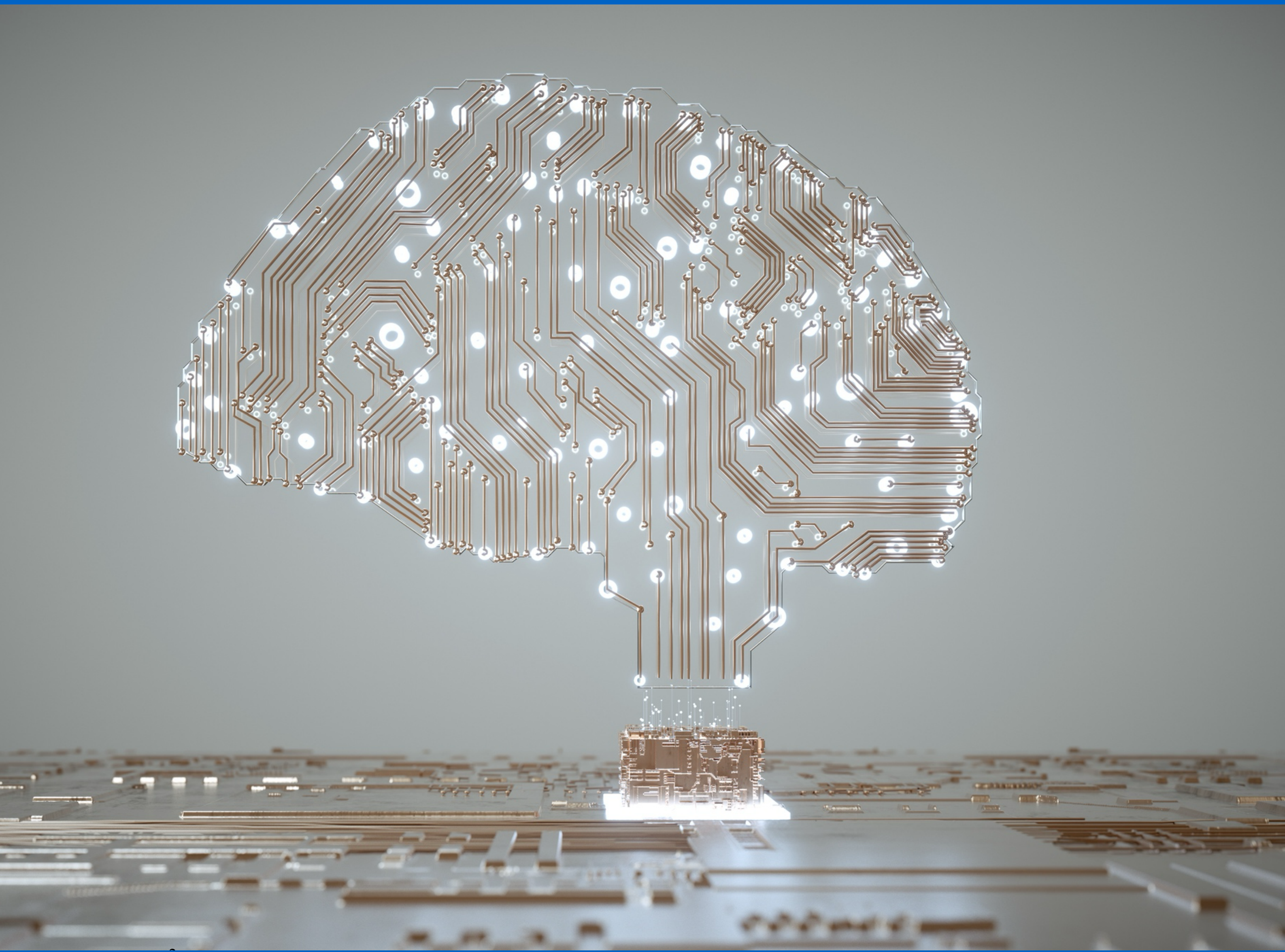
LinkedIn Economic Graph



Generative AI's Influence on Employment Patterns

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Economic Graph White Paper

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In this study, we investigate the differential impacts of Generative Artificial Intelligence (GAI) on workers in the US using LinkedIn data, both overall and by their educational attainment levels. We find a gradual shift away from GAI-disrupted occupations over the past six years towards potentially augmented or insulated roles, particularly pronounced among higher-educated workers. Through an analysis of occupational transitions, we make predictions under various scenarios of GAI impact, examining the proportions of workers within different GAI occupation classifications, transitions from employment to non-employment, and shifts in occupational categories. While workers with higher educational attainment tend to exhibit higher rates of occupational mobility, the differential effects of GAI on employment and occupational changes underscore the importance of considering educational disparities in the context of technological advancements.

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Introduction

Generative AI (GAI) tools, such as Copilot, ChatGPT, and Gemini, have the potential to fundamentally change how people work and their productivity. 75% of knowledge workers using AI at work and 79% of work leaders stating their company needs to adopt AI to stay competitive (Microsoft & LinkedIn, 2024). However, not all workers will be equally impacted. In our prior work, we classified each occupation to one of three groups, based on their skill composition: those likely to be insulated from the impacts of GAI, those likely to be augmented, and those likely to be disrupted.

Our prior report found that GAI is likely to have unequal effects on workers, depending on their skills level (Kimbrough & Carpanelli, 2023). Unlike previous technological advancements that primarily affected workers in lower-skilled roles or in jobs with lower-education requirements, the GAI technological wave will likely affect some of the highest-skilled and highest-educated jobs as well as those with lower educational attainment.

Skills-based GAI occupation classification (GAI-Group)

Augmented occupations are those which use many skills that are complemented by GAI. For example, software engineers may automate some of their coding work with GAI, focusing more of their time on GAI-complementary skills, such as cross-functional influencing and stakeholder engagement.

Examples: Software engineer, data analyst, web designer, nutrition assistant

Disrupted occupations are those which stand to see significant change from GAI, but do not rely as much on GAI-complementary skills. For instance, language translators' skills stand to shift from doing translations from scratch to reviewing and certifying machine-generated translations, or to specializing on specific legal or literary domains.

Examples: Customer service representative, administrative assistant, legal associate

Insulated occupations are those that have a relatively small proportion of GAI-replicable skills in their core skills. For example, real estate agents might utilize GAI for writing house descriptions, but core relationship management skills would be insulated from GAI.

Examples: teacher, nurse, locksmith

Source: Kimbrough & Carpanelli (2023)

There is a rich history of research evaluating the impact of technological development on workers. For example, while wage inequality has grown over time, and many have attributed this to technological innovation which favors the more skills, higher-paid workers, Card & DiNardo (2002) argue against this hypothesis by examining the data and underlying models. They suggest the need for a much more nuanced understanding of changes in wage inequality as well as the impact of technology on different groups of workers (see also Acemoglu & Autor, 2011; Card & DiNardo, 2006). However, automation can indeed exacerbate inequality, especially if the speed of adoption is fast and is accompanied by the creation of new tasks (Acemoglu & Restrepo, 2018).

While it is still early days for GAI, there is a fast-growing literature on how this technology may or has impacted employment outcomes across different groups. Based on an occupational task analysis, Eloundou et al. (2023) estimate that 80% of US workers could have at least 10% of their tasks automated by large language models, and 19% of these workers could have more than

50% of tasks automated. Moreover, their work suggests that higher-income workers are particularly exposed to such automation. A separate paper by Felten et al. (2023) agree, and expands the demographic impact analysis to show that highly-educated, highly-paid, white-collar occupations may be most exposed to generative AI.

To expand current understanding, in this report we focus on the impacts of GAI on workers' job outcomes, both overall and depending on their educational attainment. We leverage recent estimates of occupational transitions using data from LinkedIn members' profiles, limiting our attention to US workers. The methodologies for scoring occupations' GAI complementarity and replicability with occupations' skills, for classifying occupations into groups based on those scores, and for simulating the predicted impacts of GAI on different groups under different scenarios are all described in the appendix.

We examine three outcomes:

1. Proportion of members working within each GAI occupation classification (GAI group)
2. Proportion of members who transition from working to not working (which includes retirement and other voluntary separations as well as involuntary separations such as lay-offs)
3. Proportion of members who change occupations

Key findings

Historical trends and current rates

- On aggregate, over the past six years, workers have already been trending away from occupations classified as disrupted by GAI, and into occupations potentially augmented or insulated from GAI.
- While all education groups have been moving away from GAI-disrupted occupations, bachelor's degree holders had the fastest decline in the share of workers in disrupted roles.
- Compared to workers with lower educational attainment (high school or associate's degrees), higher education workers (bachelor's and graduate degree) are more likely to be in augmented and insulated occupations, and less likely to be in disrupted occupations.
- On average, the share of workers in augmented occupations has been increasing. However, workers with higher educational attainment have been trending towards jobs in augmented occupations at the fastest rate.
- Workers with higher educational attainment have tended to exit employment at a lower rate but change occupations at a higher rate than lower education workers.

We next examine predictions under five different scenarios with respect to the extent to which GAI complements or replicates skills. This allows us to investigate potential employment outcomes across the next year depending on GAI impact patterns without making concrete claims to what those GAI impact patterns will be.

Potential scenarios

Scenario 1 (Status quo): GAI has no impact on demand for workers and observed employment patterns.

Scenario 2 (Gradual integration): The impact of GAI is low on both skill complementarity and skill replicability.

Scenario 3 (Heightened exposure): There is a large impact on skill replicability, exposing occupations which use such skills. The impact on skill complementarity is low.

