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Generative AI and Career Choices

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Abstract
The economic impact of technological change will critically depend on how future workers invest in their human capital. Yet, little is known about how future workers themselves evaluate and choose their educational and occupational paths in light of emerging technologies. This paper examines how adolescents currently at the schoolto-work transition stage value working with generative artificial intelligence (GenAI) in their future occupations, and how automation risk and opportunities for continuing education shape these preferences. We field a discrete-choice experiment among a nationally representative sample of over 7,000 Swiss adolescents aged around 15. We find that adolescents generally exhibit an aversion to collaborating with GenAI at work, with females consistently more averse than males. However, preferences are nuanced: adolescents welcome greater GenAI collaboration, provided that GenAI usage levels remain moderate and that it is not accompanied by increases in jobautomation risk. Finally, continuing education opportunities in occupations improve attitudes towards working with GenAI across genders. Our results challenge simple narratives of technology acceptance or rejection, revealing that adolescents' willingness to work with GenAI depends on how it is implemented — its intensity, associated displacement risks, and accompanying skill development — rather than the technology itself. Our findings suggest that the way future workers value GenAI collaboration in their career choices critically depends on its intensity and on the interplay with automation risk and AI-related educational opportunities.

JEL classification
I24, J24, O33

Keywords
occupational choice, gender gaps, GenAI, choice experiment, continuing education, automation risk

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1 Introduction

Technological advancements in artificial intelligence (AI), robotics, and other digital technologies are shaping our societies and the future of work. The economic impact of technological change will critically depend on the process of human capital adjustments, namely on the "race between education and technology" (Autor, Goldin and Katz, 2020; Katz, 2025). Thus, understanding the changing nature of the demand and supply of skills and talent is of fundamental importance. Yet, the supply side of this race remains poorly understood. In particular, little is known about how future workers themselves evaluate and choose occupations in light of emerging technologies—a critical gap given the rapid rise of generative artificial intelligence (GenAI) and its potentially substantial labor market consequences. By relying on a choice experiment focusing on a nationally representative sample of over 7,000 Swiss adolescents, we provide evidence on the following questions: How do future workers value working with GenAI in their future jobs? What role do perceptions of automation risk, opportunities for continuing education, and the intensity of GenAI collaboration play?

While a large economic literature examines the labor market impacts of automation and, more recently, of GenAI (Acemoglu and Restrepo, 2019; Acemoglu et al., 2022; Autor et al., 2024; Autor and Thompson, 2025), most of this work focuses on the demand side of the labor market (Brynjolfsson, Chandar and Chen, 2025; Demirci, Hannane and Zhu, 2025; Hui, Reshef and Zhou, 2024). By contrast, much less is known about the supply side of the labor market. In particular, the growing economic literature is limited to how workers respond to pre-GenAI innovations in their education choices (e.g. Giacomo and Lerch, 2023) and their perceptions of automation technology (Cattaneo, Gschwendt and Wolter, 2025; Golin and Rauh, 2022), how workplaces adopt GenAI (Bick, Blandin and Deming, 2024; Carvajal, Franco and Isaksson, 2024; Handa et al., 2025; Hartley et al., 2025; Humlum and Vestergaard, 2024), and how GenAI affects productivity and worker outcomes (Brynjolfsson, Li and Raymond, 2025; Dell'Acqua et al., 2023; Fouarge et al., 2025; Haslberger, Gingrich and Bhatia, 2023).

Goller, Gschwendt and Wolter (2025) provide first evidence on labor market responses to GenAI, showing that Swiss students shifted occupational search away from GenAI-exposed fields following ChatGPT's release. This leaves a central question: do adolescents avoid GenAI-exposed occupations because they associate GenAI collaboration with higher automation risk; do they avoid GenAI collaboration itself because they prefer other, e.g., hands-on or people-centric work; or would they welcome GenAI but require training to use it confidently? The distinction is pivotal because it governs willingness to invest in GenAI-intensive training.

A better understanding of future workers' preferences for occupations involving GenAI collaboration is crucial for workers, firms, and policymakers. If future workers resist collaboration with GenAI, this will likely worsen their labor market opportunities, and firms may face severe skill-supply constraints, driving greater investments in automation or offshoring. Policymakers may want to anticipate a potential GenAI skill mismatch early in adolescents' career choices, as this would allow them to implement appropriate policies to mitigate an undersupply of labor. If adolescents prove willing to train in GenAI, the policy challenge shifts from fostering interest to building high-quality, equitable, and inclusive training pathways. Yet current policy and workplace planning operate largely in the dark: we lack quantitative evidence of adolescents' preference for GenAI-collaborative work.

We conduct a discrete-choice experiment among Swiss adolescents at the critical juncture of their transition from school to work. Specifically, we conduct our analysis using a nationally representative sample of more than 7,000 Swiss adolescents around the age of 15, who are either about to enter or have recently entered the labor market. At this age, adolescents must decide whether to pursue a specific apprenticeship (vocational education and training) or otherwise continue with general education, which allows them to enter university programs upon completion. In our experiment, respondents choose three times between two multi-year training programs (apprenticeship/ university degree) that they would invest in learning over the next several years. The programs differ in terms of GenAI collaboration at work, automation risk, availability of continuing education opportunities, and gross monthly salary. While the choice scenario is hypothetical, it reflects realistic decision-making: adolescents in our sample have recently decided or will decide in the near future which career path to pursue.

Switzerland represents an ideal setting for this study. It ranks first among 139 economies in the Global Innovation Index for the 15th consecutive year (WIPO, 2025) and has particularly high potential for GenAI development and adoption (EPFL, 2025). These features enable us to study occupational preferences in a context in which GenAI adoption is imminent and where human capital investments in both vocational and academic tracks matter substantially.

The paper makes three main contributions to the literature. First, we provide causal evidence on the role of GenAI in shaping career choices among a large nationally representative sample of adolescents at a critical juncture of their school-to-work transition.

Second, we provide evidence on the role of GenAI relative to automation risk and continuing education opportunities. That is, we explicitly separate workers' perceived automation risk from their willingness to collaborate with GenAI. Understanding the extent to which workplace continuing education opportunities affect career choices is especially important given the rapid pace of GenAI adoption across occupations and the uncertainty it creates about workers' need to upskill and reskill to remain competitive in the labor market.

Third, we examine the heterogeneity by socio-demographic characteristics, with a focus on gender differences. We relate to the literature on gender gaps in education and labor market choices (e.g., Conde-Ruiz et al., 2024; Strobl and Wunsch, 2023), gender differences in risk attitudes (e.g., Borwein et al., 2026; Filippin, 2022), and willingness to work with technology. Recent research provides descriptive evidence showing that women compared to men are less likely to use generative AI tools (e.g., Aldasoro et al., 2024; Carvajal, Franco and Isaksson, 2024; Cazzaniga et al., 2025; Otis et al., 2024).

We find that adolescents exhibit an overall aversion to GenAI collaboration at work, with females more averse than males. However, preferences are nuanced. Adolescents welcome higher GenAI collaboration intensity, provided it is not accompanied by an increase in job automation risk, and as long as GenAI usage levels remain moderate. When usage levels are already high, adolescents, particularly females, have a strong aversion to working with GenAI. Finally, continuing education opportunities in occupations improve attitudes toward working with GenAI among both genders. These findings suggest that future workers value GenAI-collaboration depending critically on its intensity and the interplay with automation risk and educational opportunities.

The remainder of the paper is organized as follows. Section 2 presents the institutional background of the study, with a description of the Swiss education system and the stage at which students make a high-stakes decision about their career trajectories. Section 3 describes the methodology underlying the experiment, the experimental design, its implementation, and the timeline of data collection. Section 4 describes the dataset, the analytical sample, and the estimation method. Section 5 reports the empirical findings, robustness, and heterogeneities. Finally, section 6 discusses the results, their limitations, and presents concluding remarks.

2 Background and institutional setting

Swiss adolescents make their first high-stakes education and career decision at the end of compulsory schooling (K+9), typically around age 15. In their final year of compulsory education, students must decide whether to pursue vocational education and training (VET) or general education at the upper secondary level. This institutional timing is critical to our study because adolescents face a narrow window during which their preferences regarding technology, automation, and continuing education influence their substantial investment decisions in human capital. Approximately two-thirds of students choose the vocational education and training pathway, which allows them to learn an apprenticeship occupation both at school and in a training firm. The remaining one-third of students opt for general education (baccalaureate schools), which allow students upon graduation to directly enroll in a university program (FSO, 2022; SCCRE, 2023).

All Swiss adolescents face a high-stakes decision at the end of compulsory schooling, requiring them to actively evaluate different career pathways. They must first decide between the VET and the general education track. Next, they must decide which particular occupation or field within that track to pursue. Within the VET track, students select one apprenticeship to undertake for the next 3 to 4 years from a pool of approximately 240 occupations. Notably, apprenticeship graduates typically continue to work in their trained occupations for many years after graduation (FSO, 2020). Within the general track, adolescents typically choose a study profile—such as an economics, musical, modern languages, or classical languages profile. Importantly, these decisions substantially shape adolescents' future labor market opportunities and earnings (see e.g., FSO, 2025; SCCRE, 2023), and require them to form detailed preferences over their future field of work—what sector they enter, which tasks they perform, and how much they collaborate with technology or people.

Before making this high-stakes decision, adolescents need to inform themselves in depth, considering not only their current skill match to and preferences for an educational track or occupation but also the expected development of their aspired occupation. In particular, students may not want to invest in pursuing an occupation whose work tasks will change substantially in the future, decrease in demand, or even become obsolete due to technological advancements.[1] A recent study by Goller, Gschwendt and

[1]In fact, previously widespread apprenticeships, such as typesetters or watchmakers, have evolved into niche occupations as a result of shifting demand driven by technological change.

Wolter (2025) shows that Swiss students responded to the introduction of GenAI by adjusting their occupational choices, moving away from potentially GenAI-exposed occupations. Their findings may indicate uncertainty about future skill demand in GenAI-exposed occupations, uncertainty about the future demand for such occupations, or a general aversion to GenAI collaboration in their future jobs. This responsiveness underscores the relevance of studying how adolescents value working with GenAI at the precise moment they commit to multi-year training programs.

