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Credentials gap and automation: Does the replacement of jobs disproportionately impact workers in educationally mismatched occupations?

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Abstract: *Credential gap refers to workers having more (overeducated) or less (undereducated) formal education than their occupations require. This study investigates whether prospective automation of occupations is related to the credential gap. Using quantitative Ordinary Least Squares (OLS) regressions and data from Gmyrek et al. (2023), Frey and Osborne (2017) and Burning Glass in 102 occupations, I find that computerization automation is associated with undereducated occupations, while there are no clear statistical effects for AI automation. These results suggest that traditional computerization may help ease skills shortages by reducing the need for extensive educational credentials, whereas AI-driven automation may not yet influence credential structures, highlighting policy and educational planning challenges in aligning college workforce training with evolving technological demands.*

Keywords: Credentials gap, automation, AI, artificial intelligence, computerization, educational mismatch, overeducation, undereducation

INTRODUCTION

Within higher education research, substantial attention has been given to the overeducation of the workforce, where workers possess more formal schooling than is required for the job (McGuinness, 2006; Marioni, 2021). Conversely, in the case of undereducation, employers face shortages of workers with necessary credentials, thus forcing them to settle for less credentialed workers (Alpin et al., 2006). Parallel to these trends, automation and artificial intelligence (AI) is predicted to displace workers with fewer academic credentials (Frey and Osborne, 2017). More recent academic studies have shown that it is highly credentialed workers including in STEM fields that are more likely to be impacted by technological job displacement (Rawashdeh, 2025). The expected job market disruptions from advancements in AI have increased global calls for a change in college STEM curriculums to allow college graduates to keep up with advances in AI (Khan et al., 2024).

PROBLEM STATEMENT

Despite extensive debates on educational and technological trends in the labor market, there have been no academic studies using distinct measures of automation, such as computerization and AI, to examine how they affect occupations that are characterized by overeducation or undereducation. The present study fills this gap with the aim to identify the relationship between different forms of automation and the credential status of jobs.

Depending on which jobs are targeted by automation, there are different implications for colleges and STEM programs. If overeducated jobs are displaced, the competition for the remaining jobs could intensify, thus making the overeducated mismatch even worse and leading more workers to question the value of a college degree. This outcome would make it difficult for college STEM programs to offer job market relevant educational programs. On the flipside, automation may also target undereducated occupations with substantial skills shortages for displacement. Employers may prefer to develop automation technologies in response to the absence of highly credentialed workers. Such a trend would relieve the pressure on college STEM programs to produce the required graduates in the undereducated occupations.

Using credential gap data from Burning Glass, automation scores on AI and computerization by Gmyrek et al. (2023) and Frey and Osborne (2017) respectively, I find that computerization displacement is associated with undereducated occupations, while there are no clear statistical effects for AI automation on the credential gap. The computerization effects are consistent with the skills shortage argument favoring automation. As a result, pressure on college STEM programs to expand degree production to have enough graduates will be relieved, while advances in AI gradually ease the skills shortage. The following research questions are included for this study:

- Does computerization automation disproportionately affect over- or undereducated occupations?
- Does AI automation disproportionately affect over- or undereducated occupations?

LITERATURE REVIEW

Educational mismatches have been an important concern in the education literature (Christou et al., 2026; Dinku et al. 2026; Jayasinghege et al., 2026). The overeducation phenomenon has been researched by Randall Collins (1979) theory of credential inflation, where more and more jobs require a college education to preserve the status and power of occupational insiders with the college diplomas. In this account, academic credentials are an employer's screening mechanism that proxy desirable employee traits like intelligence, discipline and mental maturity as opposed to a conferrer of job skill. The outcome of credential inflation is massive educational expansion, but at the expense of lowering the value of the degree, as more and more graduates are slotted into positions that they are overqualified for (Collins, 1979). Overeducated workers earn less income than their co-workers in a well-matched job (Marioni, 2021; Arranz & Garcia-Serrano, 2025). Women are more likely to be overqualified and tend to earn less than men (Frank, 1978). During an economic crisis when workers have more difficulties to obtain jobs, they are more likely to settle for jobs they are overqualified for (Borgna et al., 2019). Overeducation is correlated with a higher unemployment rate and lower overall economic output (Summerfield, 2021). Overeducated workers face a higher risk of unemployment than the well-matched educated workers (Schmelzer & Schneider, 2020). Sociological research demonstrates that overeducation is problematic beyond the immediate labor market effects. Overqualified workers report lower job satisfaction and do not believe in an effort-based achievement ideology (Vaisey, 2006; LaRochelle & Hango, 2016). Overqualified workers report lower general life satisfaction and lowered social and political participation (Chen & Hu, 2023). Thus, the unmitigated push toward higher education could backfire due to a poor labor market for recent college graduates (Yamada, 2015; Livingstone, 2019).

