

Are We Automating the Joy Out of Work? Designing AI to Augment Work, Not Meaning

ANONYMOUS AUTHOR(S) and JASPREET RANJIT, University of Southern California, United States

KE ZHOU, Nokia Bell Labs, United Kingdom

SWABHA SWAYAMDIPTA, University of Southern California, United States

DANIELE QUERCIA, Nokia Bell Labs, United Kingdom

Prior work has mapped which workplace tasks are exposed to AI, but less is known about whether workers perceive these tasks as meaningful or as busywork. We examined: (1) which dimensions of meaningful work do workers associate with tasks exposed to AI; and (2) how do the traits of existing AI systems compare to the traits workers want. We surveyed workers and developers on a representative sample of 171 tasks and use language models to scale ratings to 10,131 tasks across all U.S. computer-assisted tasks. Worryingly, we find that tasks that workers associate with a sense of agency or happiness may be disproportionately exposed to AI. We also document HCI design gaps: developers report emphasizing politeness, strictness, and imagination in system design; by contrast, workers prefer systems that are straightforward, tolerant, and practical. To address these gaps, we call for AI whose design explicitly centers meaningful work and worker needs, proposing a five-part research agenda.

CCS Concepts: • Human-centered computing → HCI design and evaluation methods; Empirical studies in HCI; • Applied computing → Psychology.

Additional Key Words and Phrases: Human-centered AI, Future of work, Automation and Augmentation, Meaningful Work, Value Alignment

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1 Introduction

Public debate about AI and occupations often focuses on job loss versus job growth. Some studies have predicted broad job displacement [32, 34, 91], while others have anticipated growth, with AI complementing workers in ways that are associated with higher productivity and the emergence of new roles [9, 17, 18, 23, 66, 67, 79]. These outcomes are not fixed, however, and are widely argued to vary with how teams design AI systems. In this paper, *AI* refers to software systems (e.g., LM tools, agents) that automate or augment computer-based tasks by generating, transforming, or routing information. By *teams*, we mean the broader set of actors involved in AI system development, including developers, UI/UX designers, product managers, and others who contribute to how these systems are built and used.

Authors' Contact Information: Anonymous Author(s); Jaspreet Ranjit, jranjit@usc.edu, University of Southern California, Los Angeles, CA, United States; Ke Zhou, Nokia Bell Labs, Cambridge, United Kingdom; Swabha Swayamdipta, University of Southern California, Los Angeles, CA, United States ; Daniele Quercia, Nokia Bell Labs, Cambridge, United Kingdom.

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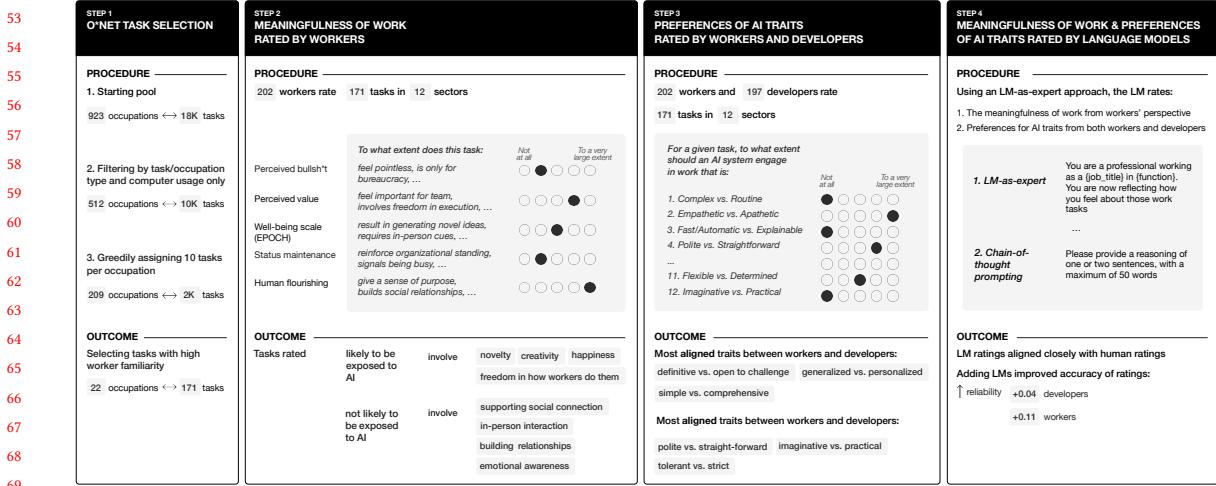


Fig. 1. Overview of Study Design: Worker and developer perspectives on meaningful work and AI system design in the U.S. labor force. (*Step 1*) Workplace tasks were restricted to those primarily completed on a computer and performed daily or weekly, then filtered by Prolific availability, AI Impact Index, and worker familiarity. (*Step 2*) Workers rated tasks across five dimensions: perceived bullshit^t, perceived value, well-being scale, status maintenance, and human flourishing. Tasks more likely exposed to AI scored higher on novelty, creativity, happiness, and freedom, while those less likely emphasized emotional awareness, in-person interaction, relationships, and social connection. (*Step 3*) Workers and developers rated which psychological traits an AI system should possess when augmenting tasks. When designing AI augmented tasks, developers emphasized polite, strict and imaginative systems whereas workers preferred straightforward, tolerant, and practical systems. (*Step 4*) LMs were prompted as experts to simulate worker and developer ratings, with moderate to high intra-class correlation with human responses.

Because the very possibility of drawing a clear distinction between automation and augmentation is debated in the literature [1, 7, 8, 31], with different works adopting different operationalizations (e.g., based on time saved by AI to do a task [28]), we clarify our terminology as follows: throughout, we use *AI exposure* [31], our main construct of interest, to refer to tasks that current or near-term AI systems could plausibly perform or substantially speed up, operationalized as those above the 75th percentile of the distribution of the patent-based AI Impact Index [79]; *AI automation* for cases where AI can perform a task end-to-end with minimal or no human involvement; and *AI augmentation* for cases where AI supports or enhances human work, while humans retain primary responsibility and decision-making authority, with human involvement measured, for example, using the scale in [80].

To inform AI design, we examine: (1) Which tasks are likely to be exposed to AI? (2) How do workers evaluate these tasks in their daily work? (3) Do AI teams design systems that meet workers' needs? When these three aspects align, growth-oriented scenarios become more plausible; when any one fails, organizations may face greater waste and resistance, in the workplace and beyond.

The bulk of existing research lies in economics and has concentrated on the first aspect: identifying which tasks are exposed to AI, and measuring the resulting labor-market effects. This body of work forms the backbone of the literature: it maps technologies (e.g., via patents [9, 79]) to tasks, and quantifies how AI is associated with changes in occupations [43, 58, 79, 80]. A growing line of research has used LMs to annotate tasks [28]; for example, labeling a task as ‘exposed’ when AI is defined as enabling at least a 50% reduction in reported time to complete the task at equal or higher quality. By this definition, one study estimated that LMs are estimated to be relevant for the majority of tasks in just 1.8% of U.S. occupations, but this share is estimated to reach over 46% when AI is considered together

105 with productivity software [28]. Yet, the same study also estimated that only about 1.86% of tasks are fully automatable
106 without human oversight [28]. Therefore, while complete automation is uncommon, augmentation is expected to play
107 the larger role [59]. In customer support, for example, the use of generative AI systems is estimated to be associated
108 with roughly 14% higher measured agent productivity, on average, with increases of about 35% in the number of issues
109 resolved per hour for less-experienced workers [80].

110 The second and third aspects: (2) how workers evaluate tasks exposed to AI, and (3) whether teams design AI to
111 meet workers' needs, remain underexplored. These gaps present a promising research agenda for HCI. Recent work
112 has begun to map where workers prefer human intervention, suggesting that workers report being comfortable with
113 AI handling information-centric tasks, while preferring to focus on interpersonal and organizational work [80]. Yet,
114 despite rich literature on meaningful work in management science [11, 39, 52, 56, 76, 77, 85] and on human-centered
115 systems in HCI [3, 64, 65, 81], we still know little about which dimensions of meaningful work workers associate with
116 tasks potentially exposed to AI, and whether AI teams design AI tools with the traits workers want. To address this gap,
117 we asked two research questions:
118

119 (RQ1) Which dimensions of meaningful work do workers associate with tasks exposed to AI in their daily work?
120

121 (RQ2) Do teams design AI systems with traits that align with the traits workers want?

122 In so doing, we made the following main contributions:

- 123 (1) We identified Prolific workers who reported high familiarity with a representative set of 171 tasks spanning
124 22 occupations drawn from the U.S. Department of Labor's Occupational Information Network (O*NET)
125 (methodology in Section 3.1; task representativeness in Figure 2).
- 126 (2) We conducted a scoping review of research on meaningful work (Section 3.2), which informed the construction
127 of survey items for workers (Section 3.3). Building on recent work specifying desirable AI traits across occu-
128 pations [26], we then developed parallel survey modules: one for workers, eliciting the traits they want AI to
129 possess (Section 3.3), and one for developers, eliciting the traits they intend to design in AI systems (Section 3.4).
- 130 (3) We administered the surveys to 202 previously identified workers and to a new sample of 197 developers across
131 171 tasks in 12 sectors (Section 3.5). We then scaled up their responses by measuring LM agreement with
132 human ratings and, under reasonable agreement, generated task-level annotations for 10,131 tasks across 512
133 occupations and 19 sectors (Section 3.6). We make these two human-generated datasets publicly available so
134 that future research can explore alternative methods for generating synthetic data from them.
- 135 (4) Our first main contribution, addressing RQ1 (Section 4.1; Figure 3), shows that tasks identified as likely to be
136 exposed to AI are more strongly associated by workers with novelty/creativity, positive affect, and autonomy
137 (Figure 4). This challenges the usual narrative that automation mainly targets routine tasks [79]. By contrast,
138 tasks rated as unlikely to be exposed to AI are more often linked by workers to emotional awareness, in-person
139 interaction, relationship building, and social connection (Figure 5).
- 140 (5) Our second main contribution, in addressing RQ2 (Section 4.2; Figure 6), reveals clear gaps between workers'
141 preferences and developers' design intentions: workers prefer straightforward systems, whereas developers
142 intend to design polite systems (Figure 6), consistent with reports of LM sycophancy [24], which is a systematic
143 bias of LMs toward agreeing with users' views irrespective of correctness. More generally, developers favor
144 polite, strict, and imaginative systems, whereas workers often describe these design choices as unnecessary
145 friction or rigidity rather than genuine support. By contrast, both groups converge on the need of personalized
146 systems.

¹⁵⁷ Our contributions and findings motivate design principles that aim to preserve meaningful work and better align
¹⁵⁸ with worker needs (Section 5), culminating in a five-part research agenda for HCI researchers (Section 6 and Table 2).
¹⁵⁹

¹⁶⁰ 2 Related Work

¹⁶² To mirror our research questions in Section 1, we review two strands of literature: (1) which tasks can be exposed to AI
¹⁶³ (Section 2.1), and (2) how teams design AI to meet workers' needs (Section 2.2; RQ2). We then add a third strand on the
¹⁶⁴ meaningfulness of work by conducting a formal scoping review (Section 3.2; Appendix Table 5).
¹⁶⁵

¹⁶⁶ 2.1 Tasks exposed to AI

¹⁶⁸ Across field deployments, controlled trials, and exposure analyses, three properties are often associated with AI exposure
¹⁶⁹ being likely: (1) the task can be decomposed into explicit steps; (2) the work can be partitioned into sub-tasks under
¹⁷⁰ human direction; and (3) outputs can be checked against clear rules, tests, or ground truth. These properties are common
¹⁷¹ in computer-based workflows [28, 32]. In such settings, LMs can accelerate routine components while people supply
¹⁷² context and judgment. For example, laboratory studies report faster completion and higher quality in settings where
¹⁷³ humans set goals and verify results [17, 20, 23, 66, 67].
¹⁷⁴

¹⁷⁶ However, studies also report that few tasks can be automated end-to-end, whereas many can be augmented, often
¹⁷⁷ within existing human workflows [28, 32]. Patent-to-task analyses document substantial AI exposure in skilled, non-
¹⁷⁸ routine domains (e.g., clinical image review, routing, programming) where professionals nonetheless retain final
¹⁷⁹ responsibility [79, 91]. AI exposure is already evident across domains: in software development, AI supports debugging
¹⁸⁰ with error traces, proposes refactoring, generates tests, analyzes logs, and prepares code reviews [67]; in professional
¹⁸¹ writing, workers use AI to outline, draft, adjust tone, convert formats, and check citations and style [45, 66]; and in
¹⁸² specialist review, clinicians use AI to prepare imaging pre-reads, and draft reports for subsequent human review and
¹⁸³ sign-off [79].
¹⁸⁴

¹⁸⁶ Even when many tasks could be exposed to AI, empirical studies find that workers often report preferring to retain
¹⁸⁷ activities involving judgment, interpersonal interaction, and coordination [9, 18, 28, 32], while accepting greater AI
¹⁸⁸ exposure for repetitive digital work [9, 18, 28, 32].
¹⁸⁹

¹⁹⁰ 2.2 How teams design AI to meet workers' needs

¹⁹² Prior work suggests that, when tasks feel more meaningful, workers often report preferring to maintain ownership;
¹⁹³ when they feel less meaningful, workers report being more willing to offload work to AI. Workers judge AI systems
¹⁹⁴ typically along two dimensions: warmth (benevolent intent), and competence (ability) [33]. People are more willing
¹⁹⁵ to delegate work when they believe the AI system is competent at it [29]. Design choices are reported to shape these
¹⁹⁶ beliefs: anthropomorphic features or friendly conversational styles can make AI systems seem warmer and more capable
¹⁹⁷ in experimental settings [51, 57]. When people further attribute a 'mind' to AI in such studies, they tend to collaborate
¹⁹⁸ with it more, and also blame it more when it makes errors, with these effects amplified by human-like cues [38, 90].
¹⁹⁹ HCI studies show that cues about system expertise, humanness, and fit to the setting influence perceived warmth and
²⁰⁰ competence, with expertise cues most strongly predicting reported trust and use [48, 49]. To complicate matters, system
²⁰¹ developers often evaluate the trustworthiness of a system differently than system users do [53, 54, 89].
²⁰²

²⁰⁵ While the warmth–competence framework advances theory, workers rarely judge AI in simple binary terms. Recent
²⁰⁶ evidence suggests people judge whether AI is suitable for a job by the traits the job requires [26]. Dong et al. [26] finds
²⁰⁷ that traits such as fairness, sincerity, warmth, competence, determination, intelligence, tolerance, and imagination were
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treated as distinct dimensions in assessing whether AI is suitable for a job. Additional studies similarly find that expert cues and context-task fit increase acceptance in workplace settings [49] where examples include interface features that calibrate reliance (e.g., uncertainty cues, targeted explanations), reduce over-reliance, and help people make better decisions [29, 55, 88]. In cooperative tasks, people rely on AI more when it seems warm and competent than when it simply performs well [60]. This suggests that AI system design should distinguish relevant traits based on roles (e.g., fairness for managers, sincerity for clinicians) [60]. In our work, we examine which traits workers want in tasks exposed to AI, and which traits developers design for, revealing role-specific priorities (e.g., fairness for managerial tasks; sincerity for clinical tasks).

Research Gap. Prior work has identified which tasks are exposed to AI and has explored design choices that promote trust and reliability [47]. Yet two important questions remain underexplored. First, we lack understanding of how AI exposure reshapes the meaningfulness of work, and whether tasks exposed to AI feel purposeful to workers or feel merely like bureaucratic busywork. Second, we do not know whether teams design AI systems with the traits that workers actually want. Related work in high-stakes domains such as the judiciary has begun to surface user expectations and requirements for AI tools [82], but little is known about how these expectations translate to everyday work practices across occupations. In the pursuit of productivity and speed, with the introduction of AI, teams may risk changes to autonomy, care for others, excellence, and fairness [43], qualities that prior work links to experiences of meaningful work.

3 Methods

To close this gap, we addressed two research questions (RQs):

- (RQ1) Which dimensions of meaningful work do workers associate with tasks exposed to AI in their daily work?
- (RQ2) Do teams design AI systems with traits that align with the traits workers want?

To answer these two questions, our methodology followed four steps (Figure 1). First, we selected representative tasks from the O*NET 29.3 database¹, and recruited samples of workers and AI developers on the crowd-sourcing platform of Prolific. We initially identified 171 tasks spanning 22 representative occupations (Section 3.1). By “representative”, we mean that the task sample was stratified to approximate the distribution of occupational sectors reported by the U.S. Bureau of Labor Statistics, ending up with modest deviations (Figure 2). Second, we conducted a scoping review synthesizing research on the meaningfulness of work (Section 3.2). Guided by this review, we measured workers’ experiences using items that capture the meaningfulness of work (Q1–Q33; Section 3.3). We then measured workers’ and developers’ views on the design of AI systems using items capturing design traits (Q34–Q45; Section 3.4). Third, we administered the survey to workers and developers under consistent protocols on Prolific (Section 3.5). Fourth, to scale the analysis, we used LMs to simulate workers and developers, generated task-level annotations for 10,131 tasks across 512 occupations and 19 sectors, and validated the model-derived annotations against our human data to assess reliability (Section 3.6).

¹<https://www.onetcenter.org/database.html> accessed July 2025

261 3.1 Selecting Tasks and Recruiting Workers and Developers

262 O*NET 29.3 Database. The O*NET database provides standardized information on U.S. sectors², occupations and their
263 associated tasks. It organizes 923 occupations into sectors where each occupation is broken down into task statements³
264 describing work activities. In total, O*NET contains 18,796 tasks, where each task is classified as *core* or *supplementary*,
265 and annotated with how frequently it's performed (e.g., yearly or less, monthly, weekly, daily, or hourly)⁴.
266

267
268 Selecting Tasks Exposed to AI. Our study primarily focuses on workplace tasks likely to be exposed to AI. We follow
269 prior work [80], and apply a multi-step filtering pipeline (Step 1; Figure 1) to identify a representative set of tasks for our
270 study. First, we ensured each task is classified as either *core* or *supplementary* to ensure its relevance to the occupation.
271 Then, we characterized and filtered occupations and tasks by two criteria as determined by GPT-4o annotations in line
272 with [80]: (1) the *occupation* primarily involves computer use and, (2) the *task* can be completed on a computer. Upon
273 manual inspection, we found that GPT-4o occasionally excluded occupations (e.g., nursing, education professionals)
274 that are widely recognized as exposed to AI [70, 74, 75]. To ensure these occupations were represented in our dataset,
275 we manually curated and included a list of 427 occupations that were exempted from these filters, with examples shown
276 in Appendix Table 4. Following these filtering steps, our dataset contained 10,131 tasks spanning 512 occupations.
277

278
279 Recruiting Workers and Selecting Tasks Familiar to Them. We used Prolific to recruit U.S. workers and developers
280 (Appendix Table 7). We applied the “work function” screener to identify participants likely to be familiar with the tasks
281 they evaluated. Both workers and developers were compensated at a rate of \$11 per hour. Each O*NET occupation was
282 mapped to one of 21 work functions (Appendix Table 3), yielding 4,473 tasks across 209 occupations. To keep surveys
283 tractable and reduce participant fatigue, we downsampled to at most 10 tasks per occupation using a greedy selection
284 criterion based on task frequency annotations (e.g., daily) and estimated AI exposure [79], resulting in 2,078 tasks
285 across 209 occupations. Our study required participants who were experts in their domains, which made recruitment
286 especially challenging: if participants are not familiar with the tasks they are asked to evaluate, their responses risk
287 being speculative rather than grounded in real-world practice. To target U.S. workers who are experts in their domains,
288 we first ran a preliminary survey which identified workers that: (1) belonged to one of 21 professional work functions
289 on Prolific, (2) passed attention checks, and (3) reported being highly familiar with at least one O*NET task in their
290 occupation. Following this rigorous pre-screening, we recruited 202 workers, excluding those who failed our attention
291 checks. From these responses, we retained tasks rated as “Very familiar” or “Extremely familiar” by at least three
292 participants, producing a final set of 171 tasks across 22 occupations and 12 sectors. This subset provided broad coverage
293 (12 of 22 total sectors in O*NET), while focusing on tasks that were central to the occupation (i.e., core or frequently
294 performed), likely to be exposed to AI, and validated as highly familiar to workers.
295

296 302 Recruiting Developers. For developers, we focused on U.S.-based AI practitioners who met the following screening
297 criteria: weekly AI use (ranging from once a week to multiple times daily), individual contributor or non-manager
298 role, employment in coding, technical writing, or systems administration, and primary function in engineering (e.g.,
299 software) or research. We recruited 197 developers who each rated 10 tasks, drawn from the same pool of tasks
300 the workers rated. Each task received ratings from at least three distinct developers. Given the heterogeneity of ‘AI
301

302
303 ²Sectors refers to O*NET major groups <https://www.onetcenter.org/taxonomy/2019/structure.html>.

304 ³https://www.onetcenter.org/dictionary/29.3/excel/task_statements.html

305 ⁴https://www.onetcenter.org/dictionary/29.3/excel/task_ratings.html

313 developers' on Prolific and the ambiguity of O*NET task descriptions that allows for interpretive variation, we detail
314 the distribution of developers' technical roles, AI usage patterns, and work functions are shown in Appendix Figure 7
315 to better characterize their expertise. The majority of developers in our sample hold software, data, IT infrastructure, or
316 ML/AI engineering roles. Developers also reported extensive use of AI tools in their workflow, including LLM-based
317 assistants, code-generation tools, data-analysis systems, and ML model development, indicating active engagement with
318 contemporary AI technologies. Work-function distributions further show representation across engineering, research,
319 analytics, and operations roles.
320

322 3.2 Scoping Review on Meaningfulness of Work

324 After selecting tasks and recruiting workers, we next determined which questions would best capture the extent to
325 which workers perceive their tasks as 'meaningful'. To ground these questions in the literature, we conducted a scoping
326 review following the five-stage framework in [6]:
327

329 **Step 1. Identifying the research question.** The main research question was: *What are the documented, theorized,*
330 *or studied dimensions of task meaningfulness, symbolic work, impression management, and status signaling in today's*
331 *workplaces?* This question was broad enough to cover both personal views of meaningfulness, and the social or symbolic
332 factors that can make work performative, strategic, or status-driven.
333

335 **Step 2. Identifying relevant literature.** To ensure cross-disciplinary coverage, we went on Google Scholar and JSTOR,
336 and we used the Boolean search string: ("meaningful work" OR "task significance" OR "work motivation"
337 OR "symbolic work" OR "impression management" OR "status threat" OR "performative work") AND
338 (work OR job OR employee OR organization OR organization OR labor OR labor). The review included only
339 English-language, peer-reviewed work, with no date restrictions.
340

343 **Step 3. Selecting the articles.** We used the following inclusion rules: articles must discuss task meaningfulness,
344 symbolic or performed work, status signaling, or impression management in a work or organizational setting; both
345 empirical and theoretical work was eligible; and full-text access had to be available. Articles outside of work or
346 organizational settings, and those limited to consumer behavior or marketing without reference to employees or
347 task meaning, were excluded, resulting in 56 articles. After removing duplicates and screening titles and abstracts, 42
348 remained for full-text review, and we included 21 that met all criteria.
349

351 **Step 4. Charting the data.** We coded each article with a structured form. Key fields included: main constructs (e.g.,
352 task significance, performative work); theory used (e.g., Job Characteristics Model, Institutional Theory, Impression
353 Management Theory); measures (e.g., Work and Meaning Inventory); and main findings or arguments.
355

356 **Step 5. Collating, summarizing, and reporting the results.** We reviewed 21 articles across psychology, sociology,
357 anthropology, and ethics on what work means to people and to society (Appendix Table 5). The studies show how
358 people judge their own work, how organizations shape those judgments, and how societies value different kinds of
359 work. Examples include David Graeber's critique of "bullshit jobs" [37], a tested questionnaire for meaningful work
360 [83], and research linking work to identity and status [69]. Key theoretical lenses include job characteristics theory,
361 which emphasizes task significance, task identity, and autonomy [41]; impression management, which explains how
362

365 workers perform roles for symbolic or strategic ends [14, 35]; institutional theory, which highlights symbolic work and
366 routine, ceremonial task structures [61]; and models of status signaling at work [12, 68].