GenAI is pertinent for both vocational and general education pathways. While pre-GenAI digitalization primarily substituted mid-skill routine work and complemented high-skill non-routine tasks (Autor, Levy and Murnane, 2003; Goos and Manning, 2007; Gschwendt, 2022), GenAI has substantial potential for both automation and augmentation across occupations and skill levels, including non-routine cognitive tasks typical of general-educated workers (Eloundou et al., 2024; Felten, Raj and Seamans, 2023; Gmyrek et al., 2025). Recent evidence shows that although GenAI use is most prevalent among white-collar workers, it is also widespread among blue-collar workers (Bick, Blandin and Deming, 2024; Humlum and Vestergaard, 2024), and firms may reduce entry-level training positions in mid-skill occupations in response to GenAI-driven automation (Gschwendt and Schilter, 2025). As the use of GenAI is increasingly important across workplaces and is projected to expand further, it is expected to become an integral component of many more occupations and may even drive the development of entirely new roles. Moreover, experts and policymakers increasingly call for teaching GenAI skills in both vocational and general education in response to rising demand (SRF News, 2025).

Switzerland, like many high-income countries, exhibits persistent occupational gender segregation (SERI, 2024; SKBF, 2023). Moreover, recent research has provided descriptive evidence showing that women are less likely to use generative AI tools (Aldasoro et al., 2024; Carvajal, Franco and Isaksson, 2024; Cazzaniga et al., 2025; Otis et al., 2024), and the gender gap in generative AI use is particularly large among 18-24 year-olds (WEFSRF News, 2024). We thus analyze preferences for GenAI separately for females and males, contributing to the economic understanding of gender segregation related to the uptake of technology (Seufert et al., 2025).

The Swiss setting offers distinct advantages for studying these preferences. Switzerland ranks first among 139 economies in the Global Innovation Index for the 15th consecutive year and relies on strong public–private partnerships for GenAI adoption (EPFL, 2025; WIPO, 2025). Unlike in many countries, where career decisions are made over several years, Swiss students typically choose their career path in the final year of compulsory education. This permits the study of the entire future workforce at the same age and across the full ability distribution in both academic and vocational tracks. Moreover, substantial cultural variation exists across the three language regions, including differences in the uptake of school technology (Oggenfuss and Wolter, 2024). This variation enables us to conduct heterogeneity analyses and address potential concerns regarding the country's high levels of innovation and GenAI adoption.

3 Experimental setup

In Subsection 3.1 we first describe the general idea of choice experiment, followed by Subsection 3.2 in which we give a detailed overview of our design.

3.1 Experimental method

Discrete-choice experiments (DCEs) are frequently used by applied economists for eliciting individual preferences in settings that range from labor-market choices to healthcare and environmental policy. DCEs assume that overall utility is the sum of the marginal utilities obtained from well-defined attributes, building on random-utility maximization (McFadden, 1974) and Lancaster's theory of consumer choice (Lancaster, 1966). Respondents therefore reveal the relative value of each attribute by making trade-offs in carefully designed hypothetical choice sets. We apply this approach to measure how adolescents assess key characteristics of prospective occupations when deciding on their initial career pathway. Notably, the aim of this study is not to predict career choices. Rather, the aim is to understand how adolescents value different occupational attributes when making career choices.

The method is particularly well-suited to adolescent career decisions because it sidesteps two empirical hurdles that plague revealed-preference data. First, we do not need to reconstruct the unobserved set of alternatives each adolescent actually considers in their career choice. Second, by holding all non-experimental job attributes constant across alternatives, we mitigate the potential correlation between observable and unobservable characteristics that usually biases estimates based on realized choices. Each respondent faces three paired comparisons of hypothetical occupations that differ only in the experimentally manipulated attributes, providing a clearer picture of how adolescents value different occupational attributes in their career decision-making process.

Although discrete-choice experiments (DCEs) are now widely used across economics, their external validity is still questioned because respondents evaluate hypothetical rather than real decisions (e.g., Loomis, 2011; Menapace and Raffaelli, 2020). Nevertheless, as argued by Cattaneo, Gschwendt and Wolter (2025) and supported by studies that compare stated choices with revealed preferences and choices (Mas and Pallais, 2017; Wiswall and Zafar, 2018), carefully designed DCEs can closely approximate actual market behavior, especially when they focus on decisions for which respondents already have concrete real-life reference points. This condition is met in our study because Swiss pupils must choose an educational track and often even sign apprenticeship contracts around age 15.[2] Thus, our survey respondents were already confronted with – or even finalized – a real career decision by the time they took the survey.

3.2 Experimental design

In our survey, each adolescent completes three choice tasks containing two occupation profiles and must indicate which corresponding multi-year program they would prefer to enroll in. The occupations vary in monthly gross salary, whether continuing education is commonly encouraged by employers, the risk of automation associated with each occupation, and the proportion of daily tasks that are completed with the help of GenAI.[3]

Each attribute reflects a unique concept. Continuing education captures the notion that adolescents need to invest, also outside of working hours, into learning new technologies and improving their social skills to perform their tasks well. The occupation's risk of automation is the risk that the adolescents' profession will be completely replaced by new technologies such as robots and artificial intelligence in the next 5 years.[4] The automation risk definition emphasizes the replacement of the entire occupation, not just job loss at a single firm. GenAI usage captures the proportion of tasks that adolescents complete with the help of GenAI tools, such as ChatGPT, that is, in direct collaboration with GenAI.

We specifically include both automation risk and GenAI usage as these are two dis-

[2] If the student is underage, de facto the parents need to sign the contract.

[3] For this paper, we use four attributes (see Table 1). The number of attributes and choice sets minimizes the risk that respondents are overwhelmed by the latter, while simultaneously allowing a rigorous analysis of respondents' preferences for GenAI collaboration.

[4] We adjust the definition of automation risk used in Cattaneo, Gschwendt and Wolter (2025).

tinct concepts. Occupations that require a high intensity of GenAI usage are not necessarily at a high automation risk, nor are occupations that require a low intensity of GenAI usage necessarily at low automation risk. Including both automation risk and GenAI usage allows us to disentangle students' preference for GenAI usage from their fear of becoming obsolete because of GenAI. As students may associate an increase in GenAI usage with higher automation risk, the introductory text, preceding the choice sets, clarifies the distinction between GenAI and automation risk by explicitly stating that occupations can be automated by technologies, including AI.

To introduce adolescents to these concepts, they read an introductory text before choosing between occupations. The text serves first, the purpose of setting a stage that adolescents can identify with. While the situation is hypothetical, deciding on a career path is not a far-fetched and abstract task for the respondents, as they have recently decided or will decide in the near future which career path to take. Second, the text highlights that the choices vary only in the listed attributes. The text is phrased in a way that both adolescents from the VET and general tracks can identify with the choice scenario. Specifically, the introductory text explicitly notes that the multi-year program might take the form of an apprenticeship or a university program. Third, the introductory text serves to explain the terminology, ensuring that all adolescents have a common baseline understanding of continuing education, automation risk, and GenAI usage. The introductory text and example of a choice situation are available in Figure B.1.

The attributes describing the alternatives and their levels are reported in Table 1. We selected the levels based on the existing research focusing on artificial intelligence, automation, continuing education, and youth career choices. We use three sources to calibrate the attribute levels for GenAI usage intensity and automation risk: (i) recent task-based estimates of GenAI exposure (Bick, Blandin and Deming, 2024; Felten, Raj and Seamans, 2023; Gmyrek et al., 2025; Handa et al., 2025); (ii) forward-looking automation-risk scores (Frey and Osborne, 2017; Webb, 2020); and (iii) information on occupational distributions from the Swiss Labour Force Survey (FSO, 2024). Notably, levels were set to roughly reflect plausible conditions at labor-market entry–depending on the track and degree, in around 4 to 10 years. "Small", "medium" and "large" GenAI usage levels correspond to 10%, 40% and 70% of tasks. The automation risks levels are 10%, 30% and 50%.

Levels for monthly gross wage center on the rounded median full-time salary (CHF

Table 1: Levels of choice set attributes

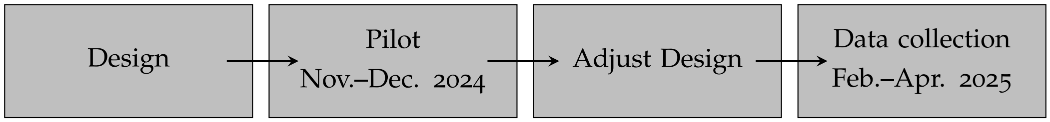
Attribute	Levels
Monthly gross wage (CHF)	- 6,500 - 7,000 - 7,500
AI usage	- A small proportion of tasks (10%) - Almost half of tasks (40%) - A large proportion of tasks (70%)
Automation risk	- Minimal risk (10%) - Moderate risk (30%) - High risk (50%)
Continuing education	- Yes - No

7,000) for 35- to 45-year-olds from the Swiss Labour Force Survey (FSO, 2024) and vary by ± CHF 500. The wage range is rather narrow, as pilot work showed that larger wage gaps dominated adolescents' choices, and we wanted to prevent wages from crowding out attention to the non-wage attributes. Finally, the continuing education attribute captures whether workers in an occupation are expected to engage in regular training outside working hours (e.g., in new technologies or social skills) to maintain a high standard of work performance.

Prior to launching the main survey, we administered a pilot study to verify that respondents clearly understood both the task instructions and the wording of every attribute–level combination. A convenience sample of 88 lower-secondary pupils (mean age = 14.6) participated in the pilot (see Figure 1 for the timeline).

In the last step of developing our DCE, we had to select the choice sets. Including four occupational attributes with two to three levels each allows a total of 1,431 distinct choice sets. To minimize the number of choice sets each respondent needs to evaluate and to maximize the precision of the estimates (Rose and Bliemer, 2009), we create a D-efficient block design using the software Ngene. Specifically, we use Ngene to create a D-efficient panel mixed-logit design based on parameter estimates and standard deviations from our pilot survey. In our final design, each respondent answers 3 choice sets; that is, we split the 24 choice sets into eight blocks. Using this blocking technique has the advantage of minimizing the risk that respondents have to process more information

Figure 1: Time line



than they are cognitively able or willing to, while allowing us to efficiently estimate respondents' preferences across the entire sample (Louviere and Woodworth, 1983).[5] A detailed list of all choice sets is available in B.1.

4 Data and estimation method

In Subsection 4.1 we describe our sample. In Section 4.2 we describe the estimation method.

4.1 Data

Our main sample consists of a nationally representative sample (cantons, age, gender) of Swiss adolescents aged between 13 and 16 years and who are about to or have just entered the labor market. To reach adolescents, the choice experiment was embedded into the so-called "Nahtstellenbarometer" survey (School-to-Work Transition Barometer), conducted online from February to April 2025. The Nahtstellenbarometer is commissioned by the Swiss State Secretariat for Education, Research and Innovation and administered by GFS Bern, a private market research institute. It is conducted biannually and provides the national and local authorities with timely information about the initial phase of students' transition from compulsory schooling to post-compulsory education and training.

