How GenAI-Driven Automation Prospects Shape Firms' Training Decisions

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- Firm training is essential for
  - skill development of the active workforce
  - labor market entry & acquisition of occupation-specific skills of apprentices
- Generative AI (GenAI) allows the automation of skilled tasks, altering skill demand

- Firm training is essential for
  - skill development of the active workforce
  - **labor market entry & skill acquisition of future workers**
- Generative AI (GenAI) allows the automation of skilled tasks, altering skill demand

$\rightarrow$ **Our research question:**

How will post-GenAI automation reshape firms' **decisions to train apprentices?**

$\rightarrow$ Explored theoretically and experimentally

Summary

Research Question: How will automation driven by GenAI reshape firms' decisions to train apprentices?

Empirical Strategy & Data: Vignette experiment as part of a survey among 3,006 training firms in Switzerland in 2024

Findings:

- Firms reduce their apprenticeship positions more
  - the higher the automation intensity, and
  - the sooner its implementation
- Responses to automation intensity and timing vary by
  - occupations' routine intensity and worker retention share, and
  - firms' size and capital intensity

Digital technology and skill demand

- Pre-GenAI digital transformation: (Autor et al., 2003; Katz and Murphy, 1992)
  - Substitution of low-skilled and routine workers
  - Complementarity with high-skilled and non-routine cognitive workers
- GenAI and skill demand:
  - Negative short-time effects on skilled cognitive workers (Demirci et al., 2025; Eloundou et al., 2023; Felten et al., 2023; Hui et al., 2023) and entry-level workers (e.g., Brynjolfsson et al. 2025)
  - Uncertainty about mid-term effects on skill demand

Digital technology and firm training

- Emerging literature shows mixed effects of pre-GenAI digital technology on firm training (Brunello et al., 2023; Gathmann et al., 2024; Heß et al., 2023; Muehlemann, 2024) Literature
- Still unexplored how post-GenAI automation will reshape firms' training decisions

Apprenticeship training in Switzerland

- About 70% of Swiss youth start apprenticeships after compulsory school, choosing from over 230 occupations for 3-4 years
- Firms train apprentices mainly for two reasons: (Lindley, 1975; Stevens, 1994; Wolter and Ryan, 2011)
  - As cheap substitutes for unskilled labor
  - As investments in future skilled workers

Model

- 3-period Stevens (1994) training model with tradeoff:
  - invest in training apprentices who become – with a certain conversion rate – future skilled workers
  - spend money to hire skilled workers
- Task-based Acemoglu and Restrepo (2019) automation with two tasks being perfect complements
- Partial equilibrium model with
  - Wages fixed
  - Prices given by a Cournot model with M firms automating at the same time

Hypotheses

The experiment

Experiment embedded in a survey with 3,006 recruiters in training firms in Switzerland (2024, 63% response rate) completing 3 vignettes:

Due to developments in artificial intelligence (AI) and robotics, certain professions will be partially automated. Imagine an internal analysis of your firm shows that in **t** *years* **p** *% of tasks of a trained* **o** *will be automated. However, no tasks will be automated over the next* **t** *years. By how many percent would you reduce the number of apprenticeships for* **o***?*

- **o**: Occupation for which firm offers the most apprenticeship positions
- **p**: Percentage of tasks that are automated: 20, 40, 60
- **t**: Number of years until no automation happens: 2, 4, 6

Table: Effect on apprenticeships reduction, baseline

	(1)
Share of tasks automated (10 ppt.)	1.448***
	(0.103)
Time until automation (years)	-0.470***
	(0.098)
Firm FE	✓
N	8927
Mean of Dep. Var.	11.354

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table: Occupation type

	(1)	(2)	(3)
Share of tasks automated (10 ppt.)	1.448***	1.191***	1.570***
	(0.103)	(0.118)	(0.148)
Time until automation (years)	-0.470***	-0.365***	-0.540***
	(0.098)	(0.113)	(0.142)
Routine occupation * Share of tasks automated (10 ppt.)		0.851***	
		(0.252)	
Routine occupation * Time until automation (years)		-0.461*	
		(0.236)	
Manual occupation * Share of tasks automated (10 ppt.)			-0.293
			(0.211)
Manual occupation * Time until automation (years)			0.092
			(0.200)
Firm FE	✓	✓	✓
N	8927	8435	8435
Mean of Dep. Var.	11.354	11.153	11.153

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table: Retention share

	(1)	(2)
Share of tasks automated (10 ppt.)	1.448***	1.685***
	(0.103)	(0.146)
Time until automation (years)	-0.470***	-0.644***
	(0.098)	(0.136)
High Retention share * Share of tasks automated (10 ppt.)		-0.519**
		(0.204)
High Retention share * Time until automation (years)		0.386**
		(0.195)
Firm FE	✓	✓
N	8927	8927
Mean of Dep. Var.	11.354	11.354