367 Guided by our coding, we grouped the articles into two analytic levels that together capture the primary sources of
368 experienced meaningfulness:

370 **Micro level (individual appraisal).** Articles that tied meaningful work to how people judged their tasks and
371 roles. Findings included task-level features and personal attitudes such as satisfaction, engagement, motivation,
372 and performance [41, 83].

374 **Macro level (organizations, institutions, and society).** Articles that explained how society, fields, and orga-
375 nizations ranked different kinds of work and set scripts and norms that shaped meaning, identity, and claims to
376 self-worthiness [12, 14, 35, 61, 68, 69]. This set also reported cases where tasks lacked recognized value and
377 thus felt meaningless [37].

379 At the micro level, individuals treated meaningful work as an attitude tied to satisfaction, engagement, motivation,
380 and performance. At the macro level, cultural valuations and organizational scripts shape identity and sense making,
381 establishing the norms and constraints that enabled or limited those appraisals.

383 Prior work has combined insights from the micro and macro levels to explain how individual experiences are
384 shaped by broader organizational and cultural forces. For example, Carton [19]'s study of the National Aeronautics and
385 Space Administration (NASA) in the 1960s argues that macro-level leader 'sense-giving' can recalibrate micro-level
386 experiences. He illustrates how leaders may reshape how people view their work through mid-level links. Using
387 President Kennedy as an example, the study describes leaders as defining a main aim (advancing science), setting a
388 dated goal ('land a man on the Moon before 1970'), outlining a few key steps (Mercury, then Gemini, then Apollo; later
389 a six-step plan sometimes called the 'ladder to the Moon'), and using clear language that ties the goal to shared values
390 such as knowledge and peace. In Carton's account, this plan made the ultimate goal feel more attainable, gave staff
391 clearer stepping stones, clarified their perceived role in the process, and was associated with staff describing daily tasks
392 in mission terms ('putting a man on the Moon', even 'advancing science'). Carton interprets these shifts as aligning
393 motivation, engagement, and performance more closely with the organization's purpose. In a complementary line of
394 work, Bailey et al. [10] integrate psychological and sociological perspectives on how people find work meaningful. They
395 draw on first-person accounts from nurses, creative artists, and lawyers: occupations chosen for their clear contrasts in
396 task content, workplace rules, and room for professional choice, and emphasize the connection between individual
397 experiences and broader organizational purpose for understanding how people experience meaning at work.

403 3.3 Questions about Dimensions of Meaningful Work to Administer to Workers (Q1-33)

405 We started with two levels: *individual appraisal* (micro), and *organizational, institutional, and societal valuation* (macro).
406 First, to measure valuation beyond the individual, we drafted *Perceived Bullsh*ttness* survey items (Q1–Q5; [36]) and
407 *Status Maintenance* survey items (Q11–Q16; [13, 15]). Second, to measure individual appraisal, we drew on *Perceived*
408 *Value* (Q6–Q10; [40, 84]), the *EPOCH well-being scale* (Q17–Q21; [58]), and *Human Flourishing* (Q22–Q33; [87]). See
409 Step 2 in Figure 1 and Appendix Table 6 for our complete survey items.

412 **Perceived Bullsh*ttness [36] (Q1-5).** These five questions measure the extent to which participants view their tasks as
413 pointless, bureaucratic, or not contributing to the goals of their organization. Example survey items include: 'I perform
414 this task only to satisfy bureaucracy or appearances' and 'This task does not contribute to the goals of my organization'.
415

417 These items build on Graeber [36]’s theory of ‘bullshit jobs’, which introduces the concept of ‘bullshit’ jobs as roles
418 that are perceived as worthless, even by those performing them. Graeber [36] argues that these roles can contribute to
419 psychological distress and can erode workers’ sense of purpose and motivation.
420

421
422 **Perceived Value [40, 84] (Q6-10).** These questions assess the extent to which workers perceive a task as meaningful
423 or contributing to the success of their organization. This aligns with the three psychological states (e.g. experienced
424 meaningfulness, experienced responsibility for the outcomes of the work, and knowledge of the results) described in
425 Hackman and Oldham [40]’s Job Characteristics Model. Specifically, this outcome is observed, if an individual ‘*learns*
426 (knowledge of results) that he *personally* (experienced responsibility) has performed well on a task that *he cares about*
427 (experienced meaningfulness)’ [40]. Our survey items reflect this framework by assessing whether workers feel they
428 ‘receive useful feedback about how well this task is done.’ (Q9; knowledge of results), ‘has the freedom to decide how
429 to carry out this task’ (Q8; experienced responsibility), and ‘provides a sense of accomplishment’ (Q10; experienced
430 meaningfulness). This framework is further supported by prior work on meaningful work [84], which shows that seeing
431 one’s work as contributing to a greater good is associated with higher well-being and job satisfaction (Q6: ‘This task is
432 important to the success of my team or organization’).
433

434
435 **Status Maintenance [13, 15] (Q11-16).** These questions assess the extent to which workers continue performing a
436 task to preserve their professional standing, visibility, and perceived competence. Example survey items include ‘I feel
437 this task signals to others that I am busy or valuable’, and ‘I worry that letting go of this task could reduce my influence
438 or visibility’. These items are derived from prior work on impression management motives [15] where employees
439 engage in behaviors intended to influence how others perceive their abilities, dedication, or value to the organization.
440 Furthermore, related work from consumer research [13] emphasizes how lack of leisure time and ‘busyness’ serve as
441 status symbols, and they show how individuals may continue to pursue low-value tasks that make workers appear
442 ‘busy’ because these tasks serve as signals of competence and provide visibility even if they contribute little to core
443 performance outcomes.
444

445
446 **EPOCH [58] (Q17-21).** These questions capture the extent to which the task requires fundamental human capabilities
447 that prior work argues enable workers to excel in areas where AI is less likely to succeed. Drawing on the EPOCH
448 framework [58], we include items reflecting five dimensions that are particularly challenging to expose to AI: (1) empathy
449 and emotional intelligence (‘This task requires recognizing and responding appropriately to the emotions of others’),
450 (2) presence, networking and connectedness (‘This task benefits significantly from in-person interaction, non-verbal
451 cues, or spontaneous communication’), (3) opinion, judgment and ethics (‘This task involves making decisions that
452 require moral reasoning, accountability, or subjective judgment’), (4) creativity and imagination (‘This task requires
453 generating novel ideas, approaches, or solutions beyond standard procedures’), and (5) hope, vision and leadership
454 (‘This task involves setting direction, motivating others, or showing perseverance toward a long-term goal’).
455

456
457 **Human Flourishing at Work [87] (Q22-33).** These questions were adapted from VanderWeele [87]’s multidimensional
458 framework of work and flourishing. This framework conceptualizes flourishing as encompassing domains beyond
459 immediate job performance, including well-being, purpose, and social connection. We included survey items to capture
460 six domains: (1) Happiness and life satisfaction (e.g., ‘How much would this task make you feel satisfied or content
461 with your work?’), (2) Mental and physical health (e.g., ‘To what extent would this task support your mental health?’),
462

(3) Meaning and purpose (e.g., ‘To what extent would this task feel meaningful or worthwhile?’), (4) Character and virtue (e.g., ‘To what extent would this task allow you to act in accordance with your values or integrity?’), (5) Close social relationships (e.g., ‘To what extent would this task help you build or strengthen relationships with colleagues or clients?’), and (6) Financial and material stability (e.g., ‘To what extent would this task contribute to your sense of job or financial security?’).

469 470 471 472 473 474 475 476 477 3.4 Questions about AI Design Choices for AI Exposure to Administer to both Workers and Developers 478 (Q34-45)

479 Even when workers wish to use AI, prior studies show that AI tools often fail to meet their needs due to limited
480 understanding of which psychological traits workers expect AI systems to exhibit [26, 80]. Adoption and acceptance
481 of AI technologies depend on the extent to which these systems align with user values and expectations [86]. Yet,
482 value alignment is dynamic: values emphasized at the design stage often diverge from those prioritized by users
483 once technologies are deployed in real contexts [46]. Prior work has shown that values essential to effective task
484 performance (e.g., empathy, fairness, creativity) are rarely embedded into the design of AI systems [58]. To investigate
485 this gap, we assessed workers’ preferences for how an AI system should behave, if their tasks were exposed to it.
486 Specifically, Questions 34–45 (Step 3 in Figure 1, and Appendix Table 6) asked participants to rate the importance of
487 twelve psychological traits for an AI system to exhibit: four traits that we introduced (Q34–Q37: creativity, empathy,
488 explainability, and openness to challenge) based on the HCI literature [3, 65, 81], and eight traits taken from Dong et al.
489 [26] (Q38–Q45: fair, warm, sincere, tolerant, competent, determined, intelligent, and imaginative).
490
491

492 3.5 Administering Questions to Workers and Developers 493

494 We administered two complementary surveys: one to workers, and the other to developers. The worker survey was
495 designed to capture perceptions of workplace tasks and preferences for AI system behavior and consisted of Questions
496 1–45. The developer survey was designed to only capture preferences for AI system behavior and, thus, consisted of
497 Questions 34–45 (Appendix Table 6). Each item was rated on a 5-point Likert scale (1 = Strongly disagree, 5 = Strongly
498 agree). Both surveys concluded with the Human Agency Scale (HAS) [80] (e.g., Q48), which assessed desired levels
499 of human–AI collaboration. The scale ranges across varying degrees of human involvement: from AI agent drives
500 task completion (HAS H1–H2), to equal partnership (HAS H3), to human drives task completion (HAS H4–H5). In the
501 survey, workers were asked: *‘If AI were to assist in this task, how much of your collaboration would be needed to complete
502 this task effectively?’* Response options reflected the five HAS categories, allowing us to examine worker preferences for
503 human intervention and to contrast these with the intervention priorities of developers.
504
505

506 3.6 Scaling and Validating Responses with Language Models 507

508 To enable larger-scale analysis, we evaluate whether LMs can act as annotation assistants to simulate the distribution of
509 worker and developer responses. Recent work has demonstrated the promising potential of LMs as annotation assistants
510 in social science settings [71, 72, 78] where LMs can approximate human judgments in large scale surveys [5].
511

512 We used in-context learning with GPT-4o, applying chain-of-thought prompting [92] to adopt the persona of either
513 a worker or a developer for a given occupation. This procedure is briefly described in Step 4 of Figure 1, and the
514 prompts are fully detailed in Appendix Tables 9 and 10. Our approach aligns with prior work on LM-as-an-Expert
515 prompting [44, 62, 93], which has been validated as a method for eliciting domain-specific expertise from LMs. We then
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520

521 assessed the external validity of our findings based on LM-generated annotations (i.e., whether the patterns we report
522 are consistent with and generalize to human judgments) using three complementary strategies:
523

524 (1) **Testing whether incorporating the LM as an additional annotator improved inter-rater agreement.**

525 To evaluate the reliability of human annotations, we first assessed the reliability using only human annotators
526 ('experts') by calculating intra-class correlation coefficients (ICC) and mean absolute differences (MAD) at the
527 task level for items with at least three expert ratings. For the worker survey, experts alone achieved a mean ICC of
528 0.634 (moderate-to-good agreement; 95% CI = [0.602, 0.664]). Adding the LM as an additional annotator increased
529 the mean ICC to 0.742 (good agreement; 95% CI = [0.722, 0.760]), a statistically significant improvement of
530 +0.108 (95% CI = [0.093, 0.124]). For developer responses, experts alone achieved a mean ICC of 0.629 (moderate
531 agreement; 95% CI = [0.578, 0.676]). Adding the LM increased the mean ICC to 0.673 (moderate agreement; 95%
532 CI = [0.627, 0.713]), representing a statistically significant improvement of +0.044 (95% CI = [0.032, 0.058]). For
533 workers, LM ratings differed from experts by about 1.10 Likert points (normalized MAD = 0.276), only slightly
534 higher than expert-expert disagreement (0.255). For developers, LM-expert differences averaged 1.31 points
535 (normalized MAD = 0.328), which was not statistically significantly different from expert-expert disagreement
536 (0.324). To further assess whether ICC improvements reflected genuine alignment rather than artifacts of
537 increased rating stability, we conducted a robustness analysis by comparing the real LM's contribution to
538 that of a randomized version that preserved its overall rating distribution but no longer reflected task-level
539 correspondence with human ratings, by randomly shuffling its existing ratings. We then repeatedly added
540 this randomized LM to the human ratings and recomputed ICC across 1,000 bootstrap samples. Adding the
541 randomized LM yielded modest ICC increases (+0.079 for workers; +0.016 for developers), showing that some
542 improvement comes from variance stabilization. However, these increases were significantly smaller than those
543 from the real LM (+0.108 for workers; +0.044 for developers; $p < .0001$). This indicates that the ICC gains arise
544 from substantive alignment between the LM and human annotators, not statistical artifacts.
545

546 (2) **Comparing annotation distributions between LM and human raters, supplemented with qualitative**

547 **analyses.** Across the dimensions of meaningful work, LM ratings closely tracked human ratings, with only
548 minor differences in distributional shape (Appendix Figure 8). In addition to computing global reliability indices,
549 we examined the percentage of large discrepancies, defined as cases where human and LM ratings differed by
550 two or more points on the 5-point Likert scale. Whereas a one-point difference can be attributed to normal
551 subjectivity, a gap of two points or more represents a substantive divergence in interpretation [21]. Identifying
552 such items provides a diagnostic lens on the alignment of LM outputs with human ratings, revealing systematic
553 areas of disagreement that global coefficients such as ICC may obscure. We find that only 0.87% of tasks exhibit
554 such significant discrepancies. Across dimensions, the *EPOCH* questions showed the highest divergence at
555 2.92%, followed by *AI Design Choices* questions at 1.75%. All remaining dimensions (aside from a few AI-trait
556 questions) had negligible discrepancy rates, each below 1%. In these few cases, we observed that both LM and
557 human interpretations were reasonable when viewed from different contextual perspectives (Appendix Table
558 8). For example, the LM perceived the task '*review, classify, and record survey data in preparation for computer*
559 *analysis*' as a routine procedure with minimal emotional demands, whereas a human annotator emphasized its
560 creative and moral judgment aspects. Crucially, these divergences are best understood as subjective differences
561 rather than systematic bias, and, as we show in our third strategy, they do not affect the substantive results
562 when analyses are replicated using only human ratings.
563

- 573 (3) **Replicating the main analyses using only human ratings.** We replicated the core analyses that we will
 574 present in Section 4 using only human ratings. The replication yielded results that were highly consistent
 575 with those based on LM-generated ratings across both research questions, thereby providing a direct test of
 576 robustness. For RQ1 (Appendix Figure 9), humans and LMs agreed on 6 of the 7 meaningful-work dimensions
 577 that differentiated tasks likely to be exposed to AI from those unlikely to be exposed. The only exception
 578 was ‘*requires novel ideas or creativity*’. For RQ2, we conducted a head-to-head comparison between human
 579 ratings and LM-simulated ratings on our subset of 171 tasks. As shown in Appendix Tables 17 and 18, the
 580 pattern of worker–developer misalignment produced by human raters closely tracks the pattern produced by
 581 LM-simulated raters, with consistent rankings across high-, mixed-, and aligned traits. The strongest pattern
 582 was workers emphasizing straightforward traits, and developers emphasizing politeness traits, which was
 583 reproduced almost exactly in human-only ratings. Divergences appeared only in secondary dimensions (e.g.,
 584 ‘*handle complex vs. routine work*’, ‘*precise vs. simple*’). Manual review suggests this reflects sectoral biases
 585 introduced by the smaller, occupation-concentrated human sub-sample rather than any substantive difference
 586 in trait interpretation. Importantly, none of these divergences alter the main inferences: the central dimensions
 587 of meaningful work, and the dominant sources of worker–developer disagreement are consistent across LM
 588 and human annotations.

589 These results indicate that, in our setting, GPT-4o can serve as a reliable additional annotator for both worker and
 590 developer perspectives without reducing inter-rater reliability. We therefore used LM-generated ratings to scale our
 591 analysis to the full set of 10K O*NET tasks, spanning all 19 occupational sectors. The LM-annotated dataset provides
 592 broader coverage than the worker and developer surveys, with task distributions more closely aligned with the Bureau
 593 of Labor Statistics (Figure 2), supporting large-scale analysis of workforce patterns.

600 4 Results

601 Before presenting the results in depth, we provide a brief overview with references to the sections where each finding
 602 is discussed. In summary, we observed that:

- 603 (1) *Creative and high-agency tasks are more exposed.* Across sectors, tasks in the likely-to-be-exposed group tend
 604 to emphasize creativity, positive affect, and autonomy (Section 4.1). Sectors with higher scores on these traits
 605 include Arts, Architecture & Engineering, Computer & Mathematics, and Life, Physical, & Social Science
 606 (Figure 4). This pattern contrasts with the familiar narrative that automation will primarily absorb routine tasks,
 607 freeing workers to concentrate on higher-value activities such as strategy and design. Our results suggest a
 608 more complex trajectory. Generative systems are already used to draft text, suggest layouts, start campaigns, run
 609 simulations, and infer likely emotional responses. In our data, these uses are associated with tasks that workers
 610 describe as meaningful because they reflect taste, judgment, and authorship. Rather than being confined to
 611 low-level chores, AI systems are increasingly entangled with how people add value to work: from generating
 612 first ideas to editing, selecting, and retaining accountability.
- 613 (2) *Social and face-to-face tasks are less exposed.* Tasks rated as not likely to be exposed depend more on emotion,
 614 in-person contact, social ties, and support (Section 4.1). These cluster in Community & Social Service, Education,
 615 Healthcare, and Sales (Figure 5).
- 616 (3) *Worker–Developer misalignment.* We finally found systematic misalignment between how workers want AI
 617 systems to behave and how developers intend to design them (Section 4.2). Developers tend to emphasize
 618

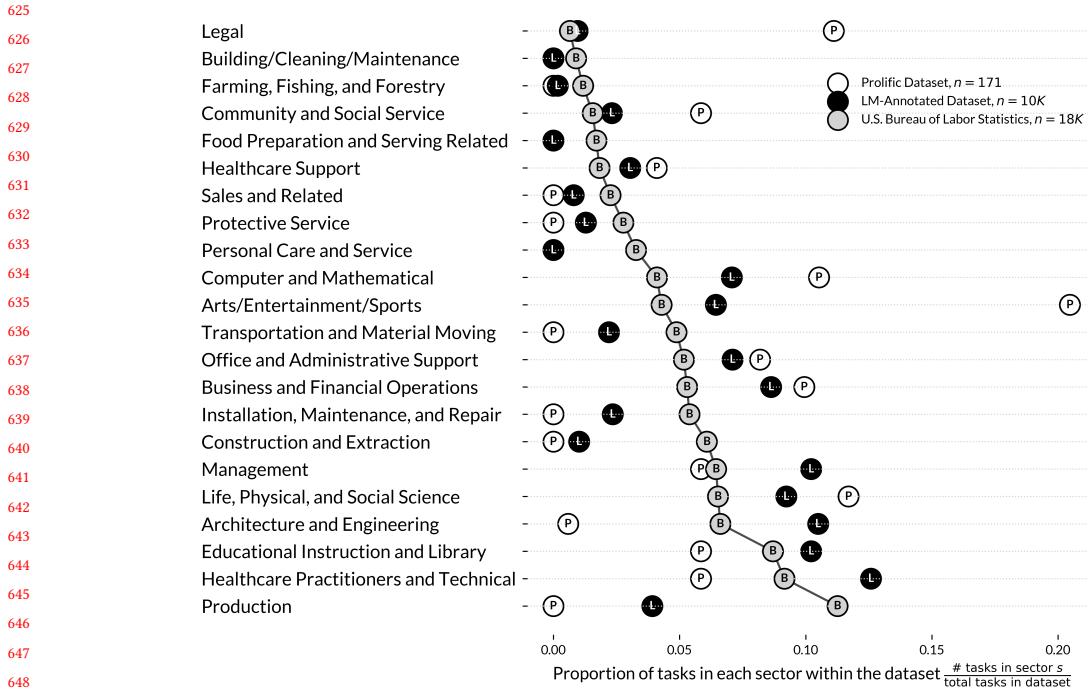


Fig. 2. Proportions of tasks across occupational sectors in three datasets: Prolific (n=171), LM-annotated (n=10K), and U.S. labor statistics (n=18K). The Prolific sample covers 12 sectors (based on available occupations), the LM-annotated dataset covers 19 sectors, and the U.S. Bureau of Labor Statistics dataset covers all sectors. The distributions of Prolific and LM-annotated tasks are broadly similar across sectors, indicating that LM annotations capture sector patterns consistent with worker data.

politeness, strictness, and imagination, especially in high-stakes or highly structured domains whereas workers often describe such traits as sources of delay or rigidity rather than support.

4.1 Which dimensions of meaningful work do workers associate with tasks exposed to AI? (RQ1)

Our goal in RQ1 is to examine whether tasks that are more likely to be exposed to AI differ systematically in the significance they hold for workers. Do they call for novel ideas? Are they associated with feelings of agency? Do workers link them to relationship building or emotional awareness?

To test this, we partitioned our tasks into likely-to-be-exposed vs. not-likely-to-be-exposed groups, and restrict the sample to computer-based occupations [80]. We then fit item-wise linear mixed-effects models on the 33 worker survey items (Q1–Q33), using exposure likelihood as a fixed effect and random intercepts for sector and occupation. We first identify which dimensions of meaningful work are disproportionately exposed to AI, then examine sector-level patterns, and provide task examples that align with statistically significant dimensions of meaningful work.

