The Organizational Correlates of Automation Depend on Job Status

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Abstract

In many professions, human workers are now being displaced by robots. This trend towards automation has led to much research interest in the impact and correlates of automation on workplace contexts and workplace behavior. However, this research has typically modeled automation as a single process which has the same implications for all employees. Drawing from the rich psychological literature on power and status, we show that automation may have different implications for high-status and low-status employees. For high-status jobs (e.g., optometrists), we find that automation is linked to higher levels of responsibility, teamwork, decision impact, and job competition. In contrast, level of automation within low-status jobs (e.g., fast food workers) is only linked to less regular work schedules. This research suggests that automation may have very different implications for low-status and high-status workers.

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Automation has a surprisingly long history. As early as the 16th century, a clergyman named William Lee invented a method of mechanizing the looms that produced stockings (Lewis, 1986). Lee's patent application for the invention was rejected by Queen Elizabeth I, who was concerned manual stocking-knitters would lose their work if the process was mechanized. However, even the Queen of England could not stop the rising influence of workplace automation. More than four hundred years later, a widely cited 2013 study found that as many as 47% of jobs could be lost to current automation technology, and that this number would only grow in the years to come (Frey & Osborn, 2013). A website, www.willrobotstakemyjob.com, will even estimate the probability that any job will be automated in the near future.

Over the last several decades, as automation has become more widespread and salient to American workers, it has also become a growing area of study within industrial-organizational psychology and social psychology. Numerous researchers cite the potential impact of automation on many outcomes relevant to the workplace. For example, studies have argued that automation may compromise ethical hiring practices (Bigman et al., 2020), may lead to more workplace competition due to lower availability of jobs (Acemoglu & Restrepo, 2019), may lead to reduced trust in an organization's decision-making (Dietvorst, Simmons, & Massey, 2015), may improve teamwork (Joe et al., 2014; Wright & Kaber, 2005), and may even lead to greater workplace productivity and employee freedom within organizations (Chui, Manyika, & Miremadi, 2015; Do & Chang, 2008).

This previous literature shows that interest in automation is growing across the social sciences, from economics, to industrial-organizational and social psychology, to sociology.

However, one limitation of this literature is that it considers automation as a single construct, describing differences between jobs that have a high risk of automation (e.g., cashier positions, pilots) and a low risk of automation (e.g., nurses, authors; Georgieff & Milanez, 2021). A growing body of research suggests that automation can take many different shapes across occupational fields, with different implications for automation's impact on decision-making, teamwork, competition, and other metrics (Balfe, Sharples, & Wilson, 2015). The goal of this paper is to explore how these impacts can vary across low-status (cashiers, nurses) and high-status (pilots, authors) workers. However, we begin by reviewing the ways that automation has been defined and differentiated in the literature.

Distinguishing Different Forms of Automation

Starting from the 1940s, automation has been classically defined as "the use of largely automatic equipment in a system of manufacturing or other production process" (Oxford Languages). In research on workplace behavior, scholars typically use this term to describe cases in which embodied robots or disembodied artificial intelligence programs replace human employees, which leads to an urgent need to redefine tasks currently performed by human workers (Chui, Manyika, & Miremadi, 2015). Several papers have argued that automation, so defined, has the benefit of increasing cost efficiency for organizations, but simultaneously raising employee job insecurity (Yam et al., 2021) and lowering job satisfaction (Schwabe & Castellacci, 2020). Yet these general findings obscure the fact that automation can mean different things across different jobs. A pilot and a manufacturing plant worker can both depend highly on machines and artificial intelligence in the workplace, but their experiences of machines and AI may be very different, and automation can play very different roles in these industries.

An emerging body of research has helped illuminate subtypes of automation which have key differences.

One distinction is between “mechanization” and “computerization.” The concept of mechanization dates to the industrial revolution, and it was defined in 1934 as “the use of tools or equipment of any kind to aid the human brain and muscle.” (Jerome, 1934). Computerization is a far more recent change and refers to increased reliance on artificial intelligence and computing systems to make decisions. Classic concerns about workplace automation often focus on manufacturing workers losing their jobs to mechanization (Coupe, 2019). However, many people have also lost their jobs to computerization, including managers and physicians (Chui, Manyika, & Miremadi, 2015). Both mechanization and computerization ultimately produce the same results: causing drastic changes in the workplace by replacing or supplementing human labor with machines, computers, and artificial intelligence.