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table: Firm characteristics

	(1)	(2)
Share of tasks automated (10 ppt.)	1.448***	1.131***
	(0.103)	(0.180)
Time until automation (years)	-0.470***	-0.169
	(0.098)	(0.163)
High CI * Share of tasks automated (10 ppt.)		0.553**
		(0.221)
High CI * Time until automation (years)		0.071
		(0.211)
<10 employees * Share of tasks automated (10 ppt.)		-0.060
		(0.224)
>99 employees * Share of tasks automated (10 ppt.)		0.822***
		(0.299)
<10 employees * Time until automation (years)		-0.383*
		(0.208)
>99 employees * Time until automation (years)		-0.635**
		(0.279)
Firm FE	✓	✓
N	8927	8927
Mean of Dep. Var.	11.354	11.354

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Conclusions

- First evidence on how post-GenAI automation can be expected to affect apprenticeship training
- Training firms can be expected to reduce apprenticeship positions in response to automation expectations
- Response heterogeneity by occupation type – due to varying task reallocation potential?
- Response heterogeneity by firm size and capital intensity

Acemoglu, D. and Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives*, 33(2):3–30.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*.

Brunello, G., Rückert, D., Weiss, C., and Wruuck, P. (2023). Advanced Digital Technologies and Investment in Employee Training: Complements or Substitutes? *SSRN Journal*.

Brynjolfsson, E., Chandar, B., and Chen, R. (2025). Canaries in the Coal Mine? Six Facts about the Recent Employment Effects of Artificial Intelligence.

Demirci, O., Hannane, J., and Zhu, X. (2025). Who Is AI Replacing? The Impact of Generative AI on Online Freelancing Platforms. *Management Science*, page mnsc.2024.05420.

Eloundou, T., Manning, S., Mishkin, P., and Rock, D. (2023). GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models.

Felten, E. W., Raj, M., and Seamans, R. (2023). How will Language Modelers like ChatGPT Affect Occupations and Industries? *SSRN Journal*.

Gathmann, C., Kagerl, C., Pohlan, L., and Roth, D. (2024). The pandemic push: Digital technologies and workforce adjustments. *Labour Economics*, 89:102541.

Heß, P., Janssen, S., and Leber, U. (2023). The effect of automation technology on workers' training participation. *Economics of Education Review*, 96:102438.

Hui, X., Reshef, O., and Zhou, L. (2023). The Short-Term Effects of Generative Artificial Intelligence on Employment: Evidence from an Online Labor Market.

Katz, L. F. and Murphy, K. M. (1992). Changes in Relative Wages, 1963-1987: Supply and Demand Factors. *The Quarterly Journal of Economics*, 107(1):35–78.

Lindley, R. M. (1975). The Demand for Apprentice Recruits by the Engineering Industry, 1951-71. *Scottish J Political Eco*, 22(1):1–24.

Muehlemann, S. (2024). AI Adoption and Workplace Training. *SSRN Journal*.

Stevens, M. (1994). An Investment Model for the Supply of Training by Employers. *The Economic Journal*, 104(424):556.

Wolter, S. C. and Ryan, P. (2011). Apprenticeship. In *Handbook of the Economics of Education*, volume 3, pages 521–576. Elsevier.

Digital technology and firm training

Emerging literature shows mixed effects of digital technology on firm training:

- Workers exposed to automation participate less in training as firms cut support (Heß et al., 2023).
- Advanced digital technologies can reduce firm-sponsored training, acting as substitutes (Brunello et al., 2023).
- Contrarily, digital investments during the pandemic increased German firms' training needs and provision (Gathmann et al., 2024).
- Pre-generative AI adoption was linked to more apprenticeship contracts, especially in SMEs (Muehlemann, 2024).

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Hypotheses I

- ✓ H1: Higher automation intensity leads to a greater reduction in apprenticeship positions.
- ✓ H2: Earlier implementation of automation results in a greater reduction in apprenticeship positions.
- ✓ H3: A higher retention share of trained apprentices amplifies the effect of automation intensity and timing on apprenticeship reduction.

✓ Model-grounded ? Not yet model-grounded

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Hypotheses II

- ? H4: A higher potential for task reallocation within an occupation mitigates the effect of automation intensity and timing on the reduction of apprenticeship positions.
- ? H5: Cognitive occupations respond more strongly to automation intensity and timing in terms of apprenticeship reduction.
- ✓ H6: Larger firms respond more strongly to automation intensity and timing in terms of apprenticeship reduction.

✓ Model-grounded ? Not yet model-grounded

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Table: Sample characteristics

	Mean
Firm size	
Small (<10 employees)	0.499
Medium (10 – 99 employees)	0.285
Large (100+ employees)	0.200
Language region	
German region	0.628
French region	0.271
Italian region	0.085
Sector	
Agriculture	0.052
Industry	0.278
Services	0.653