Scenario 4 (Broad augmentation): There is a large impact on how GAI complements skills, and occupations which employ such skills see increases in productivity and demand for workers. The impact on skill exposure is low.

Scenario 5 (Paradigm shift): There are large impacts of GAI arising from both skill complementarity and skill exposure. Demand for occupations changes depending on their use of complemented or exposed skills.

We summarize the main findings of our paper under each scenario.[1]

Scenario 1: Status quo

- Our baseline from pre-GAI trends, which assumes that the best predictor for occupation transitions and our outcomes is the year before GAI.

Scenario 2: Gradual integration

- If both skills complementarity and skill replicability are only lightly impacted, we predict very small changes relative to status quo.
- There are very small increases out of disrupted occupations and into insulated occupations and not working.

Scenario 3: Heightened exposure

- All education groups see a decrease in the share of workers in augmented and disrupted occupations and an increase in the share of workers in insulated occupations.
- Bachelor's degree holders widen their advantage over high school graduates in employment in augmented occupations, and high school graduates become proportionally more likely to work in insulated occupations. The higher likelihood of high school graduates to work in disrupted occupations than bachelor's graduates drops substantially due to an outsized decrease in participation by high school graduates.
- This is the scenario with the largest increase in the share of members not working. Because the increase from GAI is proportionally bigger for bachelor's degree graduates than high school graduates, the gap between these two groups narrows from 30.4% higher under status quo (2.6% of high school graduates transitioning to non-work the following year, compared to 2.0% of bachelor's degree holders) status quo, to 9.2% higher under this scenario (5.4% of high school graduates, compared to 5.0% of bachelor's graduates).
- People switch occupations year-to-year more than under status-quo, which tends to widen even more for higher education workers (e.g.,

[1] Our five scenarios are described by the intensity of impact on complementary and replicability of skills. We acknowledge that what will occur will be more nuanced, with for example the intensity of the impact varying across industries, occupations, and times. This may be due to speed of adoption of GAI, barriers to usage, and other factors. It is outside of the scope of this paper to test differentiation of scenarios across the economy or across time.

under status quo high school graduates switch occupations 12.3% less than bachelor's degree holders, while under this scenario they switch 14.6% less).

Scenario 4: Broad augmentation

- The largest share of workers in augmented occupations are under this scenario across education groups, benefiting lower education workers the most (narrowing existing high school/bachelor's gap from -8.8% to -5.4%).
- Participation in disrupted occupations decreases for all education groups, but by less than under scenarios 3 and 5. High school graduates' higher share working in disrupted occupations compared to bachelor's decreases.
- For all education groups, there is a decrease in the share not working, and disproportionately for lower education workers. Under status quo, high school graduates are 34.6% more likely to be not working than bachelor's graduates. Under scenario 3, that drops to 12.8%.
- Only small increases in occupation-switching predicted for all education groups with no appreciable changes in gaps.
- This is the only scenario where we have a predicted decrease in the share who exit employment compared to status quo. The high school/bachelor's gap decreases somewhat.

Scenario 5: Paradigm shift

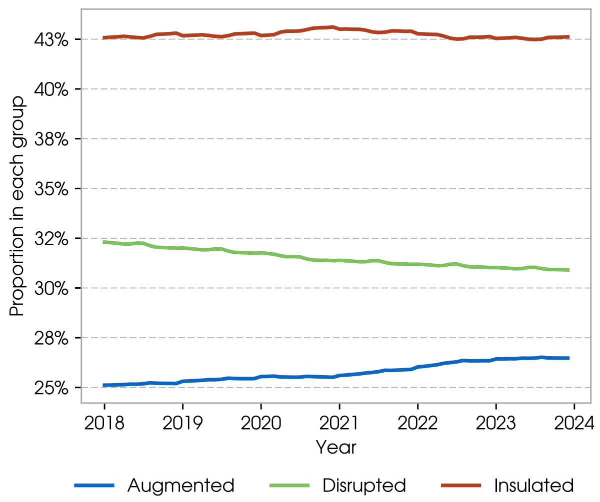
- For all education groups, an increase in workers in augmented occupations relative to status quo, but slightly more for lower education workers.
- This is the scenario with the lowest participation in disrupted occupations for all education groups, but a large shift in the gaps. Under status quo, high school graduates are predicted to be 7.8% more likely to be in disrupted occupations than bachelor's degree holders, but under this scenario, the gap shrinks to 0.8%.
- Participation in insulated occupations increases for all groups, but more so for lower education workers. High school graduates are predicted to move from 1.3% less likely than bachelor's degree holders to work in insulated occupations to 4.0% more likely.
- We predict slight increases in the proportion exiting employment in all groups, but more so for higher education. The high school/bachelor's gap drops in half, from 30.4% to 14.0%.
- This is the scenario with the most occupation changing, but relatively similarly across education groups, with only small changes in gaps.

Modeling projected gaps

In order to explain the intuition behind our approach, we first present one outcome–the share of people in each of the GAI groups–for the overall population (that is, not by education). Figure 1 presents the estimated shares of workers in each group each month over the last six years. In order to calculate how groups have transitioned between GAI groups over time, we examined the occupations each month, and

Figure 1

Share of members in each GAI group



map this according to the 2023 categorizations in Kimbrough and Carpanelli (2023).[2]

We find over the past six years that workers have been shifting away from jobs that we would in 2023 classify as disrupted by GAI (exemplified by the downward slope on the green line), and shifting towards augmented jobs (see text box on page 1 for examples). Insulated jobs have remained relatively stable, with a highpoint at the start of 2021, potentially due to pandemic restrictions.

We next examine US LinkedIn member data from February 2022 through 2024 on US members. We use changes in employment status and which occupation group (of over 600) each person reports working in from each month in 2022 to the same month in 2023 for example. For each rolling 12-month span, we calculate the share of people in employment status or occupation *i* who are not working or work in each of the occupations 12 months later. We averaged these ratios across all 12 months to create predictions of how workers will transition in the future—a Markov Chain transition matrix. Note that we also tested a model where this transition matrix was estimated not just over the period from 2022 to 2023 each month, but over the past six years. The results were very similar, and so in this paper we only report the results from the 2022 to 2023 transition matrix. The appendix contains more details on the methodology.

From this, we can calculate any number of occupational choice decisions across a one-year period. We take the same matrix generated above of each transition and use it to predict what fraction would be in each occupation one year later, if the same trends continued. This forms *Scenario 1 (Status quo)*, and would intuitively approximately represent a continuation of the above trend line. We then examine four alternative scenarios. These are briefly summarized in the text box above and the assumptions mathematically are explained in the appendix. Here we provide a little more discussion into the nature of each scenario.

Scenario 2 (Gradual integration) explores a scenario where GAI does have impacts on how skills are used, but the impact is low for both skill complementarity and skill replicability. In other words, estimates and predictions for worker occupational transitions are based on the assumption that the impact of both GAI skill

[2] In sensitivity analysis, we test this on a sample of members who have belonged to LinkedIn since at least January 2018, in Appendix Figure A.1. This allows GAI groups. The results are qualitatively similar.

complementarity and exposure to GAI-replicable skills is low. In other words, a job with skills which are complemented by GAI but no skills replicated by GAI would see a slight increase in demand. A job with skills replicated by GAI but none complemented would see a slight decrease in demand. A job with both complemented and replicated skills would have uncertain impacts on the share working in each occupation, and may not change at all.

Scenario 3 (Heightened Exposure) represents a scenario where the impact is low from GAI skill complementarity, but high from GAI-replicable skill replicability. Estimates and predictions for worker occupational transitions are based on the assumption that the impact of GAI skill complementarity is low—having very little impact—but that the impact of GAI-replicable skills is high, which could decrease overall demand for workers in these occupations. This would generally be considered a bad case scenario for the labor market, although as we discuss below, there are some disparities between lower and higher education workers that end up narrowing under this scenario.

Scenario 4 (Broad augmentation) presents a case where the Impact is high from GAI skill complementarity, but low from GAI-replicable skill exposure. Occupations that utilize these GAI-complementary skills thus see an increase in demand, and there is wider increases in worker productivity with likely increases in overall employment as a result as well.

Scenario 5 (Paradigm shift) shows the case when the impact is assumed to be high from GAI skill complementarity as well as from GAI-replicable skill exposure. As suggested by the name, this would lead to the most dramatic shifts in demand for different occupations (some increasing, others decreasing) depending on which skills are utilized in the job, and how they are complemented or replicated by GAI.

These scenarios are predicted by shifting the empirically estimated probabilities of transitioning from occupation *i* to occupation *j* (for each occupation pair) based on occupation *i* and occupation *j*'s scores on GAI-replicable skills and GAI-complementary skills (Kimbrough & Carpanelli, 2023). While we explain this in more detail in the appendix, intuitively, demand for occupation *i* decreases by a little if it has a below average score of GAI-complementarity under the scenario of low impact from complementarity, and a lot under the scenario of high impact. Demand for occupation *i* decreases if it has an above average score on GAI-replicability in the same way.