Another distinction is between “automation” and “augmentation.” Scholars have proposed that this may be the most useful distinction between different forms of automation because it separates jobs where human employees will be aided (augmented) by machines from jobs where human employees will be replaced (automated) by machines (Raisch & Krakowski, 2021). Similar to the case of computerization, employees are less intimidated by augmentation, and research indicates that this lack of intimidation may be justified. Through the collaboration between human employees and machines, machines can take on increasingly advanced tasks. Meanwhile, human employees can not only transform to managerial roles, but also dedicate more time to irreplaceable tasks, such as decision-making and innovation (David, 2015; Haefner et al., 2021).

These distinctions are not only helpful from a semantic perspective; they also help predict how different jobs may change as working robots become more prevalent. Robot-augmented jobs may be far less threatening than robot-automated jobs, with consequences for workplace contexts and employee behavior. We next explain how these differences may intersect with low- and high-status jobs because of psychological and economic forces.

Job Status may Moderate the Relationship Between Automation and Workplace Outcomes

Traditionally, experts have focused on occupation status when estimating the likelihood that jobs will be automated in the future. On average, between 9-47% of American jobs are estimated to be at risk of automation (Arntz, Gregory, & Zierahn, 2017; Frey & Osborn, 2013), but this number is significantly higher for lower status blue-collar jobs than higher status white-collar jobs (Cortes, Jaimovich, & Siu, 2017; Patel et al., 2018). Many papers have built on these estimates to suggest that blue-collar workers feel significantly more threat from automation than white-collar workers (Gruchmann et al., 2021).

However, status may not only change the likelihood that workers' jobs are automated; it may also change how workers experience automation. Previous research on power and status suggests that higher levels of power and status facilitate an "approach" motivation in which individuals are more likely to act on the world and solve problems with a gain frame, whereas lower power and status encourage an "avoidance" motivation in which individuals are more likely to avoid potential harms and solve problems with a loss frame (Cho & Keltner, 2020; Keltner, Gruenfeld, & Anderson, 2003). For example, high-power individuals are more likely to pursue creative ideas that have greater risk for failure but also greater potential for high reward, compared to low-power individuals (Galinsky et al., 2008). This difference in approach motivation may impact how people in high-power vs. low-power jobs interpret the rise of automation. High-power workers may view automation as an *opportunity* for increasing productivity through partnership with machines, whereas low-power workers may view automation as a *threat* to their livelihood, because they may be more likely to be replaced by a machine (Blascovich & Mendes, 2000).

This psychological difference between high-power and low-power people's perception of automation also matches economic projections for how automation may differentially affect people in relatively high-status and low-status jobs. Projections from Davenport & Kirby (2015) suggest that, in the future, there will be three kinds of occupations: High-status human-led jobs which require high levels of leadership and decision-making, middle-status augmented jobs where humans work together with machines and artificial intelligence algorithms to perform tasks, and low-status jobs which are fully automated.

In sum, both psychology and economics research suggest that automation may look different, and may have different outcomes, for high-status and low-status workers. High-status workers may be more likely to experience automation as *augmentation* (collaboration with machines), both because of a general approach-orientation towards cultural change (Keltner, Gruenfeld, & Anderson, 2003), and because new technology in high-status jobs (e.g., new programming languages and algorithms) are meant for collaboration with humans instead of replacement (Davenport & Kirby, 2015). In contrast, low-status workers may be more likely to experience automation as *automation* (replacement by machines), because of these same factors.

These different experiences of automation may entail different impacts of automation for low-status and high-status positions. In high-status positions, automation may create more opportunities for workplace freedom, more opportunities for collaboration and teamwork, and more competition, which are all correlates of success at work (Scott, 2004). In contrast, automation may not affect these outcomes, or may negatively affect these outcomes, for low-status positions.