There are also empirical studies that make the opposite finding of undereducation, resulting in the filling of graduate-level jobs with many non-graduates. Undereducation disproportionately benefits white males in the labor market, who more easily obtain graduate-level jobs without the necessary qualifications (Alpin et al., 2006). The underqualified tend to work in supervisory positions and have been internally promoted within organizations (Tijdens & van Klaveren, 2011). A corollary to the undereducation literature is the focus on skills shortages, where job openings are not filled at all, filled with significant delay or with employees with fewer credentials. Skills shortages are known to result in the cancellation of innovative projects that negatively impact the broader economy (Horbach & Rammer, 2021). At the economy-wide level, there has been criticism about the existence of a skills shortage (Cappelli, 2015), even if undereducation might be a phenomenon in specific organizations or industries.

Educational mismatches co-evolve with changing technological skill requirements in the labor market. The increasing dependence of societies on technology is an intrinsic aspect of the modern capitalist economy (Schumpeter, 2013). The percentage of jobs predicted to be automated range from 9% to 47% (Arntz et al., 2016; Frey & Osborne, 2017; Ellingrud et al., 2023). Automation may displace some jobs as technology takes over human labor tasks, but it may also generate employment by increasing productivity, lowering product prices and increasing sales (Aghion et al. 2021). Once consumer demand is saturated, employment tends to decrease (Bessen, 2019). 1990s and 2000s data show that robot use is associated with higher productivity, lower output prices and stable employment (Graetz & Michaels, 2018). Greater technology use could generate new jobs in client tech support or labeling data to train algorithms (Shestakofsky, 2017; Tubaro, 2019; Casilli, 2025). Automation can increase the pay for remaining workers, who specialize in skills that are not taken over by machines (Bessen et al., 2022). On the other hand, automation can deskill tasks, allowing more people to access these jobs and driving down pay (Braverman, 1974; Downey, 2021).

THEORETICAL FRAMEWORK

The educational mismatch and automation literature raise the question in how they are related. I summarize the literature described in this section as the educational mismatch-automation framework. The high societal interest in obtaining college credentials is related to the pace of technological progress. Goldin & Katz (2008) describe the continuous race between education and technology. New technology increases the demand for skilled workers. The education system responds by offering more slots for graduates. If the supply of educated workers grows faster than demand (overeducation), then there will be a compression of wages, because the overeducated workers will have to compete with many other workers with university degrees and thereby accept lower pay that is in line with the wages of less educated workers. Conversely, if technological change raises the demand for educated workers more than the supply (undereducation), then the wages of the high-education workers will rise exorbitantly given their scarcity in the labor market. Thus, technical innovation in the broader economy has an impact on the demand and supply of college-educated workers, but the relative extent must be established empirically.

Technology could also lower the demand for certain workers. Acemoglu & Restrepo (2019) describe the distinction between task-reinstating and task-reducing forms of technology. Task-reinstating automation creates new tasks for human workers, e.g. inventing computers create demand for computer coders. Task-reducing automation replaces tasks for human workers, e.g. elevator buttons replace elevator operators. Acemoglu & Restrepo (2019) find that since the late-1980s the US economy has moved in a task-reducing direction. Technology no longer complements but now displaces labor. Similarly, AI is expected to negatively impact professional and white-collar workers with college degrees, as AI deskills work and makes educated workers replaceable by non-educated workers (Xue et al., 2022). Increased AI reliance has detrimental effects on human cognitive skills, expert judgment, decision-making, integration of declarative knowledge, and problem-solving (MacNamara et al., 2024). Given that these are the skills that are required in educated jobs, cognitive deskilling is more significant in these occupations. This could imply that the recent technologies might target educated workers for automation, which could exacerbate the societal issue of overeducation.

On the other hand, it is possible that automation targets occupations with undereducated workers because employers facing such skills shortages will alleviate the problem by automating labor processes. Cybersecurity is an industry with a severe labor shortage. The need to secure vulnerable IT systems in companies and organizations is quite significant, and that is where AI automation would alleviate these labor shortages (Smith, 2018). Industrial countries like Austria have resorted to a combination of automation and labor migration to alleviate the labor shortages coming from an aging society and shrinking demographics (Ghodsi et al., 2025). Increased AI exposure boosts the wages of all workers using AI, but even more so for those with higher levels of education (Madon, 2024), which is consistent with the claims in the skills shortage literature.