The response rate is exceptionally high, at 68%. This is due to the survey's official nature. Including our choice experiment did not cause systematic attrition, as the response rate did not decrease compared to the previous years, and students did not systematically drop out of the survey when answering the choice questions.

Our analysis sample comprises data of 7,285 respondents from all Swiss language

[5]For instance, Cattaneo, Gschwendt and Wolter (2025) use this approach to create their choice sets. We follow their argumentation.

regions (German, French, Italian).[6] The dataset provides detailed information about the respondent's socio-demographic characteristics including age, gender, migration status, parents' level of educational attainment, academic performance including test scores in mathematics, main language of instruction, and English, educational track (i.e., vocational vs. general education), as well as preferences for job-related characteristics.

The descriptive statistics in Table 2 highlight the major advantage of our sample, which is representative of future workers across Switzerland. Of the 7,285 respondents, 50% are male and the mean age is 15. 66.4% are from the German-speaking part of Switzerland, followed by 29,0% from the French-speaking, and 4,5% from the Italian-speaking regions. In terms of additional socio-demographic characteristics, about 15% of respondents are foreign-born.

Adolescents are from the entire academic achievement distribution. On average, around 31% of adolescents have very good self-reported math grades, and a substantial share of 44% have a grade lower than 4.5. To pass students need a grade 4, with 6 being the highest grade. The shares look similar for school language grades and English; though slightly more students have a very good grade in English (42%); 32% have a good grade in school language and 25% of students have a good grade in English.

The sample represents the future Swiss workforce across vocational and academic professions. 38.5% of the sample aspires to attend/or are in the vocational track, 36.7% aspire to attend or are in general education, and the remaining 24.7% have no clear preference yet or did not indicate their preferences. Table 2 shows significant gender differences in current school track and (self-declared) grade averages in Mathematics, school language, and English. Female students, on average, have better grades in languages and enroll more frequently in general education than their male counterparts.

[6] We apply sample weights provided by the survey institute. For details see https://cockpit.gfsbern.ch/de/cockpit/nahtstellenbarometer-2025. 280 respondents are aged 13; 273 are from the Italian language region, where transition from lower into upper secondary happens earlier than in the rest of Switzerland.

Table 2: Sample characteristics

	Full sample (1)	Females (2)	Males (3)	p-value (4)
Socio-demographic characteristics				
Age	15.120	15.115	15.124	0.609
	(0.791)	(0.791)	(0.791)	
Swiss born	0.848	0.844	0.853	0.182
	(0.359)	(0.363)	(0.355)	
Mother has tertiary degree	0.390	0.392	0.389	0.966
	(0.488)	(0.488)	(0.488)	
Father has tertiary degree	0.408	0.404	0.412	0.052
	(0.492)	(0.491)	(0.492)	
German language region	0.664	0.667	0.662	0.781
	(0.472)	(0.472)	(0.473)	
French language region	0.291	0.288	0.294	0.429
	(0.454)	(0.453)	(0.456)	
Italian language region	0.045	0.046	0.044	0.504
	(0.207)	(0.209)	(0.206)	
School grades				
Math: below good (≤4.5)	0.442	0.473	0.412	0.000
	(0.497)	(0.499)	(0.492)	
Math: good (5)	0.242	0.216	0.266	0.000
	(0.428)	(0.411)	(0.442)	
Math: very good (5.5+)	0.316	0.311	0.322	0.187
	(0.465)	(0.463)	(0.467)	
School language: below good (≤4.5)	0.387	0.300	0.470	0.000
	(0.487)	(0.458)	(0.499)	
School language: good (5)	0.313	0.321	0.306	0.057
	(0.464)	(0.467)	(0.461)	
School language: very good (5.5+)	0.300	0.379	0.224	0.000
	(0.458)	(0.485)	(0.417)	
English: below good (4.5)	0.325	0.281	0.368	0.000
	(0.469)	(0.449)	(0.482)	
English: good (5)	0.250	0.247	0.252	0.646
	(0.433)	(0.431)	(0.434)	
English: very good (5.5+)	0.425	0.472	0.379	0.000
	(0.494)	(0.499)	(0.485)	
Track and Preferences				
Vocational track	0.373	0.335	0.409	0.000
	(0.484)	(0.472)	(0.492)	
General education	0.324	0.376	0.275	0.000
	(0.468)	(0.484)	(0.446)	
No clear track preference	0.304	0.290	0.317	0.025
	(0.460)	(0.454)	(0.465)	
High preference for people work	0.314	0.380	0.251	0.000
	(0.464)	(0.486)	(0.434)	
High preference for manual work	0.251	0.206	0.293	0.000
	(0.434)	(0.405)	(0.455)	
Number of observations	7,285	3,649	3,636	

Note: This table reports the mean values of respondents' characteristics and background. Population weights applied. Column 4 reports the p-value of the two-sided t-test of equivalence (females/males) for the unweighted sample. In the Swiss context grade 6 is the maximum, and students need at least grade 4 to pass the exam. Students have a "high preference" for people or manual work when indicating at least a 4 on a 6-point Likert scale, i.e., that working with people/hands is somewhat important; low otherwise. Students have a preference for the vocational track if they have already started an apprenticeship or signal that they want to start an apprenticeship or a preparatory course. Students have a preference for the general track when they are currently enrolled in a baccalaureate school, or state that they want to continue with the baccalaureate school. Students have no clear preference when we have no information on what they aspire to do after compulsory schooling, or when they signal interest in both the general education and vocational tracks.

4.2 Estimation method

To examine adolescents' preference for occupational attributes, we use McFadden's (1974) random utility model, stating that adolescent i's utility from choosing occupation j in choice set s is given by:

$$U_{ijs} = CP_{ijs} + e_{ijs} \qquad i = 1, ..., N; \quad j = A, B; \quad s = 1, 2, 3 \tag{1}$$

where CP_{ijs} represents the systematic component of the overall utility, and e_{ijs} represents a random term. We assume the adolescent chooses the occupation A or B, which provides the higher utility, and that e_{ijs} is independently extreme value type-I distributed. Therefore, the probability of choosing j takes the form:

$$Prob(y_{is} = j) = \frac{exp(CP_{ijs})}{\sum_{l=A,B} exp(CP_{ils})} \tag{2}$$

where y_{is} denotes the choice observed for adolescent i in choice set s. We consider a linear specification for CP_{ijs} of the form:

$$CP_{ijs} = \alpha_{ij} + A'_{ijs}\delta_i \tag{3}$$

where A_{ijs} is the vector of the four attributes describing occupation j for adolescent i in choice set s. α_{ij} is an alternative-specific intercept and accounts for the general preferences of individuals for an alternative, e.g., for the alternative being displayed first or on the left side. The parameter vector δ_i captures the adolescents' individual preferences for the four occupational attributes. Apart from the wage parameter—set to a log-normal form—each parameter is assumed as normally distributed.

To account for preference heterogeneity in occupational choices among adolescents, we employ a mixed logit model that allows for individual-specific parameters (McFadden and Train, 2000). We estimate the model directly in willingness-to-pay (WTP) space, which allows us to interpret the resulting parameters, δ_i, as an adolescent's WTP for the non-monetary attributes in terms of monthly wages.[7] The WTP measures indicate

[7] We specify the model in WTP space rather than preference space. This choice does not substantively affect our findings, as results are qualitatively and quantitatively similar when estimated in preference space. For a detailed discussion on the advantages and disadvantages of each method, see Hole and Kolstad (2012); Scarpa, Thiene and Marangon (2008); Train and Weeks (2005); Train (2016). Additional tables of results in the preference space are available upon request.

how much adolescents would pay for a *change* in a specific continuous attribute, such as GenAI usage, or *having* a binary attribute, such as continuing education, while keeping their overall utility constant. That is, the WTP values indicate, for instance, how much adolescents would be willing to forgo or require to be compensated in order to be indifferent between an occupation with a given GenAI usage and an occupation with a 20-percentage-point higher GenAI usage (see e.g. Table 3). A positive (negative) WTP coefficient indicates a positive preference (dispreference) for an increase in the attribute, meaning adolescents require monetary compensation (meaning adolescents are willing to forgo monthly wages).

In the main analysis, we exclude 87 respondents who have no positive preference for wage. To identify these respondents, we calculate individual-level preferences for wage using the mixlbeta option of the Stata command mixlogit, which implements the method proposed by Revelt and Train (2000).[8]

5 Results

This Section presents the findings of the empirical analysis. We begin by presenting the main results of the discrete-choice experiment, followed by robustness checks and heterogeneity analysis by socio-demographic characteristics. Subsection 5.1 presents mean preferences for an increase in GenAI collaboration, automation risk, and having continuing education opportunities. Subsection 5.2 presents interaction effects between GenAI usage and automation risk and continuing education. Subsection 5.3 presents adolescents' preferences for an increase in GenAI collaboration at different intensity levels. Subsection 5.4 presents heterogeneity effects by gender and adolescents' preferences for working with their hands and with people.

5.1 Adolescents' preferences for GenAI, continuing education and automation risk

We begin by analyzing the mean preferences of future workers regarding GenAI usage, continuing education, and automation risk. Table 3 reports mean willingness-to-pay (WTP) estimates for occupation attributes from mixed logit models in the WTP space:

[8] In Appendix Table 16 we include respondents with negative or no wage preference. The results are quantitatively and qualitatively in line with the results based on our preferred sample specification (see Table 4).

the full sample in column 1, females in column 2, and males in column 3. Each attribute's WTP is derived from respondents' estimated wage sensitivity.

On average, respondents are indifferent between training for an occupation with and without continuing education when the former pays 639 less per month, indicating a strong preference for training in occupations that include continuing education. CHF 639 corresponds to 9.1% of a median monthly gross salary of CHF 7,000. Subsequently, we will use CHF 7,000 as the reference to calculate the effects in terms of a percentage of a monthly salary. In contrast, respondents exhibit a strong aversion to automation risk: to be indifferent between an occupation at a given risk level and one with a 20–percentage–point higher risk, the latter would need to pay CHF 853 (12.2%) more per month.[9] By comparison, aversion to higher GenAI usage at work is smaller in magnitude: respondents require CHF 113 (1.6%) more per month for a 20–percentage–point increase in GenAI usage intensity. Overall, adolescents exhibit a modest aversion to higher GenAI usage, even when automation risk is accounted for separately.

