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AI Implementation at Work: Worker Preferences for Task Changes

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Abstract

This paper examines preferences for AI-enabled changes in task composition and possibly facilitating job characteristics in a discrete choice experiment among workers in a multinational manufacturing firm. The firm implements an AI tool transforming workers' core task of classifying electronic components in two successive stages: (1) *augmenting AI* including a decision support feature and (2) *autonomous AI* automating easy classification tasks. Workers have to choose between jobs that differ in five characteristics: the AI-enabled change in their classification task, breaks, autonomy, training, and a salary increase. The results show that workers prefer the changes induced by augmenting AI over autonomous AI. Workers would forgo a moderate salary increase when their core task is supported by the augmenting AI. Moreover, the perceived usefulness of the augmenting AI negatively moderates the preference for autonomous AI. These results suggest that human-AI complementarity is favorable while simultaneously posing disadvantages for stepwise implementation strategies.

JEL classification

J24, J81, L60, M50, O33

Keywords

Artificial intelligence (AI), task composition, augmentation, automation, perceived usefulness of technology, willingness to pay, discrete-choice experiment

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AI Implementation at Work:
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1. Introduction

Artificial intelligence (AI) increasingly automates human tasks, altering occupational task content and job quality (Litwin et al., 2022). These transformations raise critical questions as to how workers value these task changes, and under what conditions they support AI adoption in their workplace.

Various studies highlight that workers' acceptance of AI depends on perceptions of automation risk and job security. However, less is known about workers' preferences regarding how AI reshapes their tasks. This is particularly relevant because AI can either augment or substitute for human labor (Acemoglu & Restrepo, 2020). On the task level, these two mechanisms – task augmentation and substitution – may have distinct implications for workload and task intensity which could influence worker well-being.

To facilitate AI-enabled changes in task composition and mitigate potentially adverse effects, recent work design strategies attempt to place workers at the centre of AI transformation and gear job characteristics towards the new demands created by AI. Yet, effectively aligning AI-enabled work changes to workers' needs requires an understanding of how workers perceive these changes in their jobs. This is a largely unexplored dimension of the AI transformation that would offer insight into how employers can enhance support for AI among their workforces.

By connecting the literature on task-based models of technological change, work design, and technology acceptance, we examine workers' preferences for AI-enabled work changes. More specifically, we ask:

(1) Do workers prefer AI-enabled changes in their task composition?

(2) What is the relative importance of other job characteristics for an optimal design of AI-augmented jobs?

(3) Does the perceived usefulness of workplace technology moderate preferences for AI-enabled changes in task composition?

We address these research questions in a discrete choice experiment (DCE) based on a real-world AI implementation in assembly lines of a multinational manufacturing firm in the automotive industry. We ask quality control operators across eight countries to choose between two realistic scenarios that reflect their jobs as bundles of a core task and other job characteristics that might be relevant for the AI support across the affected workers. The core of our DCE consists of an AI-enabled change in the composition of workers' main task of visually classifying electronic components. As the focal attribute of our DCE, we vary workers' initially fatiguing component classification task and two modified versions of this task in which certain parts of this task are reallocated to AI. For these two AI-enabled versions of workers' core task, we distinguish between: (1) *augmenting AI* providing decision support to the workers and (2) *autonomous AI* substituting the majority of component classification cases. In addition to the modified task composition, we include four job characteristics that might contribute to an optimal design of the AI-transformed job: break schedules, training opportunities, worker autonomy and salary increase. Thus, the DCE captures workers' trade-offs between AI-enabled changes in task composition and compares the resulting preferences to other job characteristics that might be relevant in the AI-enabled transformation of work.

We contribute to existing literature in three ways. First, we contribute to the emerging research on workers' attitudes toward AI by focusing on their preferences for specific AI-enabled changes impacting their work. With this, our study is the first to assess the worker perspective on changes in task composition based on two different forms of human-AI interactions. For this purpose, we generate data from within the firm and add to the body of

much-needed field-based industry studies (Litwin et al., 2022). Second, we enrich the work design literature by identifying which job characteristics workers value most when AI reshapes their tasks. This enables us to assess the relative importance of AI-enabled changes in workers' task composition compared to other job characteristics contributing to an optimal design of AI-augmented jobs, from the workers' perspective. Third, as a crucial component of technology acceptance, we assess whether the perceived usefulness of the workplace technology takes a moderating role in workers' preferences for AI-enabled task changes.

2. Related Literature

2.1 AI Adoption and its Implications for Task Composition

The hypothetical job scenarios designed in this study build on a theoretical basis combining the task-based framework (Autor et al., 2003) to conceptualize how AI reshapes task composition, and the Job Characteristics Model (Hackman & Oldham, 1976) to establish the relative value of context-specific job characteristics. Moreover, we draw on the Technology Acceptance Model (TAM, (Venkatesh & Bala, 2008)) to measure workers' evaluation of their workplace technology and examine it as a moderator of their AI preferences.

The task-based framework (Autor et al., 2003) is the most commonly used approach to study how technological change transforms work. Over the years, it has been extended to fit recent technological advancements (Acemoglu & Restrepo, 2018, 2022; Autor, 2015, 2022). The framework posits that the impact of technologies on occupations and their extent of automatability depends on the occupational task content and the nature of these tasks. In line with this framework, various studies confirm that AI can impact work through the main channels[1] of (1) substituting for human labor in tasks, or (2) augmenting human capabilities in

[1] Acemoglu and Restrepo (2018, 2022) further define mechanisms such as reinstatement through new tasks, capital accumulation and deepening of automation. As this study focuses on the worker perspective and these mechanisms are not directly observable in our experimental setting, we focus on the simplified distinction between substitution and augmentation.

tasks; i.e., increasing productivity through human-AI complementarity (Acemoglu & Restrepo, 2018, 2022; Agrawal et al., 2019; Autor, 2015, 2022).

However, less is known about how workers perceive the AI-enabled changes in their task composition. Various studies show that AI affects job quality with respect to work intensity, which comprises of the task volume, pace and complexity (Hünefeld et al., 2025; Litwin et al., 2022). By substituting or augmenting tasks, AI can reduce or intensify quantitative work metrics such as workload and time pressure (Litwin et al., 2022). Moreover, AI can also alter other aspects of work such as worker autonomy, cognitive load, task meaningfulness, stress and job insecurity (Nazareno & Schiff, 2021). As substitution and augmentation shape these aspects of work in different ways, different types of AI may have distinct implications for job quality and work design.

Yet, to date, no study examines how workers assess such AI-enabled changes at the task level, nor differentiates workers' perceptions of task changes enabled specifically by substituting versus augmenting AI. This is an underexplored distinction that could inform the design of a human-centric AI transformation.

2.2 Worker Attitudes Towards Substituting and Augmenting AI

A limitation of the task-based framework is that it entirely attributes the potential effects of AI to the properties of the technology, meanwhile ignoring the role of contextual factors such as the employers and workers involved in its adoption and use (Bailey, 2022; Litwin et al., 2022). A growing body of research examines how workers generally perceive AI automation, arguing that their acceptance depends on their attitudes towards a myriad of potential effects of AI, and their awareness of automation risk (Brougham & Haar, 2018; Golin & Rauh, 2022; Kelly et al., 2023; Nazareno & Schiff, 2021; Parker & Grote, 2022). Evidently, workers are not neutral towards automation risk. Perceptions of general and AI-related automation risk have been linked to declines in workers' well-being and job satisfaction (Brougham & Haar, 2018;

Giuntella et al., 2023; Nazareno & Schiff, 2021; Patel et al., 2018; Schwabe & Castellacci, 2020). Moreover, Cattaneo et al. (2025) find that workers are willing to accept lower wages in exchange for lower automation risk in their jobs. It is noteworthy that, across studies, the adverse effects of automation risk are primarily driven by workers who are most exposed to displacement in their routine tasks: i.e., low- or medium-skilled workers (Cattaneo et al., 2025; Giuntella et al., 2023; Golin & Rauh, 2022; Schwabe & Castellacci, 2020). These studies show that workers' attitudes about automation risk are an important factor likely to be entangled with workers' experiences of AI-enabled changes in their own tasks. These experiences in turn can inform work design strategies to better align AI-enabled task changes to workers' needs and make AI implementation more human-centric (Lovejoy et al., 2021; Parker & Grote, 2022).

However, considering changes in task composition as the single relevant work design factor neglects the relevance of other job characteristics that might facilitate AI implementation in the workplace. Among others, these characteristics include compensating wages (Acemoglu & Restrepo, 2018; Litwin et al., 2022), job autonomy, skill variety, feedback, and social interaction (Parker & Grote, 2022). According to dominant work design theories such as the Job Characteristics Model (Hackman & Oldham, 1976), these factors are closely linked to worker motivation and job satisfaction, and therefore, essential for worker well-being (Lovejoy et al., 2021).

To date, little is known about how workers assess the value of these job characteristics in the context of AI implementation, specifically in relation to AI-enabled changes in their tasks. We therefore connect the task-based framework of technological change (Autor et al., 2003) and the Job Characteristics Model (Hackman & Oldham, 1976) as a theoretical foundation to design hypothetical job profiles to be assessed by workers. With that, our study is the first to scrutinize workplace-level AI transformation by not only examining workers' preferences for AI-enabled changes in their tasks but also comparing them to preferences for

other modified job characteristics. As a core outcome of our study, this comparison offers a novel lens to grasp work design preferences from workers' viewpoints.