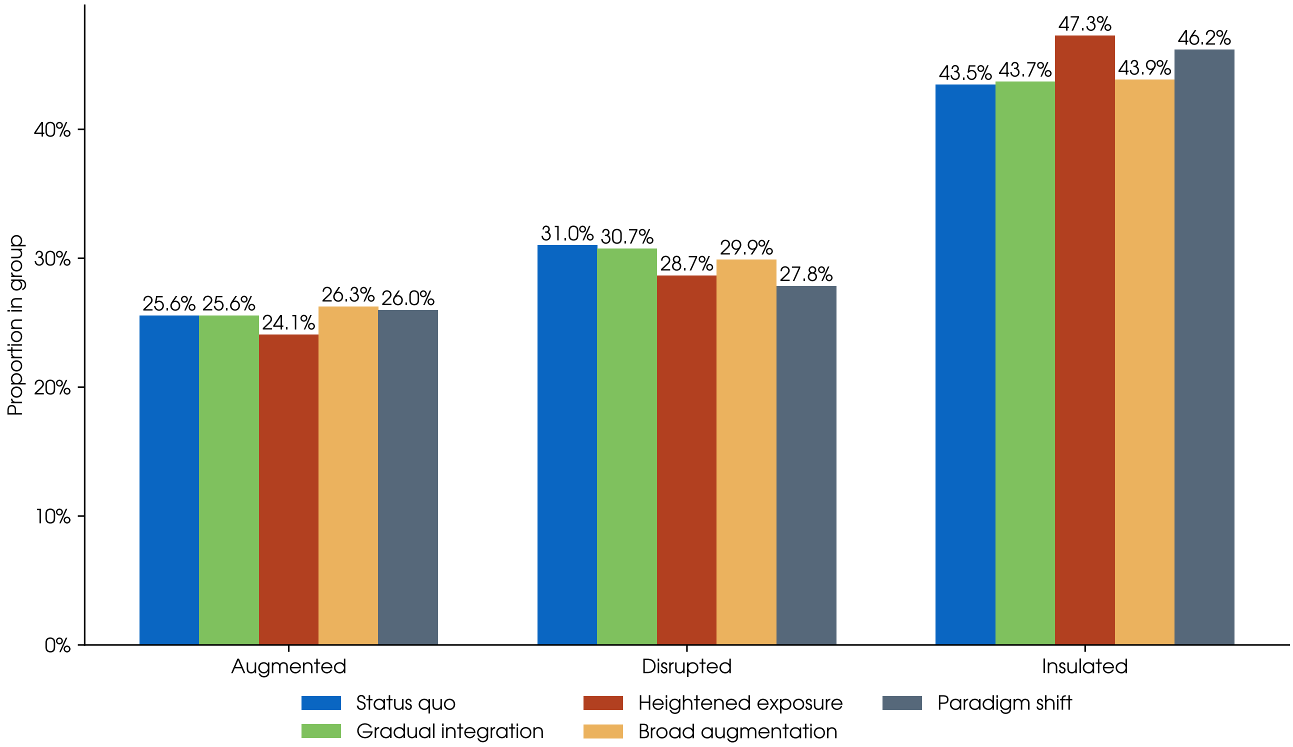
Overall predicted changes

GAI groupings

We first predict how the share of people working in each GAI group would change under the different scenarios. Figure 2 demonstrates the predicted shares of the share of workers in each of the three GAI groups under the four scenarios one year from now, contrasted with status quo. Consider for example the share in augmented occupations. Under the *status quo* scenario, the share of workers would be predicted to grow gradually (reflecting the trend over the past few

Figure 2

Predicted shares in each GAI group by scenario in one year



years observed in Figure 1), and result in 25.6% of the sample working in augmented occupations.[3]

However, under the *heightened exposure* scenario (the complementarity impact of GAI is low but the exposure impact is high), a larger share of workers will transition out of augmented occupations. Under the *gradual integration* scenario (low impact of both exposure and complementarity), the bar is almost identical to *status quo* for augmented occupations, but is slightly lower for disrupted occupations and higher for insulated occupations. Under the *broad augmentation* scenario (the impact of GAI is high from complementarity of GAI and low from exposure), the projected fraction of people in augmented occupations is predicted to increase relative to *status quo*.

We can also easily contrast across GAI groups. Consider the case again of the *broad augmentation* scenario. In that case, we predict fewer workers will be employed in disrupted occupations than under *status quo*, while more will work in augmented and insulated occupations. On the other hand, under the *heightened exposure* scenario, we predict even fewer people working in disrupted occupations. However, those workers would not primarily transition into augmented occupations this time

[3] Note this is somewhat different (and in this case, smaller) than the proportions shown in Figure 1. That is because Figure 1 relies on a balanced sample, and so is over-represented by slightly older, more senior people (given they have had to have been members of LinkedIn since 2018).

as in the *broad augmentation* scenario, but instead to disrupted occupations.

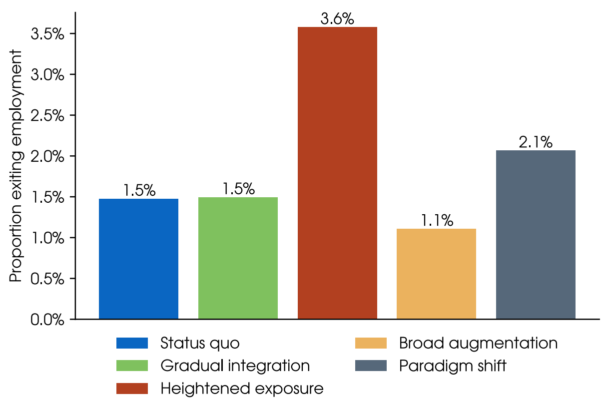
It is important to note, the magnitudes we assume under the different scenarios have a degree of subjectivity (what constitutes a large impact versus a small) and are not entirely data-driven, of necessity. Instead, they are illustrative of different potential scenarios for use in comparison. For that reason, we would not for example mean to imply we are claiming that if there is low complementarity from GAI but high exposure, the fraction of workers in insulated occupations would increase to 47.3% instead of 43.5% under no change (as shown in Figure 2). Instead, we encourage examination of the overall trends (not levels achieved), and even more so, comparison across educational groups under the different scenarios as done below.

Proportion of members exiting employment

We next investigate the share of workers who are predicted to move from working to not working.

Figure 3

Predicted proportion exiting employment



This could occur for many reasons, including unemployment or separation from the labor force, either temporarily (voluntarily employment gaps, including for parental leave) or permanently (e.g., retirement).

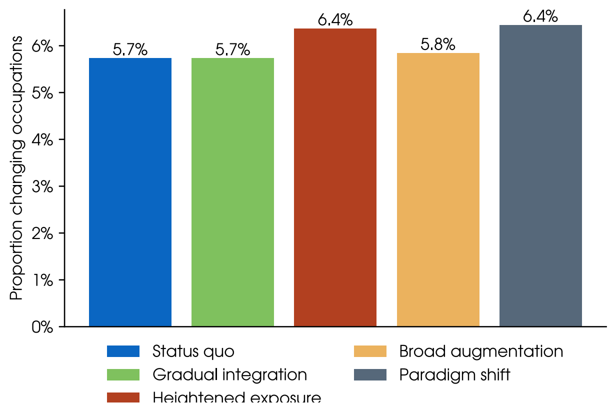
We predict that the share of people exiting employment stays approximately the same under gradual integration, decreases slightly under broad augmentation, increases slightly under the paradigm shift, and increases substantially under heightened exposure (Figure 3). These trends show the importance of which scenario plays out, and the risks inherent in situations where skills are replicable by GAI as well as the strong insulating effect skills augmentation plays.

Proportion of members changing occupations

Even if people do not exit work, they may switch occupations. This may occur for many reasons, including voluntary and planned career changes as well as unplanned or layoff-pressured

Figure 4

Predicted proportion changing occupations



changes. Figure 4 presents the prediction. Under status quo, we predict 5.7% of the workers would change occupations (given by the typical occupation change in the past year). This is also what would occur under gradual integration. However, under any of the scenarios with a large impact on either skills augmentation or skills replicability, there would be an increase in the share of workers changing occupations—the most in the case of heightened exposure or paradigm shift, at 6.4%.

Summary of findings for overall predictions

Table 1 helps summarize all of these findings in a more qualitative manner.

Predicted changes by education level

We turn our attention to the share of workers in each GAI group by education level, as we did in our example above.

Shares over time

We first show the historical trends in each educational group, as we did in Figure 1 above for the overall population. While we found in Figure 1 that overall, workers were shifting towards augmented occupations years before GAI, these same trends are not repeated for each education group. In fact, we find that lower education workers (high school and associate) have been trending away from augmented occupations since years before, while higher education workers (bachelor's and graduate degree holders) have been trending towards augmented occupations. This means the gap

Table 1

Summary of Predicted Impacts of Scenarios

Impact of…		GAI-replicable skills	
		Low	High
GAI-complementary skills	Low	**Gradual integration** ≈ Augmented ↓ Disrupted ↑ Insulated ↑ Exit work ≈ Change occ	**Heightened exposure** ↓↓ Augmented ↓↓ Disrupted ↑↑ Insulated ↑↑ Exit work ↑↑ Change occ
GAI-complementary skills	High	**Broad augmentation** ↑↑ Augmented ↓↓ Disrupted ↑ Insulated ↓↓ Exit work ↑ Change occ	**Paradigm shift** ↑ Augmented ↓↓ Disrupted ↑↑ Insulated ↑↑ Exit work ↑↑ Change occ

↓↓ and ↑↑ : changes exceeding 2% from status quo
↓ and ↑ : changes between 0.1% and 2% from status quo
≈ : changes between 0 and 0.1% from status quo

was already increasing in the occupations poised most to benefit from GAI.

On the other hand, the trend shown in Figure 1 of workers moving away from disrupted occupations for years prior to the introduction of GAI is revealed on average for each of the education groups. However, bachelor's degree holders had the fastest rate of decline in their participation in GAI-disrupted occupations.