The baseline results reported in Table 3 are robust to inattention checks and alternative empirical specifications. We address potential respondent inattention in two ways. First, in all our WTP estimations, we exclude 87 respondents who show a negative or no preference for wage.[10] Second, in Table 17, we exclude respondents who completed the choice experiment particularly quickly and may not have carefully considered their choices. Excluding these respondents does not qualitatively change the results presented in Table 3. Thus, we argue that inattention is not a significant issue in our study. Additionally, Table 18 in the appendix reports the results, which allow for cross-variable correlation. Results are qualitatively similar to the results reported in Table 3, which do not account for cross-variable correlation.

[9] The implied WTP to avoid a 20-percentage-point increase in automation risk amounts to about 12% of the Swiss gross median monthly wage. Its absolute magnitude is substantially smaller than the WTP of 34% of the median wage reported by Cattaneo, Gschwendt and Wolter (2025) for a 20-percentage-point increase in automation risk among adults aged 25–65. This is unsurprising given the different respondent populations and settings. Adolescents at the career-choice transition point have longer adjustment horizons and lower sunk human capital, and Cattaneo, Gschwendt and Wolter (2025) find lower aversion to automation risk among younger individuals, both of which predict smaller WTP for automation risk in our setting. The two experiments also differ in the attributes included, limiting cross-study comparability.

[10] Negative wage coefficients violate the monotonicity of preferences assumed by WTP models and mechanically inflate absolute WTP for non-wage attributes. To enforce a minimal rationality/attention screen, we estimate individual-specific wage sensitivities using the Revelt and Train (2000) mixlbeta Stata procedure and exclude respondents with negative or zero wage preference; each respondent answered only three choice sets, so occasional sign reversals are plausibly noise or inattention rather than true wage aversion. Our main specification, therefore, removes these 87 cases; including them yields qualitatively identical results and similar magnitudes (Appendix Table 16).

Table 3: WTP for occupational attributes

	Full sample	Females	Males
	(1)	(2)	(3)
Mean			
Continuing education	638.59***	605.68***	672.72***
	(32.66)	(45.27)	(46.73)
Higher automation risk (20 ppt.)	-853.07***	-919.71***	-789.64***
	(26.68)	(40.18)	(35.05)
Higher GenAI usage (20 ppt.)	-113.08***	-186.55***	-48.78***
	(12.04)	(18.52)	(16.05)
Number of observations	43,710	21,894	21,816

Note: This table reports adolescents' willingness to pay for i) having continuing education, ii) a 20-percentage-point higher automation risk, and iii) a 20-percentage-point increase in GenAI usage for the full sample, and for the female and male subsamples. Positive values indicate that adolescents are willing to forgo monthly salary. Negative values indicate that adolescents need to be compensated. We control for the randomization order of options A and B. WTP coefficients are estimated using a mixed-logit model in the WTP-space. Significance levels: *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01

Motivated by the literature on gender differences in occupational choice and technology affinity, we next examine these differences. Future workers' WTP for continuing education is statistically indistinguishable between male and female respondents, but aversion to automation risk is significantly stronger among females: compared to males, they require a CHF 130 (1.8%) higher monthly wage premium for a 20–percentage point increase in automation risk, indicating a higher risk aversion among female adolescents. The gender gap is slightly larger for GenAI usage: females require a CHF 187 (2.7%) monthly wage premium—more than three times the male premium of CHF 49—for a 20-percentage-point increase in GenAI collaboration intensity.

To understand potential drivers of the gender difference in preferences for GenAI collaboration, Table 15 presents estimation results of a multivariate regression of individual WTP for higher GenAI usage (20ppt) on key respondent characteristics. These characteristics include socio-demographic attributes, school grades, and preferences for track and tasks. The results indicate that none of the available respondent characteristics can explain the gender difference. Across females and males, the results suggest that being in the French and Italian language regions is associated with a decrease in WTP for GenAI usage compared to the German language region (see also Tables 13 and 12). It is precisely the Italian-speaking regions that also have the lowest Internet and computer usage across primary and secondary schools in 2024 (Oggenfuss and Wolter, 2024).

5.2 GenAI usage and interactions with continuing education and automation risk

If adolescents associate an increase in GenAI collaboration with a simultaneous increase in automation risk, this association could potentially drive their preferences. Conversely, occupational continuing education opportunities may increase confidence in GenAI collaboration skills and mitigate concerns about deskilling and machine subordination. Table 4 reports estimates for all occupation attributes and interactions between higher GenAI usage and continuing education, as well as between higher GenAI usage and higher automation risk. Results are reported for the full sample and for split samples by gender.

Accounting for these interactions, the full sample reveals a preference for higher GenAI usage when automation risk and continuing education are held constant. Adolescents are willing to accept a CHF 101 lower monthly wage in exchange for a 20-percentage-point higher GenAI usage, provided the two occupations do not differ in automation risk and neither involves continuing education. However, this preference for GenAI vanishes when GenAI usage and automation risk rise simultaneously: the sum of the main effect (CHF 101) and the interaction with automation risk (CHF -218) equals CHF -117, which is statistically significant. With continuing education present and automation risk unchanged, adolescents value higher GenAI collaboration more strongly: they are willing to accept a CHF 157 (2.2%) lower monthly wage for a 20-percentage-point increase. When both continuing education is present and automation risk increases, the implied WTP for higher GenAI usage is CHF -61.[11]

The stronger dispreferences of females than males toward increased GenAI collaboration identified in the baseline model (see Table 3) remain stable when accounting for interactions with continuing education and automation risk, although nuanced patterns emerge among females. Both females and males exhibit a dispreference for GenAI collaboration when combined with an increase in automation risk and no continuing education. However, females value higher GenAI collaboration only when continuing education is present, whereas males prefer higher GenAI usage also combined with no increase in automation risk and no continuing education.

[11]Our results are robust to different specifications presented in Tables 19 and 20 in the Appendix.

Table 4: WTP for occupational attributes, with GenAI interactions

	Full sample (1)	Females (2)	Males (3)
Mean			
Continuing education	550.61***	516.29***	581.81***
	(49.61)	(69.85)	(70.61)
Higher automation risk (20 ppt.)	-491.96***	-528.77***	-452.66***
	(44.24)	(73.19)	(66.98)
Higher GenAI usage (20 ppt.)	101.49***	57.62	142.25***
	(27.02)	(46.64)	(38.01)
x cont. education	55.72***	58.19**	51.68**
	(17.12)	(24.22)	(24.54)
x higher automation risk (20 ppt.)	-218.28***	-241.08***	-197.93***
	(22.77)	(36.76)	(33.97)
Lincom effects:			
Higher GenAI (20 ppt.)	157.21***	115.81**	193.92***
cond. on cont. education	(30.12)	(49.02)	(43.23)
Higher GenAI (20 ppt.)	-116.79***	-183.47***	-55.69**
cond. on higher automation risk (20 ppt.)	(16.02)	(24.21)	(23.28)
Higher GenAI (20 ppt.)	-61.08***	-125.28***	-4.01
cond. on higher automation risk (20 ppt.) and cont. education	(15.23)	(23.84)	(20.14)
Number of observations	43,710	21,894	21,816

Note: This table reports adolescents' willingness to pay for i) having continuing education, ii) 20 ppt. higher automation risk, iii) a 20 ppt. increase in GenAI usage, iv) the combination of continuing education and an increase in GenAI, and v) a simultaneous increase in GenAI usage and automation risk for the full sample, and for the female and male subsamples. Higher GenAI usage (20 percentage points)' reports the main effect when continuing education is absent and automation risk is unchanged. '× cont. education' is the incremental effect when continuing education is present; the WTP with continuing education equals the sum of the main effect and this interaction. '× higher automation risk (20 percentage points)' is the incremental effect when automation risk rises; the WTP with higher automation risk equals the main effect plus this interaction. Positive values indicate that adolescents are willing to forgo a monthly salary. Negative values indicate that adolescents need to be compensated. We control for the randomization order of options A and B. WTP coefficients are estimated using a mixed-logit model in the WTP-space. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

In terms of magnitude, males are willing to accept a CHF 142 (2.0%) lower monthly wage for a 20-percentage-point increase in GenAI usage with automation risk held constant and no continuing education, whereas the corresponding WTP among females, CHF 58, is not statistically significant. If higher GenAI usage is accompanied by higher automation risk, females' WTP for more GenAI amounts to CHF -183 (2.6%), while males exhibit a negative and significant WTP of CHF 56 (0.8%). By contrast, in occupations with continuing education, both genders exhibit positive WTP for higher GenAI usage conditional on no automation risk increase: females are willing to accept a CHF 116 (1.7%) lower wage in exchange for 20-percentage-point higher GenAI usage, and males CHF 194 (2.8%).

Finally, with continuing education present, females exhibit a dispreference for higher GenAI usage when the increase in GenAI usage occurs simultaneously with an increase in automation risk, whereas for males it is negative but insignificant: females' WTP is CHF -125, males -4 and not statistically significant.

5.3 GenAI preference non-linearity

Since average effects can mask heterogeneous preferences for GenAI use across exposure levels, we relax the linearity assumption and allow WTP to vary across usage ranges. Table 5 reports WTP for occupation attributes when GenAI usage preference is modeled nonlinearly.

Whereas the baseline model yielded average WTPs of CHF -113 for the full sample (CHF -187 for females; CHF -49 for males), results in Table 5 reveals substantial nonlinearity by baseline usage level. At moderate GenAI usage (10%–40%), a 20-percentage-point increase is valued at CHF 215—about 3.1% of the gross median monthly wage—indicating a positive marginal valuation at moderate levels. By contrast, at higher usage (40%–70%), adolescents require CHF 462 to accept a 20-percentage-point increase—about 7% of the gross median monthly wage—implying a sizable disutility at higher intensity. Gender differences mirror this pattern: WTP does not differ significantly between females and males at moderate usage intensities. At high usage levels female adolescents require CHF 633 (9.0%)—nearly double the male premium of CHF 329 (4.7%)—for the same 20-percentage-point increase.

5.4 Heterogeneity for GenAI usage by track and task preferences

Given that occupational choices and occupational gender segregation are strongly associated with task preferences, we analyze heterogeneity by respondents' preferences for working with their hands and with people. We ask respondents *"How important is it to you in your future career... ...to work with people every day? ...to work with your hands?*.