METHODS AND MATERIALS

Research Design

This study employs a cross-sectional, quantitative research design to examine the association between occupational exposure to automation and the credential gap across U.S. occupations. The analysis integrates publicly available and secondary data sources derived from multiple empirical studies (see Data Collection Instruments and Sources). Ordinary Least Squares (OLS) regression models are used to estimate the relationship between automation exposure and the educational mismatch represented by the credential gap, controlling for demographic and labor market characteristics.

Sample and Sampling Technique

The study sample comprises 102 occupations identified through the Standard Occupational Classification (SOC) system. These occupations represent the subset of the 196 occupations reported in the 2014 Burning Glass dataset that could be directly matched with automation exposure data from Frey and Osborne (2017) and Gmyrek et al. (2023). All occupations were included based on the availability of overlapping data across all relevant sources. This approach allows for comparability between automation measures and educational characteristics.

DATA COLLECTION AND ANALYSIS

Data Collection Instruments and Sources

Data for the dependent and independent variables were compiled from various sources. They are recognized institutional and scholarly repositories, ensuring methodological rigor, and strengthening the validity, reliability and trustworthiness of the findings:

Burning Glass (2014): Provided data on the credential gap, calculated from real-time job postings and worker education levels for 2013. Burning Glass is a widely used, proprietary labor market analytics platform, ensuring construct validity by drawing from a large, verified dataset of employer-demand signals.

Frey and Osborne (2017): Provided computerization exposure scores based on expert assessments of task automation potential using the O*NET occupational database. The inclusion of domain experts and the application of a Gaussian Process classifier contribute to high methodological reliability and replicability.

Gmyrek et al. (2023): Provided AI exposure scores derived from interactive querying of ChatGPT to assess the susceptibility of occupations to GPT-based automation. The design of this measure, using consistent occupation-level comparisons, enhances internal validity and supports temporal relevance to modern AI capabilities. Their methods section includes the prompts to generate the data allowing other researchers to reproduce the AI exposure variable.

Bureau of Labor Statistics (BLS): Furnished occupational-level control variables, including demographic and employment characteristics. The BLS is a primary federal source of economic and labor market data, ensuring high credibility, comparability, and reliability of demographic and labor market indicators.

Procedures

The study proceeded in several stages. First, datasets were harmonized using SOC codes to ensure consistent occupational mapping. Second, all automation exposure values originally ranging from 0 to 1 were rescaled to percentages (multiplied by 100) for comparability with the credential gap measure. Third, missing values in control variables were addressed through K-Nearest Neighbors (KNN) imputation. This non-parametric method identifies the most similar occupations based on observed characteristics to estimate missing values, thereby preserving multivariate relationships and minimizing bias. The resulting complete dataset supports reliable estimation and interpretation of regression results.

Data Analysis Techniques

The analysis used bivariate and multivariate OLS regression models to test hypotheses on automation and the credentials gap. Two models were estimated separately to avoid multicollinearity between AI exposure and computerization exposure, which were moderately correlated (Pearson $r = 0.36$). The dependent variable, the credential gap, was treated as a continuous measure. OLS was chosen due to its appropriateness for continuous outcomes and its interpretability regarding the direction and magnitude of relationships among variables.

Operational Definitions

Credential Gap (Dependent Variable): Defined as the difference between the share of job postings requiring a bachelor's degree and the share of current workers in an occupation holding that degree. A negative value indicates overeducation, while a positive value indicates undereducation (Burning Glass, 2014). The highest credential gap occupations are ship engineers, plasterer/ stucco masons and administrative assistants, while the lowest credential gap occupations are economists, social workers and family therapists (Table 1).

AI Exposure (Independent Variable 1): Measures the degree to which occupations are susceptible to automation by AI technologies, based on iterative GPT querying (Gmyrek et al., 2023). Higher percentages represent greater exposure.

Computerization Exposure (Independent Variable 2): Represents the degree of exposure to mechanization and task-based automation as assessed by Frey and Osborne (2017). Higher percentages signify a greater likelihood of computer-based substitution.

Control Variables: Include occupational median age, percentage of women, percentage of white workers, median weekly wages, and total employment, aggregated from BLS data.