Likely-to-be-exposed vs. Not-likely-to-be-exposed Tasks. We divided our 10,131 tasks (LM-annotated) into two groups: *likely-to-be-exposed* vs. *not-likely-to-be-exposed*. We used AII [79] to estimate the likelihood that workplace tasks will be exposed to AI. Following Shao et al. [80], we further restricted both groups to occupations and tasks that are

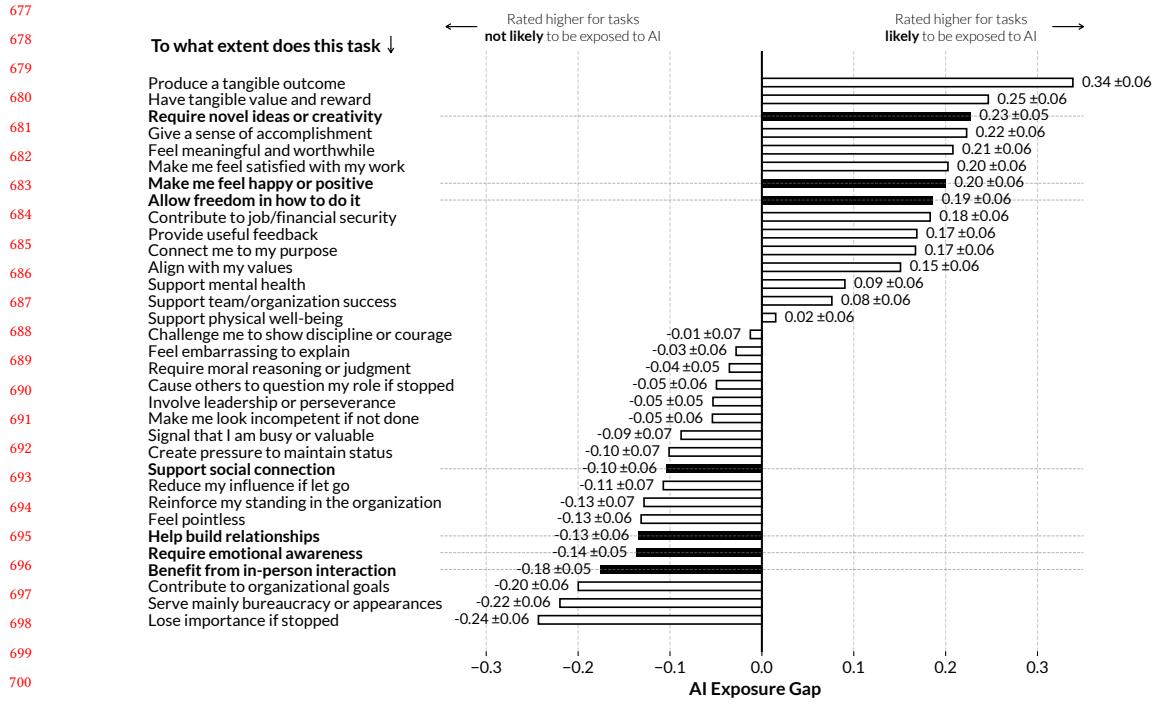


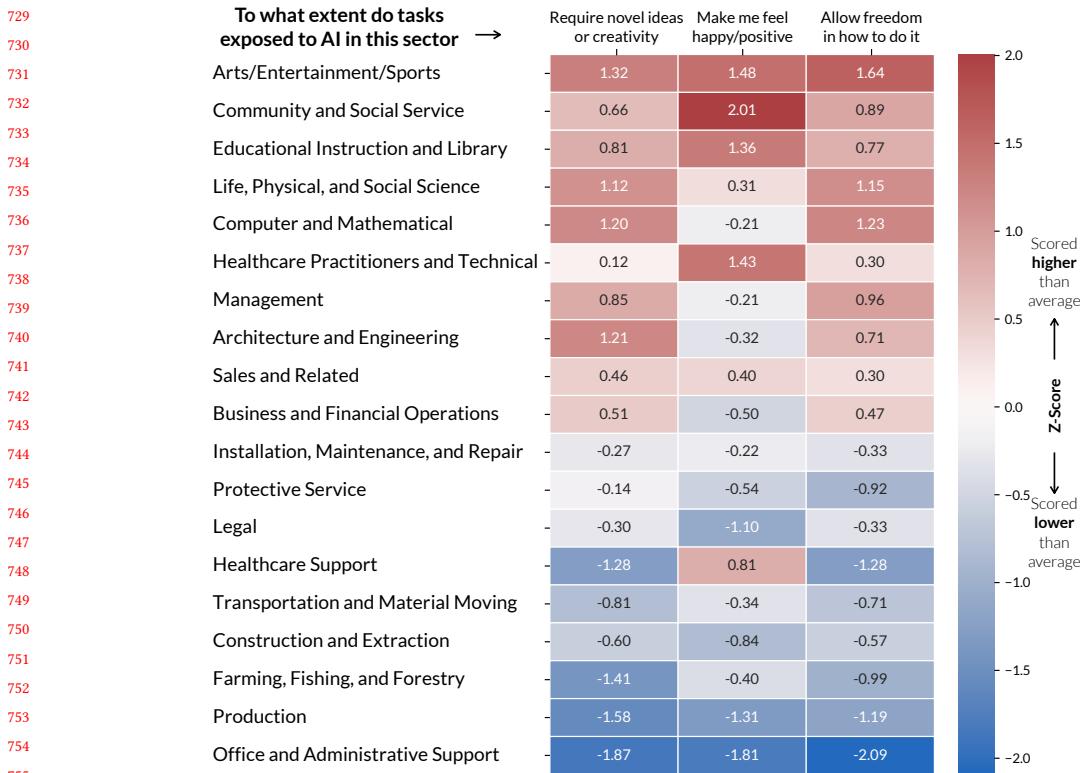
Fig. 3. AI Exposure Gap by dimensions of meaningful work (rows). The higher the gap, the more strongly that dimension is associated with tasks likely to be exposed AI. This gap is computed as the difference of how important a dimension is between two groups of tasks: those that seem more likely to be exposed to AI and those less likely. We estimate the gaps and 95% confidence intervals with mixed-effects models. Bold names and corresponding black bars indicate differences that are statistically significant. Tasks rated likely to be exposed tend to involve novelty, creativity, happiness, and freedom in how workers do them. Tasks rated not likely to involve emotional awareness, in-person interaction, building relationships, and supporting social connection.

primarily performed on a computer according to O*NET, resulting in 3,179 tasks across 426 occupations and 19 sectors in the likely-to-be-exposed group, and 2,349 tasks across 381 occupations and 19 sectors in the not-likely-to-be-exposed group.

Linear Mixed-Effects Regression Model. We estimate whether tasks likely to be exposed to AI systematically differ in their meaningfulness to workers as compared to tasks not likely to be exposed. For each task t , we computed the importance of each dimension d of meaningful work (e.g., requiring novel ideas or creativity, help build relationships). To estimate whether each dimension was more or less important in tasks likely to be exposed than in tasks not likely to be exposed, we fit a linear mixed-effects regression of the form:

$$z(y_{t,d}) = \beta_0 + \beta_1 \cdot \text{AIExposure}_t + u_s + u_{o(s)} + \epsilon_{t,d},$$

where $z(y_{t,d})$ is the z -score of the rating $y_{t,d}$ a worker gave to the importance of dimension of meaningful work d for task t ; AIExposure_t is a binary variable equal to 1, if task t is likely-to-be-exposed, or equal to 0, if task t is not-likely-to-be-exposed; β_0 is the fixed effect intercept, representing the baseline importance of dimension d for not-likely-to-be-exposed tasks ($\text{AIExposure}_t = 0$); β_1 is the fixed effect of AI exposure, estimating the mean difference



756 Fig. 4. Association of tasks exposed to AI in each of the sectors (in the *rows*) with subset of three dimensions of meaningful work
 757 (creativity, positive affect, and autonomy in the *columns*). Sectors are sorted by the average z-score across the three dimensions.
 758 Creative and socially-oriented sectors (arts, community service, education, life sciences) are associated with tasks exposed to AI that
 759 emphasize novelty, positivity, and freedom. In contrast, routine and manual sectors (office support, production, farming) score much
 760 lower.

761
 762
 763
 764 in worker ratings between likely-to-be-exposed and not-likely-to-be-exposed tasks. Given that tasks are nested within
 765 occupations, which, in turn, are nested within sectors, to account for varying baselines within sectors and occupations,
 766 we also included a random intercept u_s for sector s , and random intercept $u_{o(s)}$ for occupations nested within sector s ,
 767 followed by $\epsilon_{t,d}$, which is the residual error term for task t on dimension d . Models were estimated using maximum
 768 likelihood (restricted maximum likelihood, REML, disabled). For each dimension, we report β_1 (the difference in worker
 769 ratings for likely-to-be-exposed vs. not-likely-to-be-exposed tasks), its standard error, and 95% confidence intervals.
 770 To address multiple comparisons across our survey items, we applied the Benjamini–Hochberg False Discovery Rate
 771 (FDR) correction. We defined the fixed effect as statistically significant, if two conditions were met: (1) the FDR-adjusted
 772 $p < 0.05$, and (2) the effect size exceeded $\Delta \geq 0.1$ Likert points. While a threshold of 0.1 may appear small, our results
 773 are reported in aggregate across all sectors; when disaggregated at the sector level, we show that differences are often
 774 substantially larger. The latter serves as a threshold for practical significance: on a 5-point scale, a 0.1 shift represents a
 775 small but interpretable change in perceived task characteristics, ensuring that we highlight effects that are not only
 776 statistically detectable but also meaningful in practice.
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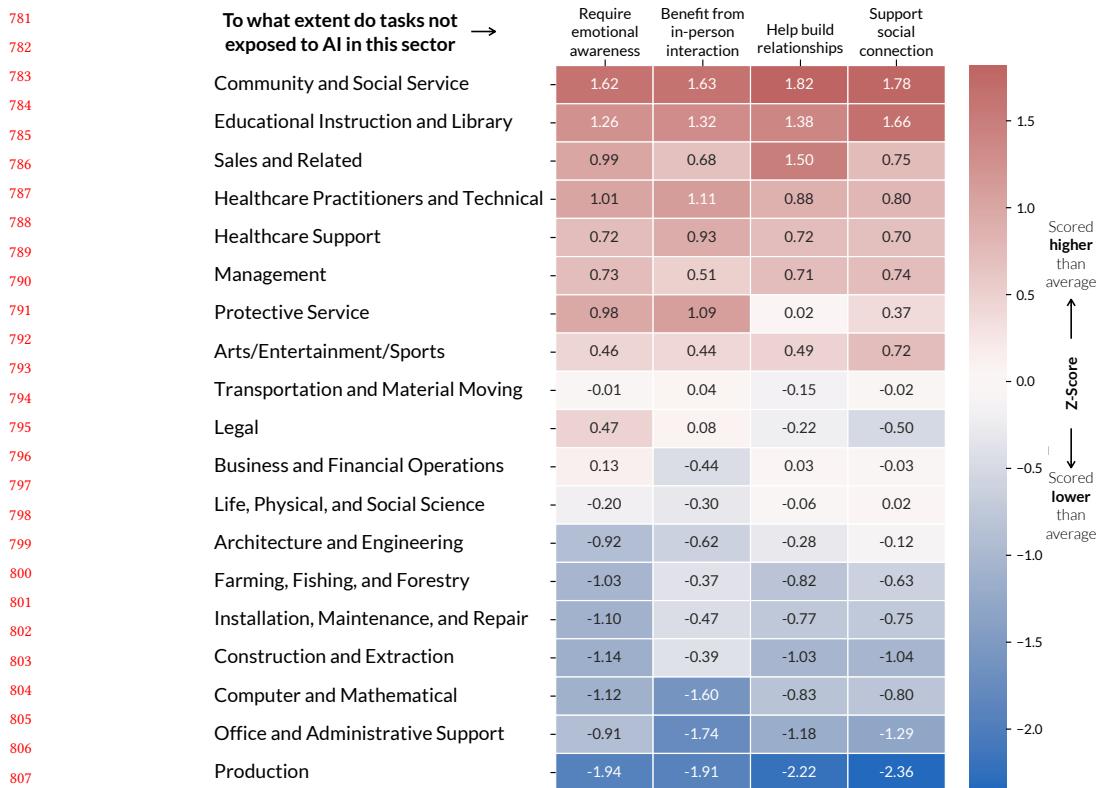


Fig. 5. Association of tasks not exposed to AI in each of the sectors (in the *rows*) with subset of four dimensions of meaningful work (emotional awareness, in-person interaction, relationship building, and social connections in the *columns*). Sectors are sorted by the average z-score across the subset of four dimensions. Human-facing sectors such as community and social service, education, and healthcare consider their tasks not exposed to AI to emphasize emotional awareness, in-person interaction, and social connection. In contrast, technical and routine sectors (e.g., production, office support, computer and mathematical) score far lower, indicating that workers in these areas view tasks not exposed to AI as less socially or emotionally significant.

The mixed-effects estimates and FDR-adjusted tests (see Appendix Table 11) yield three overarching findings about how AI exposure shapes the perceived importance of meaningful-work dimensions, and how these effects distribute across sectors:

- (1) *The tasks most exposed to AI involve creativity and high levels of individual agency, while tasks that rely on empathy, relationship-building, or in-person presence appear less exposed.* Across a subset of seven significant dimensions of “meaningful work”, those most exposed to AI emphasize novelty and creativity, personal agency, and the capacity to elicit positive emotions, whereas tasks less exposed emphasize social connection, relationship building, emotional attunement, and in-person interaction (Figure 3, and Appendix Table 11). Random-slope mixed-effects models allowing AI exposure to vary by sector showed largely consistent effects across sectors, with notable heterogeneity for visible/tangible outcomes, emotional awareness, in-person interaction, and physical well-being (likelihood-ratio tests, $p_{LR\!T} < 0.05$).

- 833 (2) *Tasks highly-exposed to AI cluster in creative, technical, and scientific domains, where AI systems increasingly sup-*
 834 *port ideation.* The greatest exposure appears in the Arts, Architecture & Engineering, Computer & Mathematics,
 835 and the Life, Physical, & Social Sciences (Figure 4). Illustratively, an Art Director “formulating basic layout
 836 design” and an Actuary “constructing probability tables for natural disasters” reflect first passes that models
 837 now credibly generate, with humans then refining the output (Appendix Table 12). These sectoral patterns
 838 align with cluster analyses of high-importance tasks (Appendix Tables 13-15). Tasks likely to be exposed to AI
 839 that evoke positive emotions are concentrated in Arts, Entertainment, Sports, & Media; Community & Social
 840 Services; and Healthcare (Figure 4).
- 841 (3) *Tasks that remain less exposed to AI are those that rely on relationships and sensitivity to context, with their value*
 842 *derived from human attention and judgment.* In Education, Sales, Community & Social Services, and Healthcare,
 843 core activities (e.g., “counseling students through intertwined academic and personal issues”, “presenting
 844 offers while preserving relationships”) depend on real-time, co-constructed meaning, and nuanced perception
 845 that resists codification (Figure 5, and Appendix Table 12). Consistent with this pattern, clusters emphasizing
 846 emotional awareness and relationship building are predominantly human-centered (Appendix Table 16).

852 4.2 Do teams design AI systems with traits that align with the traits workers want? (RQ2)

853 For RQ2 (Q34–Q45), we were interested not in dimensions of meaningful work, but in *AI traits*. That is, we asked
 854 workers and developers which traits an AI system should have. Each item defined a trait along a spectrum (e.g., Q39:
 855 “Should the AI show warmth and care, or remain neutral and businesslike?”), and participants rated their preference on
 856 a 1–5 scale. Worker responses indicated which traits an AI system should have when their tasks are exposed to it;
 857 developer responses indicated how practitioners would design such a system. Should the system be straightforward or
 858 polite? Tolerant or strict? Practical or imaginative? Flexible or determined?

859 To measure misalignment, we subtracted the rating workers assign to trait q for an AI system exposed to task t
 860 (workers rating $_{t,q}$) from the rating developers assign to the same trait for the same task (developers rating $_{t,q}$):

$$861 \Delta_{t,q} = \text{workers rating}_{t,q} - \text{developers rating}_{t,q}.$$

862 The magnitude $|\Delta_{t,q}|$ measures the size of the misalignment, while the sign indicates direction. For example, a positive
 863 $\Delta_{t,q}$ on Q39 indicates that workers preferred more warmth and care than developers, who leaned toward neutrality. We
 864 averaged task-level differences for each sector giving each task equal weight, giving us an average misalignment score
 865 per sector. To then test whether the differences between worker and developer ratings were statistically significant, we
 866 conducted a *two-sided t-test* of the null hypothesis that the mean task-level difference was zero for a given trait and
 867 sector. To account for multiple comparisons, p -values were adjusted using the Benjamini-Hochberg False Discovery
 868 Rate (FDR) procedure. A sector was labeled as significantly misaligned on a trait, if two conditions were met: (1)
 869 the FDR-adjusted $p < 0.05$; and (2) the absolute mean difference ($\frac{1}{N} \sum_{t=1}^N |\Delta_{t,q}|$; where N is the number of tasks in
 870 the sector) exceeded a threshold of 0.5 Likert points. We use 0.5 as a conservative threshold to focus on practically
 871 meaningful differences: unlike RQ1, which examined fine-grained within-task effects (where smaller shifts of 0.1 were
 872 informative), RQ2 compares worker-developer ratings aggregated across major occupational groups, where only larger
 873 gaps are more informative.

874 **Most and Least Misaligned Traits.** To analyze worker-developer misalignment, we ranked AI traits by their average

Table 1. Worker–developer misalignment by AI traits. Misalignment is defined as the average absolute difference between worker and developer ratings (Q34–Q45) of the traits they believe AI systems should possess. Differences ($\Delta_{t,q}$) are calculated as worker minus developer ratings for a given task t for a trait q , with the magnitude ($|\Delta_{t,q}|$) reflecting the size of the misalignment. Reported values are aggregated over sectors and traits are grouped into high, mixed, or aligned categories based on percentile thresholds of average absolute misalignment. # Sig. Sectors refers to the number of sectors that had statistically significant *differences* in ratings between workers and developers. The largest gaps appear for Straightforward vs. Polite, Tolerant/Open-minded vs. Strict, Practical vs. Imaginative, and Flexible vs. Determined, whereas traits such as Generalized vs. Personalized, Simple vs. Comprehensive, and Business-like vs. Warm/caring show little to no misalignment.

Trait	# Sig. Sectors	$\Sigma \Delta_{t,q} $	$\mu \Delta_{t,q} $
High misalignment			
(Q40) Straightforward vs. Polite	16	25.874	1.617
(Q41) Tolerant/Open-minded vs. Strict	5	4.449	0.890
(Q45) Practical vs. Imaginative	2	1.690	0.845
(Q43) Flexible vs. Determined	9	6.654	0.739
Mixed misalignment			
(Q34) Handle complex vs. Routine work	8	5.797	0.725
(Q35) Address emotions vs. Apathetic	4	2.849	0.712
(Q36) Explainable vs. Fast/automatic	16	10.940	0.684
(Q42) Precise vs. Simple	2	1.168	0.584
Aligned			
(Q37) Definitive vs. Open to challenge	3	1.713	0.571
(Q39) Business-like vs. Warm/caring	1	0.500	0.500
(Q38) Generalized vs. Personalized	0	0.000	0.000
(Q44) Simple vs. Insightful/Comprehensive	0	0.000	0.000

misalignment scores across sectors where worker/developer differences were statistically significant for a given sector ($FDR < 0.05$, $\frac{1}{N} \sum_{t=1}^N |\Delta_{t,q}| \geq 0.5$). Table 1 summarizes the classification of traits from most to least misaligned, while Figure 6 illustrates example occupations and tasks within each category. Sector-level misalignment scores for individual traits are reported in Appendix Tables 25–30. To summarize our results, we see that, across sectors (Figure 6), workers consistently favored straightforward systems; developers preferred polite ones. Workers wanted tolerance; whereas developers leaned towards more strict systems. Workers asked for practical systems; developers opted for more imaginative systems. Workers liked flexibility; developers nudged toward more determined systems. Where both groups aligned was telling: they valued deep understanding, personalization, and openness to challenge. That is, neither group preferred a generic system that appeared helpful but functioned as an unquestionable authority.

Also, to surface broad patterns of misalignment, for each trait, we identified tasks in the extreme percentiles of misalignment (top 99th, and bottom 1st), clustered these tasks using MPNet⁵ embeddings and K-Means clustering, and labeled the resulting clusters (Appendix Tables 19–24). To interpret these aggregate results, we distilled three recurring, salient design tensions:

- (1) *When the stakes are high, workers often treat ‘politeness’ as a delay rather than a feature.* The disagreements varied substantially across sectors. The politeness divide, in particular, was most pronounced in Production, Architecture & Engineering, and the Life, Physical, & Social Sciences, fields where vagueness can result in

⁵<https://huggingface.co/sentence-transformers/all-mpnet-base-v2>



Fig. 6. The three most misaligned AI traits (top row) and the three most aligned traits (bottom row). Larger values indicate greater disagreement between workers and developers. Scores are the absolute differences between workers' ratings of how much they want an AI system to exhibit each trait and developers' ratings of how much they intend to design that trait into an AI system. Icons show which trait direction each group prefers (e.g., workers wish straightforward systems, while developers set out to design polite systems). Top contributing sectors and example tasks are listed for each trait.

wasted materials, structural failures, or flawed data. When we clustered the most misaligned tasks on politeness (Appendix Table 22). This clustering highlighted the parts of the economy that demand exacting judgment: quality control, technical design, oversight, and coordination. The corresponding tasks resemble the day-to-day activities of highly skilled workers such as planning stress tests, analyzing medical procedures to forecast outcomes, or coordinating complex projects.

- (2) *Workers wanted AI systems that are flexible; developers tended to value strictness.* Along the tolerant–strict dimension, divergences were most pronounced in Community & Social Service ($\frac{1}{N} \sum_{t=1}^N \Delta_{t,q} = +1.27$), Education

($\frac{1}{N} \sum_{t=1}^N \Delta_{t,q} = +1.07$), and Management ($\frac{1}{N} \sum_{t=1}^N \Delta_{t,q} = +0.76$) (Appendix Table 28; N is the number of tasks in a sector). Although these settings might be presumed to benefit from greater structure, in practice, “strict” software is often experienced as rigid rule-based constraints that can limit practitioner judgment. Those domains are indeed characterized by frequent exceptions, and context-sensitive decision-making: for example, accommodating late coursework without disproportionate penalty, or processing intake information that does not conform to standardized fields. In Management & Education, as shown in Appendix Table 23, task clusters include process improvement, monitoring and planning, and budget or risk management, where developers emphasize stricter standards and oversight, while workers prefer tolerance and flexibility.