Table 5: WTP for occupational attributes with GenAI dummies

	Full sample	Females	Males
	(1)	(2)	(3)
Mean			
More GenAI usage (20 ppt., between 10% and 40%)	214.99***	197.62***	230.86***
	(31.01)	(45.12)	(42.27)
More GenAI usage (20 ppt., between 40% and 70%)	-462.18***	-632.87***	-328.53***
	(35.48)	(61.46)	(42.37)
Higher automation risk (20 ppt.)	-968.53***	-1082.10***	-872.86***
	(35.90)	(58.16)	(44.56)
Continuing education	737.42***	721.69***	755.51***
	(40.35)	(58.63)	(55.36)
Number of observations	43,710	21,894	21,816

Note: This table reports adolescents' WTP for occupation attributes. Instead of a linear variable for GenAI usage intensity, two dummy variables are included, equal to 1 if the occupation features a GenAI usage of 40 % or 70 %, respectively. The WTP shown in columns (1) to (3) is calculated as the WTP for 40 % GenAI usage intensity instead of 10 %, and 70 % instead of 40 %, respectively, scaled to 20 ppt. Positive values indicate that adolescents are willing to forgo monthly salary. Negative values indicate that adolescents need to be compensated. We control for the randomization order of options A and B. WTP coefficients are estimated using a mixed-logit model in the WTP-space. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Respondents have a high preference when indicating at least a 4 on a scale ranging from (1) "Not important at all" to (5) "Very important".

Table 6 reports attribute preferences separately for individuals with high and low preferences for manual and people work, respectively. Notably, preferences for all occupational attributes differ by task orientation. The aversion to GenAI collaboration is substantially stronger among adolescents with high task preferences, particularly among those who favor hands-on tasks. Table 7 and Table 8 in the Appendix show results by task preferences and gender. The results show that gender does not drive differences in GenAI preferences by task orientation, nor vice versa. Instead, both being female and, independently, having a high preference for manual or people work are associated with a stronger aversion to GenAI collaboration in future jobs.[12]

[12]Table 15, panel C in the Appendix reports correlations between respondents' willingness to pay for an increase in GenAI usage and having high preferences for people/manual work. The difference in results between Tables 7, 8 and Table 15 is driven by different regression models: Tables 7 and 8 report mean effects by females and males separately; Table 15 reports correlations between respondents individual WTP for an increase in GenAI and student characteristics, which cannot be included in regressions in 7

Given that our sample includes students at different stages of their career choice and with varying track preferences, we examine whether track preferences and labor market status are associated with preferences for increased GenAI usage. Tables 9 and 10 show split sample regressions by track preference, and Tables 11 and 12 by labor market status. The results reveal additional variance in occupational preferences across track preferences. Notably, adolescents who are either in or interested in the general education track are relatively more open to GenAI collaboration than those who are either interested in or in the vocational track. In contrast, preferences for GenAI usage do not differ by labor market status.

Table 6: WTP for occupational attributes: Heterogeneity by high and low preference for manual and people work

	Preference for manual work		Preference for people work	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
Mean				
Continuing education	898.78***	584.69***	897.28***	550.50***
	(98.06)	(34.44)	(76.60)	(35.82)
Higher automation risk (20 ppt.)	-1127.08***	-787.04***	-960.73***	-810.63***
	(89.13)	(26.83)	(58.70)	(29.69)
Higher GenAI usage (20 ppt.)	-301.40***	-70.92***	-177.17***	-87.52***
	(39.34)	(12.01)	(25.13)	(13.97)
Number of observations	10,266	32,220	13,008	29,760

Note: This table reports adolescents' WTP for occupation attributes for respondents with high/low preference for manual and people work. Respondents have a high preference for working with their hands or with people if indicating at least a 4 "Somewhat important" on a scale between 1 and 5. Positive values indicate that adolescents are willing to forgo monthly salary. Negative values indicate that adolescents need to be compensated. We control for the randomization order of options A and B. WTP coefficients are estimated using a mixed-logit model in the WTP-space. Significance levels: *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01

and 8.

6 Conclusion and Discussion

Significant advancements in AI and other technologies are affecting labor markets, particularly in high-income countries. The increasingly rapid adoption of GenAI across occupations and sectors of the economy will likely have transformative effects on employment prospects and career dynamics over the next decades. For future workers, whether they embrace GenAI collaboration will likely impact their labor market opportunities. Understanding how future workers evaluate and value the prospect of working with GenAI in their career choices is a critical concern for firms seeking talent willing to adopt new technologies, for educational institutions designing curricula, and for policymakers anticipating labor market adjustments.

Our discrete-choice experiment among 7,285 Swiss adolescents reveals that future workers' willingness to train for GenAI-intensive occupations varies with the interplay of GenAI intensity, automation risk, and continuing education. This finding challenges a simple narrative of technology acceptance or rejection, revealing instead nuanced preferences that policy and firms can actively shape. Specifically, while adolescents exhibit an overall aversion to greater GenAI use in their future jobs, three conditions systematically reverse this aversion: holding automation risk constant, providing continuing education, and maintaining a moderate level of usage intensity.

First, adolescents value higher GenAI usage intensity when it is not accompanied by increased automation risk. In other words, much of the average GenAI dispreference reflects a perceived link between GenAI and automation risk; once higher automation risk is explicitly ruled out, increases in GenAI usage are, on average, attractive.

Second, when continuing education is present, adolescents' valuation of GenAI usage is also positive. This interaction points to a plausible mechanism: adolescents fear not GenAI itself, but rather the perceived risk of deskilling or replaceability by other workers due to the lack of specialized skills. When firms commit to training, adolescents can view GenAI not only as a tool that they can use effectively but also as one that complements their labor rather than devaluing their human capital. This is consistent with the notion that automation technologies can raise the expertise required for remaining non-automated tasks and thus increase the scarcity value of skills, whereas the opposite holds when they strip out expert tasks and leave generic work (Autor and Thompson, 2025).

Third, beyond the average effects, we document striking nonlinearities in preferences across levels of GenAI usage intensity. At moderate collaboration (in 10%–40% of tasks), adolescents exhibit a positive preference for higher GenAI usage. Yet at high usage levels (40%–70%), the same increment incurs a substantial disutility. The threshold at which preferences reverse may reflect adolescents' perception that technology may replace their expertise, leaving only undesirable work. Specifically, moderate usage may signal that human skills remain central and valued, while high usage may provoke concerns about deskilling, machine subordination, or replaceability.

In addition, our results suggest significant gender differences, with women exhibiting greater aversion to GenAI — particularly in high-usage-intensity contexts. Importantly, conventional explanations—technology exposure during compulsory schooling, grades, track choice, and task preferences—do not account for this gender gap, suggesting that other factors, such as gender-specific risk perceptions (e.g. Borwein et al., 2026) or confidence gaps, may be at play. These results are consistent with evidence from previous research highlighting women's lower likelihood of using AI tools and pointing to possible channels that may contribute to the persistence and potential widening of gender-specific segregation across occupations. Notably, we also find that opportunities for continuing education to learn new technologies and acquire related skills improve attitudes towards GenAI for both women and men.

Furthermore, preferences for GenAI also differ by adolescents' task orientation. Adolescents, both male and female, with strong preferences for manual or people-oriented work exhibit a stronger dispreference for GenAI than their peers. This may reflect a genuine comparative advantage, an interest-technology mismatch, or a perception that GenAI is incompatible with hands-on and interpersonal tasks. The latter is concerning, as it may lead students to avoid occupations in which GenAI complements human labor. For example, healthcare and many skilled trades already pair interpersonal or manual work with GenAI-supported diagnosis, planning, and troubleshooting. Guidance and curriculum exposure to such task-technology combinations could help shift preferences among these subgroups.

This study faces two limitations that are relevant for the interpretation of results. First, our choice experiment is hypothetical; respondents evaluate occupational attributes in a controlled setting rather than making real-life decisions. Hypothetical bias could overstate or understate preferences. However, the alignment with prior surveys supports the directional accuracy of our results. Adolescents' high willingness-to-pay for continuing education aligns with findings from stated-preference surveys (Zöllner, 2025), and the quantified aversion to automation risk is consistent with estimations for adults (Cattaneo, Gschwendt and Wolter, 2025). Additionally, our gender patterns align with those found by Oggenfuss and Wolter (2024). These alignments suggest that our discrete-choice experiment, though hypothetical, captures meaningful variation in preferences and is a credible tool for quantifying labor supply elasticities with respect to GenAI adoption.

Second, our sample is nationally representative of Swiss adolescents aged approximately 15, which limits the generalizability of our results to other countries, education systems, and labor market institutions. However, we can, to a limited extent, assess whether the results hold in less digitally intensive contexts by exploiting variation in digitalization trends across Swiss language regions. Notably, we find that adolescents in language regions with lower levels of school-level internet and computer use exhibit a stronger aversion to collaborating with GenAI in their future jobs, suggesting that openness to working with GenAI is lower in less digitally developed contexts.

In conclusion, our findings suggest that adolescents' willingness to work with GenAI in their future jobs depends critically on how firms and policymakers frame and implement the technology. GenAI is not inherently attractive nor repulsive to adolescents. Rather, its appeal depends on whether it is perceived as a harbinger of displacement (i.e., as already overly extensive) or as an augmenting sidekick with whom they feel they can collaborate confidently. Notably, under the reasonable assumption that individual adoption of GenAI collaboration has a positive impact on labor market opportunities, without targeted interventions, the substantial gender gap in preferences could exacerbate occupational gender segregation. Most encouragingly, the provision of continuing education emerges as a powerful lever: when firms commit to training, adolescents—female and male—become willing to pursue GenAI-intensive occupations, even though the gender gap persists. Thus, our results suggest that labor market adjustment to GenAI is shaped not only by technological inevitability but also by human capital policy. An early integration of GenAI literacy and skills is particularly relevant, as preferences formed during compulsory schooling shape high-stakes career choices and, in turn, later labor-market outcomes.

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Supplemental Appendix

Generative AI and Career Choices

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A Robustness and more

This section first presents additional analysis, followed by robustness checks of the main results.