Table 1: Highest and Lowest Credential Gap Occupations, N=102

Highest Credential Gap (Undereducation)	**Lowest Credential Gap (Overeducation)**
Ship Engineer (57%)	Economists (-52%)
Plasterers and Stucco Masons (53%)	Social Workers (-42%)
Executive Secretaries and Executive Administrative Assistants (46%)	Marriage and Family Therapists (-40%)
Farmers, Ranchers and Other Agricultural Managers (45%)	Judicial Law Clerks (-40%)
First-line supervisors of Production and Operating Workers (45%)	Mental Health and Substance Abuse Social Workers (-33%)

RESULT

Table 2 presents the descriptive statistics for all the variables included in the study.

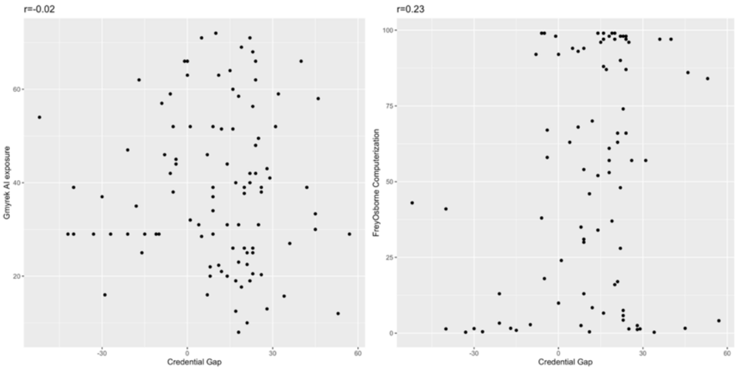
Table 2: Descriptive Statistics: Automation and Credential Gap

Descriptive Statistics: Credential Gap and Automation

Statistic	N	Mean	St. Dev.	Min	Max
Gmyrek AI	102	39.17	16.70	8.00	72.00
FreyOsborne Computerization	102	55.41	38.51	0.30	99.00
Credential Gap	102	10.58	20.89	-52	57
Median Age	102	43.17	3.87	30.50	55.80
Total Emp	102	312.09	555.32	2	3,571
% Women	102	53.47	23.77	6.00	95.60
% White	102	78.40	7.25	58.30	96.90
Median Wage Weekly	102	1,262.53	261.55	693	2,082

The correlation plot shows that there is a weak positive correlation between credential gap and computerization (Pearson r= 0.23), which means that this form of automation is positively correlated with undereducated occupations, which is consistent with the skills shortage argument. This finding is supported in the regression analysis below. The correlation between credential Gap and Gmyrek AI exposure is very weak (r= -0.02), similar to the results obtained in the regression analysis.

Figure 1: Correlation Plots for Credential Gap and Automation (AI and Computerization), N=102



The regression results are shown in Table 3. The Frey-Osborne computerization measure is positively correlated with the credential gap (Model 1), which suggests that more computerized occupations have more undereducated workers. The effect attenuates when accounting for the demographic controls but remains positive and significant at the 90% confidence interval (Model 3). For the Gmyrek AI automation measure we do not find a strong effect for credentials gap with or without controls (Model 2 and 4). As for the control variables, female-dominated occupations and higher-paid occupations tend to be overeducated, which is in line with the labor market literature (Frank 1978; Marioni, 2021; Arranz & Garcia-Serrano, 2025).

Table 3: Credential Gap and Automation

Credential Gap and Automation

	Dependent variable:			
	Credential Gap			
	(1)	(2)	(3)	(4)
FreyOsborne Computerization	0.15***		0.09*	
	(0.05)		(0.05)	
Gmyrek AI		-0.03		0.02
		(0.13)		(0.12)
Median Age			0.001	0.04
			(0.52)	(0.54)
Total Emp			0.003	0.002
			(0.004)	(0.004)

% Women			-0.24^{**}	-0.23^{**}
			(0.10)	(0.10)
% White			0.35	0.51
			(0.33)	(0.33)
Median Wage Weekly			-0.03^{***}	-0.03^{***}
			(0.01)	(0.01)
Constant	2.37	11.67^{**}	21.37	16.75
	(3.51)	(5.32)	(31.77)	(32.18)
Observations	102	102	102	102
R^2	0.07	0.0005	0.22	0.19
Adjusted R^2	0.07	-0.01	0.17	0.14
Residual Std. Error	20.19 (df = 100)	20.98 (df = 100)	19.06 (df = 95)	19.35 (df = 95)
F Statistic	8.07^{***} (df = 1; 100)	0.05 (df = 1; 100)	4.39^{***} (df = 6; 95)	3.78^{***} (df = 6; 95)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$			