Current Research

We hypothesize that the workplace correlates of automation will depend on job status. Automation may resemble “augmentation” for high-status jobs but may resemble “automation” for low-status jobs. Specifically, we predict that automation may be associated with reduced responsibility, less teamwork, lower-impact decisions, less freedom over decision-making, and less competition in low-status jobs, but that the association between level of automation and each of these variables may reverse for high-status jobs.

We tested our hypotheses using data from the O*Net program, which is the primary source of occupational data in the United States (Peterson et al., 1999). O*Net provides data sourced by human subjects concerning many job qualities and provides quantitative data on job status. With these data, we could fit multiple regressions which tested whether job status significantly moderated the organizational profiles of high- and low-automation jobs.

Method

Participants

We drew our data from O*Net, an online database of occupational information developed under the sponsorship of the U.S. Department of Labor/Employment Training Administration. O*Net features 189 job descriptors, categorized in 17 sub-categories, which are further grouped into 8 primary categories. The data is collected using a two-stage design: first, a statistically random sample of businesses with employees in the targeted occupations is selected; then, a random sample of workers in the targeted occupations within these businesses is chosen to fill out standardized questionnaires. The O*Net Data Collection Program provides several hundred ratings based on these questionnaire responses.

Since it is not feasible to have respondents provide information on every item in the survey, the questions are organized into three separate questionnaires, and respondents are randomly assigned one of the three. We analyzed responses to the work context questionnaire, which includes 57 questions on work settings, pace of work and interactions with others. We used the 2020 wave of O*Net questionnaire responses because it was the most recent wave at the time of our analyses. In total, our analyses included 175,884 total responses, although we cannot infer the exact number of employees who provided these responses--or their demographic characteristics--since O*Net provides aggregated data. Table 1 summarizes the number of participants who provided ratings for each of our key variables.

Independent Variables

Degree of Automation. Participants responded to the item "How automated is your current job" using a 1-5 scale featuring the anchors "Not at all automated (1)," "Slightly automated (2)," "Moderately automated (3)," "Highly automated (4)," "Completely automated (5)." The mean level of automation was 2.13. Jobs with high levels of automation included postal service mail sorters, medical and clinical laboratory technicians, and air traffic controllers. Jobs with low levels of automation included art therapists, midwives, clock and watch repairers, and animal caretakers.

Job Status. We operationalized job status in terms of O*Net's "job zone" variable. O*Net categorizes each occupation into one of five job zones, such that higher job zones represent occupations with more status, prestige, and training. Job zones represent: "Little or No Preparation Needed" (Job Zone 1), "Some Preparation Needed" (Job Zone 2), Medium

Preparation Needed (Job Zone 3), “Considerable Preparation Needed” (Job Zone 4), and “Extensive Preparation Needed” (Job Zone 5). More information about these job zones and the method by which they are calculated is available at https://www.onetonline.org/help/online/zones.

Dependent Variables

Impact of Decisions. Participants responded to the item “In your current job, what results do your decisions usually have on other people or the image or reputation or financial resources of your employer” using a 1-5 scale featuring the anchors “No results (1),” “Minor results (2),” “Moderate results (3),” “Important results (4),” “Very important results (5).” The mean level of decision impact was 3.82.

Responsibility for Outcomes. Participants responded to the item “How responsible are you for work outcomes and results of other workers on your current job” using a 1-5 scale featuring the anchors “No responsibility (1),” “Limited responsibility (2),” “Moderate responsibility (3),” “High responsibility (4),” “Very high responsibility (5).” The mean level of decision impact was 3.29.

Work with Group or Team. Participants responded to the item “How important are interactions that require you to work with or contribute to a work group or team to perform your current job” using a 1-5 scale featuring the anchors “Not at all important (1),” “Fairly important (2),” “Important (3),” “Very important (4),” “Extremely important (5).” The mean level of decision impact was 4.17.

Work Schedule. Participants responded to the item “How regular is your work schedule on your current job” using a 1-3 scale featuring the anchors “Regular (established routine, set schedule) (1),” “Irregular (changes with weather conditions, production demands, or contract duration) (2)," "Seasonal (only during certain times of the year) (3)." The mean level of decision impact was 1.31.