Finally, bachelor's degree holders were least likely to be in insulated occupations, a gap that has widened over time with a shallower growth trajectory than other education groups.

Current levels

We first examine the current levels of workers in each of the groups, as shown in Figure 5.

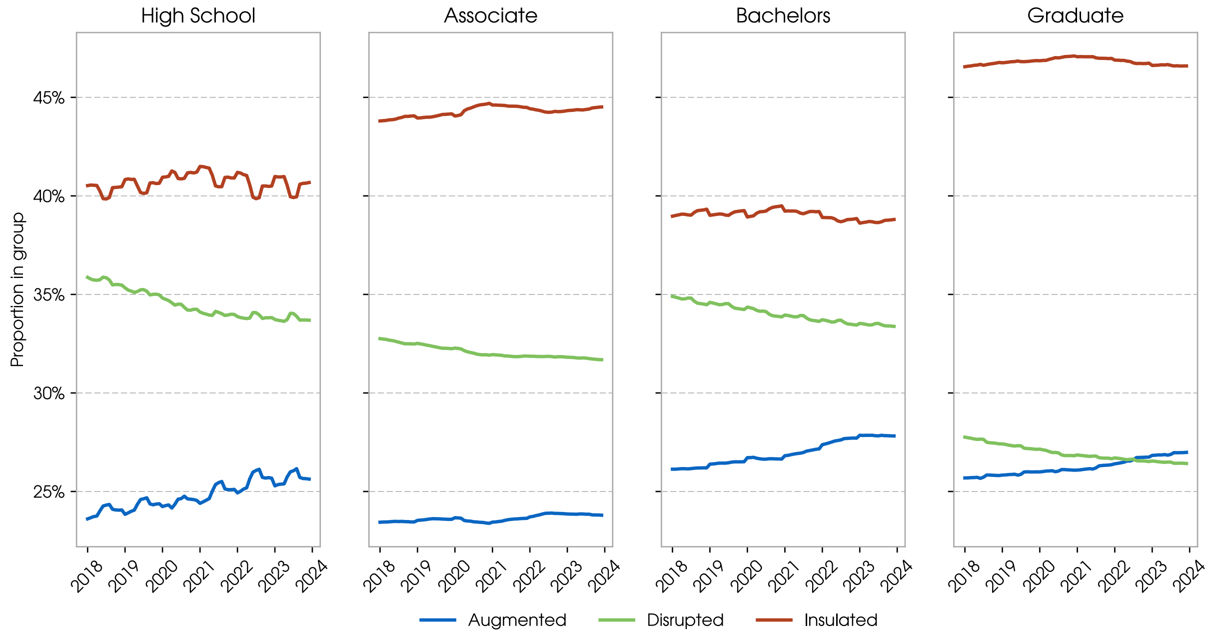
We find that overall, the largest share of workers are in insulated occupations (around 2/5ths of workers), followed by workers in disrupted occupations (around 1/3rd), and the smallest share are in augmented occupations (around 1/4).

However, there are important differences across education groups. For example, graduate and associate degree workers are more likely to be in occupations likely insulated from GAI than high school or bachelor's degree holders (such as project manager or teacher for graduate degree workers, and medical and mechanical technician for associate degree workers). On the other hand, high school and bachelor's degree holders are the most likely to be in disrupted occupations. Interestingly, bachelor's degree holders are both in the groups most likely to be disrupted and most likely to be augmented, showing how often they are in jobs with complementary skills to GAI.

One of the common comparisons we will make in this white paper is between high school graduates and bachelor's degree holders. This is shown in the table as well. Both groups have around 1/3 of their members working in disrupted occupations (such as administrative assistants and salespersons). However, bachelor's degree holders have more workers in augmented occupations (such as software engineers or marketing managers) than high school graduates (27.8% compared to 25.6%), while high school graduates have more workers in insulated occupations (40.7% versus 38.8%). These gaps may seem small, but are in reality non-negligible differences representing an underlying population of millions of workers.

Figure 5

Share of workers in each GAI group over time, by education



GAI predicted group composition

As described above, we next simulate the GAI-occupational group in which members work in the future under the five difference scenarios. We first examine this for participation in occupations belonging to the augmented group. Figure 5 presents the average participation rates one year from now for the five scenarios (including status quo). Figure 6 presents the same data but represented as percent difference between the given education group and bachelor's degree holders. This is done for ease of interpretation, to be able to with facility ascertain how each group fares relative to bachelor's degree holders, and how this differs across scenarios. It also emphasizes the goal of the simulations, which is to contrast how the gaps change across scenarios. The values in Figure 5 are completely dependent on our choice of parameters in the simulations.

In the heightened exposure scenario shown in red, all groups have lower participation in augmented occupations relative to status quo. However, Figure 6 demonstrates that this scenario would widen the gap between high school graduates and bachelor's degree holders, from 7.7% lower participation for high school graduates down to 9.8% less. On the other hand, if the complementary impact of GAI is high (i.e., either in broad augmentation or paradigm shift scenarios), then the share of people working in augmented occupations would be predicted to increase over the status quo for all education groups. However, the increase is proportionally smallest for bachelor's degree graduates, as seen by the narrowing of the gap relative to lower education levels.

Thus, for measuring the share of workers in augmented occupations in the future, the gap between bachelor's degree holders and high school workers would be largest under the heightened exposure scenario and smallest under the broad augmentation case. Interestingly, the complementarity of skills seems to dominate the replicability of skills for this

Figure 6

Share of members in each GAI group by education

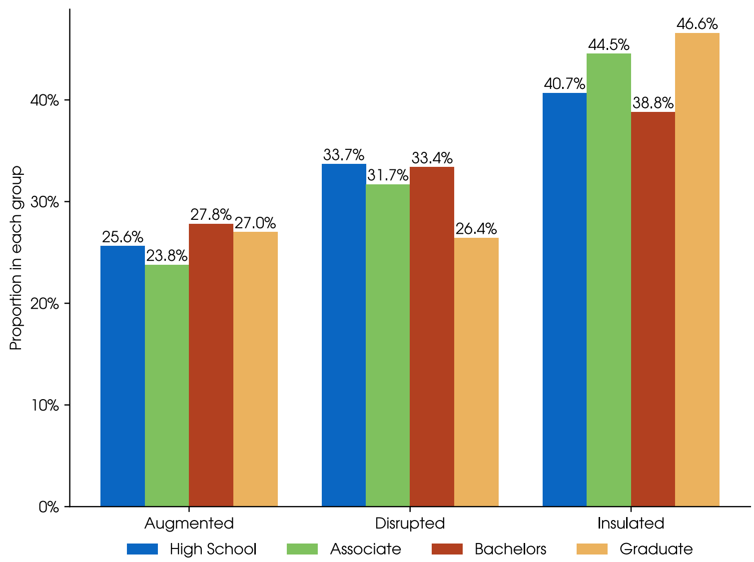


Figure 7

Share of workers in augmented occupations one year from now, by education

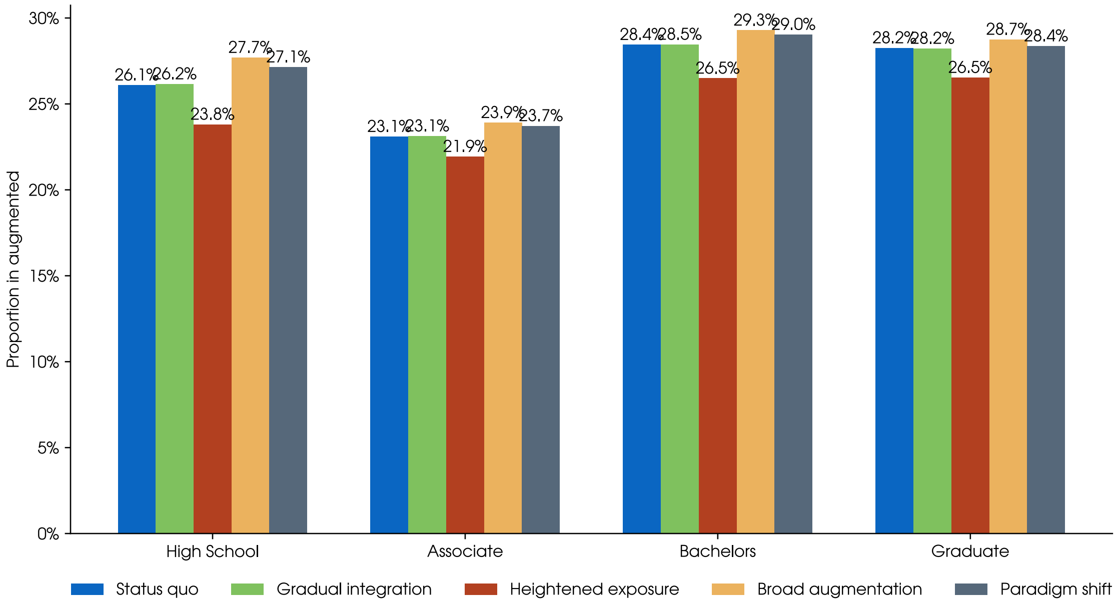
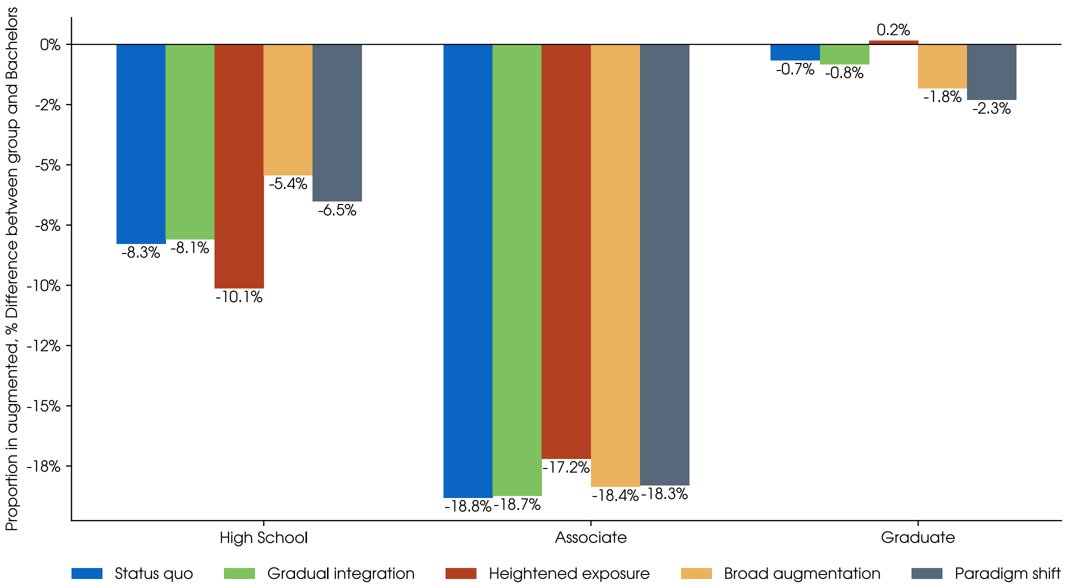