Furthermore, our study focuses on workers' preferences for two distinct versions of AI, based on its impact on their task composition. Specifically, the initially fatiguing decision-making task is transformed via mechanisms of augmentation (AI supports workers in all their decisions) or substitution (AI automates the majority of decisions).

In our study, augmenting AI serves as decision-making support while keeping the workers in the loop, asserting them as an essential part of the production process (Zeba et al., 2021). Whether workers appreciate or resist such human-AI interaction in their workplace is not evident. Even though previous studies found that people generally tend to mistrust algorithmic recommendations, recent evidence suggests that the reliance on algorithmic suggestions can vary across contexts, and even shift from algorithm aversion towards algorithm appreciation (Burton et al., 2020; Dietvorst et al., 2015; Logg et al., 2019). That makes workers' preferences for the decision-making support in the augmenting AI stage an open question that we aim to address.

Moreover, the task version reshaped by the augmenting AI is in line with human-centered automation approaches that keep workers accountable for the work process while simultaneously neither underloading nor overloading them (Parker & Grote, 2022). In comparison to the cognitively highly fatiguing baseline task, the task reshaped by the augmenting AI may thus alleviate the cognitive load inherent to the job. Hence, we expect that the task modified by augmenting AI may appeal to the operators more than their baseline task. This leads to the following hypothesis:

> **H1a:** Workers prefer the task composition reshaped by augmenting AI over their baseline task.

Autonomous AI, on the other hand, substitutes most of the decisions made by the workers, allowing them to focus on more complex cases and devote more time to their

component classifications. This task version aligns with a common consequence of substitution: It makes the remaining human task more difficult (Parker & Grote, 2022). Given the increasing difficulty of the remaining decisions, workers may perceive an increase in task complexity (Vereycken et al., 2021), inducing cognitive overload (Nazareno & Schiff, 2021). Simultaneously, the decrease of task volume due to autonomous AI could signal job insecurity (Giuntella et al., 2023), or diminishing task meaningfulness (Nazareno & Schiff, 2021).

Yet, consistent with our previous expectation of cognitive load alleviation, we still expect workers to prefer the task modified by autonomous AI over their initial fatiguing task. However, when comparing the task profile related to autonomous AI with the task profile related to augmenting AI, we expect workers to value complementarity most and thus expect that workers' preference is highest for augmenting AI. This leads to the following hypotheses:

> **H1b:** Workers prefer the task composition reshaped by autonomous AI over their baseline task.
>
> **H1c:** Workers prefer the task composition related to augmenting AI over the task composition related to autonomous AI.

2.3 Perceived Usefulness of Technology as Moderating Factor for AI Preferences

To deepen our understanding of workers' trade-offs between different versions of AI-enabled task composition, we examine the potentially moderating factor of workers' *perceived usefulness* of their current workplace technology. As a core dimension in the Technology Acceptance Model (TAM) (Davis, 1989), individuals' perceived usefulness of an implemented technology is one of the key determinants of their acceptance. It is defined as "the extent to which a person believes that using (the technology) will enhance (their) job performance" (Venkatesh & Bala, 2008, p. 275). The TAM posits that when workers' experience that their workplace technology adds value to their work, its acceptance and usage are enhanced (Lichtenthaler, 2020; Venkatesh & Bala, 2008). Various studies have applied the TAM to the

context of AI introduction and show that perceived usefulness is indeed positively associated with AI acceptance across different industries (Kelly et al., 2023; Shao et al., 2025).

As a core dimension of AI acceptance, we expect perceived usefulness to take on a moderating role in the relationship between AI-enabled changes in task composition and workers' preferences. In our study context, some workers have already interacted with the augmenting AI. Considering their evaluation of its perceived usefulness as relevant to their AI preferences is worthwhile because it supplements the hypothetical nature of the DCE with an actual experiential assessment of the technology. In this framework, examining perceived usefulness as a moderator further enables us to assess how gradual AI implementation is related to workers' acceptance of more advanced AI stages. Specifically, we expect that workers who perceive their current workplace technology as particularly useful may have a higher appraisal of the status quo (Samuelson & Zeckhauser, 1988). Under such a status quo bias, workers could be more likely to anticipate costs related to the transition to a new working mode with a new technology (Joshi, 1991; Kim & Kankanhalli, 2009). We therefore expect that workers who have already experienced the augmenting AI stage in their job *and* rate it useful for their overall job performance will show a lower preference for the task reshaped by autonomous AI. This leads to the following hypothesis:

> **H2:** Workers who perceive their current workplace technology with augmenting AI as useful are less likely to prefer the task composition created by autonomous AI than the task composition related to augmenting AI.

3. Data and Method

3.1 Study context

To assess whether workers prefer AI-induced changes in task composition, we conduct a DCE in a multinational manufacturing firm in the automotive industry. Specifically, we survey quality control operators in production plants across eight countries. The assembly lines within

these production plants are specialized in surface-mount technology (SMT). The SMT production method is a highly automated process involving soldering miniature components onto printed circuit boards (see e.g., Acciani et al., 2006, for a summary of the SMT process). The flawlessness of the circuit boards is crucial as they are safety-critical for the final products. However, the SMT process is prone to producing errors on the circuit boards. These are mainly caused by increasing production speed and component density on the circuit boards. Hence, detection of defects merely performed by humans has become increasingly unreliable (Acciani et al., 2006). For the purpose of defect detection, the firm's utilized component classification process is based on a rule-based Automated Optical Inspection (AOI) software – one of the first industrial applications for computerized image analysis (Acciani et al., 2006). It provides numerous multi-angle images of solder joints and reflects potentially defect components in different colors. These "potentially defect" components are assessed by human operators in the assembly lines who are professionally trained for this type of quality control. Specifically, their task is to classify whether each component is defect (referred to as "NOK") or correct (referred to as "OK"). This visual component classification task spans over two uninterrupted hours with a high pace per component. This makes the core task a cognitively fatiguing task.

The application of artificial neural networks to this classification process posits an additional step that precedes the decision of the human operator. It introduces a classification algorithm to mimic a four-eyes principle to increase the certainty of decisions and reduce erroneous classifications. This AI intervenes in the process described above by analyzing the component images initially flagged as defective by the initial classification technology (i.e., the AOI). It then assigns one of the following labels to the component: (i) not defect (OK), (ii) truly defect (NOK), or (iii) uncertain.

The AI is introduced to the component classification process in a staggered fashion. In its first implementation stage (*augmenting AI)*, the final decision-making authority remains

with the operator in all three scenarios (i, ii, or iii). If the operator's decision is in accordance with the AI, the initial process of forwarding the OK and NOK components to their respective back-ends remains the same. However, in case of a deviation between the human decision and the AI classification, the operators are prompted to revise their decision via an automated notification in the form of a pop-up window. This pop-up is the only visible touchpoint of the operators' interaction with the augmenting AI stage.

In its most advanced maturity stage, *autonomous AI* will be permitted to forward OK components immediately to the backend, in case of high certainty. In other words, the process is planned to bypass the human judgment for the components that both the AOI and the AI label as OK. The procedure for scenarios (ii) and (iii) remains the same, with the operator keeping responsibility for the final decision. However, the automation of the majority of high-certainty decisions implies that the remaining components are more difficult to assess.

3.2 Experimental Design: Discrete Choice Experiment

Building on Bartel et al.'s (2004) description of methods to conduct insider-econometrics studies based on firm-level data, we conduct our study in a single firm and develop a narrow, "informed" survey based on various interviews and plant visits. This enables us to obtain firm-specific data on the AI implementation, underlying production processes and related worker preferences. Within the informed survey approach, we developed a DCE that provides the opportunity of experimentally manipulating characteristics in hypothetical scenarios (Aguinis & Bradley, 2014) that build on the two stages of the AI to be implemented in workers' core task. In this context, the DCE considers the quality control job as a bundle of different job attributes, which allows us to assess workers' preferences for changes in their jobs. To align all job attributes with realistic and tangible values, we inquired detailed information about the production process, the occupation and its inherent tasks from extensive, semi-structured interviews with quality control operators (i.e. the employee group involved in the DCE), their

line- and operations managers as well as other stakeholders such as AI project managers and AOI experts in the studied firm. Together with a subset of experts from the firm, we defined the relevant values for all five job attributes as specifically as possible, to minimize room for interpretation (for a detailed description of the co-creation with the firm, see Author, 2024).

Ultimately, we defined five job attributes with two to three values each, yielding a full factorial design of (3 x 2 x 3 x 2 x 3 =) 108 combinations per job. Consequently, there could be 5,778 potential job pairs, hereafter referred to as choice sets. Since this full population of choice sets was not practically feasible, we created a subset of choice sets. We use the Stata module d-create designed to calculate the most efficient fractional design out of all possible combinations (Hole, 2016; Zwerina et al., 1996), and yield a design with a subset of 200 choice sets (*D-efficiency* = 33.11) out of which a random deck of six were drawn and presented to each survey participant. Each choice set consists of two columns representing different versions of quality control operators' jobs, out of which respondents were asked to choose the job that would give them the highest level of well-being. We pre-tested the survey including six random choice sets with two firm representatives who were familiar with the quality control operator role, to assess the comprehensibility of the choice sets as well as potential excess complexity that could have induced respondent fatigue. In addition, we retrieved approval from the works' council.