- (3) *Creativity is not always a virtue.* Along the practical–imaginative dimension, developers tended to favor more imaginative systems, whereas workers prioritized pragmatism. The largest divergences were in Farming, Fishing, & Forestry ($\frac{1}{N} \sum_{t=1}^N \Delta_{t,q} = -1.33$), Production ($\frac{1}{N} \sum_{t=1}^N \Delta_{t,q} = -1.09$), and Transportation & Material Moving ($\frac{1}{N} \sum_{t=1}^N \Delta_{t,q} = -0.60$). These are domains characterized by highly structured, routine workflows (Appendix Table 30). Workers engaging in equipment checks, plant monitoring, and traffic analysis preferred systems that detect anomalies, enforce compliance, and adhere closely to task constraints rather than tools oriented toward open-ended ideation. Task-level examples are illustrative (Appendix Table 24): checking equipment to ensure proper operation (Farming); monitoring power-plant indicators to detect operating problems (Production); and studying traffic delays by recording times and vehicle counts (Transportation). Consistent with this pattern, clustering results (Appendix Table 21) indicate that the most misaligned tasks are concentrated in routine technical operations: equipment monitoring, compliance, and other highly structured activities that emphasize accuracy, continuous monitoring, and rule adherence.

5 Discussion

In Section 5.1, we relate our findings to prior work and summarize our main empirical contributions. Section 5.2 then draws out implications for the design and governance of AI systems, and Section 5.3 concludes by discussing limitations of our study and directions for future research.

5.1 Relation to Prior Work and Overview of Findings

Relation to prior work and novel contributions. Prior work has found that, in many settings, augmentation is more common than end-to-end automation [16, 43, 80]. Our task-level analysis introduces a worker-centered perspective by examining how exposure relates to how work feels to workers, and by identifying the aspects they prefer to handle through in-person, social interaction. This complements exposure inventories by bringing in how tasks are experienced by workers, and by highlighting potential implications for design [16, 43, 80]. More specifically, we make three main contributions:

- (1) *A task-level link between exposure and meaning.* We analyze how AI exposure co-varies with dimensions of meaningful work and observe a clear pattern: exposure is higher for tasks involving new ideas, positive feelings, and freedom, and lower for tasks that rely on emotional attunement and in-person relationships (Figures 3, 4, and 5) [43, 80].
- (2) *A worker–developer trait map for AI exposure.* We quantify where workers and developers differ on AI traits by sector and task. We find stable agreement on personalization and deep comprehension/insightfulness, and large gaps on “straightforward vs. polite” (Table 1, Figure 6, and Appendix Figure 10) [79].

- 1041 (3) *A scalable rating process with checks.* We pair human ratings with LM-assisted ratings to cover the largest set of
 1042 tasks present in the literature, while ensuring validity. In our data, adding the LM as an additional annotator
 1043 was associated with higher inter-rater agreement for both worker and developer instruments, and we document
 1044 where LM and human views diverge (Table 8, and Appendix Figure 8) [94].
 1045

1046
 1047 **Workers and developers differ in specific AI traits.** We briefly compare where they differ and where they agree,
 1048 and then suggest a broader design implication:
 1049

1050 *Where they differ most.* Workers want AI that is straightforward, tolerant and open-minded, practical, and
 1051 flexible. Developers plan for AI that is more polite, strict, imaginative, and determined. The biggest gaps appear
 1052 for straightforward vs. polite, tolerant vs. strict, practical vs. imaginative, and flexible vs. determined (Figure 6
 1053 and Table 1). Sector gaps for straightforward vs. polite are largest in Production, Architecture & Engineering, and
 1054 Life, Physical, & Social Sciences, with smaller gaps in Education, and Community & Social Service (Figure 10).
 1055

1056 *Where they agree.* Both groups favor deep understanding/comprehension, personalization, and openness to
 1057 challenge, with little to no systematic gap (Figure 6 and Table 1).
 1058

1059 *Design Implication.* Our results suggest that AI development teams should compare planned trait choices to
 1060 worker preferences for the target task and sector. In domains with technical judgment and oversight, large gaps
 1061 on straightforward vs. polite, and tolerant vs. strict call for careful defaults, clear settings, and a broader set of
 1062 design choices (Section 6).
 1063

1064 5.2 Implications

1065 We translate our results into three steps for deployment: design the interaction to protect meaning, measure the
 1066 outcomes that matter, and tune defaults by sector and task.
 1067

1068 *Design the interaction to protect meaning.* An interface that makes assistance easy to accept, edit, and credit
 1069 (without reducing the worker’s role) is consistent with our findings. Control stays at the task level when
 1070 the system exposes levels of help at the sub-step (by, e.g., suggesting, drafting, or executing), and defaults to
 1071 reversible suggestions that require explicit confirmation before applying changes. Clarity about edits and credit
 1072 comes from showing sources and a simple revision history, which makes authorship and changes visible in the
 1073 final output. Tone should match the work: when a straightforward style is preferred, a plain default with an
 1074 optional tone control should be suitable (Figures 6 and 10).
 1075

1076 *Measure what the design seeks to preserve.* We recommend measuring, during deployment, whether the design
 1077 preserves human control, supports learning, and assigns credit fairly, without sacrificing speed or quality. Short,
 1078 task-linked metrics should capture latency and output quality, while logs record the assistance level (suggest,
 1079 draft, execute) and the final decision-maker. Regular reviews of these logs can help teams monitor whether
 1080 deployments remain aligned with meaningful assistance rather than drift toward replacement.
 1081

1082 *Set sector-aware defaults.* We recommend setting sector-specific defaults that reflect the task differences found
 1083 in our results (Figures 6 and 10). For technical oversight and design, defaults should be simple, practical, and
 1084 adjustable. For care and education, defaults should be warm and personal while keeping limits explicit. More
 1085 generally, in contexts where emotional awareness and in-person interaction are essential, our results point
 1086

1093 toward using AI primarily for background tasks (e.g., preparing briefs, summarizing records, and flagging
 1094 anomalies), while reserving protected time for direct human engagement.
 1095

1096 Our findings suggest an *interaction-as-policy* lens: decisions about who clicks, who decides, who sees what, and
 1097 what the AI system makes easy or hard are not just UX choices but *governance* choices embedded in the interface. This
 1098 builds on HCI and STS work that treats infrastructures, defaults, and algorithms as forms of governance (e.g., code as
 1099 law, scripts that configure users, and algorithmic management in workplaces) [2, 46, 73]. This lens helps organize four
 1100 observed phenomena:
 1101

- 1102 (1) *Situated manners.* Situated manners recast politeness in HCI as a context-sensitive control, not a universal
 1103 style. “Frictionless and chatty” helps in consumer chat, but in operational work, where risk, time pressure,
 1104 irreversibility, uncertainty, and physical coupling matter, verbosity and small talk distract. The system should
 1105 default to short, clear outputs and strategic silence. Examples from Section 4: disaster-risk tables should present
 1106 the number, the limit, and the next action; for purchase offers, the system should surface price, terms, and
 1107 deadline first; in counseling, the system should adopt a warmer tone and avoid imperatives. In high-risk contexts,
 1108 the ethical choice may well be the blunt one, and the useful thing to say may be short.
 1109
- 1110 (2) *Liability anxiety.* Our results are consistent with the idea that liability concerns may contribute to preferences for
 1111 strictness. In our “Regulatory requests for information” cluster (Legal, Sales in Section 4), stricter configurations
 1112 may have reduced wrongful disclosures and minimized regulatory or contractual exposure, but may have
 1113 increased missed statutory windows and incomplete filings despite available data.
 1114
- 1115 (3) *Romanticized creativity.* Developers often romanticize creativity as “frontier intelligence”, but our findings
 1116 suggest that creativity is most helpful when tightly sequenced and scoped. In field troubleshooting, operators
 1117 want diagnosis first (fault codes, likely failure chains, next safe test). In regulatory responses, creative paraphrase
 1118 undermines audit-readiness. In customer support, agents prefer policy-aligned drafts with required fields pre-
 1119 filled over lively copy that risks unauthorized promises.
 1120
- 1121 (4) *Power structures.* Our analysis treats interaction design as a form of policy, but it is important to ask *who sets that*
 1122 *policy*. Our results show that tasks with high levels of creativity, freedom, and happiness are especially likely
 1123 to be exposed to AI. In practice, managers, vendors, and technical teams (not workers) usually decide which
 1124 tasks to expose to AI, how far to automate them, and how to evaluate success, often under pressure to improve
 1125 efficiency [50]. This pattern parallels familiar power asymmetries from work on algorithmic management, where
 1126 data-driven systems restructure tasks, monitor performance, and allocate rewards in ways that can increase
 1127 organizational control over workers [46, 73]. In our setting, interaction patterns (such as one-click automation
 1128 and suggestion-on-demand) shape whether AI replaces or supports the parts of the job that workers report
 1129 finding most meaningful. Managers, vendors, and technical teams make these decisions before workers can
 1130 consent or take part, especially in roles with low bargaining power. Therefore, beyond designing interfaces that
 1131 let individuals retain agency within a task, organizations should give workers some say over which task clusters
 1132 are candidates for automation. When such mechanisms for voice are absent, AI exposure risks deepening
 1133 existing power imbalances. Prior work on algorithmic management and worker-centered AI points to several
 1134 mitigations: involving workers and their representatives directly in technology decision-making (through, e.g.,
 1135 formal consultation and collective bargaining over AI deployments), creating worker or union “technology
 1136 representatives” with access to information about how systems allocate and evaluate work, and requiring
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1145 transparency tools or reports that surface the indicators workers need to understand and contest algorithmic
 1146 decisions [2, 22, 30, 73].
 1147

1148 5.3 Limitations

1149 This work has several broad limitations:

- 1150 (1) *Representativeness of tasks and participants.* We have focused on U.S. occupational tasks. Results may differ in
 1151 other regions or settings with other norms or tools [16]. Our worker and developer samples were recruited
 1152 through Prolific, where participants tend to be more technologically literate. As a result, perspectives from
 1153 low-wage, non-digital, or less AI-exposed occupations may be underrepresented. Although our pre-screening
 1154 procedure ensured that participants were highly familiar with the tasks they evaluated, future work should
 1155 expand to other recruitment channels (e.g., industry partnerships, unions, vocational training programs) to
 1156 capture a wider diversity of workplace contexts and skill levels. Although the distribution of technical roles,
 1157 AI usage, and work functions in our sample indicates that developers were actively engaged in building or
 1158 maintaining AI-driven systems across diverse sectors (Figure 7), we acknowledge that our samples may not
 1159 fully capture the breadth of industry roles.
 1160
- 1161 (2) *Modeling assumptions.* Our mixed-effects regression models assume linear relationships between AI exposure
 1162 likelihood and each dimension of meaningful work. While this framework is appropriate for estimating average
 1163 effects across occupations and sectors, relationships among meaningfulness dimensions may be non-linear or
 1164 interactive. For example, creativity and autonomy may jointly shape how a task is exposed to AI. Exploring
 1165 non-linearities, higher-order interactions, and potentially hierarchical or multivariate modeling structures is an
 1166 important direction for future work.
 1167
- 1168 (3) *Measurement bias in LM-assisted scaling.* We used an LM to scale ratings to roughly 10K tasks, which raises
 1169 concerns about whether it reflects worker and developer perspectives or simply produces plausible responses.
 1170 We therefore treat LM ratings as approximating the distribution of human responses rather than as ground truth,
 1171 and use the term “agreement” to avoid implying a correct answer. To justify LM-assisted scaling, we compared
 1172 empirical findings from LM vs. human ratings and observed that LM-simulated patterns of worker-developer
 1173 misalignment closely matched human-only results (Appendix Figure 9, and Appendix Tables 17 and 18).
 1174 Robustness checks further confirmed that ICC gains cannot be explained by LM stability alone, indicating
 1175 substantive alignment between LM and human judgments. However, LM ratings are more uniform and optimistic
 1176 in some sectors, and qualitative divergences remain (Appendix Table 8, and Appendix Figure 8). These findings
 1177 support using LMs for scaling, but should be interpreted cautiously, as they may miss fine-grained nuances
 1178 present in human judgments.
 1179
- 1180 (4) *Task filtering and indices of exposure.* Our task-selection pipeline reduced the full O*NET task universe to a
 1181 subset most relevant for AI exposure, which may introduce task mix bias. Although we used established filters
 1182 and impact scores [8, 79, 80], this process inevitably excludes tasks that matter in practice, especially specialized
 1183 or licensed work that participants reported low familiarity with. We restored a targeted set of tasks from
 1184 domains such as healthcare and education, and our final sample aligns with the U.S. Bureau of Labor Statistics
 1185 employment distributions, but finer-grained gaps within sectors may remain. Future work with domain experts
 1186 or professional organizations could help validate task coverage and identify activities that should be included.
 1187

1197 (5) *Interpretative variation of O*NET task descriptions.* The O*NET database consists of task statements, which are
 1198 concise summaries of work activities. As a result, workers in the same role may imagine different scenarios of a
 1199 task (e.g., ‘formulating basic layout designs’), introducing natural variation in how workers and developers judge
 1200 these activities. Such interpretive variation is inherent to standardized work taxonomies used in economics
 1201 and occupational science. In our study, we partly mitigated this variability by: (1) recruiting participants who
 1202 perform these tasks in practice; and (2) restricting the analysis to tasks workers rated as ‘highly familiar’. While
 1203 the subjective nature of our assessments warrants inherent variability in task judgments, the strong agreement
 1204 between human and LM ratings suggests that interpretation variability did not substantially impact the main
 1205 observed patterns.
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1210 6 Conclusion

1211 Our results suggest that the tasks most likely to be exposed to AI are disproportionately those that workers associate
 1212 with joy and agency: novelty and creativity, feeling happy, and having freedom in how to do the work. Yet current
 1213 design choices often appear not to match what workers say they want from AI, raising concerns that such systems may
 1214 affect how meaningful work feels. This outcome is shaped by design choices, which can, in principle, be revised. As
 1215 HCI researchers, we propose a five-part agenda detailed in Table 2.
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1218 We argue that a central risk of AI exposure is not mass unemployment but “mass demoralization”: a loss of meaning
 1219 and ownership in day-to-day work. As models generate more early-stage outputs, the visible creative steps can
 1220 feel machine-made, while human contributions can become rushed, under-resourced, and hard to recognize. The
 1221 corresponding promise, if systems are designed and governed accordingly, is a clearer and more humane division of
 1222 labor: systems that accelerate exploration and drafting, and people who retain authorship, make final judgments, and
 1223 sustain the relationships that define meaningful work.
 1224
 1225

1226 7 Ethical Considerations

1227 This study received approval through our institution’s research ethics review process. In recruiting workers and
 1228 developers on Prolific, we did not collect personally identifiable information, and participants could withdraw at any
 1229 time.
 1230

1231 Beyond procedural safeguards, the study raised three broader ethical considerations. First, surveying both workers
 1232 and developers about task-level evaluations of work and AI traits risks reinforcing stereotypes about either group’s
 1233 perspectives. For instance, developers may be framed as indifferent to meaningful work, or workers as resistant to
 1234 technology, while aggregate analyses can mask the diversity of individual viewpoints. To mitigate this, we reported
 1235 results in the aggregate but emphasized the diversity of participant perspectives. We also encourage future work to
 1236 analyze individual-level differences, including how socio-demographic characteristics shape experiences of meaningful
 1237 work.
 1238

1239 Second, our use of LMs to scale annotations introduces the risk of amplifying biases. LMs may underrepresent
 1240 perspectives from marginalized groups or impose normative judgments about what constitutes meaningful work.
 1241 To address this, we benchmarked model outputs against human responses, reported intra-class correlation metrics,
 1242 and included parallel analyses based on human-only ratings to contrast with LM-scaled analyses. We caution that
 1243 model-based scaling is an approximation, not a replacement, for direct human judgment.
 1244

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1251 Table 2. From empirical observations to research questions and developer/designer heuristics for worker-aligned AI. Each row links
our findings to specific HCI research questions, example workflows, and design heuristics aimed at preserving creativity, autonomy,
and meaning in day-to-day work.

1252	Empirical Observation + Example Workflow	Research Questions and Developer/Designer Heuristics
1253	High-agency tasks appear heavily exposed to AI. In our analysis, tasks that workers associate with a sense of agency and freedom are more likely to fall into the high-exposure-to-AI group (Section 4.1).	Research questions. (1) How does asking workers to first write a short description (2–3 sentences) of what they want the system to produce relate to perceived autonomy, satisfaction, and final quality in writing or design tasks? (2) What interaction patterns (e.g., several alternative suggestions, step-by-step assistance) are associated with workers feeling that they keep “final say” over high-agency tasks?
1254	<i>Example workflow (ideation/drafting).</i> A marketing specialist works with an AI assistant that, given a short prompt, produces full campaign drafts and subject lines, so the worker may end up editing model outputs more than starting from their own ideas and voice.	Heuristics for developers/designers. (1) Add a first step where the worker writes what they want and any limits (e.g., “Write your 2–3 key ideas before the model drafts”); (2) show several alternative suggestions (e.g., different headlines or outlines) instead of only one full replacement; and (3) make it easy to accept or reject content at the level of small pieces (sentences or sections) instead of only offering one-click “Replace all”.
1255		Where in the workflow. Ideation, outlining, first-draft generation, early revision.
1256		What success looks like. Examples of success indicators include: (1) higher “felt in control” and “this still feels like my work” ratings in in-product surveys; (2) more edits and customizations on high-meaning sections, with AI used primarily for structure and low-level polish; and (3) similar or better quality with similar time spent on creative parts, and less time on mechanical rewrites.
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1263	Joyful and creative parts of work often fall in high-exposure categories. In our analysis, tasks that workers describe as creative and enjoyable are more likely to be classified as highly exposed to AI (Section 4.1).	Research questions. (1) How does the order of work (worker makes an initial sketch and the AI helps afterwards, versus the AI creates an initial version and the worker edits it) relate to perceived joy, ownership, and long-term skill growth? (2) Which parts of a multi-step task do workers report wanting to automate (e.g., resizing and formatting) versus keep manual (e.g., core concept and overall narrative)?
1264		
1265		
1266	<i>Example workflow (design / analysis).</i> A product designer receives auto-generated page layouts and color schemes from an AI tool and then mainly cleans up edge cases, rather than exploring ideas from scratch.	Heuristics for developers/designers. (1) Break workflows into labeled stages (e.g., “brainstorm”, “structure”, “polish”), and let workers toggle AI on or off for each stage; (2) start creative fields empty and require at least a rough human sketch, prompt, or storyboard before enabling AI suggestions; (3) add a simple option such as a checkbox or tag (e.g., “I want to do this part myself”) and avoid full automation on marked stages, limiting AI to suggestions or diagnostic feedback there.
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1273	Relational work appears less exposed to AI. In our data, work that supports social connection and relationships tends to appear in the lower-exposure-to-AI group (Section 4.1).	Research questions. (1) How can AI best support, rather than substitute, relational work (e.g., coaching, mentoring, and conflict resolution), according to workers? (2) Which background tasks (e.g., summarizing histories and drafting logistics messages) do workers experience as most helpful in freeing up time for high-quality human interaction?
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1276	<i>Example workflow (teaching / care / management).</i> A teacher, manager, or clinician uses AI tools mainly for canned email replies and templated feedback, which can risk making communication feel more generic and less personal to students, team members, or patients.	Heuristics for developers/designers. (1) Use AI to prepare briefs and summaries (e.g., student history, case notes, and prior conversations) so the human arrives better informed to the interaction; (2) default automated replies to low-stakes logistics (e.g., scheduling and confirmations), and route emotionally nuanced or high-stakes messages to humans with short, editable drafts; and (3) during live calls or sessions, assign AI to silent roles (note-taking and surfacing relevant past information) rather than having it speak on the worker’s behalf.
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1283	Workers and developers differ in reported preferences for AI assistant traits. Workers in our sample consistently report preferring straightforward, tolerant, and practical systems; developers report aiming to design polite, strict, and imaginative ones (Section 4.2).	Research questions. (1) How are different trait profiles (straightforward vs. polite, and tolerant vs. strict) associated with task accuracy, correction speed, and perceived trust in high-stakes domains? (2) What interface controls do workers find most useful for quickly adjusting an AI assistant’s style to match task demands without feeling overwhelmed?
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1287	<i>Example workflow (information lookup / decision support).</i> A production engineer uses an AI assistant that responds to fault queries with long, polite paragraphs and speculative explanations, when what they want is a short, actionable checklist.	Heuristics for developers/designers. (1) Ship work tools so that, by default, they answer in a straightforward and concise way and let users change this setting for each task, if they want more politeness or detail; (2) provide a simple control (e.g., a slider) so users can choose between short vs. detailed answers and between strict vs. tolerant behavior; and (3) A/B test trait profiles against worker-centered metrics such as time-to-correction, frequency of follow-up clarifying prompts, and perceived friction.
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1295	Third, questions about meaningful work can be sensitive, as they touch on participants’ identity, job satisfaction, and professional dignity. Reflecting on whether one’s work feels undervalued or easily automated can be unsettling. To minimize potential harm, we framed survey items in neutral and respectful language, and piloted them for clarity before deployment.	Where in the workflow. Information retrieval, explanation, diagnosis, and decision support. What success looks like. Examples of success indicators include: (1) fewer cases where users report needing to skip over long, unnecessary text (e.g., collapsing long answers or repeatedly asking the system to “make it shorter”); (2) shorter time to correct or verify model outputs in structured tasks; (3) higher ratings that “the assistant speaks my language for this task” in post-task surveys.
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These considerations highlight the importance of protecting participants' dignity and avoiding overgeneralization when studying misalignment between workers and developers. Our aim is not to prescribe what should count as meaningful work, but to inform AI design choices that respect and align with workers' values.

8 Author Positionality Statement

Our research team consists of two women and two men from the United States, Asia and Southern Europe representing diverse ethnic, linguistic, and religious backgrounds. All authors have lived and worked in multiple countries, including the United States, giving us direct experience with the cultural, economic, and policy contexts relevant our study. Our combined expertise spans natural language processing, Responsible AI, computational social science, human-computer interaction, and AI ethics. One author works primarily in academia, while others have experience in both academic and applied research settings.

Our positionalities shaped how we framed the research problem, selected sectors and occupations for analysis, and interpreted findings on worker/developer perspectives to AI exposure. Having worked across different cultural and labor market contexts informed our awareness of how occupational values and AI impacts can vary across sectors, regions, and professional identities. We recognize that our perspectives are influenced by our own academic and research experiences, which may limit the range of viewpoints represented. To support more inclusive and contextually grounded research on AI and the future of work, we encourage future studies to incorporate perspectives from workers, developers, and policymakers in regions and sectors beyond those examined here.