A.1 Additional analysis

Table 7: WTP for occupational attributes: gender and MANUAL task preferences

	Females		Males	
	High man. pref.	Low man. pref.	High man. pref.	Low man. pref.
	(1)	(2)	(3)	(4)
Mean				
Continuing education	1045.49***	530.48***	792.54***	641.27***
	(161.10)	(46.90)	(120.49)	(50.42)
Higher automation risk (20 ppt.)	-1298.11***	-848.83***	-1012.84***	-726.61***
	(153.43)	(40.20)	(103.89)	(35.48)
Higher GenAI usage (20 ppt.)	-362.35***	-154.38***	-263.38***	6.20
	(64.06)	(18.93)	(49.40)	(15.46)
Number of observations	4,386	16,812	5,880	15,408

Note: This table reports adolescents' WTP for occupation attributes. Students have a "high preference" for manual work when indicating at least a 4 on a 6-point Likert scale, i.e., that working with people/hands is somewhat important; low otherwise. Positive values indicate that adolescents are willing to forgo monthly salary. Negative values indicate that adolescents need to be compensated. We control for the randomization order of options A and B. WTP coefficients are estimated using a mixed-logit model in the WTP-space. Significance levels: *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01

Table 8: WTP for occupational attributes: gender and PEOPLE task preferences

	Females		Males	
	High ppl pref.	Low ppl pref.	High ppl pref.	Low ppl pref.
	(1)	(2)	(3)	(4)
Mean				
Continuing education	789.97***	516.68***	1046.06***	584.23***
	(98.33)	(49.53)	(121.35)	(50.69)
Higher automation risk (20 ppt.)	-1045.56***	-860.25***	-843.15***	-770.56***
	(82.92)	(45.53)	(81.68)	(38.74)
Higher GenAI usage (20 ppt.)	-234.77***	-162.13***	-102.45***	-31.88*
	(37.16)	(21.30)	(32.34)	(18.75)
Number of observations	7,692	13,842	5,316	15,918

Note: This table reports adolescents' WTP for occupation attributes. Students have a "high preference" for people work when indicating at least a 4 on a 6-point Likert scale, i.e., that working with people/hands is somewhat important; low otherwise. Positive values indicate that adolescents are willing to forgo monthly salary. Negative values indicate that adolescents need to be compensated. We control for the randomization order of options A and B. WTP coefficients are estimated using a mixed-logit model in the WTP-space. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 9: WTP for occupational attributes by adolescents' educational track

	General Education	Vocational Education	Track Undecided
	(1)	(2)	(3)
Mean			
Continuing education	479.85***	796.68***	666.23***
	(41.17)	(70.49)	(62.37)
Higher automation risk (20 ppt.)	-809.89***	-925.60***	-822.37***
	(33.62)	(56.06)	(50.74)
Higher GenAI usage (20 ppt.)	-80.52***	-158.99***	-101.41***
	(16.38)	(24.88)	(21.52)
Number of observations	15,630	13,524	14,556

Note: This table reports adolescents' WTP for occupation attributes by adolescents' educational track. Column (1) shows WTP for respondents who are interested in pursuing or are pursuing general education. Column (2) shows the WTP for respondents who are interested in pursuing or are pursuing vocational education. Column (3) shows the WTP for respondents who have no clear preference, information on what they aspire to do after compulsory schooling is missing, or when they signal interest in both the general education and vocational tracks. Positive values indicate that adolescents are willing to forgo monthly salary. Negative values indicate that adolescents need to be compensated. We control for the randomization order of options A and B. WTP coefficients are estimated using a mixed-logit model in the WTP-space. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 10: WTP for occupational attributes by adolescents' educational track

	General Education	Vocational Education	Track Undecided
	(1)	(2)	(3)
Mean			
Continuing education	390.88***	736.93***	542.38***
	(62.70)	(99.36)	(91.19)
Higher automation risk (20 ppt.)	-438.52***	-524.97***	-490.32***
	(59.00)	(71.75)	(64.53)
Higher GenAI usage (20 ppt.)	153.35***	89.51*	80.07*
	(41.53)	(49.89)	(43.32)
x cont. education	48.48**	47.57	71.13**
	(22.14)	(32.49)	(33.08)
x higher automation risk (20 ppt.)	-221.38***	-252.90***	-197.33***
	(30.18)	(38.74)	(32.51)
Number of observations	15,630	13,524	14,556

Note: This table reports adolescents' WTP for occupation attributes by adolescents' educational track. Column (1) shows WTP for respondents who are interested in pursuing or are pursuing general education. Column (2) shows the WTP for respondents who are interested in pursuing or are pursuing vocational education. Column (3) shows the WTP for respondents who have no clear preference, information on what they aspire to do after compulsory schooling is missing, or when they signal interest in both the general education and vocational tracks. Positive values indicate that adolescents are willing to forgo monthly salary. Negative values indicate that adolescents need to be compensated. We control for the randomization order of options A and B. WTP coefficients are estimated using a mixed-logit model in the WTP-space. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 11: WTP for occupational attributes by adolescents' labor market status

	About to enter the labor market	Entered the labor market
	(1)	(2)
Mean		
Continuing education	606.11***	787.31***
	(34.10)	(96.98)
Higher automation risk (20 ppt.)	-852.44***	-847.93***
	(28.40)	(71.70)
Higher GenAI usage (20 ppt.)	-106.42***	-139.47***
	(12.78)	(32.83)
Number of observations	36,390	7,320

Note: This table reports adolescents' WTP for occupation attributes by adolescents' labor market status. Column (1) shows WTP for respondents who are about to enter the labor market, but are still in school. Column (2) shows the WTP for respondents who recently entered the labor market and are pursue an apprenticeship. Positive values indicate that adolescents are willing to forgo monthly salary. Negative values indicate that adolescents need to be compensated. We control for the randomization order of options A and B. WTP coefficients are estimated using a mixed-logit model in the WTP-space. Significance levels: *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01

Table 12: WTP for occupational attributes by adolescents' labor market status

	About to enter the labor market	Entered the labor market
	(1)	(2)
Mean		
Continuing education	519.96***	659.34***
	(52.57)	(133.34)
Higher automation risk (20 ppt.)	-498.40***	-454.54***
	(53.20)	(104.24)
Higher GenAI usage (20 ppt.)	104.24***	85.25
	(32.57)	(62.75)
x cont. education	53.92***	71.14*
	(18.53)	(41.35)
x higher automation risk (20 ppt.)	-213.18***	-241.68***
	(26.81)	(58.80)
Number of observations	36,390	7,320

Note: This table reports adolescents' WTP for occupation attributes by adolescents' labor market status. Column (1) shows WTP for respondents who are about to enter the labor market, but are still in school. Column (2) shows the WTP for respondents who recently entered the labor market and are pursue an apprenticeship. Positive values indicate that adolescents are willing to forgo monthly salary. Negative values indicate that adolescents need to be compensated. We control for the randomization order of options A and B. WTP coefficients are estimated using a mixed-logit model in the WTP-space. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 13: WTP for occupational attributes by Swiss language regions

	D-CH (1)	F-CH (2)	I-CH (3)
Mean			
Continuing education	864.28***	243.99***	541.89***
	(52.15)	(31.98)	(81.15)
Higher automation risk (20 ppt.)	-882.63***	-777.11***	-939.07***
	(39.84)	(30.99)	(73.50)
Higher GenAI usage (20 ppt.)	-87.87***	-143.66***	-199.95***
	(16.86)	(16.21)	(35.29)
Number of observations	19,476	17,052	7,182

Note: This table reports adolescents' WTP for occupation attributes by Swiss language regions. D-CH represents the German-speaking regions; F-CH represents the French-speaking regions, I-CH represents the Italian-speaking regions. Positive values indicate that adolescents are willing to forgo monthly salary. Negative values indicate that adolescents need to be compensated. We control for the randomization order of options A and B. WTP coefficients are estimated using a mixed-logit model in the WTP-space. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 14: WTP for occupational attributes by Swiss language regions

	D-CH	F-CH	I-CH
	(1)	(2)	(3)
Mean			
Continuing education	807.92***	139.26***	256.67**
	(78.71)	(50.03)	(127.16)
Higher automation risk (20 ppt.)	-542.94***	-359.57***	-547.21***
	(63.37)	(49.66)	(96.62)
Higher GenAI usage (20 ppt.)	122.29***	110.62***	-6.65
	(37.39)	(36.89)	(64.46)
Higher GenAI usage (20 ppt.) x cont. education	46.61*	53.62***	148.56***
	(25.33)	(18.79)	(49.46)
Higher GenAI usage (20 ppt.) x higher automation risk (20 ppt.)	-208.77***	-252.68***	-226.26***
	(31.60)	(32.21)	(47.82)
Number of observations	19,476	17,052	7,182

Note: This table reports adolescents' WTP for occupation attributes by Swiss language regions. D-CH represents the German-speaking regions; F-CH represents the French-speaking regions, I-CH represents the Italian-speaking regions. Positive values indicate that adolescents are willing to forgo monthly salary. Negative values indicate that adolescents need to be compensated. We control for the randomization order of options A and B. WTP coefficients are estimated using a mixed-logit model in the WTP-space. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 15: Pooled regression of WTP for a 20 ppt. increase in GenAI usage on student characteristics

	Females (1)	Males (2)
A Socio-demographic characteristics		
Swiss born	-10.21	-19.33
	(9.83)	(13.30)
Mother has tertiary degree	-4.76	2.54
	(8.44)	(6.61)
Father has tertiary degree	9.70	-5.18
	(8.47)	(6.60)
French language region	-26.19***	-25.27***
	(7.70)	(6.15)
Italian language region	-9.11	-26.48***
	(11.30)	(8.50)
B School grades		
Math: good	-13.21	8.67
	(9.54)	(8.75)
Math: very good	-13.33	-0.66
	(9.02)	(6.91)
School language: good	-10.13	-4.55
	(9.77)	(8.26)
School language: very good	-24.62**	-21.22**
	(10.29)	(9.46)
English: good	1.51	12.17
	(10.43)	(7.81)
English: very good	3.49	9.62
	(9.67)	(9.55)
C Track and Preferences		
High preference for people work	-13.57*	-9.50
	(7.61)	(6.64)
High preference for manual work	-24.94***	-31.99***
	(9.14)	(8.18)
General education	-15.66*	15.38**
	(9.00)	(7.50)
Vocational track	-13.62	-5.58
	(9.82)	(8.17)
Constant	-132.90***	-18.33
	(14.49)	(13.46)
Number of observations	3,115	3,001

Notes: This table presents multivariate regression results of individual WTP for higher GenAI usage (20ppt) on key respondent characteristics. Column 1 reports coefficients for female adolescents, while column 2 reports coefficients for male adolescents. We all respondents of our preferred sample for whom information on all included variables is available. Reference language region is the Italian-speaking part of Switzerland; reference school grades are below good; reference category for educational preference (general, vocational) is "no clear preference". Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

A.2 Robustness

Table 16: WTP for attributes: Including respondents with no or negative wage preference

	Full sample	Females	Males
	(1)	(2)	(3)
Mean			
Continuing education	698.3***	648.7***	695.6***
	(39.92)	(51.53)	(56.66)
Higher automation risk (20 ppt.)	-915.3***	-973.2***	-845.3***
	(33.57)	(47.22)	(42.73)
Higher GenAI usage (20 ppt.)	-133.6***	-211.3***	-58.19***
	(14.42)	(21.17)	(17.23)
Number of observations	44,232	22,116	22,116

