

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

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

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

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

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23 **1 Introduction**

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

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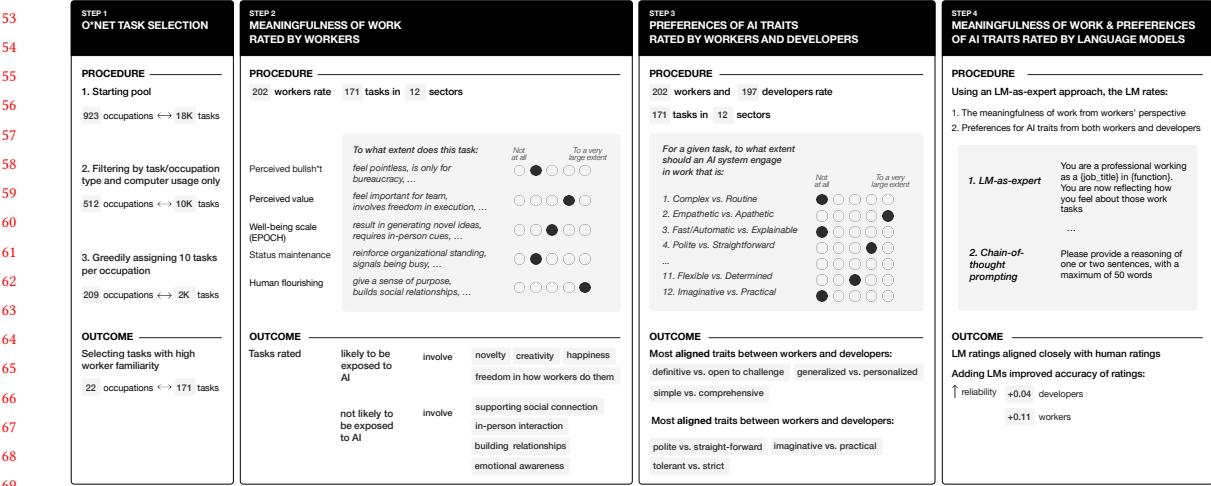
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**Fig. 1. Overview of Study Design:** Worker and developer perspectives on meaningful work and AI system design in the U.S. labor force. (Step 1) Workplace tasks were restricted to those primarily completed on a computer and performed daily or weekly, then filtered by Prolific availability, AI Impact Index, and worker familiarity. (Step 2) Workers rated tasks across five dimensions: perceived bullish\*<sup>t</sup>, 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 75<sup>th</sup> 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

123 In so doing, we made the following main contributions:  
124

- 125 (1) We identified Prolific workers who reported high familiarity with a representative set of 171 tasks spanning  
126 22 occupations drawn from the U.S. Department of Labor's Occupational Information Network (O\*NET)  
127 (methodology in Section 3.1; task representativeness in Figure 2).
- 128 (2) We conducted a scoping review of research on meaningful work (Section 3.2), which informed the construction  
129 of survey items for workers (Section 3.3). Building on recent work specifying desirable AI traits across occu-  
130 pations [26], we then developed parallel survey modules: one for workers, eliciting the traits they want AI to  
131 possess (Section 3.3), and one for developers, eliciting the traits they intend to design in AI systems (Section 3.4).
- 132 (3) We administered the surveys to 202 previously identified workers and to a new sample of 197 developers across  
133 171 tasks in 12 sectors (Section 3.5). We then scaled up their responses by measuring LM agreement with  
134 human ratings and, under reasonable agreement, generated task-level annotations for 10,131 tasks across 512  
135 occupations and 19 sectors (Section 3.6). We make these two human-generated datasets publicly available so  
136 that future research can explore alternative methods for generating synthetic data from them.  
137
- 138 (4) Our first main contribution, addressing RQ1 (Section 4.1; Figure 3), shows that tasks identified as likely to be  
139 exposed to AI are more strongly associated by workers with novelty/creativity, positive affect, and autonomy  
140 (Figure 4). This challenges the usual narrative that automation mainly targets routine tasks [79]. By contrast,  
141 tasks rated as unlikely to be exposed to AI are more often linked by workers to emotional awareness, in-person  
142 interaction, relationship building, and social connection (Figure 5).  
143
- 144 (5) Our second main contribution, in addressing RQ2 (Section 4.2; Figure 6), reveals clear gaps between workers'  
145 preferences and developers' design intentions: workers prefer straightforward systems, whereas developers  
146 intend to design polite systems (Figure 6), consistent with reports of LM sycophancy [24], which is a systematic  
147 bias of LMs toward agreeing with users' views irrespective of correctness. More generally, developers favor  
148 polite, strict, and imaginative systems, whereas workers often describe these design choices as unnecessary  
149 friction or rigidity rather than genuine support. By contrast, both groups converge on the need of personalized  
150 systems.  
151