Level of Competition. Participants responded to the item "How competitive is your current job" using a 1-5 scale featuring the anchors "Not at all competitive (1)," "Slightly competitive (2)," "Moderately competitive (3)," "Highly competitive (4)," "Extremely competitive (5)." The mean level of decision impact was 3.09.

Freedom to Make Decisions. Participants responded to the item "In your current job, how much freedom do you have to make decisions without supervision" using a 1-5 scale featuring the anchors "No freedom (1)," "Very little freedom (2)," "Limited freedom (3)," "Some freedom (4)," "A lot of freedom (5)." The mean level of decision impact was 4.11.

Analysis Plan

Our analyses estimated the relationship between automation and our key dependent variables and tested whether this relationship varied by job status. We followed a two-step approach to conduct these analyses. First, we used correlations to estimate the overall relationship between the level of automation and our dependent variables. Second, we used multiple regression to test for the interaction of automation and job status, which evaluated whether the link between automation and dependent variables varied based on job status.

Our unit of analysis was occupation, which meant that rows in our dataframe represented different occupations, and we merged occupation-level data on job status with occupation-level data on automation and our dependent variables before conducting analyses.

Results

Descriptive Statistics

We began by calculating the mean, standard deviation, and sample size for the variables in our analysis. Table 1 displays these coefficients, along with the scale for each variable to provide a reference for the mean. In general, occupations had a low mean level of automation, and higher mean levels of teamwork and freedom to make decisions. Over 20,000 observations were available for each measure, suggesting that these estimates were stable.

Table 1.

Descriptive Statistics for All Independent and Dependent Variables

Variable Name	Mean (SD)	Scale	N
Degree of Automation	2.13 (.53)	1-5	21,814
Job Status	3.19 (1.17)	1-5	21,959
Impact of Decisions	3.82 (.50)	1-5	22,095
Responsibility for Outcomes	3.29 (.62)	1-5	21,863
Work with Group or Team	4.17 (.47)	1-5	22,008
Work Schedule	1.31 (.25)	1-3	22,082
Level of Competition	3.09 (.60)	1-5	21,961
Freedom to Make Decisions	4.11 (.47)	1-5	22,102

Correlational Analyses

After calculating descriptive statistics, we next tested whether our outcome variables (e.g., impact of decisions, responsibility for outcomes) were meaningfully associated with automation and job status. To do this, we correlated automation and job status with each of the dependent variables. Table 2 shows these results. Jobs with high levels of automation were significantly more likely to involve teamwork and high responsibilities for outcomes, and significantly less likely to involve a flexible work schedule and the freedom to make decisions. However, the associations involving teamwork and responsibility for outcomes were weak. High-status jobs were more likely to involve high-impact decisions, teamwork, competition, and freedom to make decisions, but were less likely to feature a flexible work schedule.

Table 2.

Correlations between Automation, Job Status and Dependent Variables

Variable Name	Correlation with Automation	Correlation with Job Status
Impact of Decisions	0.07	0.19**
Responsibility for Outcomes	0.07*	-0.021
Work with Group or Team	0.12**	0.16**
Work Schedule Regularity	-0.23**	-0.21**
Level of Competition	-0.04	0.37**
Freedom to Make Decisions	-0.25**	0.55**

Note. * = *p*-value is below .05 but above .005; ** = *p*-value is below .005

These correlations are insightful and show differences between occupations that have low and high levels of automation. However, our key hypothesis is that the relationship between automation and these organizational variables may vary critically depending on whether jobs are higher or lower status. Bivariate correlations will not capture this moderation, so we next turned to multiple regressions where we could probe for the interaction between automation and job status on each of our dependent measures.