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1509 A Selecting O*NET Tasks

1510 In our initial filtering, we used GPT-4o judgments to determine whether a task or occupation primarily involved
 1511 computer usage. Manual inspection revealed that GPT-4o occasionally excluded occupations such as nursing and
 1512 education, which are widely recognized as being impacted by AI innovations [70, 74, 75]. To address this, we manually
 1513 curated a list of 427 occupations exempted from these filters, with examples shown in Appendix Table 4.

1514 To construct a representative sample of tasks from O*NET, we next mapped O*NET occupations to those available on
 1515 Prolific. Table 3 presents the mapping between Prolific ‘work function’ screeners and corresponding O*NET occupations.
 1516 Occupations without a Prolific mapping were excluded from our human study.

1517 Table 3. Prolific functions and their associated jobs.

Prolific Function	Mapped O*NET Occupations
Account Management	New Accounts Clerks
Administration/ Personal Assistant	Administrative Services Managers, Executive Secretaries and Executive Administrative Assistants, First-Line Supervisors of Office and Administrative Support Workers, Legal Secretaries and Administrative Assistants, Medical Secretaries and Administrative Assistants, Receptionists and Information Clerks, Secretaries and Administrative Assistants, Except Legal, Medical, and Executive
Chemical / Mechanical / Electrical / Civil Engineering	Architectural and Civil Drafters, Automotive Engineering Technicians, Chemical Engineers, Chemical Plant and System Operators, Civil Engineering Technologists and Technicians, Civil Engineers, Electrical Engineers, Electrical and Electronic Engineering Technologists and Technicians, Electrical and Electronics Drafters, Electro-Mechanical and Mechatronics Technologists and Technicians, Energy Engineers, Except Wind and Solar, Environmental Engineers, Industrial Engineers, Materials Engineers, Mechanical Drafters, Mechanical Engineering Technologists and Technicians, Mechanical Engineers, Petroleum Engineers, Transportation Engineers, Water/Wastewater Engineers
CX / Customer Experience / Support	Computer User Support Specialists, Customer Service Representatives
Data Analysis	Business Intelligence Analysts, Data Scientists, Statistical Assistants, Statisticians
Design or Creative	Art Directors, Art Therapists, Commercial and Industrial Designers, Fine Artists, Including Painters, Sculptors, and Illustrators, Graphic Designers, Interior Designers, Poets, Lyricists and Creative Writers, Set and Exhibit Designers, Special Effects Artists and Animators, Video Game Designers, Web and Digital Interface Designers
Healthcare Professional	Acute Care Nurses, Anesthesiologist Assistants, Clinical Data Managers, Clinical Neuropsychologists, Clinical Nurse Specialists, Clinical Research Coordinators, Community Health Workers, Critical Care Nurses, Cytotechnologists, Diagnostic Medical Sonographers, Emergency Medical Technicians, Family Medicine Physicians, General Internal Medicine Physicians, Health Informatics Specialists, Health Specialties Teachers, Postsecondary, Healthcare Social Workers, Home Health Aides, Hospitalists, Magnetic Resonance Imaging Technologists, Medical Appliance Technicians, Medical Assistants, Medical Equipment Preparers, Medical Equipment Repairers, Medical Records Specialists, Medical Scientists, Except Epidemiologists, Medical and Clinical Laboratory Technologists, Medical and Health Services Managers, Neurologists, Nurse Anesthetists, Nurse Midwives, Nurse Practitioners, Nursing Assistants, Occupational Health and Safety Specialists, Occupational Therapists, Orthodontists, Paramedics, Pediatricians, General, Pharmacy Aides, Physical Therapists, Physician Assistants, Physicians, Pathologists, Preventive Medicine Physicians, Psychiatric Technicians, Radiologic Technologists and Technicians, Radiologists, Registered Nurses, Surgical Assistants
Engineering (e.g. software)	Architectural and Engineering Managers, Automotive Engineers, Computer Hardware Engineers, Computer Programmers, Computer Systems Analysts, Computer Systems Engineers/Architects, Computer and Information Systems Managers, Computer, Automated Teller, and Office Machine Repairers, Electronics Engineers, Except Computer, Fuel Cell Engineers, Geothermal Production Managers, Health and Safety Engineers, Except Mining Safety Engineers and Inspectors, Human Factors Engineers and Ergonomists, Manufacturing Engineers, Mechatronics Engineers, Microsystems Engineers, Nanosystems Engineers, Radio Frequency Identification Device Specialists, Robotics Engineers, Robotics Technicians, Software Developers, Software Quality Assurance Analysts and Testers, Solar Energy Systems Engineers, Telecommunications Engineering Specialists, Validation Engineers, Web Developers, Wind Energy Engineers
Finance or Accounting	Accountants and Auditors, Bill and Account Collectors, Bookkeeping, Accounting, and Auditing Clerks, Budget Analysts, Credit Analysts, Financial Examiners, Financial Managers, Financial Quantitative Analysts, Financial Risk Specialists, Financial and Investment Analysts, Investment Fund Managers, Loan Officers, Personal Financial Advisors, Treasurers and Controllers
Fundraising	Fundraisers, Fundraising Managers
Human Resources	Compensation and Benefits Managers, Human Resources Assistants, Except Payroll and Timekeeping, Human Resources Managers, Human Resources Specialists

1559 Continued on next page

Table 3. Prolific functions and their associated jobs.

Prolific Function	Jobs
IT / Information Networking / Information Security	Computer Network Architects, Computer Network Support Specialists, Database Administrators, Information Security Analysts, Information Security Engineers, Network and Computer Systems Administrators, Security Managers, Web Administrators
Legal	Law Teachers, Postsecondary, Lawyers, Paralegals and Legal Assistants
Marketing	Advertising and Promotions Managers, Market Research Analysts and Marketing Specialists, Marketing Managers, Search Marketing Strategists
Operations	General and Operations Managers
Product or Product Management	
Project or Program Management	Information Technology Project Managers, Management Analysts, Project Management Specialists
Public Relations / Communications	Communications Teachers, Postsecondary, Public Relations Managers, Public Relations Specialists
Research	Bioinformatics Scientists, Computer and Information Research Scientists, Operations Research Analysts, Social Science Research Assistants, Survey Researchers
Sales / Business Development	Advertising Sales Agents, Demonstrators and Product Promoters, Door-to-Door Sales Workers, News and Street Vendors, and Related Workers, Driver/Sales Workers, Insurance Sales Agents, Retail Salespersons, Sales Engineers, Sales Managers, Sales Representatives of Services, Except Advertising, Insurance, Financial Services, and Travel, Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products, Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products, Securities, Commodities, and Financial Services Sales Agents, Telemarketers
Education Professional	Atmospheric, Earth, Marine, and Space Sciences Teachers, Postsecondary, Business Teachers, Postsecondary, Career/Technical Education Teachers, Middle School, Career/Technical Education Teachers, Postsecondary, Career/Technical Education Teachers, Secondary School, Computer Science Teachers, Postsecondary, Economics Teachers, Postsecondary, Education Administrators, Kindergarten through Secondary, Education Administrators, Postsecondary, Education Teachers, Postsecondary, Elementary School Teachers, Except Special Education, Engineering Teachers, Postsecondary, English Language and Literature Teachers, Postsecondary, Instructional Coordinators, Kindergarten Teachers, Except Special Education, Mathematical Science Teachers, Postsecondary, Middle School Teachers, Except Special and Career/Technical Education, Preschool Teachers, Except Special Education, School Psychologists, Secondary School Teachers, Except Special and Career/Technical Education, Self-Enrichment Teachers, Special Education Teachers, Elementary School, Special Education Teachers, Kindergarten, Special Education Teachers, Middle School, Special Education Teachers, Preschool, Special Education Teachers, Secondary School, Teaching Assistants, Postsecondary, Teaching Assistants, Preschool, Elementary, Middle, and Secondary School, Except Special Education, Teaching Assistants, Special Education, Tutors

Table 4. Representative examples of occupations not filtered out from O*NET database.

1613	Occupations
1614	Accountants and Auditors, Actors, Acute Care Nurses, Administrative Law Judges, Adjudicators, and Hearing Officers, Advertising Sales Agents, Aerospace Engineering and Operations Technologists and Technicians, Air Traffic Controllers, Ambulance Drivers and Attendants, Anesthesiologists, Animal Caretakers, Anthropologists and Archeologists, Architects, Except Landscape and Naval, Architectural and Engineering Managers, Art Directors, Athletic Trainers, Audiologists, Automotive Service Technicians and Mechanics, Bailiffs, Bill and Account Collectors, Bioengineers and Biomedical Engineers, Biological Technicians, Bookkeeping, Accounting, and Auditing Clerks, Broadcast Announcers and Radio Disc Jockeys, Budget Analysts, Bus and Truck Mechanics and Diesel Engine Specialists, Business Intelligence Analysts, Cardiologists, Career/Technical Education Teachers, Secondary School, Chemical Engineers, Chemists, Child, Family, and School Social Workers, Childcare Workers, Civil Engineers, Claims Adjusters, Examiners, and Investigators, Clinical Research Coordinators, Clinical and Counseling Psychologists, Commercial and Industrial Designers, Community Health Workers, Compliance Officers, Computer Hardware Engineers, Computer Network Support Specialists, Computer Programmers, Computer Systems Analysts, Computer and Information Systems Managers, Concierges, Conservation Scientists, Construction Managers, Cooks, Restaurant, Coroners, Credit Analysts, Critical Care Nurses, Curators, Customer Service Representatives, Dancers, Data Scientists, Database Administrators, Dental Hygienists, Dentists, General, Detectives and Criminal Investigators, Digital Forensics Analysts, Dispatchers, Except Police, Fire, and Ambulance, Editors, Education Administrators, Postsecondary, Elementary School Teachers, Except Special Education, Emergency Medical Technicians, Environmental Engineers, Epidemiologists, Executive Secretaries and Executive Administrative Assistants, Family Medicine Physicians, Fashion Designers, Financial Examiners, Financial Managers, Fire-Prevention and Protection Engineers, First-Line Supervisors of Office and Administrative Support Workers, Fitness and Wellness Coordinators, Food Scientists and Technologists, Forest and Conservation Technicians, Fundraisers, Gambling Dealers, General and Operations Managers, Geneticists, Graphic Designers, Health Education Specialists, Healthcare Social Workers, Historians, Home Health Aides, Human Resources Managers, Industrial Engineers, Information Security Analysts, Instructional Coordinators, Insurance Sales Agents, Judges, Magistrate Judges, and Magistrates, Kindergarten Teachers, Except Special Education, Lawyers, Legislators, Loan Officers, Logisticians, Management Analysts, Market Research Analysts and Marketing Specialists, Marriage and Family Therapists, Mathematicians, Mechanical Engineers, Medical and Health Services Managers, Mental Health Counselors, Microbiologists, Middle School Teachers, Except Special and Career/Technical Education, Musicians and Singers, Network and Computer Systems Administrators, Nurse Practitioners, Nursing Assistants, Occupational Therapists, Office Clerks, General, Operating Engineers and Other Construction Equipment Operators, Optometrists, Paralegals and Legal Assistants, Pediatricians, General, Personal Financial Advisors, Pharmacists, Photographers, Physical Therapists, Physicians, Pathologists, Police and Sheriff's Patrol Officers, Political Scientists, Preschool Teachers, Except Special Education, Producers and Directors, Project Management Specialists, Psychiatrists, Public Relations Specialists, Radiologists, Real Estate Brokers, Receptionists and Information Clerks, Recreation Workers, Registered Nurses, Respiratory Therapists, Retail Salespersons, Sales Managers, School Psychologists, Secondary School Teachers, Except Special and Career/Technical Education, Secretaries and Administrative Assistants, Except Legal, Medical, and Executive, Security Managers, Self-Enrichment Teachers, Social and Community Service Managers, Software Developers, Special Education Teachers, Elementary School, Speech-Language Pathologists, Statisticians, Substance Abuse and Behavioral Disorder Counselors, Surgeons, Survey Researchers, Sustainability Specialists, Tax Preparers, Taxi Drivers, Technical Writers, Training and Development Specialists, Transportation, Storage, and Distribution Managers, Tutors, Veterinarians, Veterinary Technologists and Technicians, Video Game Designers, Writers and Authors, Zoologists and Wildlife Biologists

B Scoping Review on Meaningfulness of Work

We reviewed 21 articles (as shown in Table 5 across psychology, sociology, anthropology, and ethics on what work means to people and to society as a part of our scoping review on meaningfulness of work. The studies show how people judge their own work, how organizations shape those judgments, and how societies value different kinds of work.

C Worker and Developer Survey

We provide our full survey items for meaningfulness of work and AI traits in Table 6. We also include several follow up questions related to human intervention preferences based on Shao et al. [80]. We provide a detailed overview of the demographics of our recruited Prolific participants in Table 7.

Table 6. Survey items used in the study.

ID	Survey Item
Perceived Bullshitness (Q1–Q5)	
1655	Q1 The task feels pointless.
1656	Q2 If I stopped doing this task, nothing important would change.
1657	Q3 I perform this task only to satisfy bureaucracy or appearances.
1658	Q4 This task does not contribute to the goals of my organization.
1659	Q5 I would be embarrassed to explain this task to someone outside my field.

ID	Survey Item
Perceived Value (Q6–Q10)	
1668	Q6 This task is important to the success of my team or organization.
1669	Q7 This task results in a visible or tangible outcome.
1670	Q8 I have the freedom to decide how to carry out this task.
1671	Q9 I receive useful feedback about how well this task is done.
1672	Q10 This task gives me a sense of accomplishment.
Status Maintenance (Q11–Q16)	
1674	Q11 Not doing this task might make me look less competent to others.
1675	Q12 If I stopped doing this task, others might question my role or importance.
1676	Q13 This task helps reinforce my standing in the organization.
1677	Q14 I worry that letting go of this task could reduce my influence or visibility.
1678	Q15 Even if the task feels unimportant, I feel pressure to keep doing it to maintain status.
1679	Q16 I feel this task signals to others that I am busy or valuable.
EPOCH (Q17–Q21)	
1683	Q17 This task requires recognizing and responding appropriately to the emotions of others.
1684	Q18 This task benefits significantly from in-person interaction, non-verbal cues, or spontaneous communication.
1685	Q19 This task involves making decisions that require moral reasoning, accountability, or subjective judgment.
1686	Q20 This task requires generating novel ideas, approaches, or solutions beyond standard procedures.
1687	Q21 This task involves setting direction, motivating others, or showing perseverance toward a long-term goal.
Human Flourishing (Q22–Q33)	
1691	Q22 This task makes me feel satisfied and content with my work.
1692	Q23 This task makes me feel happy and positive.
1693	Q24 This task supports my physical well-being (e.g., energy, comfort).
1694	Q25 This task supports my mental health (e.g., reduced stress, clarity, peace of mind).
1695	Q26 This task feels meaningful and worthwhile.
1696	Q27 This task helps me connect with my personal or professional purpose.
1697	Q28 This task allows me to act in accordance with my values and integrity.
1698	Q29 This task challenges me to exercise discipline, patience, or courage.
1699	Q30 This task helps me build or strengthen relationships with colleagues or clients.
1700	Q31 This task makes me feel supported and connected socially.
1701	Q32 This task contributes to my sense of job or financial security.
1702	Q33 This task helps me feel that my work has tangible value and reward.
AI Trait Preferences (Q34–Q45)	
1706	Q34 Handle more complex work rather than routine work.
1707	Q35 Focus more on addressing human needs and emotions rather than just data handling.
1708	Q36 Make fast, automatic decisions without explanation rather than decisions that are easy for people to understand.
1709	Q37 Be open to challenge or treat the decision as final.
1710	Q38 Adjust based on the individual it's helping rather than treat everyone the same.
1711	Q39 Show warmth and care rather than remain neutral and business-like.
1712	Q40 Be polite even if that means not being fully honest, rather than being sincere and straightforward.

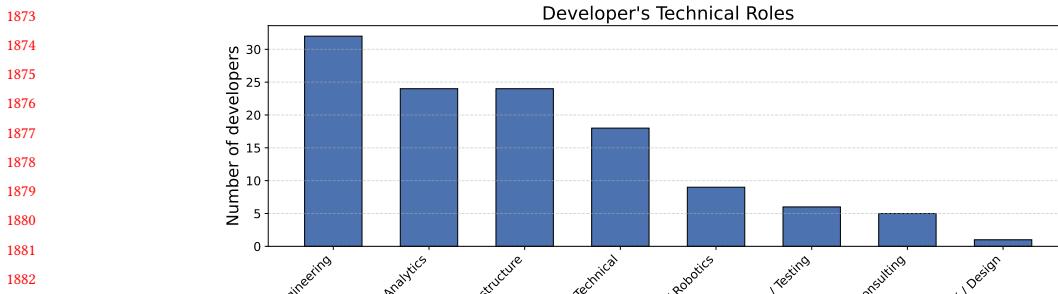
ID	Survey Item
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1719	Q41 Be strict and follow the rules exactly rather than be tolerant and open-minded.
1720	Q42 Be fast and simple even if less perfect, rather than highly skilled and precise.
1721	Q43 Be determined and persistent rather than flexible and willing to change course.
1722	Q44 Show comprehensiveness, deep understanding and insight rather than keep things simple and straightforward.
1723	Q45 Be imaginative and bring new ideas rather than stay practical and follow familiar approaches.
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Table 5. Foundational citations on the personal and the social meaning of work

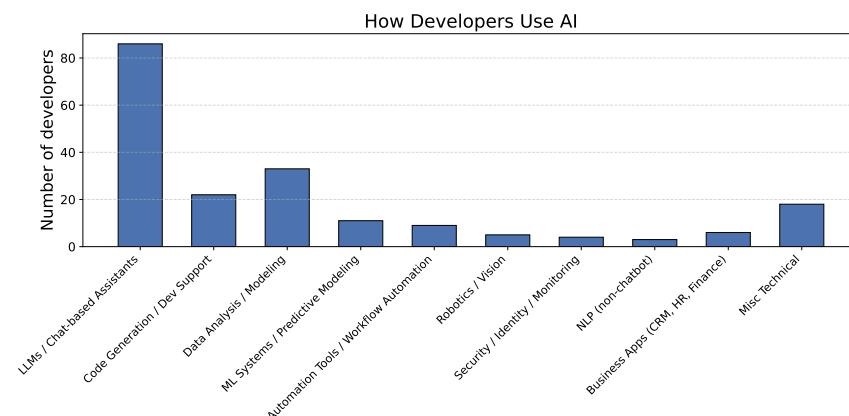
Theme	Foundational Work and Description
Bullshit Jobs, Task Meaning & Worthwhile Contributions	<p>Graeber (2018): Introduce the concept of ‘bullshit jobs,’ emphasizing tasks perceived as socially useless or performative [37].</p> <p>Hackman & Oldham (1976, 1980): specify which job features matter by developing the Job Characteristics Model, linking job design to perceived significance, autonomy, and motivation [39, 41].</p> <p>Deci and Richard (2000): Explain why certain job features matter as they meet universal psychological needs. Intrinsic goals (growth, relationships, contribution) satisfy basic psychological needs and foster well-being, whereas extrinsic goals (wealth, fame, image) do not and can undermine it[25].</p> <p>Lips-Wiersma <i>et al.</i> (2020): People find their jobs more meaningful when work feels fair, leaders act responsibly, and the work itself feels worthwhile—with “doing work that really matters” being the most important factor [56].</p> <p>Steger <i>et al.</i> (2012): Provide the Work and Meaning Inventory (WAMI) to measure perceived meaningfulness of work [83].</p> <p>Rostain and Clarke (2025): Identify three ways factory workers in France created meaning in low-skilled jobs often seen as meaningless: <i>(i)</i> using hidden skills beyond their usual tasks, <i>(ii)</i> finding small opportunities to do the work in their own way, and <i>(iii)</i> demonstrating skills that earned respect from coworkers and supervisors [77].</p> <p>Bailey <i>et al.</i> (2019): Review 71 empirical studies on meaningful work, highlighting key trends, gaps, and proposing a research agenda [11].</p> <p>Bailey <i>et al.</i> (2025): Show people see work as meaningful when they believe it makes a real difference to others or to society. This depends on three things: <i>(i)</i> the person’s own belief that their work matters, <i>(ii)</i> recognition from others, and <i>(iii)</i> confidence that they can do the work well [10].</p>
Task Status, Impression Management, Identity Formation & Symbolic Work	<p>Meyer & Rowan (1977): Propose that organizations adopt formal structures symbolically to gain legitimacy [61].</p> <p>Hamilton <i>et al.</i> (2022): Show how job status during COVID-19 affected people’s sense of dignity and meaning, as being labeled ‘furloughed’ left some feeling excluded or undervalued [42].</p> <p>Bolino <i>et al.</i> (2008): Review motivations and behaviors related to impression management at work [14].</p> <p>Rosso <i>et al.</i> (2010): Identify two core mechanisms by which work becomes meaningful: agency (creating meaning through personal actions such as autonomy, mastery, competence, and self-identity) and communion (creating meaning through connection with and service to others). These mechanisms operate across four sources of meaning: the self, others, the work context, and the spiritual life [76].</p> <p>Lepisto and Pratt (2017): Distinguish between meaningful work as realization (fulfilling personal potential) and as justification (contributing to broader social or moral good) [52].</p> <p>Tomlinson and Souto-Otero (2025): Explore how recent UK graduates defined meaningful work. Identified three dimensions: meaning in work <i>(i)</i> as self-expression and self-actualization, <i>(ii)</i> through relationships and social relatedness, and <i>(iii)</i> as societal contribution [85].</p> <p>Morabito <i>et al.</i> (2025): Explored how early-career veterinarians in Canada perceived meaningful work. It showed that personal fulfillment through making a difference, creativity and problem-solving, social connection, and professional growth jointly shaped meaningful work [63].</p> <p>Bellezza <i>et al.</i> (2017): Argue that busyness serves as a modern status symbol [12].</p> <p>Rafaeli & Pratt (2006): Discuss identity and symbolic expression in work settings [69].</p>
Status Threat in Social Psychology	<p>Pettit <i>et al.</i> (2010): Examine reactions to the threat of losing status within groups [68].</p> <p>Anderson <i>et al.</i> (2012): Explore conditions under which individuals prefer lower-status roles to maintain group dynamics [4].</p>
Work Motivation & Utility Theory	Eccles & Wigfield (2002): Outline expectancy-value theory as a foundation for understanding task utility and motivation [27].

Table 7. Demographic characteristics of participants recruited from Prolific.