3.3 DCE Attributes and Values

Table 1 shows an overview of the attributes and their corresponding values as they were presented to the respondents. A screenshot of an example choice set is presented in Figure A.1. The five job attributes are the AI-enabled change in task composition, breaks, training, worker autonomy and salary. The attributes and the choice of their corresponding values are subsequently outlined in detail.

[[Table 1 near here]]

3.3.1 AI-Enabled Change in Task Composition

We include the implementation stages of AI in the DCE by focusing on their impact on the composition of the quality control operators' core task. The corresponding attribute (labelled *job content*) consists of three dimensions: (1) the number of components to be assessed per minute (or hour) as an indicator for workload and required pace, (2) the complexity of the assessed components as an indicator for the difficulty of the task, and (3) whether or not there is decision-making support through a pop-up window (here: the AI). Dimensions (1) and (2) reflect work intensity (Hünefeld et al., 2025), and respective alterations based on the AI. We have to bundle these dimensions in one attribute as the dimensions are interrelated in reshaping quality control operators' task through augmented and autonomous AI, respectively.

The first attribute value (hereafter referred to as "*No AI*") represents the operators' baseline task with the initial component classification technology prior to the AI implementation. It entails the assessment of *50-100 easy-to-assess component images per minute without any decision support*. This baseline task is highly fast paced (up to more than one decision per second) with inherent repetitiveness stemming from many assessments that can be classified relatively easily. The number of potential errors that can be quickly recognized and resolved is high.

The second attribute value (hereafter referred to as *augmenting AI*) represents the first implementation stage of the AI. It is operationalized as the *assessment of 30-60 mostly easy-to-assess component images per minute with decision support by a pop-up window*. The number of images per minute is lower because the highly certain errors are being classified by AI immediately, without the operator seeing them. The decision support in this case represents the AI flagging a deviation of the operator's decision with the AI component classification through a pop-up message, prompting the operators to reconsider their decision. The final decision remains with the operator.

The third attribute value (hereafter referred to as *autonomous AI*) reflects the second implementation stage of the AI. It describes the assessment of *10-30 difficult-to-assess component images per hour without any decision support*. In this stage, AI runs autonomously for all cases with high certainty in classification. Consequently, operators would only receive the highly complex, difficult-to-assess images that autonomous AI cannot classify under the required certainty threshold.

3.3.2 Breaks

During a regular shift, the quality control operators alternate between the component classification task, and other operational production tasks every two hours. Performing two uninterrupted hours of optical classification is a repetitive and cognitively fatiguing task. Within these two-hour slots, the workers are not permitted to interrupt their work because halting the production line would hamper overall productivity. However, once the AI functions in autonomous mode, it performs the vast majority of the highly repetitive tasks. This allows for more flexibility and freedom to take informal breaks within the shift, which could reduce workers' strain and increase their well-being at work (Meijman & Mulder, 1998; Zhu et al., 2019). Although the types of activities that workers engage in during these breaks may have different implications for their recovery (Trougakos & Hideg, 2009), we disregard the specific break activities they individually choose for, and merely include two attribute values: whether flexible breaks are (1) allowed or (2) not.

3.3.3 Training

According to the Job Characteristics Model, a task is perceived as more meaningful when it requires the use of various skills (Hackman & Oldham, 1976). In this context, AI adoption has the potential to increase the skills requirements for the occupation (Autor, 2015; Bessen, 2019; Vereycken et al., 2021). To enhance their sustainable employability in their job, workers need

to be equipped with the required new skills – especially those working in occupations with higher automation risk (Bessen, 2019; Nedelkoska & Quintini, 2018). Moreover, workers' training is related to various positive workplace outcomes such as a higher productivity (De Grip & Sauermann, 2013) and job satisfaction (Georgellis & Lange, 2007).

As the implementation of autonomous AI increases job complexity, the quality control operators might prefer training to extend their job-specific skills in order to better cope with increased complexity of their job. We here include three attribute values: (1) the workers merely receive *basic training*, (2) they receive additional training on detecting errors and describing their cause (*intermediate training*), or (3) they receive training that additionally covers eliminating the cause of errors (*advanced training*).

3.3.4 Worker Autonomy

Worker autonomy is a job characteristic that is increasingly discussed in the context of AI adoption (Giering & Kirchner, 2025; Parker & Grote, 2022; Vereycken et al., 2021). The Job Characteristics Model defines autonomy at work as "the degree to which the job provides substantial freedom, independence and discretion to the individual (worker) in scheduling the work and in determining the procedures (to be carried out)" (Hackman & Oldham, 1976, p. 258). Autonomy at work is strongly related to workers' motivation, performance and satisfaction (Bakker & Demerouti, 2007; Hackman & Oldham, 1976). Yet, depending on how AI is implemented and how this impacts a worker's job tasks, worker autonomy can either increase, remain unchanged or diminish (Giering & Kirchner, 2025; Lovejoy et al., 2021; Parker & Grote, 2022; Vereycken et al., 2021).

In our study, the quality control operators face the same daily schedule, where they initially conduct the classification task for two uninterrupted hours, alternating with two hours of operational work in the production line. Autonomous AI is expected to allow for more flexibility and autonomy on the job, enabling the workers to also choose other tasks in the

production line. Parker & Grote (2022) describe this as greater self-direction at work in the context of AI adoption. Hence, we include two attribute values: (1) classification and line work alternate (*No autonomous task choice*) and (2) free choice between classification, line work and other tasks (*Autonomous task choice*).

3.3.5 Willingness to Pay

To identify the value workers attach to the non-monetary attributes included in the DCE, we are interested in estimating workers' willingness to pay (WTP) for these attributes (Stern, 1978). Previous examples for studies of WTP across workers are workplace safety and enjoyment of work (Anelli & Koenig, 2025), job security, work flexibility and potential for earnings growth (Wiswall & Zafar, 2018) and recently, automation risk (Cattaneo et al., 2025). To measure respondents' WTP, we include a salary increase as an attribute in the DCE. As both the level and currency of workers' wages differ across the surveyed countries, we include three relative salary increases, which were defined in consultation with the corporate stakeholders based on the collective bargaining bandwidths in Germany. These attribute values are: (1) no increase, (2) 3 percent increase and (3) 6 percent increase.

3.4 Background Characteristics

To study preference heterogeneity, we embedded the DCE in a questionnaire to collect additional worker-specific characteristics (Atzmüller & Steiner, 2010) such as respondents' age, gender, educational background as well as country of work. Moreover, we include a variable indicating whether or not workers have already (partially) been exposed to the augmenting AI. We can easily measure this exposure by whether or not they have previously received a pop-up message while classifying component images. Additionally, we include an adapted scale for the perceived usefulness of the current component classification technology from the TAM3 (Venkatesh & Bala, 2008). Note that workers who already received a pop-up

message rate the perceived usefulness of augmenting AI embedded in their classification technology, while those who have not received a pop-up message rate the classification technology prior to AI implementation (corresponding to the job content attribute value "No AI").

3.5 Sample

Our full sample consists of 500 respondents, among which 436 are quality control operators responsible for the visual inspection and classification of electronic components. We restrict the sample to quality control operators only, as the DCE was tailored to their occupation. Within this group of workers, we obtained a response rate of approximately 69 percent. We excluded respondents who did not make any decision in the DCE. Consequently, our working sample consists of 423 quality control operators, of which 405 respondents made a choice in all six choice sets, yielding in total 4,992 observations in the DCE.

Three quarters of all respondents have indicated that they had received a pop-up message during their classification task, meaning that they have already been working with the augmenting AI stage. This does not, however, imply that they always interact with it. In practice, workers' exposure to this augmenting AI stage varies on the production line level, as the augmenting AI can be active for specific products, in a subset of production lines or at selected times only. Therefore, we keep the initial task without AI as the baseline scenario.

Table 2 provides summary statistics of observable respondent characteristics such as demographics and the perceived usefulness of the component classification technology.

[[Table 2 near here]]

The majority of respondents are female (80 percent) and middle-aged (60 percent). With respect to education, the sample is relatively homogenous: The vast majority is low to intermediately skilled, with either intermediate general education (50 percent) or vocational education (43 percent) as their highest obtained education. Only 1.5 percent have a higher

education diploma. Moreover, most respondents work in Mexico and Romania. An attempt to correct for this unbalanced country distribution is discussed in the robustness section.

4. Empirical Framework

We estimate mixed logit models to identify relative preferences for the different job attributes. Our empirical framework is based on a random utility model. The utility[2] worker *n* obtains from choosing job *j* in choice set *t* is given by:

$$U_{njt} = \beta'_n X_{jt} + \varepsilon_{njt},$$

where β_n is a vector of unobservable preferences, X_{jt} denotes a vector of the observable job attributes, and ε_{njt} is an unobserved error term which is independent and identically distributed (i.i.d.) type I extreme value. According to the framework of utility maximization, *n* chooses alternative *j* in choice situation *t* if and only if $U_{njt} > U_{nkt}, \forall k \neq j$.