Regression Analyses of Interactions

Our next analyses used multiple regression to test whether the link between automation and our dependent measures was dependent on job status. Regression allowed us to not only control for the covariation between job status and automation; it also allowed us to test for interactions between these variables in a way that is impossible with zero-order correlations. We identified significant interactions in four of our six dependent variables (impact of decisions, responsibility for decisions, work schedule flexibility, level of competition) and a marginal interaction on one of the dependent variables (working with group), such that job status moderated the association between automation and the dependent variables. The results of these regression models are displayed in Table 3.

Table 3.

Regression Results Displaying the Interaction of Automation and Job Status

Outcome	**Predictor (Model)**	***b (SE)***	***t***	***p***
Impact of Decisions	Automation	.12 (.03)	3.68	<.001
	Job Status	.10 (.01)	6.83	<.001
	Automation * Job Status	.10 (.03)	3.62	<.001
Responsibility for Decisions	Automation	.11 (.04)	2.75	.006
	Job Status	.03 (.02)	1.61	.11
	Automation * Job Status	.11 (.04)	3.09	.002
Work with Group or Team	Automation	.15 (.03)	4.76	<.001
	Job Status	.08 (.01)	5.87	<.001
	Automation * Job Status	.05 (.03)	1.92	.06
Work Schedule Regularity	Automation	-.13 (.02)	-8.24	<.001
	Job Status	-.05 (.01)	-7.52	<.001
	Automation * Job Status	.04 (.01)	3.03	.002
Level of Competition	Automation	.05 (.03)	1.36	.17
	Job Status	.19 (.02)	11.90	< .001
	Automation * Job Status	.08 (.03)	2.58	.01
Freedom to Make Decisions	Automation	-.13 (.03)	-4.83	<.001

	Job Status	.21 (.01)	17.94	<.001
	Automation * Job Status	.02 (.02)	.78	.44

Note. Automation and Job Zone have been centered in this regression model

We interpreted the interaction between job status and automation by estimating the association between automation and each outcome variable at high (+1 SD) and low (-1 SD) levels of job status. In jobs with low status, automation was not linked to impact of decisions ($b = -.003$, $p = .95$), level of responsibility for decisions ($b = -.02$, $p = .73$), and competitiveness ($b = -.05$, $p = .32$), and was strongly and negatively related to job schedule regularity ($b = -.18$, $p < .001$) and positively but weakly related to frequency of group and team-oriented work ($b = .08$, $p = .04$). However, in jobs with high status, automation was positively and robustly linked to impact of decisions ($b = .25$, $p < .001$), level of responsibility for decisions ($b = .24$, $p < .001$), group and team-oriented work ($b = .21$, $p < .001$), level of competition ($b = .14$, $p = .009$), and was only weakly negatively linked to work schedule regularity ($b = -.08$, $p = .001$). In sum, automation was more likely in high-status jobs to connote impactful decisions, teamwork, competition, and predictable work schedules than in low-status jobs.

Discussion

How do highly automated jobs differ from less automated jobs? Past research from organizational and social psychology provides several possible ways that these jobs may differ, ranging from their level of competition (Bessen, 2016), flexibility in decision-making (Karuppan, 2004), and the impact of decision-making (Dietvorst, Simmons, & Massey, 2015). However, we suggest that automation does not affect all jobs in the same way. Instead, the correlates of workplace automation depend on job status. With a large dataset of employee ratings from the O*Net program, we find that automation is significantly linked to more impactful decision-making, a greater frequency of team- and group-work, and greater competition, but only among high-status jobs. Among low-status jobs, automation was only linked to less regular work schedules.

These results support our theory that high-status workers are more likely to experience automation as augmentation—in which robots assist rather than replace people at work—both because of psychological and economic factors. In contrast, low-status workers are more likely to experience automation as replacement (Varghese, 2017). This phenomenon also suggests that automation may be too broad of a construct for research. Research organizations such as O*Net may need to reword the current definition of workplace automation by distinguishing the concept of augmentation from automation or using other terms to identify the roles of machines in the workplace for the purpose of evaluations and research. In addition, O*Net may seek to distinguish between jobs which are being automated by physical machines (mechanization) and jobs which are being automated by computers or AI (computerization).