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

203 While the warmth–competence framework advances theory, workers rarely judge AI in simple binary terms. Recent  
 204 evidence suggests people judge whether AI is suitable for a job by the traits the job requires [26]. Dong et al. [26] finds  
 205 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 database<sup>1</sup>, 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).

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

### 261 3.1 Selecting Tasks and Recruiting Workers and Developers

262 **263 O\*NET 29.3 Database.** The O\*NET database provides standardized information on U.S. sectors<sup>2</sup>, occupations and their  
 264 associated tasks. It organizes 923 occupations into sectors where each occupation is broken down into task statements<sup>3</sup>  
 265 describing work activities. In total, O\*NET contains 18,796 tasks, where each task is classified as *core* or *supplementary*,  
 266 and annotated with how frequently it's performed (e.g., yearly or less, monthly, weekly, daily, or hourly)<sup>4</sup>.  
 267

268 **269 Selecting Tasks Exposed to AI.** Our study primarily focuses on workplace tasks likely to be exposed to AI. We follow  
 270 prior work [80], and apply a multi-step filtering pipeline (Step 1; Figure 1) to identify a representative set of tasks for our  
 271 study. First, we ensured each task is classified as either *core* or *supplementary* to ensure its relevance to the occupation.  
 272 Then, we characterized and filtered occupations and tasks by two criteria as determined by GPT-4o annotations in line  
 273 with [80]: (1) the *occupation* primarily involves computer use and, (2) the *task* can be completed on a computer. Upon  
 274 manual inspection, we found that GPT-4o occasionally excluded occupations (e.g., nursing, education professionals)  
 275 that are widely recognized as exposed to AI [70, 74, 75]. To ensure these occupations were represented in our dataset,  
 276 we manually curated and included a list of 427 occupations that were exempted from these filters, with examples shown  
 277 in Appendix Table 4. Following these filtering steps, our dataset contained 10,131 tasks spanning 512 occupations.  
 278

279 **280 Recruiting Workers and Selecting Tasks Familiar to Them.** We used Prolific to recruit U.S. workers and developers  
 281 (Appendix Table 7). We applied the “work function” screener to identify participants likely to be familiar with the tasks  
 282 they evaluated. Both workers and developers were compensated at a rate of \$11 per hour. Each O\*NET occupation was  
 283 mapped to one of 21 work functions (Appendix Table 3), yielding 4,473 tasks across 209 occupations. To keep surveys  
 284 tractable and reduce participant fatigue, we downsampled to at most 10 tasks per occupation using a greedy selection  
 285 criterion based on task frequency annotations (e.g., daily) and estimated AI exposure [79], resulting in 2,078 tasks  
 286 across 209 occupations. Our study required participants who were experts in their domains, which made recruitment  
 287 especially challenging: if participants are not familiar with the tasks they are asked to evaluate, their responses risk  
 288 being speculative rather than grounded in real-world practice. To target U.S. workers who are experts in their domains,  
 289 we first ran a preliminary survey which identified workers that: (1) belonged to one of 21 professional work functions  
 290 on Prolific, (2) passed attention checks, and (3) reported being highly familiar with at least one O\*NET task in their  
 291 occupation. Following this rigorous pre-screening, we recruited 202 workers, excluding those who failed our attention  
 292 checks. From these responses, we retained tasks rated as “Very familiar” or “Extremely familiar” by at least three  
 293 participants, producing a final set of 171 tasks across 22 occupations and 12 sectors. This subset provided broad coverage  
 294 (12 of 22 total sectors in O\*NET), while focusing on tasks that were central to the occupation (i.e., core or frequently  
 295 performed), likely to be exposed to AI, and validated as highly familiar to workers.  
 296