Notes: This table reports adolescents' willingness to pay for i) having continuing education, ii) 20 ppt. higher automation risk, iii) a 20 ppt. increase in GenAI usage. Positive values indicate that adolescents are willing to forgo monthly salary. Negative values indicate that adolescents need to be compensated. We control for the randomization order of options A and B. WTP coefficients are estimated using a mixed-logit model in the WTP-space. The sample includes respondents with no or negative wage preference. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 17: WTP for attributes: Excluding respondents with low experiment completion times

	Full sample	Females	Males
	(1)	(2)	(3)
Mean			
Continuing education	661.14***	621.31***	702.41***
	(36.44)	(50.04)	(52.64)
Higher automation risk (20 ppt.)	-912.43***	-965.78***	-861.92***
	(31.07)	(46.05)	(41.71)
Higher GenAI usage (20 ppt.)	-123.99***	-203.45***	-51.86***
	(13.80)	(21.63)	(17.79)
Number of observations	34,938	17,700	17,238

Notes: This table reports adolescents' willingness to pay for i) having continuous education, ii) a 20-percentage-point higher automation risk, and iii) a 20-percentage-point increase in GenAI usage for the full sample, and for the female and male subsamples. The sample excludes respondents whose time spent on any choice set was below the 10th percentile. Positive values indicate that adolescents are willing to forgo monthly salary, thus signaling a preference for the attribute. Negative values indicate that adolescents need to be compensated, thus signaling a dispreference for the attribute. We control for the randomization order of options A and B. WTP coefficients are estimated using a mixed-logit model in the WTP-space. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 18: WTP for attributes: Allowing correlation across variables

	Full sample	Females	Males
	(1)	(2)	(3)
Mean			
Continuing education	576.66***	577.08***	573.03***
	(42.16)	(75.94)	(82.77)
Higher automation risk (20 ppt.)	-779.78***	-848.05***	-728.96***
	(25.74)	(37.42)	(34.73)
Higher GenAI usage (20 ppt.)	-93.54***	-147.05***	-52.61**
	(15.35)	(25.24)	(21.28)
Number of observations	43,710	21,894	21,816

Notes: This table reports adolescents' willingness to pay for i) having continuing education, ii) 20 ppt. higher automation risk, iii) a 20 ppt. increase in GenAI usage. Positive values indicate that adolescents are willing to forgo monthly salary, thus signaling a preference for the attribute. Negative values indicate that adolescents need to be compensated, thus signaling a dispreference for the attribute. We control for the randomization order of options A and B. WTP coefficients are estimated using a mixed-logit model in the WTP-space, allowing dependent variables to correlate. Significance levels: *p < 0.10, **p < 0.05, ***p < 0.01

Table 19: WTP for attributes: Interactions

	Full sample	Females	Males
	(1)	(2)	(3)
Mean			
Continuing education	509.56***	417.64***	618.99***
	(76.68)	(107.66)	(113.14)
Higher automation risk (20 ppt.)	-487.39***	-554.92***	-454.78***
	(48.89)	(71.78)	(53.96)
Higher GenAI usage (20 ppt.)	108.27***	62.86	133.52***
	(28.32)	(47.04)	(37.65)
Higher GenAI usage (20 ppt.) x cont. education	60.61***	64.23**	49.40*
	(18.71)	(26.89)	(29.37)
Higher GenAI usage (20 ppt.) x higher automation risk (20 ppt.)	-113.47***	-125.34***	-91.74***
	(12.77)	(19.64)	(13.84)
Cont. education x higher automation risk (20 ppt.)	20.80	61.67	-25.86
	(30.52)	(44.84)	(42.27)
Number of observations	43,710	21,894	21,816

Notes: This table reports adolescents' willingness to pay for i) having continuing education, ii) 20 ppt. higher automation risk, iii) a 20 ppt. increase in GenAI usage, iv) the combination of an increase in GenAI and continuing education/increase in automation risk, and v) a simultaneous increase in GenAI usage, automation risk, and having education for the full sample, and for the female and male subsamples. Positive values indicate that adolescents are willing to forgo monthly salary, thus signaling a preference for the attribute. Negative values indicate that adolescents need to be compensated, thus signaling a dispreference for the attribute. We control for the randomization order of options A and B. WTP coefficients are estimated using a mixed-logit model in the WTP-space. Significance levels: *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01

Table 20: WTP for attributes: Triple interaction model

	Full sample	Females	Males
	(1)	(2)	(3)
Mean			
Continuing education	260.62	2.21	509.43**
	(174.84)	(284.51)	(247.66)
Higher automation risk (20 ppt.)	-615.25***	-754.34**	-481.02**
	(111.07)	(300.28)	(189.14)
Higher GenAI usage (20 ppt.)	13.20	-89.36	89.63
	(76.90)	(208.89)	(110.55)
Cont. education x higher automation risk (20 ppt.)	228.11	402.73	31.74
	(144.02)	(270.26)	(225.85)
Higher GenAI usage (20 ppt.)			
x cont. education	218.06**	327.26	110.70
	(108.97)	(203.39)	(159.86)
x higher automation risk (20 ppt.)	-158.69***	-143.55	-152.53*
	(58.40)	(181.08)	(84.65)
x higher automation risk (20 ppt.) x cont. education	-114.06	-187.10	-37.46
	(78.56)	(160.50)	(121.46)
Number of observations	43,710	21,894	21,816

Notes: This table reports adolescents' willingness to pay for i) having continuing education, ii) 20 ppt. higher automation risk, iii) a 20 ppt. increase in GenAI usage, iv) the combination of an increase in GenAI and continuing education/increase in automation risk, and v) a simultaneous increase in GenAI usage, automation risk, and having education for the full sample, and for the female and male subsamples. Positive values indicate that adolescents are willing to forgo monthly salary, thus signaling a preference for the attribute. Negative values indicate that adolescents need to be compensated, thus signaling a dispreference for the attribute. We control for the randomization order of options A and B. WTP coefficients are estimated using a mixed-logit model in the WTP-space. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

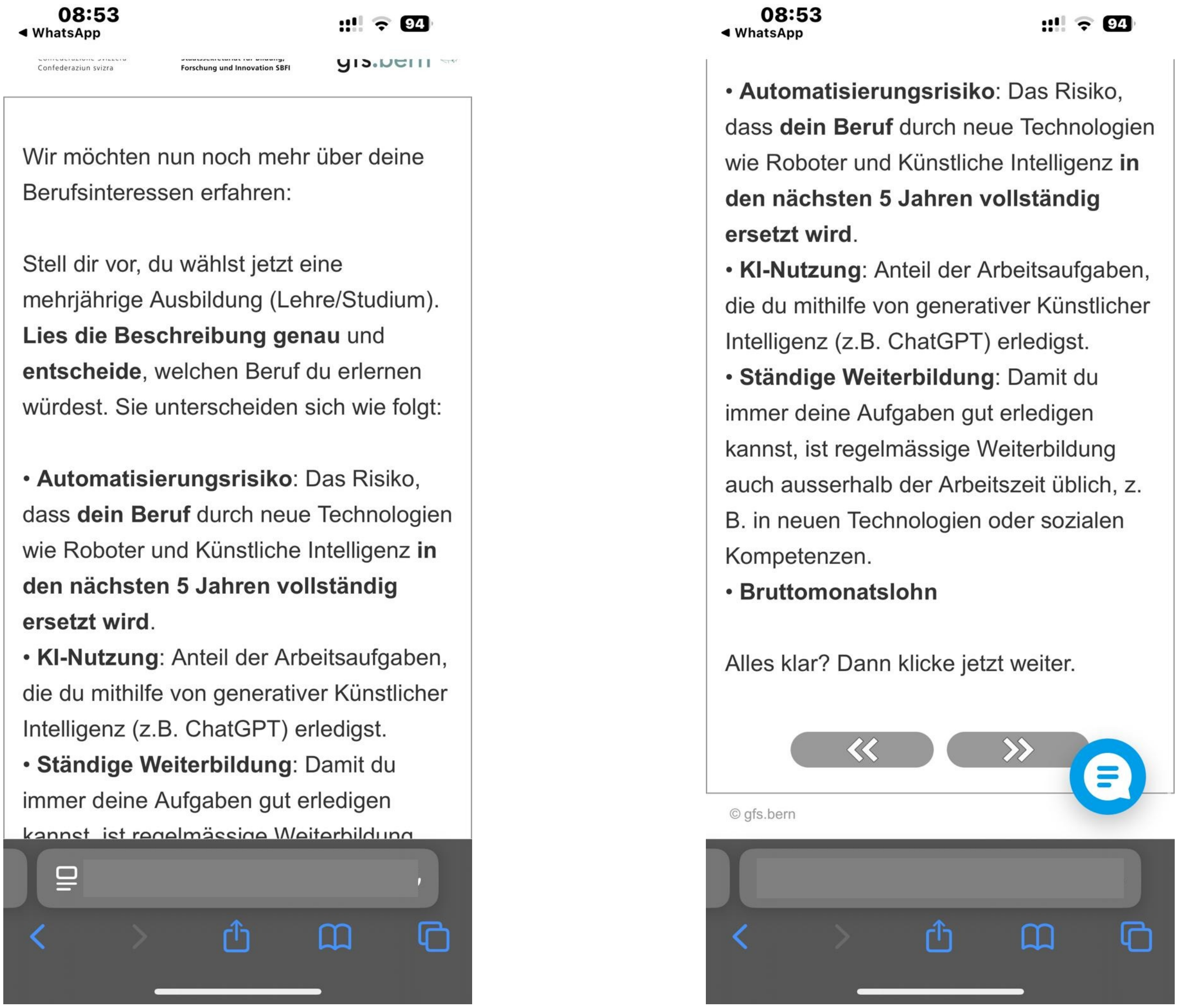
B Data appendix

This section first provides a detailed description of the choice experiment, followed by a detailed description of all main variables used in the analyses.