The mixed logit allows the coefficients β_n to vary across decision makers. The distribution of β_n is denoted $f(\beta_n|\theta)$, described by the parameter θ through its mean and covariance. Thus, the unconditional probability of decision maker *n* choosing job *j* in choice set *t* is the integral of the conditional probability over all possible values of β_n, depending on the parameters θ (Revelt & Train, 1998; Train, 2009):

$$P_{njt} = \int \left(\frac{\exp(\beta'_n X_{jt})}{\sum_k \exp(\beta'_n X_{kt})} \right) f(\beta_n|\theta) d(\beta_n).$$

The sequence of choices made by decision maker *n* in all *T* choice-sets, conditional on β_n is given by the product of standard logit choice probabilities:

$$S_n(\beta_n) = \prod_{t=1}^{T} \frac{\exp(\beta'_n X_{jt})}{\sum_k \exp(\beta'_n X_{kt})}.$$

As β_n remains unobserved, the unconditional probability for the sequence of choices made by decision maker *n* is the integral of the conditional probability of the sequence of choices over the joint density $f(\beta_n|\ \theta)$.

[2] In the DCE, we frame worker's utility as their well-being (see e.g., Kahneman et al., 2004; Korpi, 1997).

$$S_n(\theta) = \int S_n(\beta_n) f(\beta_n|\theta) d(\beta_n).$$

This integral does not have a closed-form solution and is therefore approximated by maximum likelihood simulation. We estimate $\hat{S}_n(\theta)$ by summing randomly drawn values of β_n from distribution $f(\beta_n|\theta)$ to calculate the product of standard logits $S_n(\beta_n)$. This is repeated and the choice probability approximated by the average of $S_n(\beta_n)$'s:

$$\hat{S}_n(\theta) = \frac{1}{R} \sum_{r=1}^{R} S_n(\beta_n^{r|\theta}),$$

where *R* is the number of repeated draws of β_n, and $\beta_n^{r|\theta}$ is the *r*-th draw from the distribution $f(\beta_n|\theta)$. $\hat{S}_n(\theta)$ is the simulated probability of the sequence of choices made by decision maker *n*. The parameters θ are estimated by maximizing the simulated log-likelihood function $LL(\theta) = \sum_n \ln S_n(\theta)$. Following Lancsar et al. (2017), we trade off accuracy with computational estimation time, and use 200 Halton draws for the simulation. A comparison of the number of Halton draws can be found in Table A.4.

We follow Caliendo et al. (2024) in their approach for model selection and compare a mixed logit model with uncorrelated random parameters to an alternative mixed logit with correlated random parameters. Table A.3 compares the estimation results for both models. As the signs and significance of coefficients remain stable, and the Akaike as well as Bayesian Information Criterion are both lower in the uncorrelated model, we continue with the uncorrelated model as our preferred model specification. In all models, we add a dummy variable for the placement of the job within the DCE (i.e., left or right) to control for common response patterns.

5. Results

5.1 Quality Control Operators' Preferences for Job Attributes

Table 3 displays the marginal effects as well as WTP estimations for the various job attributes. The table shows that quality control operators prefer a job with their task modified by augmenting or autonomous AI. The probability that workers choose the task reshaped by

augmenting AI is 10% higher than the probability of choosing the baseline task without AI. The difference is statistically significant at the one percent level. The probability that the quality control operators choose the task reshaped by autonomous AI is 3% higher than the choosing the baseline task. This difference is significant at the five percent level. These findings support hypotheses H1a and H1b. Table 3 also shows that the quality control operators prefer the task with augmenting AI far above its autonomous counterpart, which supports hypotheses H1c.

[[Table 3 near here]]

With respect to the other job characteristics, the preferences for breaks and worker autonomy are statistically significant at the five percent level, though modest in effect size. Relative to their respective baseline values, flexible breaks as well as worker autonomy increase the choice probability of the job by 2%.

Operators' preference for a job with intermediate and advanced training schemes is significantly higher than for a job with only the basic training. Specifically, intermediate and advanced training increase workers' choice probability by 4% to 5%, respectively. Both marginal effects are statistically significant at the one percent level each. However, they do not significantly differ from each other, implying that respondents are indifferent between intermediate and advanced training.

The salary increase appears to be the most important job characteristic. The probability of choosing the job with a 3% or 6%-increase is 11% to 22% higher than choosing the job without a salary increase, respectively. Both effects differ significantly from their reference category at the one percent level.

When comparing the estimation results for all attributes, workers' preference for working with augmenting AI appears to be significantly higher than all other attributes, except for the salary increase. Workers seem to value working with augmenting AI to the same extent

as a salary increase of 3%. Workers' preference for working with autonomous AI is comparable with their preferences for breaks, and worker autonomy.

5.2 Willingness to Pay for AI-Augmented Job Content

Column 2 in Table 3 shows results for workers' willingness to pay (WTP) for the various job attributes, given by $WTP_X = \beta_X / \beta_{salary}$. As our salary attributes in the DCE were categorical rather than continuous, we define β_{salary} as the average marginal utility of a 1%salary increase, calculated by $\beta_{salary} = 1/2 * (\beta_{3\%\ increase}/3 + \beta_{6\%\ increase} / 6)$.

On average, respondents are willing to forgo a salary increase of 2.8% if their task is supported by augmenting AI. This estimate is statistically significant at the one percent level. However, workers' willingness to pay for working with autonomous AI is only 0.7% and only marginally significant. This WTP is comparable with their WTP for breaks and worker autonomy. The positive WTP implies that workers do not need to be compensated when autonomous AI is introduced.

5.3 Robustness of Results

We tested the robustness of our main results in various alternative models. As shown in Table A.2 and Table A.3, the estimation results from our preferred mixed logit specification with uncorrelated parameters are robust to different regression models as well as to a mixed logit model with an alternative assumption of correlated random parameters. Furthermore, as shown in Table A.4 the size, sign, and significance of the coefficients of our preferred specification remain stable across a number of alternative specifications ranging between 200 and 1000 Halton draws in the maximum likelihood simulation.

Moreover, we modified the sample to detect any potential inconsistencies. As a general test of response behavior in the DCE, we restricted the sample to only those respondents who have made all six choices. Table A.5 shows that the estimation results remain stable.

With respect to the respondents' country of work, we obtained an uneven distribution of observations per country (see Table 1). Particularly for Mexico and Romania, there are many observations. To check whether respondents in these countries drive the results, we remove them from the sample. Results are reported in Table A.5. The estimates in the modified samples remain relatively stable. If any, the only noteworthy change is the increase of the coefficient of autonomous AI, signaling that in the other countries, the preference for the more complex job content is even higher than for the full sample.

5.4 Heterogeneous Effects

Next, we explore whether there are heterogeneous effects of workers' demographic background as well as for the perceived usefulness of the currently used component classification technology including the augmenting AI. Therefore, we extend the initial model specification by the interaction term $X_{jt} * Z_n$, yielding $U_{njt} = \beta'_n X_{jt} + \gamma' X_{jt} * Z_n + \varepsilon_{njt}$, with Z_n representing a vector of the decision-maker n's age, gender and the perceived usefulness of the component classification technology, and γ a vector of coefficients for the interaction term between job attributes X_{jt} and the individual characteristics Z_n.

5.4.1 Heterogeneous Effects of Demographic Variables

Table 4 shows the estimation results when extending the preferred model specification with an interaction term between the values of the AI attribute and gender and age dummies. We do not find any significant interaction effects and the signs of the base effects remain positive. The magnitude of the marginal effect of the augmenting AI increases slightly, while the marginal effect of autonomous AI is no longer significant.

We did not analyze heterogeneity based on differences in respondents' educational background because the studied job inherently requires intermediate level education, which is also reflected in 90% of the sample having obtained this level of education (See Table 2).

[[Table 4 near here]]

5.4.2 Heterogeneous Effects of the Perceived Usefulness of Augmenting AI

To explore whether the preference for the task composition reshaped by autonomous AI differs based on workers' perceived usefulness of the component classification technology, we add a separate interaction term for this construct to the preferred model. As the majority of the sample has previously been exposed to the augmenting AI stage, we only focus on the interaction with the autonomous AI stage. To disentangle the preferences of the exposed and non-exposed workers, we split the sample into workers with and without previous exposure to augmenting AI. Columns 1 and 2 in Table 5 show a negative interaction between autonomous AI and a high perceived usefulness of the current classification technology, only significant for workers who have already worked with augmenting AI. The interaction effect is not significant for those who have not been exposed to AI yet. This result supports our hypothesis H2: Those who found working with augmenting AI highly useful for their performance, have a lower preference for their tasks reshaped by the autonomous AI stage.

[[Table 5 near here]]

6. Discussion and Conclusion

In this paper, we have investigated workers' support for AI implementation in the workplace by exploring how workers perceive AI-enabled changes in the task composition of their job alongside other job characteristics. We use a discrete choice experiment (DCE) based on a real-world AI implementation in assembly lines of a multinational manufacturing firm in the automotive industry. We focus on the quality control operators in whose jobs AI is implemented in two stages. In the first stage, AI provides decision support to the workers (*Augmenting AI*) while it substitutes for the majority of the quality control cases in the second stage (*Autonomous* AI).