Figure 8

Gap in the share of workers in augmented occupations one year from now, relative to bachelor's degree holders' employment in augmented occupations



outcome between these groups, as the gap would still be narrower in the paradigm shift scenario than under status quo.

For the other two GAI occupation classifications (disrupted and insulated), we present the levels (such as is done in Figure 7) for discussion while presenting the gaps (such as is done in Figure 8) in the appendix.

We next examine the share of workers in occupations we predict to be disrupted by GAI, shown in Figures 9 and A.3. Under the gradual integration scenario, we predict very small decreases in the share of workers working in disrupted occupations, as we might expect.

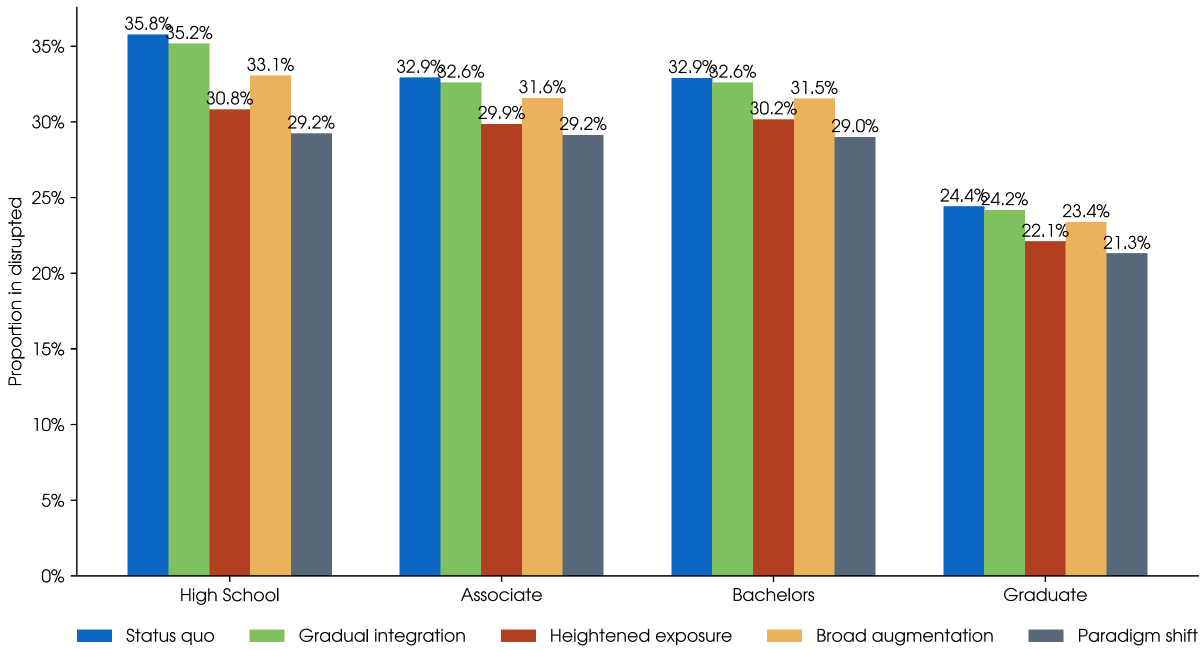
This does not have large impacts on the observed gaps; the largest reduced gap is for high school graduates who are 7.8% more likely to work in disrupted occupations than bachelor's degree graduates under status quo, but a slightly smaller 6.9% more likely under gradual integration.

On the other hand, under all three of the other scenarios, each education group sees a bigger decrease in participation in disrupted occupations. This is especially true for bachelor's degree holders, which narrows some of the gaps.

If the impact replicability of skills is high (heightened exposure scenario or paradigm shift scenario), then there is a much larger decrease in the share of workers in disrupted occupations across the board. While this doesn't alter the gap between bachelor's graduates and either associate degree graduates (about as likely) or graduate degree graduates (more likely), it has a large impact on the gap between high school graduates compared to bachelor's degree

Figure 9

Predicted share of workers in disrupted occupations one year from now, by education



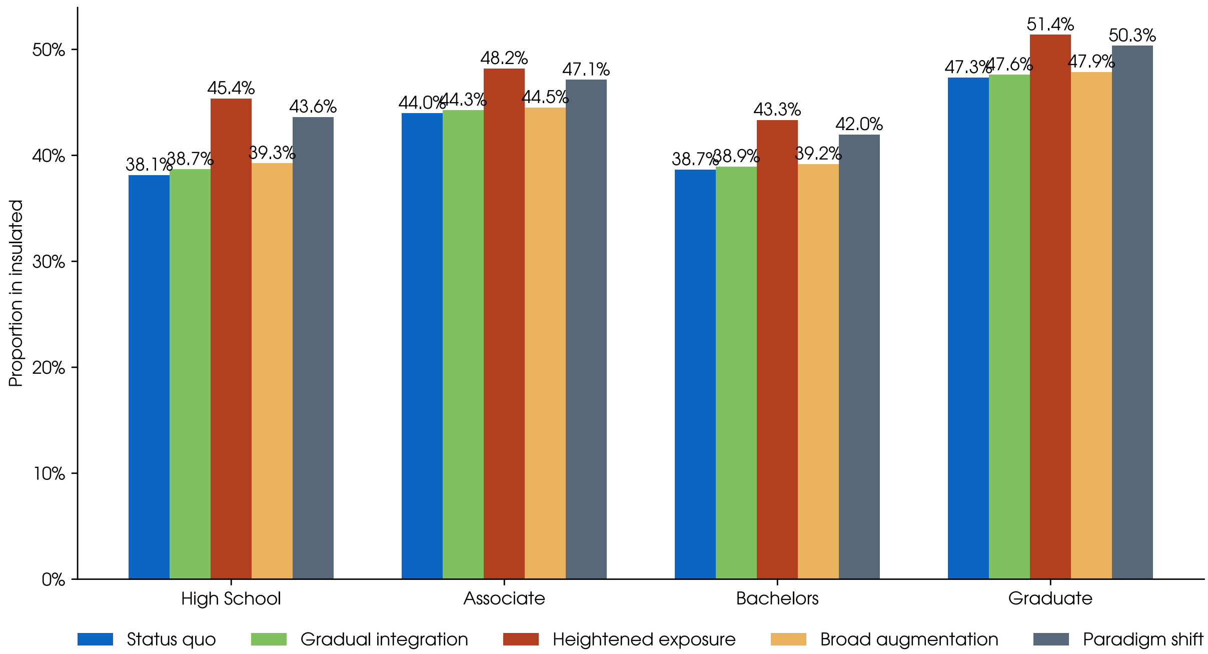
graduates. They are 7.8% more likely to be in disrupted occupations under status quo, but 0.3% less likely than bachelor's degree graduates under the paradigm shift scenario. The impact under the broad augmentation scenario is not as strong as either of the other two scenarios, although it also leads to less participation in disrupted occupations, especially for bachelor's degree holders, narrowing the gap compared to status quo.

We next look at how participation in insulated occupations changes under different scenarios, shown in Figures 10 and A.4. Under all scenarios and for each education group, participation in insulated occupations is predicted to increase relative to status quo, pre-GAI. However, the extent to which it changes varies greatly. There are once again only minor increases in participation under the gradual integration scenario, and only minor narrowing of gaps closer to zero.
The largest changes occur under scenarios when the impact from replicability of skills by GAI is high, namely the heightened exposure scenario and the paradigm shift scenario. In these cases, workers are more likely to work in insulated occupations.

Under the heightened exposure scenario, participation in insulated occupations is higher than any other scenario. This leads to high school graduates being only 1.0% less likely than bachelor's degree holders to be 5.1% more likely. On the other hand, it decreases the higher levels that associate and graduate degree holders work in insulated occupations relative to bachelor's degree holders. The same is true also for the other case of high impact from skill

Figure 10

Predicted share of workers in insulated occupations one year from now, by education



replicability, the paradigm shift scenario, although not to quite as large of an extent.

For the broad augmentation scenario, when the replicability impact of GAI is low, there is only a small increase in the share of workers in insulated occupations across education groups. This leads to virtually unchanged gaps between education groups.

