than merely entertained. Linking perceived needs to subsequent realised hiring and training in register data would show whether stated needs are followed by investment, and for which firms.

For policy, the main implication is a cautious one. The firms that most often report anticipated needs for digital competence in these data are the firms that already have it: large, R&D-active, skill-rich firms with broad digital competence profiles. If skills policy is informed by expressed demand, it will tend to be pulled toward those firms. Whether the low reported needs among other firms reflect limited requirements or limited recognition is, as discussed, not something these data can settle; but the possibility of the latter suggests that policies aimed at smaller and less digitalised firms may need to address the identification of competence needs, not only their fulfilment. The role-level results also indicate that digital competence needs are not confined to technical or administrative functions. Among firms with an advanced digital profile, anticipated needs for both technical specialists and general digital competence are frequently located in product development, business analysis and decision-making roles, which is relevant for the design of training provision. This is broadly in line with recent survey evidence on SME digitalisation, which finds that smaller firms consistently trail larger ones in digital capability and AI uptake (Bianchini and Lasheras Sancho 2025), and with evidence from US job postings that AI-adopting firms shift skill requirements toward managerial and coordination roles (Alekseeva et al. 2026).

7. Conclusion

This paper has described how Swedish firms' self-reported needs for digital competence varied across firms in 2020, using a survey of 2,479 firms linked to register and innovation survey data. Perceived needs are more common among firms that already hold a broad set of digital competences, that are larger, that undertake R&D, and that have more highly educated workforces. The differences are, however, more specific than a simple ordering would suggest: they lie mainly in anticipated recruitment rather than in internal competence development, and, for AI and automation competence, workforce education and firm size, in decision-making rather than administrative roles.

These are cross-sectional associations in self-reported data, and we have set out several interpretations that the data cannot distinguish between. The contribution is to document the patterns in enough detail that subsequent work, with longitudinal data and direct measures of the relevant mechanisms, can examine why they arise and whether they have changed.

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APPENDIX

Box 1. Main variables and their role in the analysis

Variable	Definition	Role in this study
Current digital competence profile	Seven binary indicators of whether the firm reports having employees with competence in AI and automation, business systems (databases), social media, cybersecurity, data analytics, IT infrastructure, and websites and e-commerce, from the 2020 survey.	Explanatory variables, entered separately. The indicators describe the firm's competence profile; they are not a validated digital maturity scale and are not combined into a composite.
AI and automation competence	Binary indicator of whether the firm reports possessing AI and automation competence. Reported by 16% of firms; the least common of the seven indicators.	Explanatory variable of particular interest, interpreted conditional on the other six indicators.
Perceived competence need (overall)	The firm's statement of whether it needs to develop (train existing employees) or recruit digital competence today, and whether it expects to need to do so within three years.	Outcome variables (Table 3). Self-reported; not a measure of realised investment or of awareness of competence gaps.
Perceived competence need (by role)	The firm's statement of whether it anticipates needing technical specialists or general digital competence in administrative positions and in decision-making positions.	Outcome variables (Table 4). Self-reported, as above.
Firm characteristics	Size category, R&D activity (CIS 2020), share of employees with tertiary education, exporter status, MNE group membership, two-digit NACE sector (register data).	Conditioning variables.

Supplementary estimates.

Tables A-1 and A-2 report the multinomial logit estimates of Table 3 when the indicators of current digital competence are defined, respectively, as competence held in-house (Table A-1) and competence sourced externally (Table A-2). The main patterns in Table 3 are present in both: AI and automation competence is associated with a higher probability of anticipated recruitment within three years (8.4 points in-house, 12.9 points external) and not with a higher probability of internal development, and the size and education gradients are similar.

Table A-1. Multinomial logit: perceived competence need categories and firm characteristics, digital competence held in-house (average marginal effects).