B.1 Description of the choice experiment

Figure 2: Introductory text of choice set as seen on a phone

(a) Introductory text I **(b)** Introductory text II



Note: Figures a and b show the introductory text on a phone. Students had to scroll down to read the entire text and in order to proceed to the next page. *English translation of the entire introductory text:*

We would now like to learn more about your career interests: Imagine that you are now choosing a multi-year training program (apprenticeship/degree). **Read the description carefully** and **decide** which profession you would like to learn. They differ as follows:

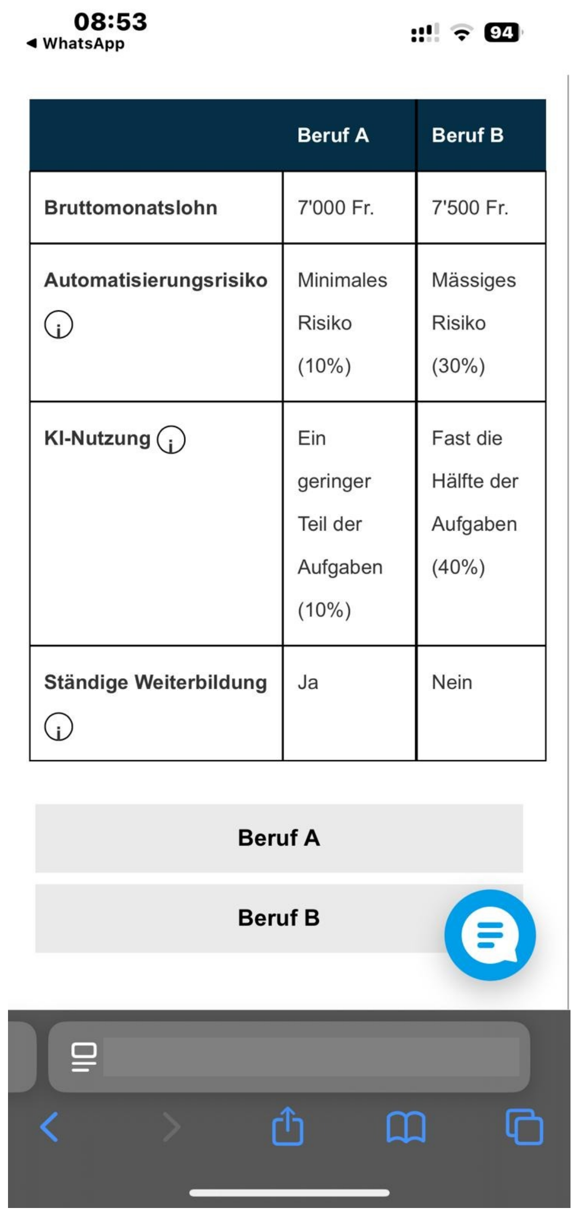
- **Automation risk**: The risk that **your occupation** will be **completely replaced** by new technologies such as robots and artificial intelligence **in the next 5 years**.
- **AI usage**: The proportion of your work tasks that you complete with the help of generative artificial intelligence (e.g., ChatGPT).
- **Continuing training**: To ensure that you can always perform your tasks well, regular training outside of working hours is common, e.g., in new technologies or social skills.
- **Gross monthly salary**

All clear? Then click to continue.

Figure 3: Example of one choice set as seen on a phone

(a) Part I

(b) Part II



Note: Figures a and b show an example of a choice set as it appears on a phone. Students can tap the info button to read the definition provided in the introductory text. By clicking on the speech bubble, students receive help from the survey institute.
English translation: Which profession would you choose? Occupation A / Occupation B. Followed by attributes: Gross monthly salary; Automation risk; AI usage; Continuing education

Table 21: Choice sets used in the choice experiment

Choice set	Block	Alternative	Monthly gross salary	Automation risk	GenAI usage	Continuing education
1	2	1	7'500 CHF	Minimal risk (10%)	A small proportion of tasks (10%)	No
1	2	2	6'500 CHF	High risk (50%)	A small proportion of tasks (10%)	Yes
2	4	1	6'500 CHF	Moderate risk (30%)	Almost half of tasks (40%)	Yes
2	4	2	7'000 CHF	Moderate risk (30%)	Almost half of tasks (40%)	No
3	3	1	7'500 CHF	High risk (50%)	A small proportion of tasks (10%)	Yes
3	3	2	6'500 CHF	Minimal risk (10%)	A large proportion of tasks (70%)	Yes
4	4	1	7'500 CHF	High risk (50%)	A large proportion of tasks (70%)	No
4	4	2	7'000 CHF	Moderate risk (30%)	Almost half of tasks (40%)	Yes
5	4	1	7'000 CHF	Minimal risk (10%)	A small proportion of tasks (10%)	Yes
5	4	2	7'500 CHF	Moderate risk (30%)	A large proportion of tasks (70%)	Yes
6	1	1	7'500 CHF	Moderate risk (30%)	Almost half of tasks (40%)	Yes
6	1	2	6'500 CHF	Minimal risk (10%)	A small proportion of tasks (10%)	No
7	2	1	7'000 CHF	Minimal risk (10%)	A small proportion of tasks (10%)	Yes
7	2	2	7'500 CHF	Moderate risk (30%)	Almost half of tasks (40%)	No
8	1	1	7'000 CHF	Moderate risk (30%)	Almost half of tasks (40%)	No
8	1	2	7'000 CHF	High risk (50%)	A large proportion of tasks (70%)	Yes
9	3	1	7'000 CHF	High risk (50%)	A large proportion of tasks (70%)	No
9	3	2	6'500 CHF	Minimal risk (10%)	A small proportion of tasks (10%)	No
10	2	1	6'500 CHF	Moderate risk (30%)	Almost half of tasks (40%)	No
10	2	2	7'500 CHF	High risk (50%)	Almost half of tasks (40%)	Yes
11	3	1	6'500 CHF	Minimal risk (10%)	A large proportion of tasks (70%)	No
11	3	2	7'000 CHF	High risk (50%)	A small proportion of tasks (10%)	No
12	1	1	6'500 CHF	High risk (50%)	A large proportion of tasks (70%)	Yes
12	1	2	7'500 CHF	Minimal risk (10%)	A large proportion of tasks (70%)	No
13	6	1	6'500 CHF	High risk (50%)	A small proportion of tasks (10%)	Yes
13	6	2	7'500 CHF	Minimal risk (10%)	A small proportion of tasks (10%)	No
14	8	1	7'000 CHF	Moderate risk (30%)	Almost half of tasks (40%)	No
14	8	2	6'500 CHF	Moderate risk (30%)	Almost half of tasks (40%)	Yes
15	7	1	6'500 CHF	Minimal risk (10%)	A large proportion of tasks (70%)	Yes
15	7	2	7'500 CHF	High risk (50%)	A small proportion of tasks (10%)	Yes
16	8	1	7'000 CHF	Moderate risk (30%)	Almost half of tasks (40%)	Yes
16	8	2	7'500 CHF	High risk (50%)	A large proportion of tasks (70%)	No
17	8	1	7'500 CHF	Moderate risk (30%)	A large proportion of tasks (70%)	Yes
17	8	2	7'000 CHF	Minimal risk (10%)	A small proportion of tasks (10%)	Yes
18	5	1	6'500 CHF	Minimal risk (10%)	A small proportion of tasks (10%)	No
18	5	2	7'500 CHF	Moderate risk (30%)	Almost half of tasks (40%)	Yes
19	6	1	7'500 CHF	Moderate risk (30%)	Almost half of tasks (40%)	No
19	6	2	7'000 CHF	Minimal risk (10%)	A small proportion of tasks (10%)	Yes
20	5	1	7'000 CHF	High risk (50%)	A large proportion of tasks (70%)	Yes
20	5	2	7'000 CHF	Moderate risk (30%)	Almost half of tasks (40%)	No
21	7	1	6'500 CHF	Minimal risk (10%)	A small proportion of tasks (10%)	No
21	7	2	7'000 CHF	High risk (50%)	A large proportion of tasks (70%)	No
22	6	1	7'500 CHF	High risk (50%)	Almost half of tasks (40%)	Yes
22	6	2	6'500 CHF	Moderate risk (30%)	Almost half of tasks (40%)	No
23	7	1	7'000 CHF	High risk (50%)	A small proportion of tasks (10%)	No
23	7	2	6'500 CHF	Minimal risk (10%)	A large proportion of tasks (70%)	No
24	5	1	7'500 CHF	Minimal risk (10%)	A large proportion of tasks (70%)	No
24	5	2	6'500 CHF	High risk (50%)	A large proportion of tasks (70%)	Yes

Note: This table reports all choice sets used in the choice experiment. Each student was randomly allocated to one block out of 8, each block incorporating three distinct choice sets. Each choice set has two alternatives 1 and 2. Whether alternative 1 or 2 was shown left or right/ top or bottom, was randomized. Each alternative varies in four attributes: monthly gross salary, automation risk, GenAI usage, and continuing education.

B.2 Description of student characteristics

This section briefly describes the variables that we use in the analysis. For a detailed description of the choice set variables, see also Sections 3.

Swiss born. We ask the entire sample: "Were you born in Switzerland?" giving students the options "Yes", "No", "Don't know", "No answer". Students are Swiss-born when answering "Yes", and not Swiss-born when answering "No".

Parental education. We ask students, "Does your mum or dad have a university degree (university, technical college, or teacher training college)?". Students could choose between "No", "Father" "Mother", "Both", "No answer". We define "Father has tertiary education" if students answered that their father or both parents have tertiary education. Similarly, we define "Mother has tertiary education" if students answered that their mother or both parents have tertiary education.

Swiss language regions. We have information on whether German, French, or Italian is the main language spoken by the student. Respectively, we assign students to the German, French, or Italian-speaking part of Switzerland.

School grades. We ask students, "What were your last report card grades in mathematics, school language, and English?" The answer options were: "very good (grade 6)", "good to very good (grade 5-6)", "good (grade 5)", "sufficient to good (grade 4-5)", "sufficient (grade 4)", "unsatisfactory (grade 3 or lower)", "no answer". We define three categories of grades for those students who answered a grade: 1) below good; 2) Good; 3) Very Good.

Educational track. Students are assigned to either i) having a preference for the vocational education and training track, ii) having a preference for the general education track, or iii) having no clear preference for a track (yet). Students have a preference for the vocational track if they either have already started an apprenticeship or signal that they want to start an apprenticeship or a preparatory course. Students have a preference for the general track when students are currently enrolled in secondary school ("Langzeitgymnasium") , which allows students upon completion to enter a university program or state that they want to continue with a baccalaureate school ("Gymnasium") that allows students to enter a university program upon completion. Students have no clear preference when we have no information on what they aspire to do after compulsory schooling, or when signaling interest in both the general education and vocational education and training tracks.

Alternatively, we look at whether students have already entered the labor market or will do so in the near future. All students who already started an apprenticeship at the time of the survey have entered the labor market; the rest are still in school.

Preferences for type of work. To measure students' preference to work with their hands and people, we ask students the following question: "How important is it to you in your future career...
...to work with people every day?
...to work with your hands?
Students can answer by choosing one option from "Not important at all", "Not very important", "Neither important nor unimportant", "Somewhat important", "Very important", or "No answer". Students are assigned "high preference" when indicating at least a 4 "somewhat important"; low otherwise if not indicating "No answer".