We show that workers prefer the AI-enabled changes in the composition of their task over their initially fatiguing task. We can explain the higher preference for AI-enabled task profiles compared to the baseline task by the salient benefits for the workers: Both the augmenting and autonomous stages of the AI alleviate the cognitive load inherent to the baseline task of assessing a large number of component images in a high pace. In comparison to the baseline task, the changes in task composition in both stages of the AI implementation display decreased worker inputs required for the task, potentially making the job more appealing.

In line with our expectations, workers appear to prefer their task with augmenting AI that offers them decision support over the task reshaped by autonomous AI that merely leaves the remaining complex tasks to the workers. This magnitude of the preference for augmenting AI amounts to that of a 3%-increase in salary, which significantly exceeds the magnitudes of the preferences for flexible breaks, worker autonomy and training. More specifically, respondents are on average willing to forgo a moderate salary increase when they can trade their fatiguing baseline task for the task supported by augmenting AI. Meanwhile, workers' willingness to pay for the task reshaped by autonomous AI is only marginally significant. Moreover, we find that quality control operators who perceive the augmenting AI as useful have a lower preference for the task reshaped by the autonomous AI stage.

There are several potential explanations for these results. First, the salient difference between the three task profiles before and after the implementation of AI is a substantial workload reduction via a decrease in the number of component checks. While the slight reduction in the augmenting AI stage may signal a relief in the fatiguing task, the stronger reduction in the autonomous AI stage may also invoke respondents' concerns about job insecurity. Brauner et al. (2023) and Nazareno & Schiff (2021) argue that workers – despite their understanding that AI can pose a threat to jobs through substitution – often do not

understand that their own job might be affected in the future. Meanwhile, demographic groups most susceptible to automation – such as women and low and intermediately skilled workers – respond to automation risk more strongly (Cattaneo et al., 2025; Giuntella et al., 2023; Lane et al., 2023; Schwabe & Castellacci, 2020). This general fear of technological substitution seems particularly applicable to our sample, considering that most of the quality control operators are females and low-to medium-educated workers.

Second, augmenting AI is probably most appealing for workers because the decision-making support leaves them in the lead. According to the work design literature, this task version mirrors human-centric AI implementation (Parker & Grote, 2022). Workers in our study did not seem to have negative perceptions of the decision-making support feature. This aligns with algorithm appreciation literature more than with algorithm aversion that would suggest workers to want to rely less on algorithmic advice (Burton et al., 2020). In this case, supported decision-making may probably even signal improved quality of work output. Venkatesh & Bala (2008) show that this higher output quality predicts technology acceptance. The improved quality of work can further reduce user resistance when occurring jointly with a decrease in required effort (Joshi, 1991; Kim & Kankanhalli, 2009).

Third, a potential explanation for autonomous AI to be less appealing than augmenting AI aligns with the notion that the resulting increase in task complexity may result in stress-inducing, cognitive overload (Nazareno & Schiff, 2021; Parker & Grote, 2022). Argued from the theoretical perspective of status quo bias (Samuelson & Zeckhauser, 1988), anticipating this overload could increase workers' resistance towards a cognitively more challenging job (Kim & Kankanhalli, 2009). The results of our heterogeneity analysis align with this rationale by suggesting that respondents who perceived a high usefulness of the augmenting AI are less likely to prefer the more complex task created by autonomous AI. This finding provides a counterintuitive perspective on firms' approaches to stepwise AI implementation, because it

implies that success in early implementation stages does not promise the acceptance of more advanced stages.

Our DCE allows us to gauge workers' perspectives on AI-enabled work changes independent of the firm's actual AI rollout schedule. We built highly specific and realistic scenarios of the implementation of an AI-tool based on extensive interviews and pre-testing with experts in the firm (cf. Aguinis & Bradley, 2014). This emphasizes the single-firm context of the DCE, which limits the generalizability of our findings. Therefore, the findings may be specific to the studied occupation or perhaps similar intermediate-level occupations in highly automated manufacturing settings. More occupation-specific discrete choice studies – particularly for high-level occupations – should identify workers' preferences for task changes and job characteristics to inform adequate work design in jobs susceptible to AI transformation.

Furthermore, we would like to critically reflect on the operationalization of our AI attribute. We believe that our approach of not mentioning the AI involvement in the attribute explicitly might rule out any confounding perceptions of AI (Brauner et al., 2023; Brougham & Haar, 2018) that could have influenced workers' preferences. Moreover, the attribute values each include three dimensions of the tasks of many workers: frequency of handling, difficulty and decision-making support. Although we cannot determine one of these dimensions as the main driver of workers' AI preferences, their specific roles and interplay among each other pose an interesting field for future studies.

Nevertheless, our study can inform corporate practice by demonstrating how to utilize workers' perspectives on AI implementation in the workplace as a signal of their support for AI-tools in the work process. Our results suggest that for the successful implementation of AI, employers should prioritize human-AI complementarity, i.e., deploying AI particularly as a supporting system for the worker. This also means that employers should keep workers involved in their task-level decision-making, to maintain task meaningfulness and mitigate

potential reluctance towards the task changes induced by AI. In addition, our results suggest that the implementation of augmenting AI does not need to be facilitated by salary increases in order to gain AI acceptance among the workforce, as workers seem to prefer the related changes in their task above their initial job content. This might particularly hold when workers' tasks are quite repetitive. Finally, our findings suggest that a stepwise implementation of AI could be an obstacle to the acceptance of more advanced, autonomous AI, if workers strongly prefer augmentation over automation.

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Ethical approval

The research project ai:conomics has been ethically approved before data collection by Maastricht University's Ethical Review Committee Inner City faculties (ERCIC) under protocol number ERCIC_301_03_11_2021.

Data Statement

Due to confidentiality agreements with the studied firm, and the sensitive nature of some questionnaire items, the firm and individual respondents were informed that raw data would remain confidential and would not be shared.

References

Acciani, G., Brunetti, G., & Fornarelli, G. (2006). Application of neural networks in optical inspection and classification of solder joints in surface mount technology. *IEEE Transactions on Industrial Informatics*, *2*(3), 200–209. IEEE Transactions on Industrial Informatics. https://doi.org/10.1109/TII.2006.877265

Acemoglu, D., & Restrepo, P. (2018). Artificial Intelligence, Automation, and Work. In *The Economics of Artificial Intelligence: An Agenda* (pp. 197–236). University of Chicago Press.

Acemoglu, D., & Restrepo, P. (2020). The wrong kind of AI? Artificial intelligence and the future of labour demand. *Cambridge Journal of Regions, Economy and Society*, *13*(1), 25–35.

Acemoglu, D., & Restrepo, P. (2022). Tasks, Automation, and the Rise in U.S. Wage Inequality. *Econometrica*, *90*(5), 1973–2016. https://doi.org/10.3982/ECTA19815

Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction. *Journal of Economic Perspectives*, *33*(2), 31–50. https://doi.org/10.1257/jep.33.2.31

Aguinis, H., & Bradley, K. J. (2014). Best practice recommendations for designing and implementing experimental vignette methodology studies. *Organizational Research Methods*, *17*(4), 351–371.

Anelli, M., & Koenig, F. (2025). *Willingness to Pay for Workplace Amenities* (Discussion Paper No. 2100). Centre for Economic Performance, London School of Economics and Political Science.

Atzmüller, C., & Steiner, P. M. (2010). Experimental Vignette Studies in Survey Research. *Methodology*, *6*(3), 128–138. https://doi.org/10.1027/1614-2241/a000014

Author. (2024). *Measuring the Effects of AI in the Workplace: Co-Creating a Research Approach with Companies*.

Autor, D. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives*, *29*(3), 3–30. https://doi.org/10.1257/jep.29.3.3

Autor, D. (2022). *The labor market impacts of technological change: From unbridled enthusiasm to qualified optimism to vast uncertainty* (No. W30074). National Bureau of Economic Research.

Autor, D., Levy, F., & Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration*. *The Quarterly Journal of Economics*, *118*(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Bailey, D. E. (2022). Emerging Technologies at Work: Policy Ideas to Address Negative Consequences for Work, Workers, and Society. *ILR Review*, *75*(3), 527–551. https://doi.org/10.1177/00197939221076747

Bakker, A. B., & Demerouti, E. (2007). The Job Demands-Resources model: State of the art. *Journal of Managerial Psychology*, *22*(3), 309–328. https://doi.org/10.1108/02683940710733115

Bartel, A., Ichniowski, C., & Shaw, K. (2004). Using "Insider Econometrics" to Study Productivity. *The American Economic Review*, *94*(2), 217–223.

Bessen, J. E. (2019). *Automation and Jobs: When Technology Boosts Employment* (SSRN Scholarly Paper No. 2935003). https://doi.org/10.2139/ssrn.2935003

Brauner, P., Hick, A., Philipsen, R., & Ziefle, M. (2023). What does the public think about artificial intelligence?—A criticality map to understand bias in the public perception of AI. *Frontiers in Computer Science*, *5*. https://doi.org/10.3389/fcomp.2023.1113903

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization*, *24*(2), 239–257.