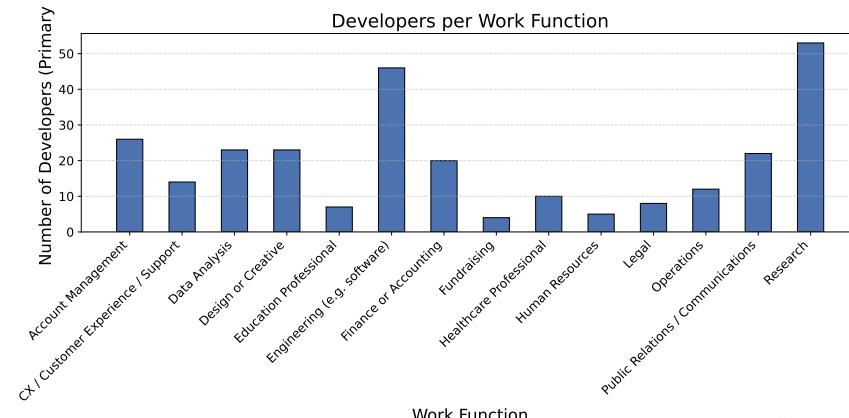
Demographics	Workers (N=202)	Developers (N=197)
Mean age (SD)	42.63 (13.05)	36.68 (10.29)
Gender		
Male	34.03%	64.46%
Female	61.94%	28.42%
Non-binary / Other	0%	0%
Consent Revoked	4.03%	7.11%
Employment status		
Full-time	46.94%	69.54%
Part-time	16.29%	13.71%
Unemployed/Other	4.03%	1.52%
Consent Revoked/No data available	15.22%	23.80%



(a) Distribution of developers across major technical role categories, including software engineering, data/analytics, IT infrastructure, ML/AI engineering, QA/testing, and related roles.



(b) Types of AI technologies used by developers in their daily work, including LLM-based assistants, code-generation tools, data/modeling systems, ML pipelines, automation tools, and domain-specific applications.



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(c) Primary work functions represented in the developer sample across organizational domains such as engineering, research, operations, finance, education, and customer support.

Fig. 7. Overview of developer backgrounds across three dimensions: (a) technical role categories, (b) AI usage types, and (c) work functions. Together these characterizations show that the developer sample consists primarily of practitioners working in software, data, IT, and ML/AI roles who actively engage with modern AI tools and contribute to AI-enabled workflows across diverse organizational sectors.

1925 D Scaling and Validating Responses with LMs

1926 Figure 8 shows the distributions of annotations for five dimensions of meaningful work across 12 occupational sectors,
 1927 comparing LM annotations with human annotations. For *Perceived Bullshitness* (*bs*), both LM and human annotators
 1928 generally agree that these occupations are not “bullshit”. However, humans still display more variation across sectors,
 1929 identifying certain support and service roles as slightly more bullshit-like, while LM minimizes such distinctions. Across
 1930 other traits, i.e., *Perceived Value* (*value*), *Status Maintenance* (*status*), , *Human Flourishing* (*flourishing*) and *Psychological*
 1931 *Traits of AI Behavior* (*ai*), LM annotations are clustered near the high end of the scale with relatively smaller variations
 1932 across almost all sectors. In contrast, human annotations reveal greater differentiation between occupation sectors.
 1933 Finally, for *EPOCH*, there are relatively high variations for both LM and human annotations. Overall, LM annotations
 1934 are more uniform and optimistic, often clustering near the high values, whereas human annotations reveal richer
 1935 variability across occupation sectors.

1936 Table 8 provides several examples where LM annotations deviate from human annotations. For *perceived bullshitness*,
 1937 LM rated legal tasks such as drafting wills or contracts by Lawyers as entirely non-pointless (0.0), emphasizing their
 1938 essential and substantive nature, while humans reported moderate meaningfulness (1.93), reflecting their perception of
 1939 some bureaucratic routine. For *perceived value*, planning projects for Poets, Lyricists, and Creative Writers was rated
 1940 higher by LM (3.8) than humans (2.0), highlighting LM’s focus on tangible outcomes, autonomy, and team contribution.
 1941 For *status maintenance*, managerial tasks like setting prices as General and Operations Managers received higher LM
 1942 ratings (3.83) than human ratings (1.89), reflecting LM’s weighting of visibility, authority, and organizational standing.
 1943 In contrast, for *EPOCH*, Survey Researchers reviewing and recording data were rated very low by LM (0.40) but high by
 1944 humans (3.20), indicating that humans derive well-being and satisfaction from task completion, whereas LM views these
 1945 tasks as routine and procedural. For *human flourishing*, conducting new employee orientations as Human Resources
 1946 Specialists was rated higher by LM (3.50) than humans (1.69), reflecting LM’s emphasis on purpose, social connection,
 1947 and personal growth. Finally, for *psychological trait of AI behavior*, recruiting sponsors or volunteers for Fundraisers
 1948 was rated higher by LM (3.08) than humans (0.94), highlighting LM’s prioritization of emotional engagement, tailored
 1949 reasoning, and insight, while humans perceive the task primarily as functional.

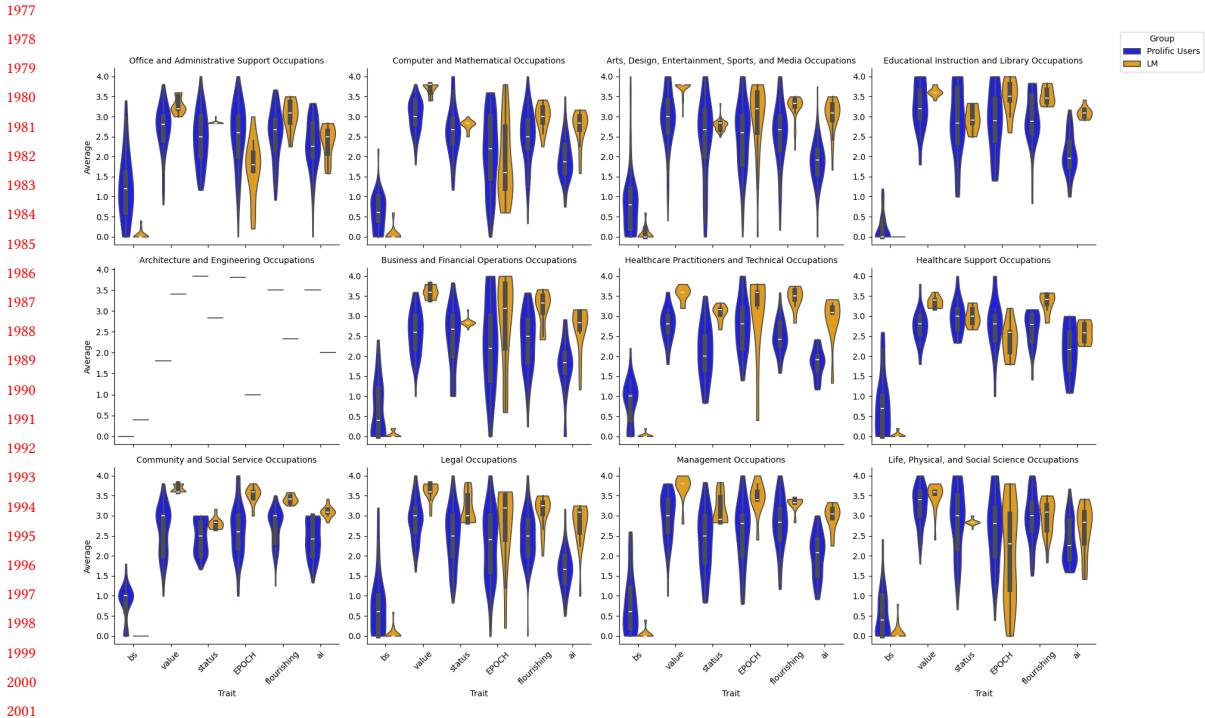


Fig. 8. Distribution comparison of dimensions of meaningful work between the LM and Prolific users across different sectors.

Table 9. Full LM survey prompts for Workers

Worker Prompt	
2007	You are a professional working as a {job_title} in {function}. You are now reflecting how you feel about those work tasks.
2008	In {function}, consider the task: {task}
2009	For each question (Q1–Q45), rate each sentence below from 0 to 4 based on how much you agree with it (0 means strongly disagree, 1 means disagree, 2 neutral, 3 agree and 4 means strongly agree). Before giving each answer, provide a reasoning of one or two sentences, with a maximum of 50 words. Name the reasonings as “Reason_1” to “Reason_45” respectively.
2010	Q1. The task feels pointless.
2011	Q2. If I stopped doing this task, nothing important would change.
2012	Q3. I perform this task only to satisfy bureaucracy or appearances.
2013	.
2014	.
2015	.
2016	.
2017	Q44. Show deep understanding and insight rather than keep things simple and straightforward?
2018	Q45. Be imaginative and bring new ideas rather than stay practical and follow familiar approaches?
2019	For each question (Q46–Q48), select only one option (single lowercase letters from a to e). Before giving each answer, provide a reasoning of one or two sentences, with a maximum of 50 words. Name the reasonings as “Reason_46” to “Reason_48” respectively.
2020	Q46 (Human Needs). What kind of personal need does this task mostly fulfill for you?
2021	a. Basic needs (e.g., survival, security, routine necessities)
2022	b. Safety needs (e.g., stability, health, financial security)
2023	c. Social needs (e.g., belonging, connection, community)
2024	d. Self-esteem needs (e.g., recognition, achievement, confidence)
2025	e. Self-actualization needs (e.g., growth, purpose, realizing potential)
2026	Q47 (Automation Desire by Workers). If an AI can do this task for you completely, how much do you want an AI to do it for you?
2027	
2028	

2029	a. Not at all (I would not want the AI to do this task for me)
2030	b. Slightly (I'd want it to do only small parts of the task)
2031	c. Moderately (I'd want it to do about half the task)
2032	d. A lot (I'd want it to do most of the task)
2033	e. Entirely (I'd want it to do the entire task for me)
2034	Q48 (Required Human Agency Scale). If AI were to assist in this task, how much of your collaboration would be needed to complete this task effectively?
2035	H1. AI handles the task entirely on its own.
2036	H2. AI needs minimal human input for optimal performance.
2037	H3. AI and human form equal partnership, outperforming either alone
2038	H4. AI requires human input to successfully complete the task.
2039	H5. AI cannot function without continuous human involvement.
2040	For Q49, select zero or multiple options (must be a combination of zero or more lowercase letters from a to g, without spaces or separators. If no option is selected, leave it blank.) Before answering, provide a reasoning of one or two sentences, with a maximum of 50 words. Name the reasoning as "Reason_49".
2041	Q49. Why would collaboration be needed for this task? Do not check any boxes if you don't think collaboration is needed.
2042	a. This task requires physical actions.
2043	b. This task involves making high-stake decisions which I would like to control.
2044	c. This task requires specific domain knowledge.
2045	d. The task involves nuanced communication or interpersonal skills.
2046	e. The task needs validation or oversight to ensure quality
2047	f. The task is dynamic and requires adapting to changing circumstances
2048	g. The task has ethical, sensitive, or subjective aspects.

Table 10. Full LM survey prompts for Developers

Developer Prompt
2051 You are a developer that is designing AI systems for a {job_title} in {function}. You are now reflecting how new AI workplace technologies should be built.
2052 In {function}, consider the task: {task}
2053 For each question (Q34–Q45), rate each sentence below from 0 to 4 based on how much you agree with it (0 means strongly disagree, 1 means disagree, 2 neutral, 3 agree and 4 means strongly agree). Before giving each answer, provide a reasoning of one or two sentences, with a maximum of 50 words. Name the reasonings as "Reason_34" to "Reason_45" respectively.
2054 Q34. Handle more complex work rather than routine work.
2055 Q35. Focus more on addressing human needs and emotions rather than just data handling.
2056 Q36. Make fast, automatic decisions without explanation rather than decisions that are easy for people to understand?
2057 Q37. Be open to challenge or treat the decision as final?
2058 Q38. Adjust based on the individual it's helping rather than treat everyone the same?
2059 Q39. Show warmth and care rather than remain neutral and business-like?
2060 Q40. Be polite even if that means not being fully honest, rather than being sincere and straightforward?
2061 Q41. Be strict and follow the rules exactly rather than be tolerant and open-minded?
2062 Q42. Be fast and simple even if less perfect, rather than highly skilled and precise?
2063 Q43. Be determined and persistent rather than flexible and willing to change course?
2064 Q44. Show deep understanding and insight rather than keep things simple and straightforward?
2065 Q45. Be imaginative and bring new ideas rather than stay practical and follow familiar approaches?
2066 For each question (Q47–Q48), select only one option (single lowercase letters from a to e). Before giving each answer, provide a reasoning of one or two sentences, with a maximum of 50 words. Name the reasonings as "Reason_46" to "Reason_48" respectively.
2067 Q47 (Automation Desire by Developers). If AI were to assist in this task, how much of user-AI collaboration would be needed to complete this task effectively?
2068 a. Not at all (I would not want the AI to do this task for the user)
2069 b. Slightly (I'd want the AI to do only small parts of the task)
2070 c. Moderately (I'd want the AI to do about half the task)
2071 d. A lot (I'd want the AI to do most of the task)
2072 e. Entirely (I'd want the AI to do the entire task)
2073 Q48 (Required Human Agency Scale). If AI were to assist in this task, how much collaboration would be needed to complete this task effectively?
2074 H1. AI handles the task entirely on its own.
2075 H2. AI needs minimal human input for optimal performance.
2076 H3. AI and human form equal partnership, outperforming either alone
2077 H4. AI requires human input to successfully complete the task.
2078 H5. AI cannot function without continuous human involvement.

2081 For Q49, select zero or multiple options (must be a combination of zero or more lowercase letters from a to g, without spaces or separators. If no option is selected, leave it blank.)
2082 Before answering, provide a reasoning of one or two sentences, with a maximum of 50 words. Name the reasoning as "Reason_49".
2083 Q49. Why would collaboration be needed for this task? Do not check any boxes if you don't think collaboration is needed.
2084 a. This task requires physical actions.
2085 b. This task involves making high-stake decisions which I would like to control.
2086 c. This task requires specific domain knowledge.
2087 d. The task involves nuanced communication or interpersonal skills.
2088 e. The task needs validation or oversight to ensure quality
f. The task is dynamic and requires adapting to changing circumstances
g. The task has ethical, sensitive, or subjective aspects.

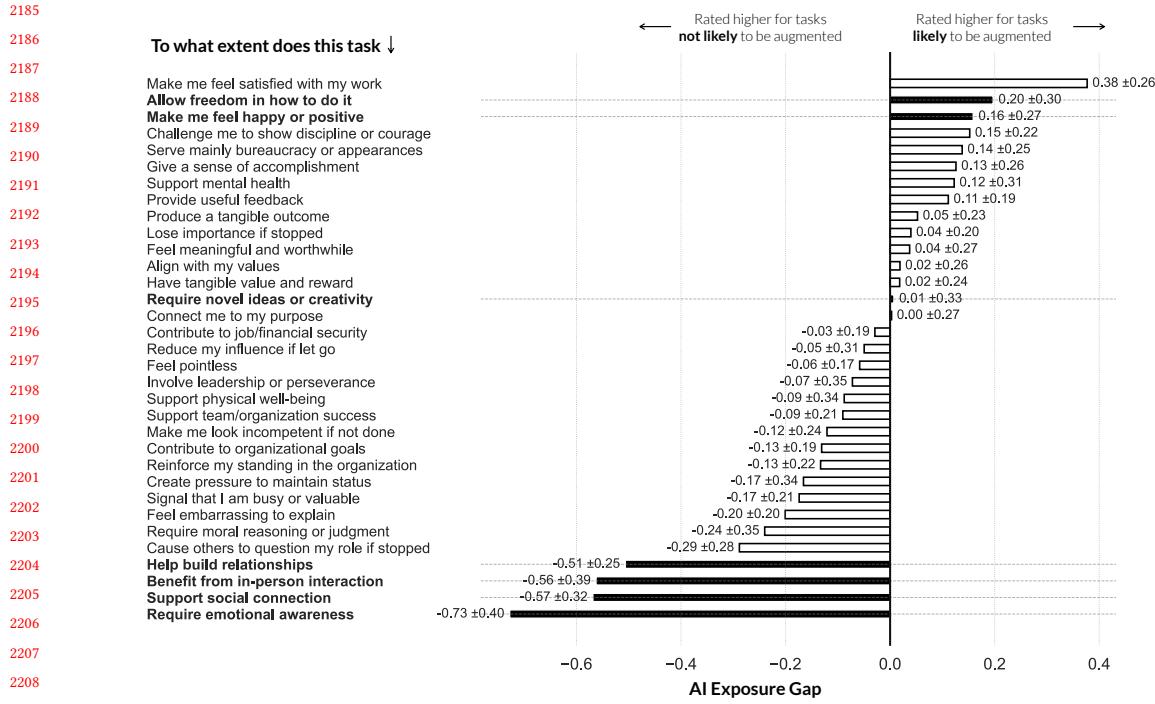
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Table 8. Example tasks with the largest differences between LM and human ratings across survey items, using a Likert scale ranging from 0 (strongly disagree) to 4 (strongly agree). The largest gaps occur when LMs emphasize functional or procedural aspects (e.g., legal drafting, survey coding), while humans evaluate tasks in terms of social, emotional, or organizational meaning (e.g., status maintenance, employee orientation). We found both LM and human interpretations can be valid in different contexts. For instance, the LM perceived the task ‘review, classify, and record survey data in preparation for computer analysis’ as a routine procedure with minimal emotional demands, whereas a human annotator emphasized its creative and moral dimensions. Such divergences reflect subjective differences that are difficult to resolve.

Dimensions of Meaningful Work	Occupation	Task Description	LM Annotation	Human Annotation	Reasoning by LM and Humans
<i>Perceived Bullsh*tness</i> (e.g., the task feels pointless)	Lawyers	Prepare, draft, and review legal documents, such as wills, deeds, patent applications, mortgages, leases, and contracts.	0.00 (Strongly disagree)	1.93 (Neutral)	<i>LM:</i> Essential, substantive, impacts clients' rights, central to organizational goals. <i>Humans:</i> Moderate meaningfulness, some bureaucratic perception.
<i>Perceived Value</i> (e.g., I have the freedom to decide how to carry out this task)	Poets, Lyricists, Creative Writers	Plan project arrangements or outlines, and organize material accordingly.	3.80 (Strongly agree)	2.00 (Neutral)	<i>LM:</i> Tangible outcomes, autonomy, team contribution. <i>Humans:</i> Recognize value but lower perceived impact.
<i>Status Maintenance</i> (e.g., This task helps reinforce my standing in the organization)	General & Operations Managers	Set prices or credit terms for goods or services, based on forecasts of customer demand.	3.83 (Strongly agree)	1.89 (Neutral)	<i>LM:</i> Visibility, authority, organizational standing. <i>Humans:</i> Less tied to status perception.
<i>EPOCH</i> (e.g., This task requires recognizing and responding appropriately to the emotions of others)	Survey Researchers	Review, classify, and record survey data in preparation for computer analysis.	0.40 (Strongly disagree)	3.20 (Agree)	<i>LM:</i> Technical, routine, procedural, minimal emotional/moral impact. <i>Humans:</i> Requires some novel ideas and sometimes requires emotional and moral judgments.
<i>Human Flourishing</i> (e.g., This task helps me build or strengthen relationships with colleagues or clients)	HR Specialists	Schedule or conduct new employee orientations.	3.50 (Agree)	1.69 (Neutral)	<i>LM:</i> Purpose, social connection, growth-oriented. <i>Humans:</i> Perceived as routine or standard procedure.
<i>Psychological Traits of AI Behavior</i> (e.g., Show warmth and care rather than remain neutral and business-like)	Fundraisers	Recruit sponsors, participants, or volunteers for fundraising events.	3.08 (Agree)	0.94 (Disagree)	<i>LM:</i> Emotional engagement, tailored reasoning, insight, creativity. <i>Humans:</i> Functional, minimal AI-alignment traits perceived.

Table 11. RQ1: Significant task dimensions ($FDR < 0.05$ and $|\Delta| \geq 0.10$). Estimates from nested RE models; Δ is the back-transformed Likert difference (likely – not-likely) where (+) means that the dimension was more exposed to AI augmentation and (-) it was less exposed to AI augmentation

Task Characteristic	β (95% CI)	Δ (95% CI)
Novel ideas/creativity (+)	0.22698 [0.17405, 0.27991]	0.29298 [0.22466, 0.36131]
Happy/Positive (+)	0.19965 [0.13789, 0.26143]	0.12675 [0.08753, 0.16596]
Freedom in how to do it (+)	0.18587 [0.12659, 0.24516]	0.11487 [0.07823, 0.15151]
In-person interaction (-)	-0.17564 [-0.23024, -0.12035]	-0.23429 [-0.30713, -0.16145]
Emotional Awareness (-)	-0.13643 [-0.19021, -0.08259]	-0.20635 [-0.28781, -0.12492]
Build relationships (-)	-0.13422 [-0.19249, -0.07594]	-0.15360 [-0.22028, -0.08692]
Socially supported (-)	-0.10393 [-0.16434, -0.04352]	-0.10683 [-0.16893, -0.04473]



2207
 2208 Fig. 9. RQ1: AI Exposure Gap by dimensions of meaningful work (rows) based on small-scale human ratings for 171 tasks. A higher gap indicates that a dimension is more strongly associated with tasks likely to be augmented by AI. The gap is computed as the difference in the perceived importance of a dimension between two groups of tasks: those more likely and those less likely to be augmented. We estimate the gaps and 95% confidence intervals by computing average differences for human ratings. Bold names and corresponding black bars indicate those statistically significant different dimensions of meaningful work identified with *LM annotations* based model (Figure 3). Results based on human ratings are highly consistent with LM annotations: tasks rated as likely to be augmented by AI tend to involve satisfaction with work, happiness, and autonomy, whereas tasks rated as not likely to be augmented tend to involve emotional awareness, in-person interaction, relationship building, and social support. One major exception is “Require novel ideas or creativity” where human annotators tended to underestimate the novelty of tasks, whereas LMs captured more nuanced distinctions.

2237 Table 12. Top sectors and exemplar tasks for each significant survey item in RQ1. For each item we select the three sectors with the
 2238 highest normalized sector mean (z-score) within the relevant subset (likely vs. not likely to be automated). Within each sector we
 2239 show one exemplar task from the 99th percentile of that item's ratings (fallback: sector max).