Our findings also advance existing research on status and power. Psychological research shows that people with more power are more likely to see obstacles as challenges and opportunities, and less likely to view them as threats (Keltner, Gruenfeld, & Anderson, 2003; Blascovich & Mendes, 2000). Therefore, high-status and low-status employees may perceive workplace automation differently, which leads them to experience automation differently at work. Higher-status employees may be encouraged to take advantage of automation to gain responsibilities and collaborate with others. On the other hand, low-status employees are more likely to see automation as a threat to their positions. This phenomenon may also generalize beyond the effects of automation. For example, high-status people may be more likely to see new technologies as tools to advance their career and improve their work, whereas low-status people may see new technologies as threats which increase job insecurity and well-being at work. In other words, perceived power and status may help people react more positively and embrace technological changes instead of rejecting them.

Limitations and Future Directions.

Our research has limitations which provide opportunities for research. Some limitations come from the fact that we needed to use secondary data from O*Net to test our hypotheses. We note several limitations in these O*Net data. First, variables were not measured on the same scale. Specifically, the work schedule variable was measured with a 3-point scale, as opposed to 5-point scales for other variables. Second, the response options for the work schedule item (regular, irregular, and seasonal) did not represent equal increments of schedule flexibility. Employees with seasonal schedules may feel that their schedule is more regular than employees with non-seasonal but irregular schedules. And third, the O*Net questionnaires were not comprehensive, and did not include psychological factors such as job satisfaction and job insecurity. We therefore encourage future research using primary research methods to use items which have the same scale, and which have validated anchors in their scales. We also encourage studies which measure a broader set of variables, including psychological variables.

Another limitation of our study was that our results only represent the U.S. workforce. In addition to status, culture may affect the way that workers perceive automation. It may also be that, if researchers replicated our results in our cultural groups, they would not find the same associations as we did. American society is Western, Education, Industrialized, Rich, and Democratic (WEIRD), and these unique attributes make American subjects psychologically peculiar (Henrich, Heine, & Norenzayan, 2010). We encourage future research to replicate and extend our findings in other regions of the world to test whether our results generalize to other cultural groups.

One final set of limitations comes from the fact that we analyzed archival data. We could only derive correlations between our independent and dependent variables, but we could not determine if these relationships were causal. We recommend future studies to focus on testing the causation between automation, job status and organizational behaviors through experiments. These experiments would be able to determine if automation causes changes in workplace contexts and workplace behaviors, and whether these changes depend on job status. It is difficult to manipulate automation or job status in a workplace setting. However, it is possible to manipulate the salience of automation, and it is also possible to manipulate people's subjective status (Jackson & Payne, 2020) in lab settings. Furthermore, longitudinal observational studies in organizations could uncover whether automation precedes changes in workplace behavior.

Conclusion

No one can foresee the future of the automated workplace. But this has not stopped research from predicting how automation will affect organizational outcomes, ranging from teamwork to well-being. To help workers in rapidly automating sectors, it is important for these predictions to be accurate. However, the accuracy of past studies may have suffered because automation has been measured as a single construct rather than a multidimensional set of factors. Here we draw from emerging literature on automation diversity and classic research on psychological status and power to show that automation may vary in its nature and implications across low- and high-status jobs. Our study of status and automation shows that automation has different correlates for low- and high-status positions. High-status automation is linked to higher levels of responsibility, teamwork, decision impact, and job competition, whereas low-status automation is only linked to having less regular schedules. We hope that our findings help employees prepare for a future where automation is ubiquitous in the workplace.

References

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, *33*(2), 3-30.

Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. *Economics Letters*, *159*, 157-160.

Balfe, N., Sharples, S., & Wilson, J. R. (2015). Impact of automation: Measurement of performance, workload and behaviour in a complex control environment. *Applied Ergonomics*, *47*, 52-64.

Bessen, J. E. (2016). How computer automation affects occupations: Technology, jobs, and skills. *Boston Univ. school of law, law and economics research paper*, (15-49).

Bigman, Y., Gray, K., Waytz, A., Arnestad, M., & Wilson, D. (2020). Algorithmic discrimination causes less moral outrage than human discrimination. https://psyarxiv.com/m3nrp/

Blascovich, J., & Mendes, W. B. (2000). Challenge and threat appraisals: The role of affective cues.