In summary, large changes would happen under the heightened exposure scenario, as fewer individuals would work in augmented and disrupted occupations while more would work in insulated occupations, and the education gap between high school graduates and bachelor's graduates would widen for augmented occupations (in favor of college graduates), widen for insulated occupations (in favor of high school graduates), and narrow to zero for disrupted occupations (away from a status quo advantage in favor of high school graduates). On the other hand, under the broadened augmentation scenario, participation in augmented occupations would increase across the board of education groups, taking away from participation in disrupted occupations. Participation in insulated occupations would increase a little across the board. Focusing on the education gap between high school graduates and bachelor's degree graduates again, this scenario would narrow the gap for augmented occupation work (from an advantage for college graduates), have little impact on the already-small gap for insulated occupation work, and narrow the gap for disrupted occupations (from an advantage for high school graduates).

Under the paradigm shift scenario, many of the above-discussed impacts of the heightened exposure scenario and the broadened augmentation scenario would slightly moderate each other while still having sizeable over impacts relative at least to status quo. The primary exception here is for participation in disrupted occupations, wherein the two impacts somewhat amplify each other and lead to even higher departures from working in disrupted occupations and, at least for the high school-bachelor's degree gap, have the largest change.

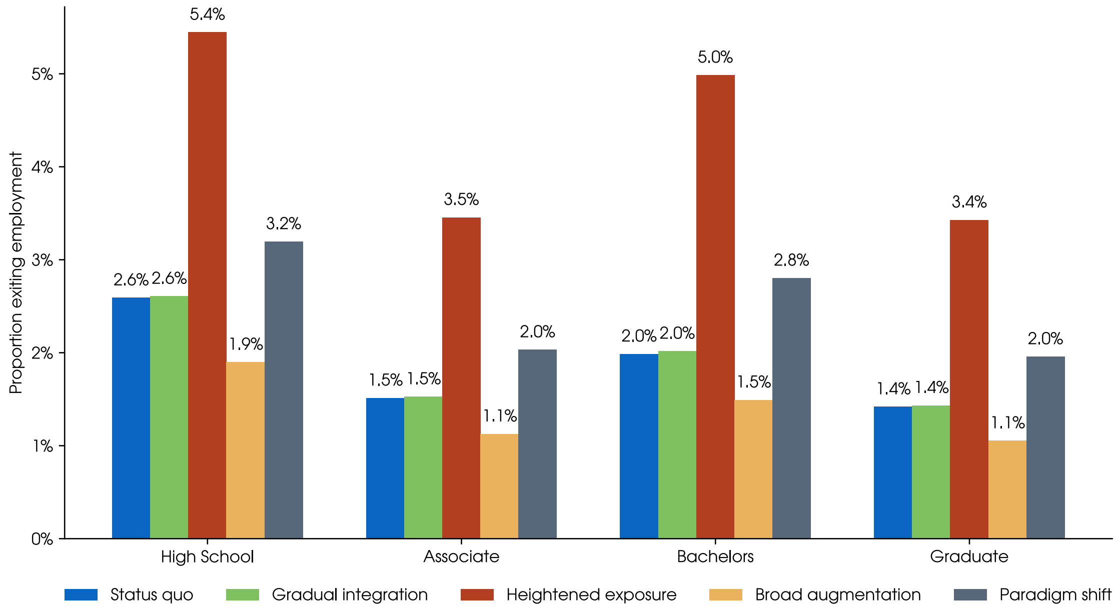
Proportion of individuals exiting employment

While workers will switch between occupational groups, some will also change whether they switch to not working at all one year later given shifts. We next simulate and estimate this outcome by scenario and education group. For example, under status quo we estimate that 2.6% of high school graduates will not be working one year from now as shown by LinkedIn profile status. This does not mean that 2.6% will lose their job, as it will include some already not working and some who exit employment, as well as be reduced by some who move from not working to working. We find similar although somewhat smaller rates under status quo.

Under the gradual integration scenario, the proportion not working is approximately the same as in status quo. However, for the heightened exposure scenario, there is a substantial increase in the share of individuals not working across all education groups. This impact is proportionately largest for bachelor's degree holders, which leads to the high school graduates having a 34.6% higher rate of not working under status quo decrease to 12.8% under heightened exposure.

Figure 11

Share of members exiting employment, by education



On the other hand, the broadened augmentation scenario would decrease the share of people not working relative to status quo for all groups. This too would widen narrow the gap between high school graduates and bachelor's degree holders, although by not as much as under the heightened exposure scenario, and for a different reason (decrease in both groups but stronger for high school graduates, instead of increase in both groups but stronger for bachelor's degree holders).

Finally, under the paradigm shift scenario, the two effects counteract each other (augmented skills decreasing the proportion not working, while replication of skills increases the proportion). The replication of skills' effect dominates, with the overall shares not working increasing slightly over status quo for each education group. The high school-bachelor's degree gap is narrowed under this scenario as well, relative to status quo.

Proportion of individuals changing occupations

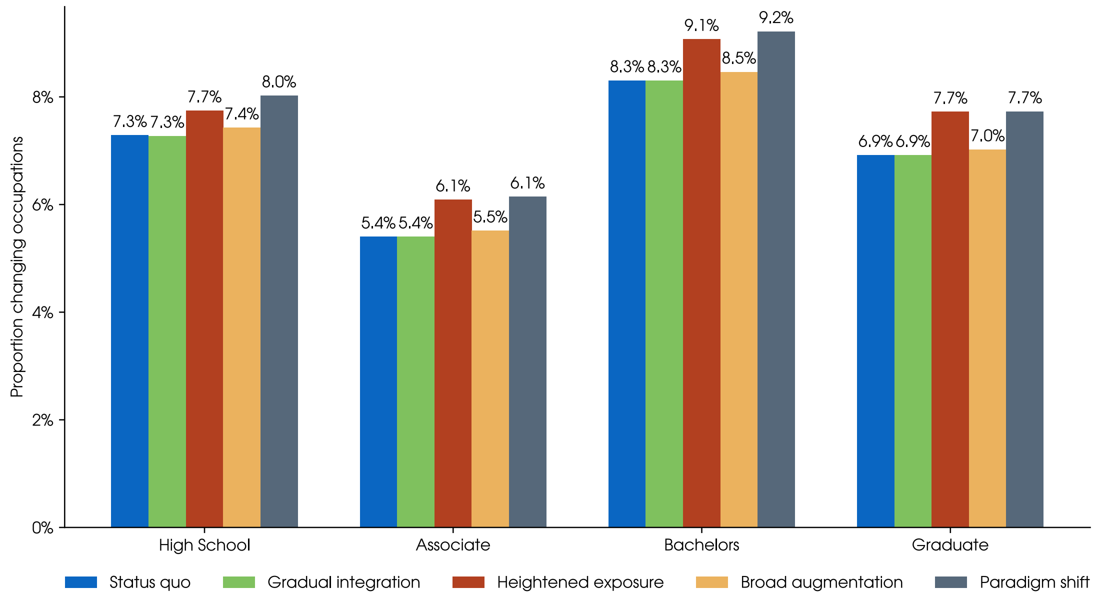
We next calculate the proportion of workers who change occupations from one year to the next under the different scenarios, as shown in Figure 12. We find that occupational changing increases under every scenario compared to status quo. However, the largest shifts are in heightened exposure and paradigm shift, both of which reflect a higher degree of impact from skill replicability of GAI. This is true across education levels, with no strong differential.

Conclusion

This research paper aimed to investigate the potential influences of GAI on employment patterns in the US under different scenarios. The primary focus is on understanding the differential impacts of GAI on workers and examining

Figure 12

Share changing occupations



potential shifts in occupational trends over time, with additional attention to how different educational groups may be impacted. The appendix discusses assumptions and limitations of the paper.

Over the past six years, a noticeable, steady shift has occurred among workers predating the release of GAI in 2022, with workers moving away from occupations which would later be susceptible to disruption by GAI and towards those that are insulated or augmented. Notably, bachelor's degree holders exhibited the fastest decline in occupations which would potentially be disrupted by GAI.[4]

Educational disparities in occupational trends are evident, with lower education workers (high school and associate) trending away from augmented occupations, while bachelor's and graduate degree holders are trending towards them. This highlights a growing gap in occupations poised to benefit from GAI. However, if GAI has a high impact complementing skills, we predict that the educational gap in augmented occupations would be narrower than if the trends continued at their historical and diverging trajectories.

Predictions reveal many other intriguing patterns. Under the heightened exposure scenario, while participation is predicted to decrease for all groups, the advantage that bachelor's degree holders would have over high school graduates in participation would increase. Similarly, the gap in the share working in disrupted occupations (with high school graduates being more likely to work there) would decrease in this scenario.

[4] From our methodology, we are unable to determine the extent to which this is driven by their choice and labor supply, compared to trends in demand for different occupations.

Scenarios with high complementary impact of skills tend to favor high school graduates more than bachelor's degree holders compared to the status quo. For example, decreasing the augmented occupation advantage over status quo virtually erases the higher rate under status quo of high school graduates working in disrupted occupations. halves the higher rate at which high school graduates leave employment each year.

Table 2 summarizes the findings descriptively. In most scenarios and for many outcomes, the predicted impacts follow in the same direction across educational groups, although the extent to which each education group differs.