Burton, J. W., Stein, M.-K., & Jensen, T. B. (2020). A systematic review of algorithm aversion in augmented decision making. *Journal of Behavioral Decision Making*, *33*(2), 220–239. https://doi.org/10.1002/bdm.2155

Caliendo, M., Cobb-Clark, D. A., Pfeifer, H., Uhlendorff, A., & Wehner, C. (2024). Managers' risk preferences and firm training investments. *European Economic Review*, *161*, 104616. https://doi.org/10.1016/j.euroecorev.2023.104616

Cattaneo, M. A., Gschwendt, C., & Wolter, S. C. (2025). How scary is the risk of automation? Evidence from a large-scale survey experiment. *Journal of Economic Behavior & Organization*, *235*, 107034. https://doi.org/10.1016/j.jebo.2025.107034

De Grip, A., & Sauermann, J. (2013). The effect of training on productivity: The transfer of on-the-job training from the perspective of economics. *Educational Research Review, Special Issue: Transfer of Training: New Conceptualizations Through Integrated Research Perspectives*, *8*, 28–36. https://doi.org/10.1016/j.edurev.2012.05.005

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.

Georgellis, Y., & Lange, T. (2007). Participation in continuous, on-the-job training and the impact on job satisfaction: Longitudinal evidence from the German labour market. *The International Journal of Human Resource Management*, *18*(6), 969–985. https://doi.org/10.1080/09585190701321112

Giering, O., & Kirchner, S. (2025). Artificial intelligence and autonomy at work: Empirical insights from Germany. *Journal for Labour Market Research*, *59*(1), 20. https://doi.org/10.1186/s12651-025-00401-5

Giuntella, O., Koenig, J., & Stella, L. (2023). Artificial Intelligence and Workers' Well-Being. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4589223

Golin, M., & Rauh, C. (2022). *The Impact of Fear of Automation* (Cambridge Working Papers in Economics) [Working Paper]. Faculty of Economics, University of Cambridge. https://doi.org/10.17863/CAM.91990

Hackman, J. R., & Oldham, G. R. (1976). Motivation through the design of work: Test of a theory. *Organizational Behavior and Human Performance*, *16*(2), 250–279. https://doi.org/10.1016/0030-5073(76)90016-7

Hole, A. R. (2016). *Creating efficient designs for discrete choice experiments*. Nordic and Baltic Stata Users Group meeting September 2016. https://www.stata.com/meeting/nordic-and-baltic16/slides/norway16_hole.pdf

Hünefeld, L., Meyer, S.-C., Erol, S., & Ahlers, E. (2025). Work intensity: Identification and analysis of key determinants. *International Journal of Workplace Health Management*, *18*(2), 238–258. https://doi.org/10.1108/IJWHM-12-2023-0177

Joshi, K. (1991). A Model of Users' Perspective on Change: The Case of Information Systems Technology Implementation. *MIS Quarterly*, *15*(2), 229–242. https://doi.org/10.2307/249384

Kahneman, D., Krueger, A. B., Schkade, D., Schwarz, N., & Stone, A. (2004). Toward National Well-Being Accounts. *American Economic Review*, *94*(2), 429–434. https://doi.org/10.1257/0002828041301713

Kelly, S., Kaye, S.-A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics*, *77*, 101925. https://doi.org/10.1016/j.tele.2022.101925

Kim, H.-W., & Kankanhalli, A. (2009). Investigating User Resistance to Information Systems Implementation: A Status Quo Bias Perspective. *MIS Quarterly*, *33*(3), 567–582. https://doi.org/10.2307/20650309

Korpi, T. (1997). Is utility related to employment status? Employment, unemployment, labor market policies and subjective well-being among Swedish youth. *Labour Economics*, *4*(2), 125–147. https://doi.org/10.1016/S0927-5371(97)00002-X

Lancsar, E., Fiebig, D. G., & Hole, A. R. (2017). Discrete Choice Experiments: A Guide to Model Specification, Estimation and Software. *PharmacoEconomics*, *35*(7), 697–716. https://doi.org/10.1007/s40273-017-0506-4

Lane, M., Williams, M., & Broecke, S. (2023). *The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers* (Working Paper No. 288; OECD Social, Employment and Migration Working Papers). OECD Publishing. https://doi.org/10.1787/ea0a0fe1-en

Lichtenthaler, U. (2020). Extremes of acceptance: Employee attitudes toward artificial intelligence. *Journal of Business Strategy*, *41*(5), 39–45.

Litwin, A. S., Hammerling, J. H., Carré, F., Tilly, C., Benner, C., Mason, S., Viscelli, S., Gutelius, B., & Theodore, N. (2022). A Forum on Emerging Technologies. *ILR Review*, *75*(4), 807–856. https://doi.org/10.1177/00197939221095527

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, *151*, 90–103. https://doi.org/10.1016/j.obhdp.2018.12.005

Lovejoy, M., Kelly, E. L., Kubzansky, L. D., & Berkman, L. F. (2021). Work Redesign for the 21st Century: Promising Strategies for Enhancing Worker Well-Being. *American Journal of Public Health*, *111*(10), 1787–1795. https://doi.org/10.2105/AJPH.2021.306283

Meijman, T. F., & Mulder, G. (1998). Psychological Aspects of Workload. In P. J. D. Drenth, H. Thierry, & C. J. de Wolff (Eds.), *Handbook of Work and Organizational Psychology* (2nd ed., pp. 5–33). Psychology Press/Erlbaum (UK) Taylor & Francis.

Nazareno, L., & Schiff, D. S. (2021). The impact of automation and artificial intelligence on worker well-being. *Technology in Society*, *67*, 101679. https://doi.org/10.1016/j.techsoc.2021.101679

Nedelkoska, L., & Quintini, G. (2018). *Automation, skills use and training*. https://www.oecd-ilibrary.org/content/paper/2e2f4eea-en

Parker, S. K., & Grote, G. (2022). Automation, Algorithms, and Beyond: Why Work Design Matters More Than Ever in a Digital World. *Applied Psychology*, *71*(4), 1171–1204. https://doi.org/10.1111/apps.12241

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. https://doi.org/10.1016/j.socscimed.2018.02.025

Revelt, D., & Train, K. (1998). Mixed Logit with Repeated Choices: Households' Choices of Appliance Efficiency Level. *Review of Economics and Statistics*, *80*(4), 647–657. https://doi.org/10.1162/003465398557735

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of Risk and Uncertainty*, *1*(1), 7–59. https://doi.org/10.1007/BF00055564

Schwabe, H., & Castellacci, F. (2020). Automation, workers' skills and job satisfaction. *PLOS ONE*, *15*(11), e0242929. https://doi.org/10.1371/journal.pone.0242929

Shao, C., Nah, S., Makady, H., & McNealy, J. (2025). Understanding User Attitudes Towards AI-Enabled Technologies: An Integrated Model of Self-Efficacy, TAM, and AI Ethics. *International Journal of Human–Computer Interaction*, *41*(5), 3053–3065. https://doi.org/10.1080/10447318.2024.2331858

Stern, D. (1978). Willingness to Pay for More Agreeable Work. *Industrial Relations*, *17*(1). https://doi.org/10.1111/j.1468-232X.1978.tb00115.x

Train, K. (2009). Mixed Logit. In *Discrete Choice Methods with Simulation* (Second edition, pp. 134–150). Cambridge University Press.

Trougakos, J. P., & Hideg, I. (2009). Momentary work recovery: The role of within-day work breaks. In S. Sonnentag, P. L. Perrewé, & D. C. Ganster (Eds.), *Current Perspectives on Job-Stress Recovery* (Vol. 7, pp. 37–84). Emerald Group Publishing Limited. https://doi.org/10.1108/S1479-3555(2009)0000007005

Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a Research Agenda on Interventions. *Decision Sciences*, *39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Vereycken, Y., Ramioul, M., Desiere, S., & Bal, M. (2021). Human resource practices accompanying industry 4.0 in European manufacturing industry. *Journal of Manufacturing Technology Management*, *32*(5), 1016–1036. https://doi.org/10.1108/JMTM-08-2020-0331

Wiswall, M., & Zafar, B. (2018). Preference for the Workplace, Investment in Human Capital, and Gender. *The Quarterly Journal of Economics*, *133*(1), 457–507. https://doi.org/10.1093/qje/qjx035

Zeba, G., Dabić, M., Čičak, M., Daim, T., & Yalcin, H. (2021). Technology mining: Artificial intelligence in manufacturing. *Technological Forecasting and Social Change*, *171*, 120971. https://doi.org/10.1016/j.techfore.2021.120971

Zhu, Z., Kuykendall, L., & Zhang, X. (2019). The impact of within-day work breaks on daily recovery processes: An event-based pre-/post-experience sampling study. *Journal of Occupational and Organizational Psychology*, *92*(1), 191–211. https://doi.org/10.1111/joop.12246

Zwerina, K., Huber, J., & Kuhfeld, W. F. (1996). A general method for constructing efficient choice designs. *Durham, NC: Fuqua School of Business, Duke University*, *7*.

Tables

Table 1. Overview of attributes and their corresponding values

Attribute	Value 1	Value 2	Value 3
Job content *(AI-enabled change in task composition)*	50-100 images per minute, easy to assess, no decision support by a pop-up window *(No AI)*	30-60 images per minute, mostly easy to assess, decision support by a pop-up window *(Augmenting AI)*	10-30 images per hour, difficult to assess, no decision support by a pop-up window *(Autonomous AI)*
Breaks	not allowed	allowed	
Training	detecting errors *(Basic training)*	detecting errors and describing their cause *(Intermediate training)*	detecting errors, describing their cause and eliminating their cause *(Advanced training)*
Task choice during shift *(Worker autonomy)*	no choice, classification and line work alternate *(No autonomous task choice)*	free choice between classification, line work and other tasks *(Autonomous task choice)*	
Salary	no increase	3% increase	6% increase

Notes: Attributes and corresponding values are displayed as they have been presented to survey respondents in the English questionnaire version. Parentheses include the corresponding value labels used throughout this paper.