297 **298 Recruiting Developers.** For developers, we focused on U.S.-based AI practitioners who met the following screening  
 299 criteria: weekly AI use (ranging from once a week to multiple times daily), individual contributor or non-manager  
 300 role, employment in coding, technical writing, or systems administration, and primary function in engineering (e.g.,  
 301 software) or research. We recruited 197 developers who each rated 10 tasks, drawn from the same pool of tasks  
 302 the workers rated. Each task received ratings from at least three distinct developers. Given the heterogeneity of ‘AI  
 303

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

305 <sup>3</sup>[https://www.onetcenter.org/dictionary/29.3/excel/task\\_statements.html](https://www.onetcenter.org/dictionary/29.3/excel/task_statements.html)

306 <sup>4</sup>[https://www.onetcenter.org/dictionary/29.3/excel/task\\_ratings.html](https://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

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

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.  
354

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:

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

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

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

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

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

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

409 **410 Perceived Bullsh\*tness [36] (Q1-5).** These five questions measure the extent to which participants view their tasks as  
 411 pointless, bureaucratic, or not contributing to the goals of their organization. Example survey items include: 'I perform  
 412 this task only to satisfy bureaucracy or appearances' and 'This task does not contribute to the goals of my organization'.  
 413

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

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

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

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 **3.5 Administering Questions to Workers and Developers**  
 492

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

503  
 504 **3.6 Scaling and Validating Responses with Language Models**  
 505

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

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

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

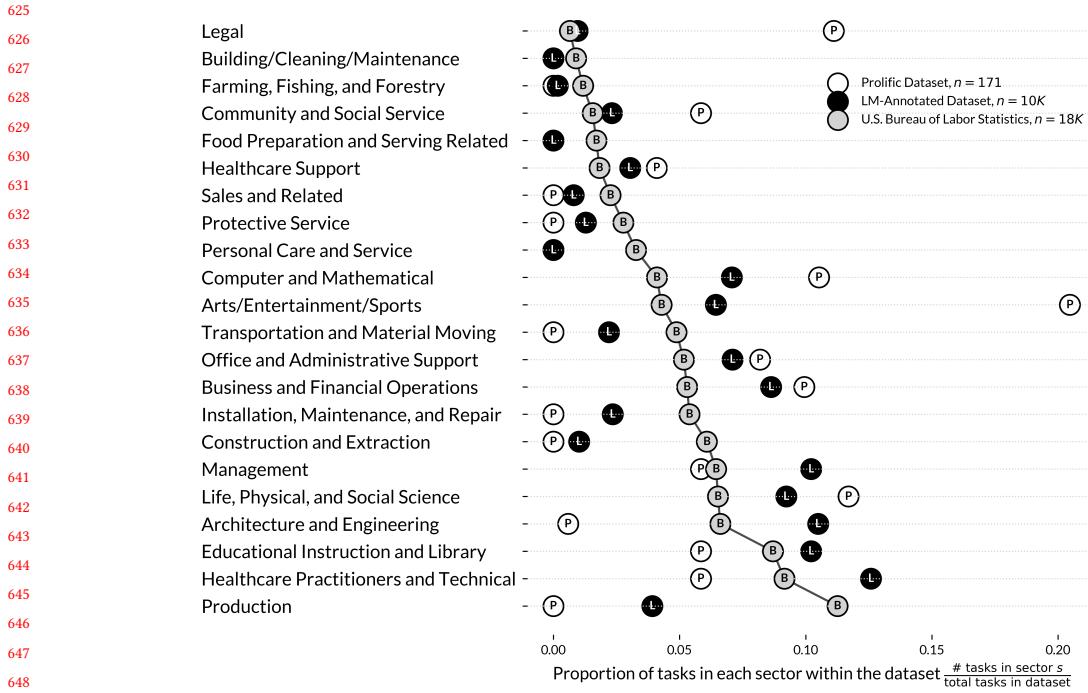


Fig. 2. Proportions of tasks across occupational sectors in three datasets: Prolific (n=171), LM-annotated (n=10K), and U.S. labor statistics (n=18K). The Prolific sample covers 12 sectors (based on available occupations), the LM-annotated dataset covers 19 sectors, and the U.S. Bureau of Labor Statistics 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