Table 2

Predicted outcomes across educational groups

	All	High school	Associate degree	Bachelor's degree	Graduate degree
Gradual integration					
Share in augmented occupations	≈	↑	↑	≈	↓
Share in disrupted occupations	↓	↓	↓	↓	↓
Share in insulated occupations	↑	↑	↑	↑	↑
Share exiting working	↑	↑	↑	↑	↑
Share changing occupations	≈	↓	≈	≈	≈
Heightened exposure					
Share in augmented occupations	↓↓	↓↓	↓↓	↓↓	↓↓
Share in disrupted occupations	↓↓	↓↓	↓↓	↓↓	↓↓
Share in insulated occupations	↑↑	↑↑	↑↑	↑↑	↑↑
Share exiting working	↑↑	↑↑	↑↑	↑↑	↑↑
Share changing occupations	↑↑	↑↑	↑↑	↑↑	↑↑
Broad augmentation					
Share in augmented occupations	↑↑	↑↑	↑↑	↑↑	↑
Share in disrupted occupations	↓↓	↓↓	↓↓	↓↓	↓↓
Share in insulated occupations	↑	↑↑	↑	↑	↑
Share exiting working	↓↓	↓↓	↓↓	↓↓	↓↓
Share changing occupations	↑	↑	↑↑	↑	↑
Paradigm shift					
Share in augmented occupations	↑	↑↑	↑↑	↑↑	↑
Share in disrupted occupations	↓↓	↓↓	↓↓	↓↓	↓↓
Share in insulated occupations	↑↑	↑↑	↑↑	↑↑	↑↑
Share exiting working	↑↑	↑↑	↑↑	↑↑	↑↑
Share changing occupations	↑↑	↑↑	↑↑	↑↑	↑↑

↓↓ and ↑↑ : changes exceeding 2% from status quo; ↓ and ↑ : changes between 0.1% and 2% from status quo; ≈ : changes between 0 and 0.1% from status quo

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Appendix

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Methodology

Data and Privacy

This body of work represents the world seen through LinkedIn data, drawn from the anonymized and aggregated profile information of LinkedIn's one billion members around the world. As such, it is influenced by how members choose to use the platform, which can vary based on professional, social, and regional culture, as well as overall site availability and accessibility.

In publishing these insights from LinkedIn's Economic Graph, we want to provide accurate statistics while ensuring our members' privacy. As a result, all data show aggregated information for the corresponding period following strict data quality thresholds that prevent disclosing any information about specific individuals.

Generative AI classifications (replicated from Kimbrough & Carpanelli 2023)

GAI-replicable and GAI-complementary skills

We identify GAI-replicable and GAI-complementary skills with the following steps:

1. We ask ChatGPT 3.5 (Feb 2023) the following prompts:
    a. GAI-replicable skills: "What are the 100 top skills that AI technologies (ChatGPT, Dall-E, LaMDA, etc.) can perform very well?"
    b. GAI-complementary skills: "What are the 100 top skills that can currently exclusively be performed by humans?"

We map these lists to LinkedIn's taxonomy with LinkedIn's taxonomy API, and we refine matches manually.

2. We expand coverage further by applying skill similarities based on skill embeddings to score kills that resemble those flagged in each list, and by manually reviewing the skills in the popular skill groups containing the skills from the previous steps.

3. For external validation, we ingest and map to our taxonomy three exposure scores from the academic literature (Webb (2019); Felten, Raj, & Seamans (2023), and Felten, Raj, & Seamans (2021)). We use these scores to train a model that learns which skills contribute more to these three rankings, and we use this model to score all skills in LinkedIn's taxonomy.

Skills-based occupation classification

For each occupation, we calculate the percentage of skills that are GAI-replicable and GAI-complementary based on each occupations' skills genome. An occupation's skills genome is the ranking of its top 100 most relevant skills, based on a TF-IDF model. In this model, skills are relevant when they tend to be disproportionately added by members in this occupation compared to other occupations.

We classify each occupation into Augmented, Disrupted, or Insulated from GAI, based on their GAI-replicable and GAI-complementary medians. Occupations with above median GAI-replicable skills and above-median GAI-complementary skills are classified as Augmented, occupations with above median GAI-replicable skills and below-median GAI-complementary skills are classified as Disrupted, and occupations with below median GAI-replicable skills are classified as Insulated.

Simulations of outcomes

In order to simulate outcomes, we first estimated a transition matrix from each occupation or not working to each occupation or not working one year later. We do so using data from hundreds of millions of US members profiles and job histories. For example, for the transition from occupation i to occupation j, we take the sample of all people in occupation i in year t and then calculate what fraction of them are working in occupation j one year later.

This estimated transition matrix forms the basis for status quo. We test both using only the most recent year (i.e., for each month in 2022, examining the occupation of the individual one year later in 2023 of the same month), as well as across the past six years in sensitivity checks.

We then calculate a counterfactual transition matrix for each of the four scenarios. Let π_{ij} be the estimated transition probability under status quo (what we observe in the data) for transitioning from occupation i to occupation j over the course of one year, and Π be the overall transition matrix. Intuitively, we estimate the shift in transitions based on changes in demand for occupation j. We do so using the formula

$$d_j^s = 1 + \theta_c^s c_j - \theta_e^s e_j$$

Here,

- c_j: occupation j's % of skills complemented by GAI
- e_j: occupation j's % of skills exposed to GAI
- θ_c^s: the extent to which skills complemented by GAI increase demand for the occupation
- θ_e^s: the extent to which skills exposed by GAI decrease demand for the occupation

Thus, having many skills that are complemented by GAI increases demand for the occupation; having many skills exposed to GAI decreases demand for the occupation. We use this to calculate the transition matrix elements under the counterfactual scenario by

$$\widetilde{\pi_{ij}^s} = \frac{d_j^s}{\sum_{k \in K} d_k^s \pi_{ik}} \pi_{ij}$$

The scaling $\sum_{k \in K} d_k^s \pi_{ik}$ is necessary to reflect the need for the rows of the transition matrix to sum to one. For example, if there is an occupation with no exposed or complemented skills, $d_j^s = 1$ and there is no shift in demand for workers for that occupation. However, if people from occupation i tend to transition into highly complemented occupations, for which demand went up, then the demand to the first occupation would decrease because of the relative shifts. The same would conversely hold for if transitions tended to happen to highly exposed occupations, which would lead to an increase in transitions into the first occupation. Our approach does not account for any general equilibrium impacts that may occur as workers move between occupations.

We test four hypothetical scenarios:

	θ_c^s	θ_e^s
Gradual integration	0.1	0.1
Heightened exposure	0.1	0.9
Broad augmentation	0.9	0.1
Paradigm shift	0.9	0.9

Using these scenarios, we can simulate out shares of employees in each occupation and not working one year from now, by using the initial shares in each occupation (and not working) and the counterfactual transition matrix Π^s. From that, we can estimate several outcomes. The ones we examine are the fraction of workers in each GAI classification, the fraction transitioning to not working, and the fraction who change occupations over the course of the year. The taxonomy we use for occupation includes just over 600 unique occupations.

Assumptions and limitations

There are a number of assumptions made in the approach of this paper which may impact the findings.

No general equilibrium effects We assume that shifts in shares of workers in occupations do not shift demand for those workers due to a larger supply, for example. Instead,

Types of occupations in each GAI group are fixed We assume that over time, occupations do not shift how much the skills used in the occupation are complemented or replicated by GAI, and also hold the skills used in each occupation constant. This is almost certainly incorrect in the long-term, and thus our projections should only be viewed with a short-term time horizon.

Introduction of new occupations If GAI itself creates new occupations, or if technology in other areas creates new occupations, we will miss the shift into and out of these. This is another reason why we only look at one-year projections.

Data estimation of Markov transition matrix The Markov transition matrix is based off of one year (Dec 2021 through Dec 2022, and one year later for each month). We also tested it with six years prior instead of only one. The goal was to estimate transitions prior to introduction of GAI to serve as status quo.

No heterogeneity in impact of GAI across industries, occupations, or time We have modeled the impact as a function only of the current top skills in an occupation and how those are complemented or replicated by GAI. However, some occupations may have more reaction to GAI than other occupations that use some of the same skills, depending on such factors as rate of adoption of GAI in the occupation and industry or digital literacy within the occupation. We also do not model shifts over time, which is why we focus only on a one-year horizon.