Table 2. Summary statistics

	N	%
Working sample	423	
Gender		
Male	86	20.3
Female	337	79.7
Age groups		
15-29	93	22.0
30-49	244	57.8
50-69	85	20.1
Highest obtained education		
Low education	21	5.3
Intermediate general education	197	50.0
Intermediate vocational education	170	43.1
Higher education	6	1.5
Exposure to augmenting AI		
No exposure	107	25.4
Previous exposure	315	74.6
Country		
China	25	6.1
Czech Republic	30	7.3
Germany	35	8.6
Hungary	7	1.7
Lithuania	14	3.4
Mexico	150	36.7
Romania	120	29.3
Malaysia	28	6.8
	M	**SD**
Perceived usefulness of technology	4.148	0.838

Notes: Number of respondents and percentage shares. The last row shows mean (and standard deviation) of perceived usefulness measured via three corresponding items from the TAM on a 1-5 Likert scale (Venkatesh & Bala, 2008). The wording of the scale was adapted to the studied classification technology.

Table 3. Marginal effects and WTP estimation from preferred mixed logit model

	(1) Mixed logit Marginal effects	(2) Mean WTP	(3) WTP 95% CI
Job content			
(Ref. = No AI)			
Augmenting AI	0.104***	2.82***	[1.998; 3.646]
	(0.013)	(0.421)	
Autonomous AI	0.030**	0.73*	[–0.041; 1.504]
	(0.014)	(0.394)	
Breaks			
(Ref. = No breaks allowed)			
Breaks allowed	0.021**	0.59**	[0.082; 1.102]
	(0.010)	(0.260)	
Training			
(Ref. = Basic training)			
Intermediate training	0.038***	1.03***	[0.321; 1.728]
	(0.012)	(0.359)	
Advanced training	0.048***	1.33***	[0.633; 2.029]
	(0.012)	(0.356)	
Worker autonomy			
(Ref. = No autonomous task choice)			
Autonomous task choice	0.022**	0.59**	[0.032; 1.140]
	(0.010)	(0.283)	
Salary			
(Ref. = No salary increase)			
3% salary increase	0.108***		
	(0.012)		
6% salary increase	0.223***		
	(0.015)		
Continuous increase			
Observations	4,992		
Individuals	423		

Notes: Marginal effects from preferred mixed logit specification (controlling for placement of job in choice-set, i.e. left vs. right) with Krinsky-Robb parametric bootstrapped standard errors in parentheses. WTP in percentage salary increase. WTP standard errors and confidence intervals are approximated based on delta method. ***p<0.01, **p<0.05, *p<0.1.

Table 4. Interaction between AI preference and gender and age dummies

	Mixed Logit Marginal Effects
Job content (Ref. = No AI)	
Augmenting AI	0.138***
	(0.028)
Autonomous AI	0.031
	(0.035)
*Gender * Job content*	
Female * Augmenting AI	-0.044
	(0031)
Female * Autonomous AI	-0.001
	(0.039)
*Age * Job content*	
Age >50 * Augmenting AI	-0.004
	(0.034)
Age >50 * Autonomous AI	-0.019
	(0.035)
Observations	4,980

Notes: Marginal effects from preferred mixed logit specification including controls for gender and age via interaction with the job content attribute. Marginal effects of remaining job attributes and placement controls omitted in table. Krinsky-Rob parametric bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Interaction between autonomous AI and perceived usefulness of currently used classification technology in sample split based on exposure to the augmenting AI stage

	(1) Exposed to augmenting AI	(2) Not exposed to augmenting AI
Job content (Ref. = No AI)		
Augmenting AI	0.100***	0.115***
	(0.016)	(0.024)
Autonomous AI	0.026	0.037
	(0.017)	(0.028)
Autonomous AI * Perceived usefulness	-0.042**	-0.023
	(0.016)	(0.025)
Observations	3,694	1,224

Notes: Marginal effects from mixed logit model with uncorrelated parameters with interactions between autonomous AI stage and perceived usefulness, with Krinsky-Rob parametric bootstrapped standard errors in parentheses. Marginal effects of remaining job attributes and placement controls omitted in table. Column (1) displays marginal effects from the specification restricted to the subsample of workers who have been exposed to the augmenting AI, i.e., who have previously received a pop-up message while classifying components. Column (2) displays marginal effects for workers who have not been exposed to augmenting AI at time of data collection. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Figure A.1. Screenshot of example choice task as presented to the respondent

Please read the job descriptions and choose which of these two jobs (A or B) would give you the **highest sense of wellbeing**.

Make your choice at the bottom of the screen.

	Job A	**Job B**
Main task	10-30 images per **hour** difficult to assess **no** decision support by a pop-up window	30-60 images per **minute** mostly easy to assess **decision support by a pop-up window**
A short interruption of the task is...	allowed	not allowed
Training for...	detecting errors describing their cause eliminating their cause	detecting errors
Task choice during shift	free choice MLV, line work and other tasks	no choice MLV and line work alternate
Net monthly pay	6% increase	no increase

	Job A	Job B
Your choice:	○	○

Table A.1. Summary statistics by previous exposure to augmenting AI stage

	Not exposed to augmenting AI	Exposed to augmenting AI	Total	P-value
N	107 (25.4%)	315 (74.6%)	422 (100.0%)	
Gender				
Male	21 (19.6%)	64 (20.3%)	85 (20.1%)	0.878
Female	86 (80.4%)	251 (79.7%)	337 (79.9%)	
Age groups				
15-29	21 (19.6%)	72 (22.9%)	93 (22.1%)	0.306
30-49	59 (55.1%)	184 (58.6%)	243 (57.7%)	
50-69	27 (25.2%)	58 (18.5%)	85 (20.2%)	
Highest obtained education				
Low education	6 (6.0%)	15 (5.1%)	21 (5.3%)	0.559
Intermediate general	55 (55.0%)	142 (48.5%)	197 (50.1%)	
Intermediate vocational	37 (37.0%)	132 (45.1%)	169 (43.0%)	
Higher education	-	-	6 (1.5%)	
Perceived usefulness of technology	4.097 (0.944)	4.165 (0.801)	4.148 (0.838)	0.479

Notes: Number of respondents per subgroup with shares in percentages in parentheses. Information on the reception of pop-up message missing for one respondent. Missing observations and cells with less than six observations are omitted in table. The last row shows mean (and standard deviation) of perceived usefulness measured via three corresponding items from the TAM on a 1-5 Likert scale (Venkatesh & Bala, 2008). The wording of the scale was adapted to the studied classification technology.

Table A.2. Robustness across different estimation models

	(1) OLS	(2) Probit	(3) Logit	(4) Conditional Logit	(5) Fixed-Effects	(6) Random-Effects	(7) Fixed-Effects Logit
Job content							
(Ref. = No AI)							
Augmenting AI	0.167***	0.166***	0.166***	0.109***	0.172***	0.167***	0.166***
	(0.0213)	(0.0212)	(0.0213)	(0.0126)	(0.0175)	(0.0164)	(0.0213)
Autonomous AI	0.0521**	0.0515**	0.0520**	0.0380**	0.0537***	0.0521***	0.0520**
	(0.0224)	(0.0223)	(0.0223)	(0.0157)	(0.0175)	(0.0165)	(0.0223)
Breaks							
(Ref. = No breaks allowed)							
Breaks allowed	0.0459**	0.0461**	0.0468**	0.0305**	0.0460***	0.0459***	0.0468**
	(0.0197)	(0.0196)	(0.0196)	(0.0122)	(0.0140)	(0.0134)	(0.0196)
Training							
(Ref. = Basic training)							
Intermediate training	0.0520**	0.0521***	0.0516**	0.0356***	0.0531***	0.0520***	0.0516**
	(0.0202)	(0.0201)	(0.0202)	(0.0135)	(0.0176)	(0.0165)	(0.0202)
Advanced training	0.0696***	0.0698***	0.0691***	0.0484***	0.0738***	0.0696***	0.0691***
	(0.0194)	(0.0195)	(0.0194)	(0.0125)	(0.0176)	(0.0165)	(0.0194)
Worker autonomy							
(Ref. = No autonomous task choice)							
Autonomous task choice	0.0421**	0.0422**	0.0424**	0.0277**	0.0421***	0.0421***	0.0424**
	(0.0213)	(0.0213)	(0.0213)	(0.0133)	(0.0140)	(0.0134)	(0.0213)
Salary							
(Ref. = No salary increase)							
3% salary increase	0.184***	0.184***	0.185***	0.144***	0.191***	0.184***	0.185***
	(0.0206)	(0.0206)	(0.0206)	(0.0151)	(0.0176)	(0.0165)	(0.0206)
6% salary increase	0.350***	0.349***	0.350***	0.231***	0.364***	0.350***	0.350***
	(0.0243)	(0.0243)	(0.0243)	(0.0163)	(0.0175)	(0.0164)	(0.0243)
Placement *(Ref. = Left)*	-0.000524	-0.000979	-0.000587	-0.000471	-0.000427	-0.000524	-0.000587
	(0.0232)	(0.0232)	(0.0232)	(0.0151)	(0.0141)	(0.0135)	(0.0232)
Constant	0.163***				0.152***	0.163***	
	(0.0294)				(0.0224)	(0.0212)	
Observations	4,992	4,992	4,992	4,992	4,992	4,992	4,992
R-squared	0.107				0.111		
Individuals	423	423	423	423	423	423	423