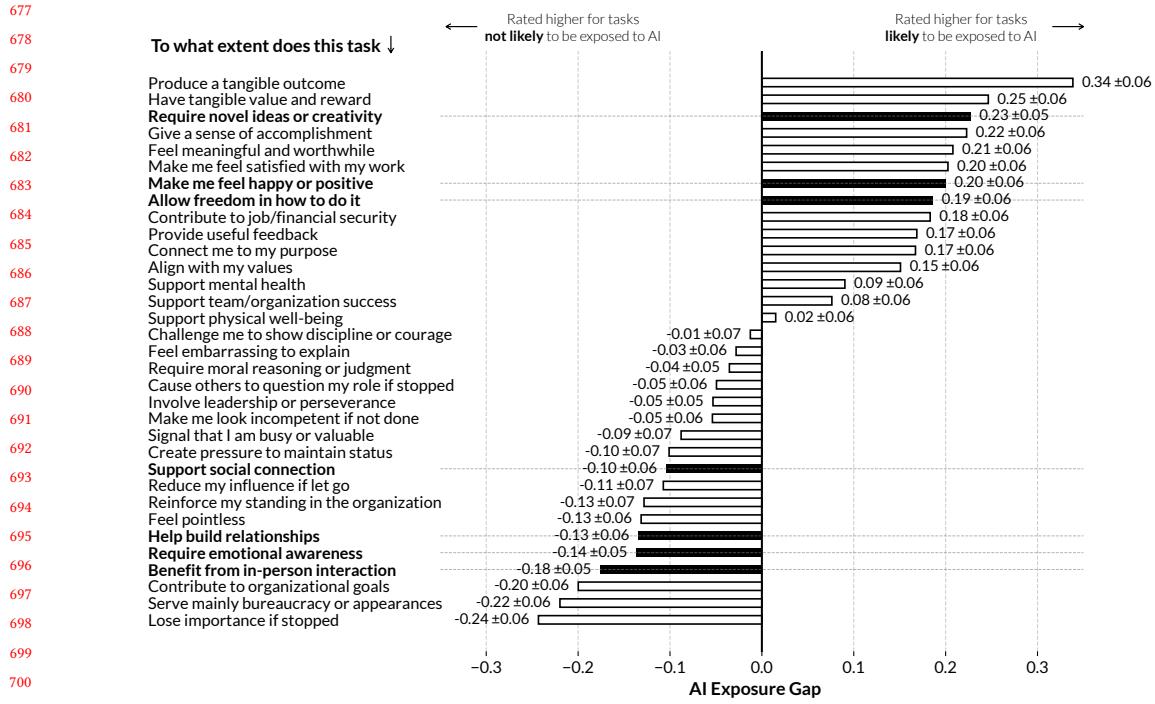


Fig. 3. AI Exposure Gap by dimensions of meaningful work (rows). The higher the gap, the more strongly that dimension is associated with tasks likely to be exposed AI. This gap is computed as the difference of how important a dimension is between two groups of tasks: those that seem more likely to be 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  $t$ ;  $\text{AIExposure}_t$  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;  $\beta_0$  is the fixed effect intercept, representing the baseline importance of dimension  $d$  for not-likely-to-be-exposed tasks ( $\text{AIExposure}_t = 0$ );  $\beta_1$  is the fixed effect of AI exposure, estimating the mean difference