Figure A.1

Share of members in each GAI panel, balanced panel

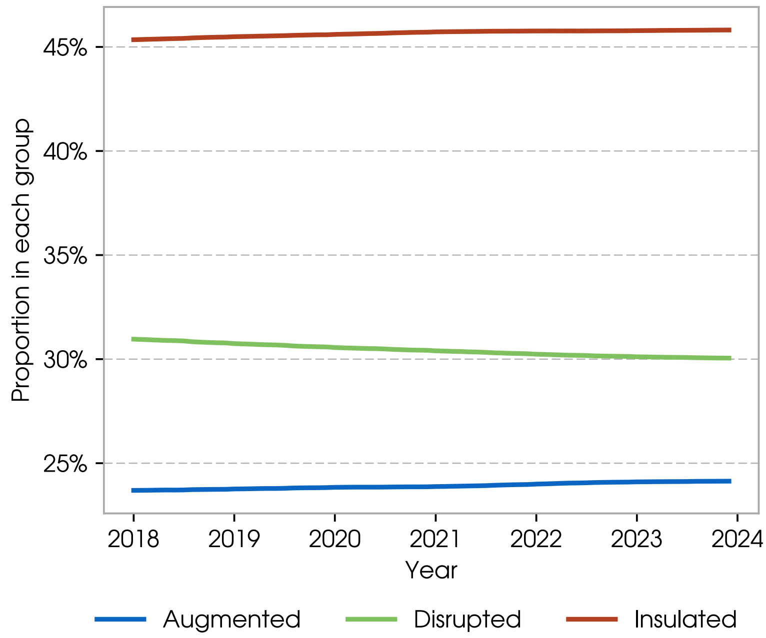

Figure A.2

Trend with balanced panel

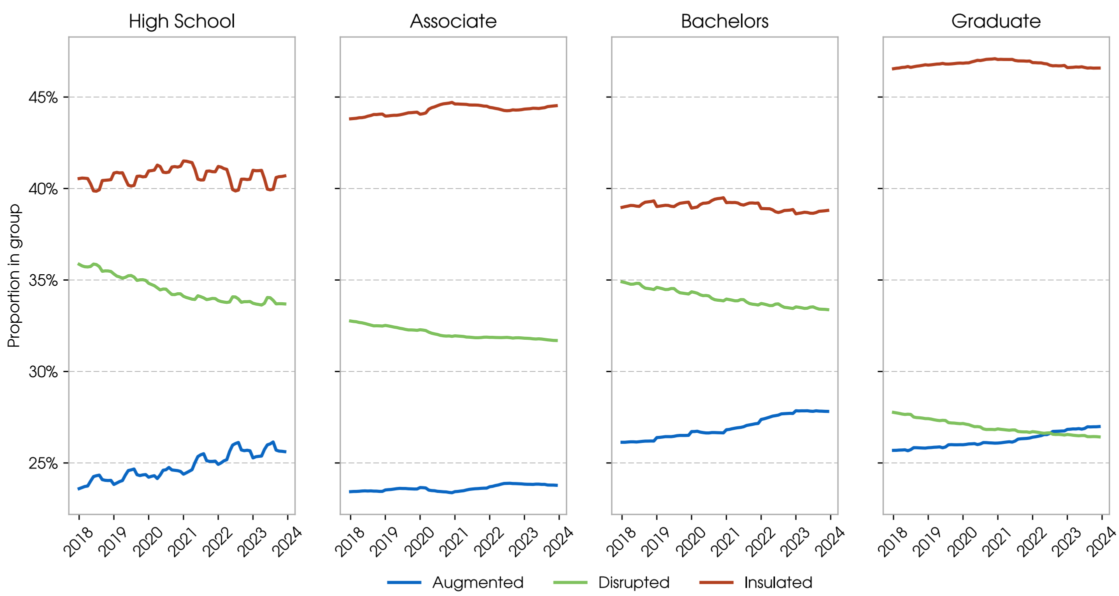

Figure A.3

Gaps in outcomes for disrupted occupations, given education group versus bachelor's degree holders

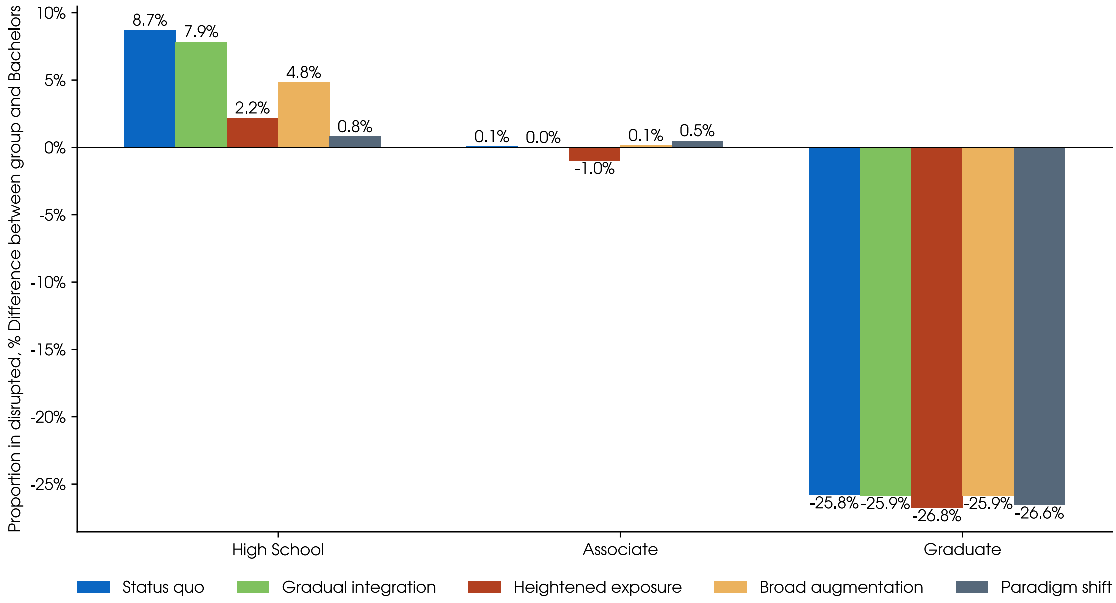

Figure A.4

Gaps in outcomes for insulated occupations, given education group versus bachelor's degree holders

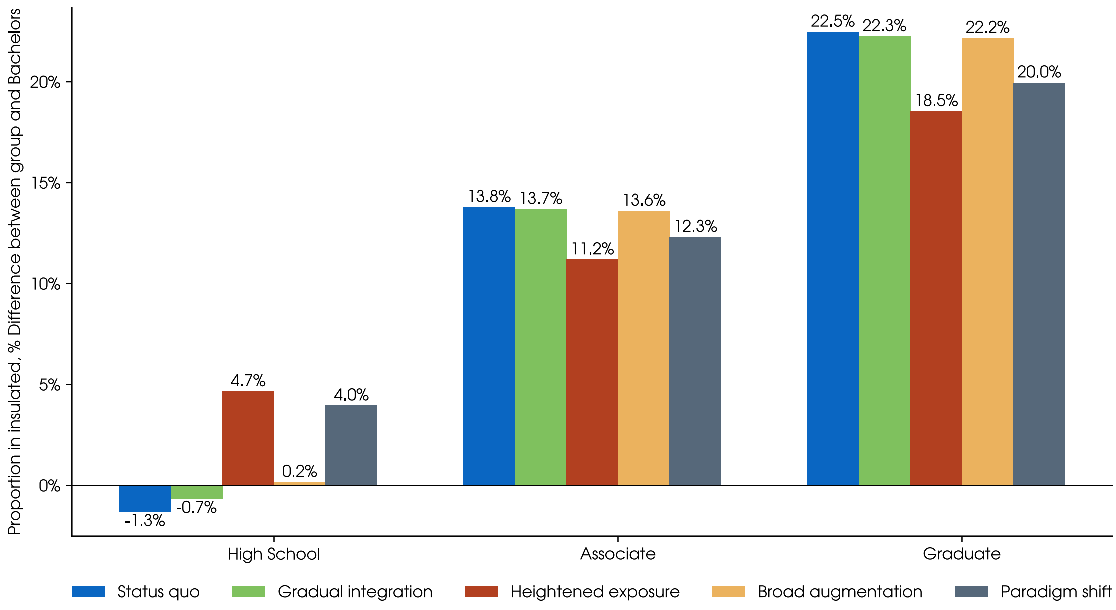

Figure A.5

Gaps in outcomes for exiting employment, given education group versus bachelor's degree holders

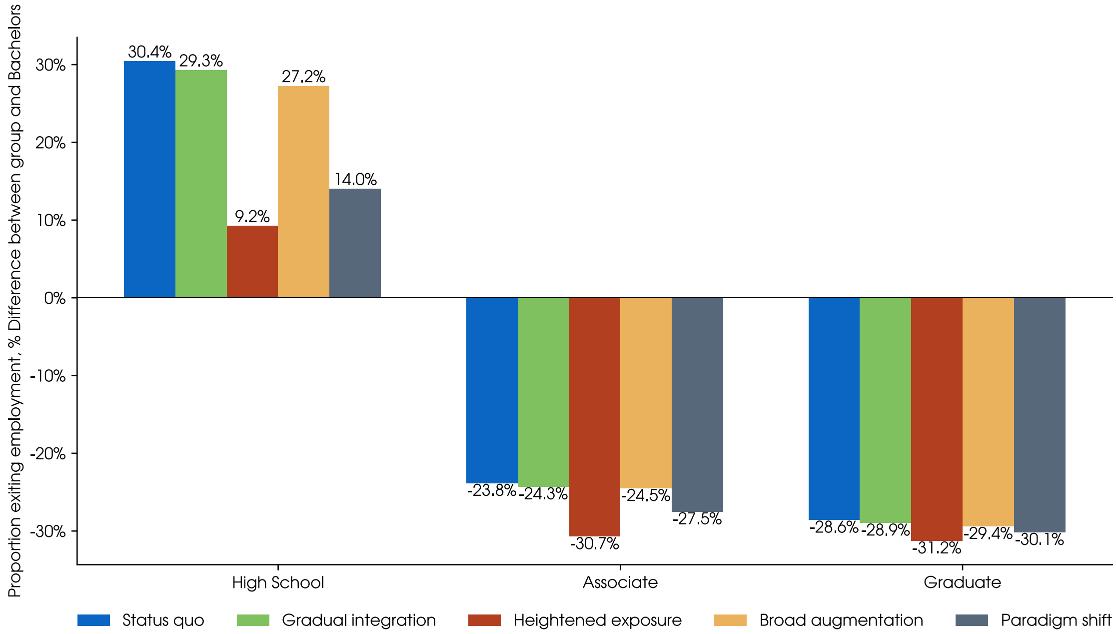

Figure A.6

Gaps in outcomes for changing occupations, given education group versus bachelor's degree holders