Notes: To ease comparability with OLS estimates, columns (2), (3), (4), and (7) contain marginal effects. Standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A.3. Comparison of mixed logit model specifications with uncorrelated versus correlated random parameters

	(1) Mixed Logit Mean Uncorrelated	(2) Mixed Logit SD Uncorrelated	(3) Mixed Logit Mean Correlated	(4) Mixed Logit SD Correlated
Job content				
(Ref. = No AI)				
Augmenting AI	0.693***	-0.498**	0.826***	0.692***
	(0.103)	(0.212)	(0.126)	(0.244)
Autonomous AI	0.180*	0.868***	0.220*	1.218***
	(0.0968)	(0.167)	(0.132)	(0.212)
Breaks				
(Ref. = No breaks allowed)				
Breaks allowed	0.145**	0.503***	0.236***	0.604***
	(0.0639)	(0.131)	(0.0760)	(0.135)
Training				
(Ref. = Basic training)				
Intermediate training	0.252***	-0.447**	0.307***	0.659***
	(0.0882)	(0.191)	(0.104)	(0.234)
Advanced training	0.327***	0.253	0.447***	0.592***
	(0.0875)	(0.211)	(0.105)	(0.192)
Worker autonomy				
(Ref. = No autonomous task choice)				
Autonomous task choice	0.144**	0.698***	0.205**	0.805****
	(0.0694)	(0.119)	(0.0847)	(0.148)
Salary				
(Ref. = No salary increase)				
3% salary increase	0.738***	-0.119	0.938***	0.845***
	(0.0965)	(0.149)	(0.121)	(0.187)
6% salary increase	1.472***	1.277***	1.730***	1.870***
	(0.149)	(0.156)	(0.186)	(0.233)
Placement *(Ref. = Left)*	-0.00989		-0.0263	
	(0.0745)		(0.0824)	
Observations	4,992		4,992	
Individuals	423		423	
Log-Likelihood	-1499.673		-1475.745	
AIC	3033.346		3041.49	
BIC	3144.111		3334.692	
Halton draws	200		200	

Notes: Columns 1 and 2 report mean coefficients from an unrestricted mixed logit model with uncorrelated random parameters, and their standard deviations, respectively. Columns 3 and 4 report mean coefficients and standard deviations of the mixed logit model with correlated random parameters, respectively. All models control for job's left or right placement within the choice set. Robust standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A.4. Preferred mixed logit model specification with varying number of Halton draws

	(1)	(2)	(3)	(4)	(5)
MEAN					
Job content (Ref. = No AI)					
Augmenting AI	0.693***	0.681***	0.677***	0.692***	0.679***
	(0.103)	(0.0994)	(0.0978)	(0.0998)	(0.0983)
Autonomous AI	0.180*	0.174*	0.178*	0.183*	0.179*
	(0.0968)	(0.0954)	(0.0953)	(0.0963)	(0.0955)
Breaks (Ref. = No breaks allowed)					
Breaks allowed	0.145**	0.142**	0.141**	0.147**	0.144**
	(0.0639)	(0.0629)	(0.0625)	(0.0640)	(0.0630)
Training (Ref. = Basic training)					
Intermediate training	0.252***	0.244***	0.244***	0.250***	0.246***
	(0.0882)	(0.0854)	(0.0858)	(0.0876)	(0.0863)
Advanced training	0.327***	0.311***	0.317***	0.324***	0.314***
	(0.0875)	(0.0835)	(0.0841)	(0.0858)	(0.0838)
Worker autonomy (Ref. = No autonomous task choice)					
Autonomous task choice	0.144**	0.140**	0.142**	0.144**	0.142**
	(0.0694)	(0.0685)	(0.0680)	(0.0687)	(0.0681)
Salary (Ref. = No salary increase)					
3% salary increase	0.738***	0.727***	0.727***	0.737***	0.729***
	(0.0965)	(0.0917)	(0.0920)	(0.0933)	(0.0922)
6% salary increase	1.472***	1.441***	1.441***	1.464***	1.451***
	(0.149)	(0.136)	(0.138)	(0.142)	(0.141)
Placement *(Ref. = Left)*	-0.00989	-0.0122	-0.0107	-0.0121	-0.0137
	(0.0745)	(0.0736)	(0.0733)	(0.0744)	(0.0735)
SD					
Augmenting AI	-0.498**	0.455**	0.460**	-0.469**	0.433*
	(0.212)	(0.215)	(0.207)	(0.212)	(0.223)
Autonomous AI	0.868***	0.843***	0.846***	0.872***	0.853***
	(0.167)	(0.160)	(0.161)	(0.159)	(0.157)
Breaks allowed	0.503***	0.472***	0.473***	0.488***	0.484***
	(0.131)	(0.138)	(0.146)	(0.150)	(0.142)
Intermediate training	-0.447**	0.452**	-0.403**	0.459**	-0.447**
	(0.191)	(0.188)	(0.197)	(0.179)	(0.194)
Advanced training	0.253	0.216	0.205	-0.246	-0.0513
	(0.211)	(0.208)	(0.192)	(0.178)	(0.170)
Autonomous task choice	0.698***	0.691***	0.687***	0.707***	0.702***
	(0.119)	(0.120)	(0.119)	(0.115)	(0.118)
3% salary increase	-0.119	-0.00853	-0.0982	-0.124	-0.122
	(0.149)	(0.149)	(0.162)	(0.183)	(0.198)
6% salary increase	1.277***	1.227***	1.233***	1.249***	1.244***
	(0.156)	(0.145)	(0.146)	(0.151)	(0.149)
Observations	4,992	4,992	4,992	4,992	4,992
Individuals	423	423	423	423	423
Log-Likelihood	-1499.673	-1501.917	-1501.139	-1499.609	-1500.331
AIC	3033.346	3035.833	3036.277	3033.219	3034.662
BIC	3144.111	3146.598	3147.042	3143.984	3145.427
Number of Halton draws	200	300	400	500	1000

Notes: Columns 1 to 5 report estimates of the uncorrelated mixed logit model with a varying number of Halton draws in maximum likelihood simulation. Robust standard errors clustered at individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A.5. Robustness of results in restricted samples excluding incomplete choice-sets, Mexico and Romania, respectively

	(1)	(2)	(3)	(4)	(5)	(6)
Sample excluding	Incomplete choice-sets		Mexico		Romania	
	Mixed Logit Mean	Mixed Logit SD	Mixed Logit Mean	Mixed Logit SD	Mixed Logit Mean	Mixed Logit SD
Job content (Ref. = No AI)						
Augmenting AI	0.676***	0.396*	0.670***	0.408	0.734***	-0.418*
	(0.0970)	(0.236)	(0.120)	(0.273)	(0.118)	(0.227)
Autonomous AI	0.158*	0.815***	0.363***	0.794***	0.292***	0.743***
	(0.0951)	(0.158)	(0.122)	(0.205)	(0.112)	(0.171)
Breaks (Ref. = No breaks allowed)						
Breaks allowed	0.137**	0.443***	0.194**	0.668***	0.181***	0.306
	(0.0625)	(0.146)	(0.0845)	(0.145)	(0.0701)	(0.251)
Training (Ref. = Basic training)						
Intermediate training	0.244***	0.359	0.286***	0.252	0.210**	0.247
	(0.0860)	(0.283)	(0.105)	(0.367)	(0.0958)	(0.211)
Advanced training	0.308***	-0.257	0.316***	-0.243	0.317***	0.339
	(0.0838)	(0.245)	(0.106)	(0.309)	(0.0984)	(0.274)
Worker autonomy (Ref. = No autonomous task choice)						
Autonomous task choice	0.141**	0.680***	0.126	0.778***	0.124	0.656***
	(0.0682)	(0.119)	(0.0896)	(0.141)	(0.0757)	(0.130)
Salary (Ref. = No salary increase)						
3% salary increase	0.745***	0.0293	0.671***	-0.267	0.672***	-0.00986
	(0.0909)	(0.212)	(0.118)	(0.314)	(0.0979)	(0.0531)
6% salary increase	1.475***	1.169***	1.389***	1.099***	1.216***	0.971***
	(0.140)	(0.143)	(0.169)	(0.192)	(0.138)	(0.156)
Placement *(Ref. = Left)*	-0.0173		-0.140		0.133	
	(0.0727)		(0.0970)		(0.0836)	
Observations	4,860	4,860	3,034	3,034	3,410	3,410
Individuals	405	405	259	259	289	289

Notes: Columns 1 and 2 report the mixed logit estimates (mean and SD) when restricting the sample to those respondents who have made a choice on all six choice tasks in the DCE. Columns 3 and 4 (5 and 6) show estimations when excluding Mexico (Romania) from the sample. Robust standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.