DISCUSSION

The findings of this study add important nuance to the literature on educational mismatch and automation. Prior scholarship has debated whether automation exacerbates or alleviates skill and credential imbalances in the labor market. Frey and Osborne (2017) proposed that lower-skilled and undereducated workers face the highest risk of technological displacement, while more recent research, such as Rawashdeh (2025), has suggested that AI increasingly threatens white-collar and STEM-intensive occupations traditionally requiring advanced credentials. The current analysis provides partial support for the earlier computerization hypothesis by showing that displacement risk, as measured by Frey and Osborne's computerization scores, is higher among undereducated occupations. This relationship indicates that earlier forms of automation substituted for labor where credential shortages existed. They mitigate workforce deficiencies rather than exacerbate overeducation. By contrast, the lack of an association between AI exposure and the credential gap demonstrates that newer generations of automation, particularly driven by machine learning and generative technologies, may not yet align with predictable credential-based patterns of labor substitution.

Theoretically, these results suggest a dynamic connection between education and automation that are part of the education mismatch-automation framework. The finding that computerization is associated with undereducated occupations aligns with the "skills-shortage" framework, which views automation as a corrective mechanism that compensates for insufficiently credentialed labor, reducing pressure on higher education systems to excessively expand degree production. However, automation targeting undereducated workers disproportionately only applies to the earlier computerization (2013) measure, not the later AI measure (2023). The neutrality of AI exposure regarding the credential gap points to a transitional phase in which automation transcends traditional educational boundaries. This has implications for higher education policy. The shifting pattern of technological displacement challenges the assumption that STEM expansion alone can shield graduates from automation-related disruption. Instead, curricula may need to evolve toward flexible, interdisciplinary competencies that prepare graduates for uncertain occupational trajectories. These findings, therefore, contribute to the broader theoretical conversation about updating curricular developments and internship pipelines in higher education systems to promote the strategic mission of colleges and universities.

CONCLUSION

The credential gap and automation are important phenomena that impact workers and the functioning and purpose of colleges and universities. This article has examined the empirical question to what extent automation is concentrated in occupations that have more overeducated or undereducated workers. The main finding is that the relationship between these two variables is dependent on the type of automation. Computerization (Frey-Osborne) is associated with the displacement of undereducated occupations, while AI automation is not associated with the disproportionate displacement of occupations by credentials gap. Thus, there is limited but not unambiguous evidence that automation is consistent with the skills gap argument, where automation can relieve the shortage of credentialed workers and reduce the burden on colleges to graduate more workers in high demand fields. While overeducation is a concern for the overall labor market, automation is not shown to make that problem worse.

There are several important limitations in this study. The Burning Glass data has only listed 196 occupations, where only 102 occupations match onto the automation data. There are 700 occupations listed in the automation data. Thus, this study contains a significant amount of missing data which reduces the generalizability of the findings. Burning Glass has released only one year of credential gap data in a report, so more recent data would improve the empirical analysis. In addition, different machine learning specifications would produce very different automation scores. The predicted automatability of occupations measured in this study is not equivalent to the actual automation of occupations. Actual automation is influenced by many different factors that might include social norms, the competitive industrial environment or the availability of training data, data centers, electricity and other inputs that are associated with AI tools. Qualitative case studies within occupations and industries could uncover the underlying motivations for automation and changes in credential requirements over time. These limitations underline the importance of conducting more academic studies with more data relating the consequences of technology to the credentials gap and higher education.

IMPLICATIONS

The displacement potential by occupation contains different implications for the legitimacy of colleges. The displacement of overeducated workers could challenge the legitimacy of colleges further as college-educated labor market entrants that already report difficulties obtaining suitable employment, e.g. PhDs working as Uber drivers, will face even more competition, thus raising the fair question whether obtaining a college education is a worthwhile endeavor. This study has not found concerns about overeducation to be applicable based on the available data. In contrast, the displacement of undereducated workers would relieve the pressure on colleges to deliver more graduates in these occupations. The relief of the skills shortage in such occupations would lower the extent of the credential gap deriving from undereducation. This latter result was obtained with computerization automation. In the case, where automation is indiscriminate with respect to the credentials gap, as in the case of AI automation, colleges and STEM programs will be facing the burden of accommodating graduates in some industries in the labor market, while being relieved to produce more graduates in other industries. Given that AI is a more recent form of automation, its labor market effects are becoming increasingly important, thus challenging the account that automation mainly targets occupations with undereducation.

University STEM programs are asked to develop AI-based curriculums and internship pipelines with AI-deploying companies that most optimally prepare students for the workforce. AI deploying companies should expand entry-level positions to mitigate skills shortages and concerns around overeducation where they arise.

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