2240 2241 Task Characteristic	2242 Exemplar task (Occupation Sector)
2243 Novel ideas/creativity (+)	2244 Formulate basic layout design or presentation approach and specify material details, such as style 2245 and size of type ... (Art Directors Arts, Design, Entertainment, Sports, and Media) 2246 Develop, present, or respond to proposals for specific customer requirements, including request 2247 for proposal responses ... (Sales Engineers Sales and Related) 2248 Prepare scale drawings or architectural designs, using computer-aided design or other tools. (Architects, Except Landscape and Naval Architecture and Engineering)
2249 Happy/Positive (+)	2250 Modify treatment plans to comply with changes in client status. (Substance Abuse and Behavioral 2251 Disorder Counselors Community and Social Service) 2252 Present lectures and conduct discussions to increase students' knowledge and competence using 2253 visual aids, such as ... (Career/Technical Education Teachers, Postsecondary Educational 2254 Instruction and Library) 2255 Create custom illustrations or other graphic elements. (Art Directors Arts, Design, Entertainment, 2256 Sports, and Media)
2257 Freedom in how to do it (+)	2258 Formulate basic layout design or presentation approach and specify material details, such as style 2259 and size of type ... (Art Directors Arts, Design, Entertainment, Sports, and Media) 2260 Develop or execute strategies to address issues such as energy use, resource conservation, recycling, 2261 pollution ... (Chief Sustainability Officers Management) 2262 Construct probability tables for events such as fires, natural disasters, and unemployment ... (Actuaries Computer and Mathematical)
2263 Emotional awareness (-)	2264 Counsel individuals or groups to help them understand and overcome personal, social, or be- 2265 havioral problems affecting ... (Educational, Guidance, and Career Counselors and Advisors 2266 Community and Social Service) 2267 Perform surgery to prepare the mouth for dental implants and to aid in the regeneration of deficient 2268 bone and gum ... (Oral and Maxillofacial Surgeons Healthcare Practitioners and Technical) 2269 Provide assistance to the public, such as directions to court offices. (Bailiffs Protective Service)
2270 In-person interaction (-)	2271 Provide assistance to the public, such as directions to court offices. (Bailiffs Protective Service) 2272 Perform surgery to prepare the mouth for dental implants and to aid in the regeneration of deficient 2273 bone and gum ... (Oral and Maxillofacial Surgeons Healthcare Practitioners and Technical) 2274 Counsel individuals or groups to help them understand and overcome personal, social, or be- 2275 havioral problems affecting ... (Educational, Guidance, and Career Counselors and Advisors 2276 Community and Social Service)
2277 Build relationships (-)	2278 Counsel individuals or groups to help them understand and overcome personal, social, or be- 2279 havioral problems affecting ... (Educational, Guidance, and Career Counselors and Advisors 2280 Community and Social Service) 2281 Present purchase offers to sellers for consideration. (Real Estate Sales Agents Sales and Related) 2282 Mentor new faculty members. (Social Work Teachers, Postsecondary Educational Instruction 2283 and Library)
2284 Socially supported (-)	2285 Counsel individuals or groups to help them understand and overcome personal, social, or be- 2286 havioral problems affecting ... (Educational, Guidance, and Career Counselors and Advisors 2287 Community and Social Service) 2288 Mentor new faculty members. (Social Work Teachers, Postsecondary Educational Instruction 2289 and Library) 2290 Plan, organize, and conduct occupational therapy programs in hospital, institutional, or community 2291 settings to help ... (Occupational Therapists Healthcare Practitioners and Technical)

2289 Table 13. K-means clustering ($k = 10$) of tasks in the 99th percentile for ‘novel ideas/creativity,’ restricted to tasks judged likely to be
 2290 augmented. Cluster labels were assigned using GPT-4o, and exemplar tasks come from sectors with the strongest heatmap z-scores.

2292 Cluster (size)	2293 Label	2294 Exemplar task (Occupation Sector)
2 (n=148)	Automated Task Management	Plan or coordinate investigation and resolution of customers’ reports of technical problems with aircraft or aerospace vehicles. (<i>Aerospace Engineers / Architecture and Engineering</i>)
6 (n=140)	Policy Development	Conduct educational programs that provide farmers or farm cooperative members with information that can help them improve agricultural prod... (<i>Agricultural Engineers / Architecture and Engineering</i>)
5 (n=128)	Innovative Solutions Evaluation	Analyze project requests, proposals, or engineering data to determine feasibility, productibility, cost, or production time of aerospace or... (<i>Aerospace Engineers / Architecture and Engineering</i>)
3 (n=124)	Sustainable Project Planning	Design environmentally sound structural upgrades to existing buildings, such as natural lighting systems, green roofs, or rainwater collect... (<i>Architects, Except Landscape and Naval / Architecture and Engineering</i>)
8 (n=112)	Creative Engineering Tasks	Plan or conduct experimental, environmental, operational, or stress tests on models or prototypes of aircraft or aerospace systems or equip... (<i>Aerospace Engineers / Architecture and Engineering</i>)
9 (n=107)	Design and Planning Tasks	Prepare scale drawings or architectural designs, using computer-aided design or other tools. (<i>Architects, Except Landscape and Naval / Architecture and Engineering</i>)
0 (n=96)	Logistics and Market Analysis	Analyze new medical procedures to forecast likely outcomes. (<i>Bioengineers and Biomedical Engineers / Architecture and Engineering</i>)
4 (n=95)	Biofuels Research and Development	Design sensing, measuring, and recording devices, and other instrumentation used to study plant or animal life. (<i>Agricultural Engineers / Architecture and Engineering</i>)
7 (n=81)	Creative Visual Production	Create custom illustrations or other graphic elements. (<i>Art Directors / Arts, Design, Entertainment, Sports, and Media</i>)
1 (n=79)	Marketing and Promotion	Confer with customers to assess customer needs or obtain feedback. (<i>Craft Artists / Arts, Design, Entertainment, Sports, and Media</i>)

Table 14. K-means clustering ($k = 10$) of tasks in the 99th percentile for ‘happy/positive’ restricted to tasks judged likely to be augmented. Cluster labels were assigned using GPT-4o, and exemplar tasks come from sectors with the strongest heatmap z-scores.

Cluster (size)	Cluster label	Exemplar task (Occupation Sector)
6 (n=124)	Client Support and Training	Plan and promote career and employment-related programs and events, such as career planning presentations, work experience programs, job fa... (<i>Educational, Guidance, and Career Counselors and Advisors / Community and Social Service</i>)
7 (n=79)	Positive Media Production	Use computers, audio-visual aids, and other equipment and materials to supplement presentations. (<i>Kindergarten Teachers, Except Special Education / Educational Instruction and Library</i>)
9 (n=72)	Patient Eligibility Assessment	Arrange for medical, psychiatric, and other tests that may disclose causes of difficulties and indicate remedial measures. (<i>Child, Family, and School Social Workers / Community and Social Service</i>)
5 (n=70)	Client Rehabilitation Plans	Modify treatment plans to comply with changes in client status. (<i>Substance Abuse and Behavioral Disorder Counselors / Community and Social Service</i>)
1 (n=50)	Training and Development	Evaluate students’ or individuals’ abilities, interests, and personality characteristics, using tests, records, interviews, or professional... (<i>Educational, Guidance, and Career Counselors and Advisors / Community and Social Service</i>)
4 (n=44)	Robotics and Mechatronics	Design advanced precision equipment for accurate or controlled applications. (<i>Mechatronics Engineers / Architecture and Engineering</i>)
0 (n=41)	Emergency Response Tasks	Provide assistive devices, supportive technology, or assistance accessing facilities, such as restrooms. (<i>Special Education Teachers, Preschool / Educational Instruction and Library</i>)
3 (n=37)	Creative Performance Tasks	Portray and interpret roles, using speech, gestures, and body movements, to entertain, inform, or instruct radio, film, television, or live... (<i>Actors / Arts, Design, Entertainment, Sports, and Media</i>)
2 (n=35)	Biofuels Innovation	Propose new biofuels products, processes, technologies or applications based on findings from applied biofuels or biomass research projects. (<i>Biofuels/Biodiesel Technology and Product Development Managers / Management</i>)
8 (n=28)	Speech and Language Therapy	Evaluate hearing or speech and language test results, barium swallow results, or medical or background information to diagnose and plan tre... (<i>Speech-Language Pathologists / Healthcare Practitioners and Technical</i>)

2393 Table 15. K-means clustering ($k = 10$) of tasks in the 99th percentile for 'giving workers freedom and agency' restricted to tasks
 2394 judged likely to be augmented. Cluster labels were assigned using GPT-4o, and exemplar tasks come from sectors with the strongest
 2395 heatmap z-scores.

2396 2397 Cluster (size)	2398 2399 2400 2401 2402 2403 2404 2405 2406 2407 2408 2409 2410 2411 2412 2413 2414 2415 2416 2417 2418 2419 2420 2421 2422 2423 2424 2425 Cluster label	2398 2399 2400 2401 2402 2403 2404 2405 2406 2407 2408 2409 2410 2411 2412 2413 2414 2415 2416 2417 2418 2419 2420 2421 2422 2423 2424 2425 Exemplar task (Occupation Sector)
3 (n=188)	Automated Security Systems	Develop computer information resources, providing for data security and control, strategic computing, and disaster recovery. (<i>Computer and Information Systems Managers/Management</i>)
4 (n=141)	Marketing and Strategy Evaluation	Identify, develop, or evaluate marketing strategy, based on knowledge of establishment objectives, market characteristics, and cost and mar... (<i>Marketing Managers/Management</i>)
0 (n=136)	Sustainability Strategies	Develop or execute strategies to address issues such as energy use, resource conservation, recycling, pollution reduction, waste eliminatio... (<i>Chief Sustainability Officers/Management</i>)
7 (n=124)	Engineering Design Tasks	Identify opportunities to improve plant electrical equipment, controls, or process control methodologies. (<i>Geothermal Production Managers/Management</i>)
1 (n=123)	Health Program Management	Maintain awareness of advances in medicine, computerized diagnostic and treatment equipment, data processing technology, government regulat... (<i>Medical and Health Services Managers/Management</i>)
6 (n=102)	Design and Layout Tasks	Plan store layouts or design displays. (<i>General and Operations Managers/Management</i>)
5 (n=71)	Environmental Planning Tasks	Manage site assessments or environmental studies for wind fields. (<i>Wind Energy Development Managers/Management</i>)
2 (n=71)	Marketing and Promotion Tasks	Develop or implement product-marketing strategies, including advertising campaigns or sales promotions. (<i>General and Operations Managers/Management</i>)
9 (n=69)	Biofuels Research and Development	Design or conduct applied biodiesel or biofuels research projects on topics, such as transport, thermodynamics, mixing, filtration, distill... (<i>Biofuels/Biodiesel Technology and Product Development Managers/Management</i>)
8 (n=44)	Training Program Development	Evaluate instructor performance and the effectiveness of training programs, providing recommendations for improvement. (<i>Training and Development Managers/Management</i>)

2445 Table 16. K-means clustering ($k = 10$) of tasks in the 99th percentile for ‘requires emotional awareness’ restricted to tasks judged
 2446 likely to be augmented. Cluster labels were assigned using GPT-4o, and exemplar tasks come from sectors with the strongest heatmap
 2447 z-scores.

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Cluster (size)	Cluster label	Exemplar task (Occupation Sector)
2 (n=185)	Emotion Awareness in Leadership	Testify in depositions or trials as an expert witness. (<i>Physicians, Pathologists/Healthcare Practitioners and Technical</i>)
7 (n=171)	Crisis Intervention and Support	Perform crisis interventions to help ensure the safety of the patients and others. (<i>Mental Health Counselors/Community and Social Service</i>)
1 (n=165)	Emotion Awareness Tasks	Provide students with disabilities with assistive devices, supportive technology, and assistance accessing facilities, such as restrooms. (<i>Educational, Guidance, and Career Counselors and Advisors/Community and Social Service</i>)
3 (n=140)	Emotion Awareness Tasks	Perform surgery to prepare the mouth for dental implants and to aid in the regeneration of deficient bone and gum tissues. (<i>Oral and Maxillofacial Surgeons/Healthcare Practitioners and Technical</i>)
6 (n=129)	Personnel Management	Direct the operations of short stay or specialty units. (<i>Hospitalists/Healthcare Practitioners and Technical</i>)
8 (n=115)	Emotion Awareness Tasks	Attend meetings, educational conferences, and training workshops, and serve on committees. (<i>Educational, Guidance, and Career Counselors and Advisors/Community and Social Service</i>)
4 (n=105)	Networking and Representation	Deliver presentations to lay or professional audiences. (<i>Preventive Medicine Physicians/Healthcare Practitioners and Technical</i>)
0 (n=104)	Emotion Awareness Counseling	Counsel individuals or groups to help them understand and overcome personal, social, or behavioral problems affecting their educational or ... (<i>Educational, Guidance, and Career Counselors and Advisors/Community and Social Service</i>)
5 (n=60)	Professional Development	Teach pharmacy students serving as interns in preparation for their graduation or licensure. (<i>Pharmacists/Healthcare Practitioners and Technical</i>)
9 (n=40)	Student Behavior Management	Establish and enforce administration policies and rules governing student behavior. (<i>Educational, Guidance, and Career Counselors and Advisors/Community and Social Service</i>)

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Table 17. RQ2: Worker–developer misalignment by AI traits with human ratings on 171 tasks. Misalignment is defined as the average absolute difference between worker and developer ratings (Q34–Q45) of the traits they believe AI systems should possess when augmenting tasks. Differences (Δ) are calculated as worker minus developer ratings, with the magnitude ($|\Delta|$) reflecting the size of the misalignment. Reported values aggregate over sectors and traits are grouped into high, mixed, or aligned categories based on percentile thresholds of average absolute misalignment. The bolded traits are those classified into the same categories based on human and LM ratings (Table 18) on the same set of 171 tasks. As with LM rating–based results, the highest misalignments in human ratings occur for Explainable vs Fast/automatic, Straightforward vs. Polite, and Emotional vs. Apathetic. However, for the highly misaligned traits, discrepancies emerge: Handle complex vs. Routine work are highly misaligned in human ratings but fall only into mixed misalignment categories in LM ratings. After manual inspection, we found that this is partly due to bias in the small-scale human ratings data, which are more concentrated in certain sectors/occupations.

Trait	$\mu \Delta $
High misalignment	
(Q36) Explainable vs. Fast/automatic	1.367
(Q40) Straightforward vs. Polite	1.211
(Q34) Handle complex vs. Routine work	1.165
(Q35) Address emotions vs. Apathetic	1.165
Mixed misalignment	
(Q43) Flexible vs. Determined	1.0917
(Q39) Business-like vs. Warm/caring	1.073
(Q41) Tolerant/Open-minded vs. Strict	1.064
(Q38) Generalized vs. Personalized	0.936
Aligned	
(Q42) Precise vs. Simple	0.936
(Q45) Practical vs. Imaginative	0.872
(Q37) Definitive vs. Open to challenge	0.853
(Q44) Simple vs. Comprehensive	0.817

2549 Table 18. RQ2: Worker-developer misalignment by AI traits with LM-simulated ratings on 171 tasks. The bolded traits are those
 2550 classified into the same categories based on human and LM ratings (Table 17) on the same set of 171 tasks.

Trait	$\mu \Delta $
High misalignment	
<i>(Q40) Straightforward vs. Polite</i>	1.936
<i>(Q36) Explainable vs. Fast/automatic</i>	0.780
<i>(Q35) Address emotions vs. Apathetic</i>	0.706
<i>(Q42) Precise vs. Simple</i>	0.670
Mixed misalignment	
<i>(Q41) Tolerant/Open-minded vs. Strict</i>	0.6514
<i>(Q39) Business-like vs. Warm/caring</i>	0.523
<i>(Q34) Handle complex vs. Routine work</i>	0.450
<i>(Q43) Flexible vs. Determined</i>	0.450
Aligned	
<i>(Q45) Practical vs. Imaginative</i>	0.404
<i>(Q37) Definitive vs. Open to challenge</i>	0.330
<i>(Q38) Generalized vs. Personalized</i>	0.275
<i>(Q44) Simple vs. Comprehensive</i>	0.110

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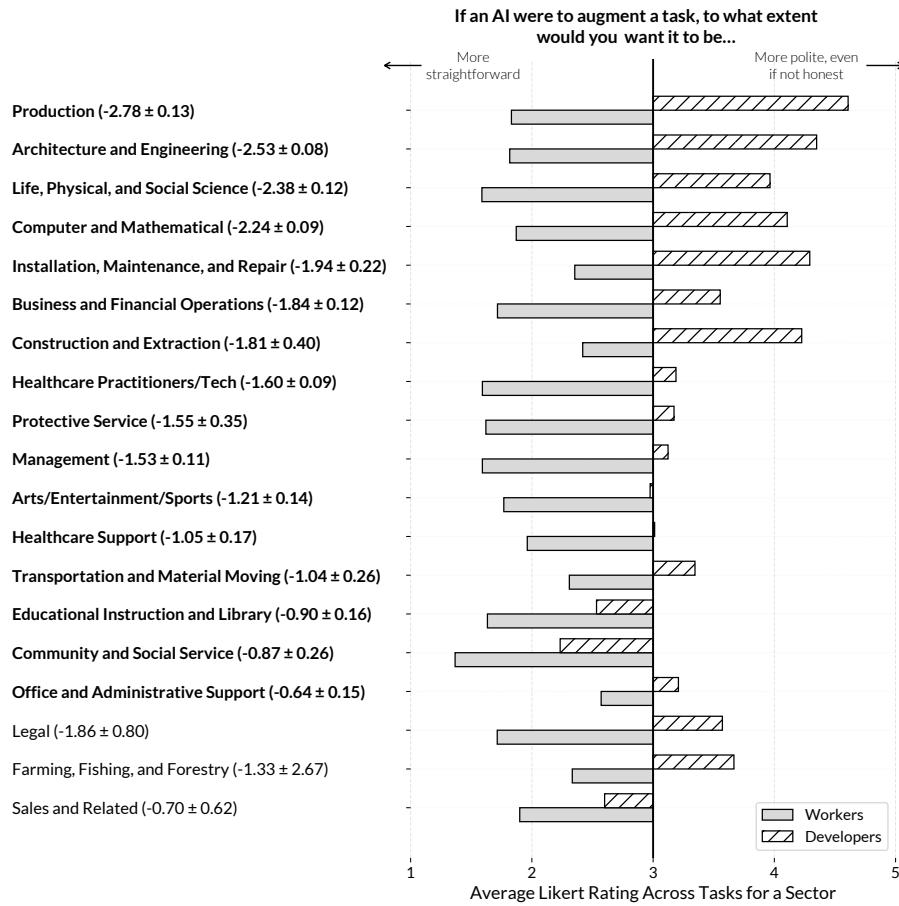


Fig. 10. Worker vs. developer preferences for AI to be straightforward or polite, by sector. Paired bars show mean Likert ratings for each group. Greater distance between bars indicates stronger misalignment; misalignment scores with standard errors are shown on the y-axis.

2653 Table 19. Clusters of tasks with the lowest worker-developer misalignment on the trait definitive vs. open to challenge, identified
 2654 using MPNet embeddings and K-means clustering. Cluster labels were generated using GPT-4o.

2656 Cluster (size)	2657 Cluster label	2658 Exemplar task (Occupation Sector)
2659 0 (n=263)	2660 Strategic Decision Making	2661 Investigate traffic problems and recommend methods to improve traffic flow or safety. (<i>Transportation Engineers / Architecture and Engineering</i>)
2662 3 (n=254)	2663 Strategic Evaluation and Analysis	2664 Analyze data on conditions such as site location, drainage, or structure location for environmental reports or landscaping plans. (<i>Landscape Architects / Architecture and Engineering</i>)
2665 5 (n=217)	2666 Flexible Decision-Making	2667 Analyze new medical procedures to forecast likely outcomes. (<i>Bio-engineers and Biomedical Engineers / Architecture and Engineering</i>)
2668 1 (n=212)	2669 Flexible Decision-Making	2670 Develop or assist in the development of transportation-related computer software or computer processes. (<i>Transportation Engineers / Architecture and Engineering</i>)
2671 2 (n=187)	2672 Research and Development Planning	2673 Prepare scale drawings or architectural designs, using computer-aided design or other tools. (<i>Architects, Except Landscape and Naval / Architecture and Engineering</i>)
2674 7 (n=168)	2675 Task Coordination and Improvement	2676 Develop processes to separate components of liquids or gases or generate electrical currents, using controlled chemical processes. (<i>Chemical Engineers / Architecture and Engineering</i>)
2677 9 (n=158)	2678 Flexible Decision Making	2679 Document equipment or process details of radio frequency identification device (RFID) technology. (<i>Radio Frequency Identification Device Specialists / Architecture and Engineering</i>)
2679 6 (n=132)	2680 Quality Control Analysis	2681 Plan or conduct experimental, environmental, operational, or stress tests on models or prototypes of aircraft or aerospace systems or equip... (<i>Aerospace Engineers / Architecture and Engineering</i>)
2681 8 (n=110)	2682 Data Analysis and Review	2683 Design sensing, measuring, and recording devices, and other instrumentation used to study plant or animal life. (<i>Agricultural Engineers / Architecture and Engineering</i>)
2683 4 (n=89)	2684 Task Evaluation and Development	2685 Train users in task techniques or ergonomic principles. (<i>Human Factors Engineers and Ergonomists / Architecture and Engineering</i>)

2705 Table 20. Clusters of tasks with the lowest worker-developer misalignment on the trait generalization vs. personalized, identified
 2706 using MPNet embeddings and K-means clustering. Cluster labels were generated using GPT-4o.

2708 Cluster (size)	2709 Cluster label	2710 Exemplar task (Occupation Sector)
2711 9 (n=278)	2712 Financial Coordination	2713 Prepare responses to customer requests for information, such as product data, written regulatory affairs statements, surveys, or questionna... (<i>Regulatory Affairs Specialists / Business and Financial Operations</i>)
2714 6 (n=255)	2715 Quality and Compliance Monitoring	2716 Examine damaged vehicle to determine extent of structural, body, mechanical, electrical, or interior damage. (<i>Insurance Appraisers, Auto Damage / Business and Financial Operations</i>)
2717 0 (n=240)	2718 Technical Project Management	2719 Develop and implement technical project management tools, such as plans, schedules, and responsibility and compliance matrices. (<i>Logisticians / Business and Financial Operations</i>)
2720 5 (n=231)	2721 Medical Task Execution	2722 Perform medicolegal examinations and autopsies, conducting preliminary examinations of the body to identify victims, locate signs of trauma... (<i>Coroners / Business and Financial Operations</i>)
2723 3 (n=211)	2724 Health Program Management	2725 Prepare reports of findings, illustrating data graphically and translating complex findings into written text. (<i>Market Research Analysts and Marketing Specialists / Business and Financial Operations</i>)
2726 1 (n=205)	2727 Marketing Strategy Development	2728 Verify and analyze data used in settling claims to ensure that claims are valid and that settlements are made according to company practice... (<i>Claims Adjusters, Examiners, and Investigators / Business and Financial Operations</i>)
2729 7 (n=171)	2730 Design and Media Tasks	2731 Compose images of products, using video or still cameras, lighting equipment, props, or photo or video editing software. (<i>Online Merchants / Business and Financial Operations</i>)
2732 2 (n=165)	2733 Energy and Resource Management	2734 Evaluate the use of technologies, such as global positioning systems (GPS), radio-frequency identification (RFID), route navigation softwar... (<i>Logistics Engineers / Business and Financial Operations</i>)
2735 8 (n=139)	2736 Communication Systems Management	2737 Investigate, evaluate, and settle claims, applying technical knowledge and human relations skills to effect fair and prompt disposal of cas... (<i>Claims Adjusters, Examiners, and Investigators / Business and Financial Operations</i>)
2738 4 (n=96)	2739 Training Program Evaluation	2740 Obtain, organize, or develop training procedure manuals, guides, or course materials, such as handouts or visual materials. (<i>Training and Development Specialists / Business and Financial Operations</i>)

²⁷⁵⁷ Table 21. Clusters of tasks with the lowest worker–developer misalignment on the trait simple vs. deeply insightful/comprehensive,
²⁷⁵⁸ identified using MPNet embeddings and K-means clustering. Cluster labels were generated using GPT-4o.