Cho, M., & Keltner, D. (2020). Power, approach, and inhibition: Empirical advances of a theory. *Current Opinion in Psychology*, *33*, 196-200.

Chui, M., Manyika, J., & Miremadi, M. (2015). Four fundamentals of workplace automation. *McKinsey Quarterly*, *29*(3), 1-9.

Cortes, G. M., Jaimovich, N., & Siu, H. E. (2017). Disappearing routine jobs: Who, how, and why? *Journal of Monetary Economics*, *91*, 69-87.

Coupe, T. (2019). Automation, job characteristics and job insecurity. *International Journal of Manpower*.

Davenport, T. H., & Kirby, J. (2015). Beyond automation. *Harvard Business Review*, *93*(6), 58-65.

David, H (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, *29*(3), 3-30.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, *144*(1), 114.

Do Cho, S., & Chang, D. R. (2008). Salesperson's innovation resistance and job satisfaction in intra-organizational diffusion of sales force automation technologies: The case of South Korea. *Industrial Marketing Management*, *37*(7), 841-847.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological forecasting and social change*, *114*, 254-280.

Galinsky, A. D., Magee, J. C., Gruenfeld, D. H., Whitson, J. A., & Liljenquist, K. A. (2008). Power reduces the press of the situation: implications for creativity, conformity, and dissonance. *Journal of personality and social psychology*, *95*(6), 1450.

Georgieff, A., & Milanez, A. (2021). What happened to jobs at high risk of automation? https://doi.org/10.1787/1815199X

Gruchmann, T., Mies, A., Neukirchen, T., & Gold, S. (2021). Tensions in sustainable warehousing: including the blue-collar perspective on automation and ergonomic workplace design. *Journal of Business Economics*, *91*, 151-178.

Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda. *Technological Forecasting and Social Change*, *162*, 120392.

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world? *Behavioral and brain sciences*, *33*(2-3), 61-83.

Jackson, J. C., & Payne, K. (2021). Cognitive barriers to reducing income inequality. *Social Psychological and Personality Science*, *12*(5), 687-696.

Jerome, H. (1934). *Mechanization in industry, no. 27*. National Bureau of Economic Research, New York.

Joe, J., O'Hara, J., Medema, H., & Oxstrand, J. (2014, June). Identifying requirements for effective human-automation teamwork. In *Proceedings of the 12th international conference on probabilistic safety assessment and management (PSAM 12, Paper# 371), (INL/CON-14-31340)*.

Karuppan, C. M. (2004). Strategies to foster labor flexibility. *International Journal of Productivity and Performance Management*.

Keltner, D., Gruenfeld, D. H., & Anderson, C. (2003). Power, approach, and inhibition. *Psychological review*, *110*(2), 265.

Lewis, P. (1986). William Lee's stocking frame: Technical evolution and economic viability 1589–1750. *Textile history*, *17*(2), 129-147.

Patel, P. C., Devaraj, S., Hicks, M. J., & Wornell, E. J. (2018). County-level job automation risk and health: Evidence from the United States. *Social Science & Medicine*, *202*, 54-60.

Peterson, N. G., Mumford, M. D., Borman, W. C., Jeanneret, P., & Fleishman, E. A. (1999). *An occupational information system for the 21st century: The development of O* NET*. American Psychological Association.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, *46*(1), 192-210.

Santos, C. D. (2018). AI: Augmentation, more so than automation.Asian Management Insights.

Schwabe, H., & Castellacci, F. (2020). Automation, workers' skills and job satisfaction. *Plos one*, *15*(11), e0242929.

Scott, S. (2004). *Fierce conversations: Achieving success at work & in life, one conversation at a time*. Penguin.

Varghese, F. C. (2017). The impact of automation in IT industry: Evidences from India. *Int. J. Eng. Sci.*, *7*(3), 5000-5004.

Wright, M. C., & Kaber, D. B. (2005). Effects of automation of information-processing functions on teamwork. *Human Factors*, *47*(1), 50-66.