	Need to develop digital competence today (1)	Need to recruit digital competence today (2)	Expected need to develop digital competence within three years (3)	Expected need to recruit digital competence within three years (4)
<i>Current digital competence (in-house)</i>				
AI and automation	−0.023 (0.028)	0.050*** (0.012)	0.008 (0.032)	0.084*** (0.027)
Business systems (database)	0.003 (0.013)	−0.011 (0.010)	0.028 (0.018)	0.039** (0.018)
Social media	0.009 (0.013)	−0.010 (0.010)	0.005 (0.018)	0.067*** (0.018)
Cybersecurity	−0.029 (0.021)	−0.020 (0.013)	0.005 (0.025)	0.070*** (0.023)
Data analytics	−0.023 (0.017)	0.001 (0.011)	0.018 (0.021)	0.113*** (0.019)
IT infrastructure (hardware and software)	0.011 (0.015)	0.012 (0.011)	0.051** (0.021)	0.049** (0.020)
Web (websites and e-commerce)	−0.064*** (0.019)	0.025** (0.011)	0.009 (0.022)	0.071*** (0.020)
<i>Other firm characteristics</i>				
Medium (50–249)	0.004 (0.014)	0.022** (0.011)	0.046** (0.019)	0.023 (0.020)
Large (250+)	−0.021 (0.030)	0.032* (0.017)	−0.023 (0.038)	0.118*** (0.033)
R&D dummy	0.021* (0.012)	0.009 (0.009)	0.010 (0.017)	0.041** (0.017)
Workers with higher education (share)	0.005 (0.029)	−0.006 (0.023)	0.075* (0.042)	0.086** (0.041)
Export dummy	0.023 (0.017)	−0.002 (0.012)	0.036 (0.023)	0.019 (0.023)
MNE	0.010 (0.016)	0.011 (0.011)	−0.032 (0.021)	0.002 (0.021)
NACE Rev. 2 sectors	Yes	Yes	Yes	Yes
Observations	2,479	2,479	2,479	2,479

Note: Dependent variable: perceived competence need category, with no current or anticipated need as the reference category. Average marginal effects with standard errors in parentheses. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table A-2. Multinomial logit: perceived competence need categories and firm characteristics, digital competence sourced externally (average marginal effects).

	Need to develop digital competence today (1)	Need to recruit digital competence today (2)	Expected need to develop digital competence within three years (3)	Expected need to recruit digital competence within three years (4)
<i>Current digital competence (external)</i>				
AI and automation	−0.043 (0.030)	0.003 (0.017)	−0.004 (0.033)	0.129*** (0.029)
Business systems (database)	−0.005 (0.014)	0.013 (0.010)	0.002 (0.019)	0.033* (0.019)
Social media	0.004 (0.017)	0.029*** (0.011)	0.014 (0.023)	0.019 (0.023)
Cybersecurity	0.011 (0.015)	−0.014 (0.012)	0.023 (0.021)	0.061*** (0.020)
Data analytics	−0.032 (0.023)	−0.007 (0.014)	0.010 (0.027)	0.039 (0.026)
IT infrastructure (hardware and software)	0.015 (0.014)	−0.009 (0.010)	0.019 (0.019)	0.021 (0.019)
Web (websites and e-commerce)	−0.027* (0.014)	0.005 (0.010)	0.037* (0.019)	0.079*** (0.019)
<i>Other firm characteristics</i>				
Medium (50–249)	−0.003 (0.014)	0.025** (0.010)	0.052*** (0.019)	0.056*** (0.020)
Large (250+)	−0.040 (0.029)	0.039** (0.016)	−0.002 (0.036)	0.209*** (0.031)
R&D dummy	0.018 (0.012)	0.012 (0.009)	0.011 (0.017)	0.046*** (0.018)
Workers with higher education (share)	−0.020 (0.029)	0.010 (0.022)	0.084** (0.041)	0.167*** (0.041)
Export dummy	0.021 (0.017)	−0.001 (0.012)	0.035 (0.023)	0.027 (0.023)
MNE	0.005 (0.016)	0.016 (0.011)	−0.021 (0.021)	0.030 (0.021)
NACE Rev. 2 sectors	Yes	Yes	Yes	Yes
Observations	2,479	2,479	2,479	2,479

Note: Dependent variable: perceived competence need category, with no current or anticipated need as the reference category. Average marginal effects with standard errors in parentheses. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.



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