2760 Cluster (size)	2761 Cluster label	2762 Exemplar task (Occupation Sector)
2763 2 (n=410)	2764 Health Program Management	2765 Monitor patients' performance in therapy activities, providing encouragement. (<i>Occupational Therapy Assistants Healthcare Support</i>)
2766 0 (n=394)	2767 Strategic Operations Management	2768 Work under the direction of occupational therapists to plan, implement, or administer educational, vocational, or recreational programs tha... (<i>Occupational Therapy Assistants Healthcare Support</i>)
2769 9 (n=360)	2770 Task Management and Support	2771 Prepare, maintain, and record records of inventories, receipts, purchases, or deliveries, using a variety of computer screen formats. (<i>Pharmacy Aides Healthcare Support</i>)
2772 4 (n=339)	2773 Sales Promotion Analysis	2774 Collect and compile data to document clients' performance or assess program quality. (<i>Speech-Language Pathology Assistants Healthcare Support</i>)
2775 8 (n=284)	2776 Biofuels Research Tasks	2777 Fabricate and fit orthodontic appliances and materials for patients, such as retainers, wires, or bands. (<i>Dental Assistants Healthcare Support</i>)
2778 3 (n=275)	2779 Quality Control Tasks	2780 Consult with managers or other personnel to resolve problems in areas such as equipment performance, output quality, or work schedules. (<i>First-Line Supervisors of Office and Administrative Support Workers Office and Administrative Support</i>)
2781 6 (n=259)	2782 Equipment Maintenance Coordination	2783 Design, fabricate, or repair assistive devices or make adaptive changes to equipment or environments. (<i>Occupational Therapy Assistants Healthcare Support</i>)
2784 5 (n=229)	2785 Evaluate Training Effectiveness	2786 Select or prepare speech-language instructional materials. (<i>Speech-Language Pathology Assistants Healthcare Support</i>)
2787 1 (n=165)	2788 Environmental Monitoring	2789 Read and effectively interpret small-scale maps and information from a computer screen to determine locations and provide directions. (<i>Public Safety Telecommunicators Office and Administrative Support</i>)
2790 7 (n=150)	2791 Biofuels Data Analysis	2792 Expose dental diagnostic x-rays. (<i>Dental Assistants Healthcare Support</i>)

2809 Table 22. Clusters of tasks with the highest worker-developer misalignment on the trait straightforward vs. polite even if not honest,
 2810 identified using MPNet embeddings and K-means clustering. Cluster labels were generated using GPT-4o.

2812 Cluster (size)	2813 Cluster label	2814 Exemplar task (Occupation Sector)
2815 8 (n=135)	2816 Quality Control Oversight	2817 Plan or conduct experimental, environmental, operational, or stress 2818 tests on models or prototypes of aircraft or aerospace systems or 2819 equip... (<i>Aerospace Engineers / Architecture and Engineering</i>)
2820 0 (n=131)	2821 Technical Design Tasks	2822 Create three-dimensional or interactive representations of designs, 2823 using computer-assisted design software. (<i>Architects, Except Land- 2824 scape and Naval / Architecture and Engineering</i>)
2825 1 (n=130)	2826 Task Coordination and Documenta- 2827 tion	2828 Prepare documentation containing information such as confidential 2829 descriptions or specifications of proprietary hardware or software, 2830 produ... (<i>Electronics Engineers, Except Computer / Architecture and 2831 Engineering</i>)
2832 6 (n=129)	2833 Data Analysis and Forecasting	2834 Determine usefulness of new radio frequency identification device 2835 (RFID) technologies. (<i>Radio Frequency Identification Device Special- 2836 ists / Architecture and Engineering</i>)
2838 9 (n=128)	2839 Technical Task Management	2840 Develop or assist in the development of transportation-related com- 2841 puter software or computer processes. (<i>Transportation Engineers / 2842 Architecture and Engineering</i>)
2845 4 (n=107)	2846 Data Analysis Tasks	2847 Store, retrieve, and manipulate data for analysis of system capabili- 2848 ties and requirements. (<i>Computer Hardware Engineers / Architecture 2849 and Engineering</i>)
2853 3 (n=103)	2854 Technical Oversight Tasks	2855 Inspect completed installations and observe operations to ensure 2856 conformance to design and equipment specifications and compli- 2857 ance with ope... (<i>Electrical Engineers / Architecture and Engineering</i>)
2860 2 (n=86)	2861 Complex Technical Tasks	2862 Conduct research related to a range of nanotechnology topics, such 2863 as packaging, heat transfer, fluorescence detection, nanoparticle 2864 disper... (<i>Nanosystems Engineers / Architecture and Engineering</i>)
2868 5 (n=78)	2869 Technical Surveying Tasks	2870 Prepare and alter trace maps, charts, tables, detailed drawings, 2871 and three-dimensional optical models of terrain using stereoscopic 2872 plottin... (<i>Cartographers and Photogrammetrists / Architecture and 2873 Engineering</i>)
2878 7 (n=77)	2879 Task Monitoring and Reporting	2880 Analyze new medical procedures to forecast likely outcomes. (<i>Bio- 2881 engineers and Biomedical Engineers / Architecture and Engineering</i>)

Table 23. Clusters of tasks with the highest worker–developer misalignment on the trait tolerant/open-minded vs. strict, identified using MPNet embeddings and K-means clustering. Cluster labels were generated using GPT-4o.

Cluster (size)	Cluster label	Exemplar task (Occupation Sector)
2 (n=20)	Strict Process Improvement	Identify opportunities to improve plant electrical equipment, controls, or process control methodologies. (<i>Geothermal Production Managers / Management</i>)
0 (n=15)	Strict Monitoring and Planning	Monitor food preparation methods, portion sizes, and garnishing and presentation of food to ensure that food is prepared and presented in a... (<i>Food Service Managers / Management</i>)
4 (n=11)	Data Analysis and Evaluation	Collect and analyze survey data, regulatory information, and data on demographic and employment trends to forecast enrollment patterns and ... (<i>Education Administrators, Kindergarten through Secondary / Management</i>)
8 (n=7)	Strict Budget Management	Develop or review budgets, annual plans, power contracts, power rates, standing operating procedures, power reviews, or engineering studies. (<i>Hydroelectric Production Managers / Management</i>)
1 (n=6)	Research and Evaluation Tasks	Conduct research to develop methodologies, instrumentation, and procedures for medical application, analyzing data and presenting findings. (<i>Epidemiologists / Life, Physical, and Social Science</i>)
9 (n=5)	Data Analysis and Marketing	Monitor and analyze sales promotion results to determine cost effectiveness of promotion campaigns. (<i>Advertising and Promotions Managers / Management</i>)
5 (n=5)	Strict Risk Management	Create scenarios to reestablish operations from various types of business disruptions. (<i>Business Continuity Planners / Business and Financial Operations</i>)
3 (n=5)	Environmental Stewardship Analysis	Provide for stewardship of plant or animal resources or habitats, studying land use, monitoring animal populations, or providing shelter, r... (<i>Natural Sciences Managers / Management</i>)
6 (n=4)	Strict Supply Chain Oversight	Establish or monitor specific supply chain-based performance measurement systems. (<i>Transportation, Storage, and Distribution Managers / Management</i>)
7 (n=4)	Rigid Web Development Guidelines	Create Web models or prototypes that include physical, interface, logical, or data models. (<i>Web Developers / Computer and Mathematical</i>)

2913 Table 24. Clusters of tasks with the highest worker–developer misalignment on the trait practical vs. imaginative, identified using
 2914 MPNet embeddings and K-means clustering. Cluster labels were generated using GPT-4o.

2916 Cluster (size)	2917 Cluster label	2918 Exemplar task (Occupation Sector)
2919 8 (n=23)	2920 Highly Structured Tasks	2921 Plan sequences of operations, applying knowledge of physical properties of workpiece materials. (<i>Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic Production</i>)
2922 1 (n=17)	2923 Technical Operations	2924 Monitor power plant equipment and indicators to detect evidence of operating problems. (<i>Power Plant Operators Production</i>)
2925 3 (n=10)	2926 Highly Practical Tasks	2927 Study traffic delays by noting times of delays, the numbers of vehicles affected, and vehicle speed through the delay area. (<i>Traffic Technicians Transportation and Material Moving</i>)
2928 6 (n=8)	2929 Routine Equipment Monitoring	2930 Operate or maintain distributed power generation equipment, including fuel cells or microturbines, to produce energy on-site for manufatur... (<i>Power Plant Operators Production</i>)
2931 2 (n=8)	2932 Highly technical lab tasks	2933 Perform laboratory procedures following protocols including deoxyribonucleic acid (DNA) sequencing, cloning and extraction, ribonucleic aci... (<i>Molecular and Cellular Biologists Life, Physical, and Social Science</i>)
2934 4 (n=6)	2935 Administrative Support Tasks	2936 Maintain databases, mailing lists, telephone networks, and other information to facilitate the functioning of health education progr... (<i>Health Education Specialists Community and Social Service</i>)
2937 5 (n=5)	2938 Data Management Tasks	2939 Enter computer commands to store or retrieve parts patterns, graphic displays, or programs that transfer data to other media. (<i>Computer Numerically Controlled Tool Programmers Production</i>)
2940 7 (n=3)	2941 Technical Calibration Tasks	2942 Pretest and calibrate anesthesia delivery systems and monitors. (<i>Anesthesiologist Assistants Healthcare Practitioners and Technical</i>)
2943 9 (n=1)	2944 Technical Source Selection	2945 Select sources from which programming will be received or through which programming will be transmitted. (<i>Broadcast Technicians Arts, Design, Entertainment, Sports, and Media</i>)
2946 0 (n=1)	2947 Strict Compliance Tasks	2948 Check building codes and zoning bylaws to determine any effects on the properties being appraised. (<i>Appraisers and Assessors of Real Estate Business and Financial Operations</i>)

2965 Table 25. Sector-level misalignment for Q37 (Final decisions < Sometimes flexible < Open to being challenged). Misalignment ($\Delta_{t,q}$)
 2966 is calculated as worker rating minus developer rating for a given task t and trait q ; negative values indicate developers preferred
 2967 systems to be more open to challenge than workers. Reported values include the average misalignment score for tasks within a sector,
 2968 its standard error (SE), 95% confidence intervals, and the number of tasks (N) within each sector.

Sector	$\frac{1}{N} \sum_{t=1}^N \Delta_{t,q}$	SE	95% CI	N
Installation, Maintenance, and Repair	-0.6	0.072	[-0.744, -0.456]	65
Architecture and Engineering	-0.567	0.024	[-0.614, -0.520]	476
Transportation and Material Moving	-0.545	0.077	[-0.700, -0.391]	55
Healthcare Practitioners and Technical	-0.48	0.03	[-0.538, -0.421]	392
Production	-0.476	0.056	[-0.586, -0.366]	166
Healthcare Support	-0.43	0.064	[-0.558, -0.303]	79
Management	-0.396	0.036	[-0.468, -0.325]	217
Computer and Mathematical	-0.392	0.021	[-0.434, -0.350]	574
Construction and Extraction	-0.387	0.11	[-0.613, -0.161]	31
Protective Service	-0.379	0.092	[-0.567, -0.191]	29
Office and Administrative Support	-0.379	0.064	[-0.505, -0.253]	182
Life, Physical, and Social Science	-0.376	0.029	[-0.434, -0.318]	279
Community and Social Service	-0.333	0.088	[-0.512, -0.154]	30
Farming, Fishing, and Forestry	-0.333	0.333	[-1.768, 1.101]	3
Business and Financial Operations	-0.325	0.029	[-0.383, -0.268]	289
Arts, Design, Entertainment, Sports, and Media	-0.261	0.032	[-0.325, -0.197]	203
Sales and Related	-0.2	0.2	[-0.652, 0.252]	10
Legal	-0.143	0.261	[-0.781, 0.495]	7
Educational Instruction and Library	-0.122	0.041	[-0.204, -0.040]	90

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3017 Table 26. Sector-level misalignment for Q38 (Generalization < Some adjustment < Personalized). Misalignment ($\Delta_{t,q}$) is calculated as
 3018 worker rating minus developer rating for a given task t and trait q ; negative values indicate developers preferred more personalized
 3019 systems than workers. Reported values include the average misalignment score for tasks within a sector, its standard error (SE), 95%
 3020 confidence intervals, and the number of tasks (N) within each sector.

Sector	$\frac{1}{N} \sum_{t=1}^N \Delta_{t,q}$	SE	95% CI	N
Life, Physical, and Social Science	-0.43	0.069	[-0.565, -0.295]	279
Business and Financial Operations	-0.367	0.054	[-0.474, -0.260]	289
Healthcare Practitioners and Technical	-0.301	0.047	[-0.393, -0.209]	392
Construction and Extraction	-0.29	0.141	[-0.577, -0.003]	31
Installation, Maintenance, and Repair	-0.246	0.17	[-0.586, 0.093]	65
Office and Administrative Support	-0.231	0.08	[-0.389, -0.072]	182
Sales and Related	-0.2	0.133	[-0.502, 0.102]	10
Computer and Mathematical	-0.199	0.048	[-0.292, -0.105]	574
Architecture and Engineering	-0.189	0.057	[-0.302, -0.076]	476
Legal	-0.143	0.261	[-0.781, 0.495]	7
Protective Service	-0.103	0.091	[-0.289, 0.082]	29
Production	-0.102	0.086	[-0.272, 0.068]	166
Management	-0.069	0.052	[-0.172, 0.034]	217
Community and Social Service	0.067	0.067	[-0.070, 0.203]	30
Healthcare Support	0.051	0.09	[-0.128, 0.230]	79
Transportation and Material Moving	0.036	0.142	[-0.248, 0.321]	55
Arts, Design, Entertainment, Sports, and Media	0.02	0.048	[-0.075, 0.114]	203
Educational Instruction and Library	0.011	0.04	[-0.069, 0.091]	90
Farming, Fishing, and Forestry	0.0	1.0	[-4.303, 4.303]	3

3069 Table 27. Sector-level misalignment for Q40 (Straightforward < Neutral < Polite even if not honest). Misalignment ($\Delta_{t,q}$) is calculated
 3070 as worker rating minus developer rating for a given task t and trait q ; negative values indicate developers preferred systems to be
 3071 more polite (even at the expense of honesty) than workers. Reported values include the average misalignment score for tasks within a
 3072 sector, its standard error (SE), 95% confidence intervals, and the number of tasks (N) within each sector.

Sector	$\frac{1}{N} \sum_{t=1}^N \Delta_{t,q}$	SE	95% CI	N
Production	-2.777	0.135	[-3.044, -2.511]	166
Architecture and Engineering	-2.532	0.085	[-2.698, -2.365]	476
Life, Physical, and Social Science	-2.376	0.116	[-2.604, -2.149]	279
Computer and Mathematical	-2.235	0.086	[-2.404, -2.067]	574
Installation, Maintenance, and Repair	-1.938	0.218	[-2.374, -1.503]	65
Business and Financial Operations	-1.837	0.118	[-2.069, -1.605]	289
Construction and Extraction	-1.806	0.403	[-2.629, -0.984]	31
Healthcare Practitioners and Technical	-1.597	0.088	[-1.770, -1.424]	392
Protective Service	-1.552	0.353	[-2.275, -0.829]	29
Management	-1.525	0.113	[-1.748, -1.303]	217
Arts, Design, Entertainment, Sports, and Media	-1.207	0.137	[-1.476, -0.938]	203
Healthcare Support	-1.051	0.169	[-1.387, -0.714]	79
Transportation and Material Moving	-1.036	0.262	[-1.562, -0.511]	55
Educational Instruction and Library	-0.9	0.156	[-1.211, -0.589]	90
Community and Social Service	-0.867	0.257	[-1.392, -0.341]	30
Office and Administrative Support	-0.637	0.154	[-0.941, -0.333]	182
Legal	-1.857	0.8	[-3.814, 0.100]	7
Farming, Fishing, and Forestry	-1.333	2.667	[-12.807, 10.140]	3
Sales and Related	-0.7	0.616	[-2.092, 0.692]	10

3121 Table 28. Sector-level misalignment for Q41 (Tolerant/Open-minded < Fair < Strict). Misalignment ($\Delta_{t,q}$) is calculated as worker rating
 3122 minus developer rating for a given task t and trait q ; negative values indicate developers preferred stricter systems than workers.
 3123 Reported values include the average misalignment score for tasks within a sector, its standard error (SE), 95% confidence intervals,
 3124 and the number of tasks (N) within each sector.

Sector	$\frac{1}{N} \sum_{t=1}^N \Delta_{t,q}$	SE	95% CI	N
Community and Social Service	1.267	0.106	[1.049, 1.484]	30
Educational Instruction and Library	1.067	0.077	[0.913, 1.220]	90
Management	0.76	0.072	[0.618, 0.902]	217
Sales and Related	0.7	0.213	[0.217, 1.183]	10
Arts, Design, Entertainment, Sports, and Media	0.655	0.059	[0.538, 0.772]	203
Healthcare Support	0.443	0.082	[0.280, 0.606]	79
Business and Financial Operations	0.415	0.057	[0.304, 0.527]	289
Healthcare Practitioners and Technical	0.401	0.047	[0.308, 0.493]	392
Life, Physical, and Social Science	0.348	0.052	[0.244, 0.451]	279
Protective Service	-0.276	0.139	[-0.562, 0.010]	29
Computer and Mathematical	0.261	0.036	[0.190, 0.333]	574
Construction and Extraction	0.161	0.105	[-0.053, 0.375]	31
Installation, Maintenance, and Repair	0.154	0.091	[-0.028, 0.336]	65
Office and Administrative Support	0.154	0.049	[0.057, 0.251]	182
Legal	-0.143	0.143	[-0.492, 0.207]	7
Architecture and Engineering	0.044	0.026	[-0.007, 0.095]	476
Production	0.024	0.023	[-0.020, 0.069]	166
Transportation and Material Moving	0.018	0.066	[-0.114, 0.151]	55
Farming, Fishing, and Forestry	0.0	0.0	[0.000, 0.000]	3

3173 Table 29. Sector-level misalignment for Q44 (Simple < Some depth < Deeply insightful/comprehensive). Misalignment ($\Delta_{t,q}$) is
 3174 calculated as worker rating minus developer rating for a given task t and trait q ; negative values indicate developers preferred systems
 3175 that are more deeply insightful and comprehensive than workers. Reported values include the average misalignment score for tasks
 3176 within a sector, its standard error (SE), 95% confidence intervals, and the number of tasks (N) within each sector.

Sector	$\frac{1}{N} \sum_{t=1}^N \Delta_{t,q}$	SE	95% CI	N
Healthcare Support	0.241	0.079	[0.083, 0.398]	79
Transportation and Material Moving	0.2	0.084	[0.032, 0.368]	55
Office and Administrative Support	0.165	0.068	[0.031, 0.298]	182
Installation, Maintenance, and Repair	0.154	0.055	[0.045, 0.263]	65
Protective Service	0.138	0.065	[0.004, 0.271]	29
Production	0.102	0.05	[0.005, 0.200]	166
Construction and Extraction	0.065	0.113	[-0.166, 0.295]	31
Arts, Design, Entertainment, Sports, and Media	0.039	0.024	[-0.008, 0.087]	203
Community and Social Service	0.033	0.033	[-0.035, 0.102]	30
Business and Financial Operations	-0.031	0.019	[-0.069, 0.007]	289
Management	-0.023	0.017	[-0.056, 0.010]	217
Educational Instruction and Library	0.022	0.016	[-0.009, 0.053]	90
Healthcare Practitioners and Technical	0.015	0.019	[-0.022, 0.053]	392
Computer and Mathematical	0.014	0.01	[-0.005, 0.033]	574
Life, Physical, and Social Science	-0.007	0.011	[-0.030, 0.015]	279
Architecture and Engineering	-0.006	0.009	[-0.024, 0.012]	476
Farming, Fishing, and Forestry	0.0	0.577	[-2.484, 2.484]	3
Legal	0.0	0.378	[-0.925, 0.925]	7
Sales and Related	0.0	0.0	[0.000, 0.000]	10

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3225 Table 30. Sector-level misalignment for Q45 (Practical < Somewhat creative < Imaginative). Misalignment ($\Delta_{t,q}$) is calculated as
 3226 worker rating minus developer rating for a given task t and trait q ; negative values indicate developers preferred more imaginative
 3227 systems than workers. Reported values include the average misalignment score for tasks within a sector, its standard error (SE), 95%
 3228 confidence intervals, and the number of tasks (N) within each sector.

Sector	$\frac{1}{N} \sum_{t=1}^N \Delta_{t,q}$	SE	95% CI	N
Production	-1.09	0.077	[-1.243, -0.938]	166
Transportation and Material Moving	-0.6	0.146	[-0.892, -0.308]	55
Farming, Fishing, and Forestry	-1.333	0.333	[-2.768, 0.101]	3
Office and Administrative Support	-0.467	0.06	[-0.585, -0.349]	182
Healthcare Practitioners and Technical	-0.439	0.051	[-0.539, -0.339]	392
Installation, Maintenance, and Repair	-0.338	0.121	[-0.579, -0.097]	65
Business and Financial Operations	-0.318	0.05	[-0.416, -0.221]	289
Life, Physical, and Social Science	-0.269	0.052	[-0.371, -0.166]	279
Management	-0.23	0.052	[-0.333, -0.128]	217
Construction and Extraction	-0.226	0.165	[-0.563, 0.112]	31
Healthcare Support	-0.203	0.094	[-0.390, -0.015]	79
Arts, Design, Entertainment, Sports, and Media	-0.182	0.047	[-0.275, -0.090]	203
Architecture and Engineering	-0.181	0.039	[-0.258, -0.104]	476
Computer and Mathematical	-0.162	0.034	[-0.230, -0.094]	574
Protective Service	-0.103	0.174	[-0.461, 0.254]	29
Sales and Related	-0.1	0.18	[-0.506, 0.306]	10
Community and Social Service	0.067	0.143	[-0.226, 0.360]	30
Educational Instruction and Library	-0.067	0.044	[-0.154, 0.021]	90
Legal	0.0	0.309	[-0.755, 0.755]	7