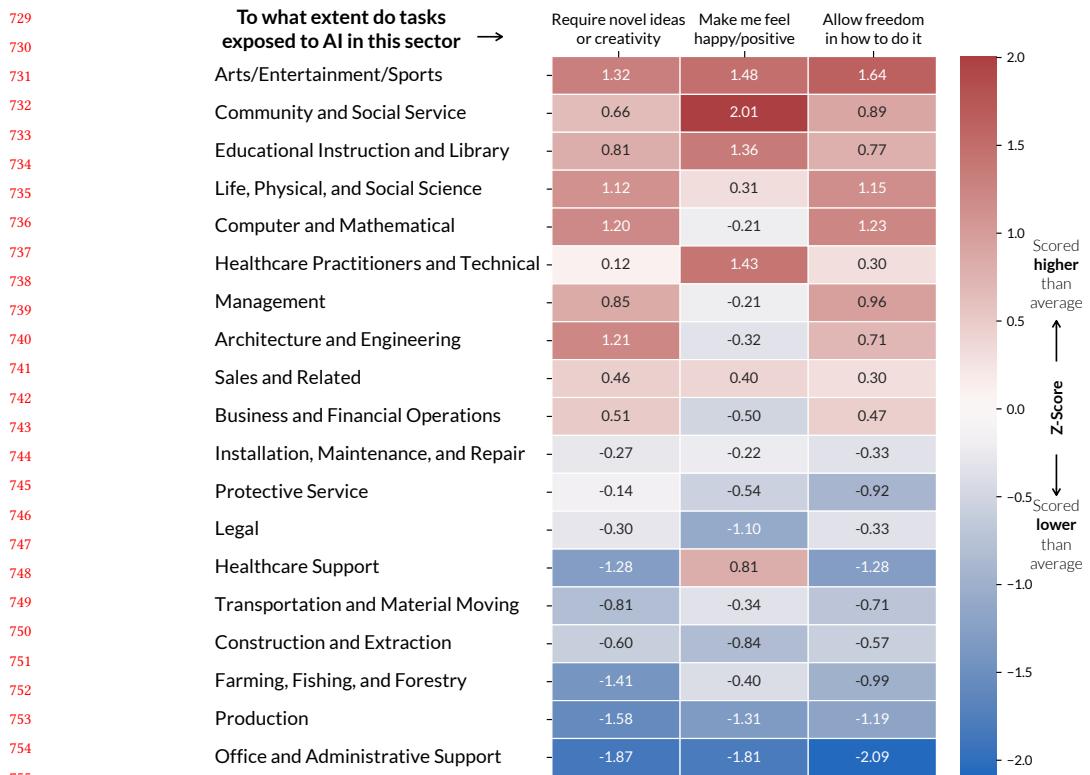


Fig. 4. Association of tasks exposed to AI in each of the sectors (in the *rows*) with subset of three dimensions of meaningful work (creativity, positive affect, and autonomy in the *columns*). Sectors are sorted by the average z-score across the three dimensions. Creative and socially-oriented sectors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

in worker ratings between likely-to-be-exposed and not-likely-to-be-exposed tasks. Given that tasks are nested within occupations, which, in turn, are nested within sectors, to account for varying baselines within sectors and occupations, we also included a random intercept  $u_s$  for sector  $s$ , and random intercept  $u_{o(s)}$  for occupations nested within sector  $s$ , followed by  $\epsilon_{t,d}$ , which is the residual error term for task  $t$  on dimension  $d$ . Models were estimated using maximum likelihood (restricted maximum likelihood, REML, disabled). For each dimension, we report  $\beta_1$  (the difference in worker ratings for likely-to-be-exposed vs. not-likely-to-be-exposed tasks), its standard error, and 95% confidence intervals. To address multiple comparisons across our survey items, we applied the Benjamini–Hochberg False Discovery Rate (FDR) correction. We defined the fixed effect as statistically significant, if two conditions were met: (1) the FDR-adjusted  $p < 0.05$ , and (2) the effect size exceeded  $\Delta \geq 0.1$  Likert points. While a threshold of 0.1 may appear small, our results are reported in aggregate across all sectors; when disaggregated at the sector level, we show that differences are often substantially larger. The latter serves as a threshold for practical significance: on a 5-point scale, a 0.1 shift represents a small but interpretable change in perceived task characteristics, ensuring that we highlight effects that are not only statistically detectable but also meaningful in practice.

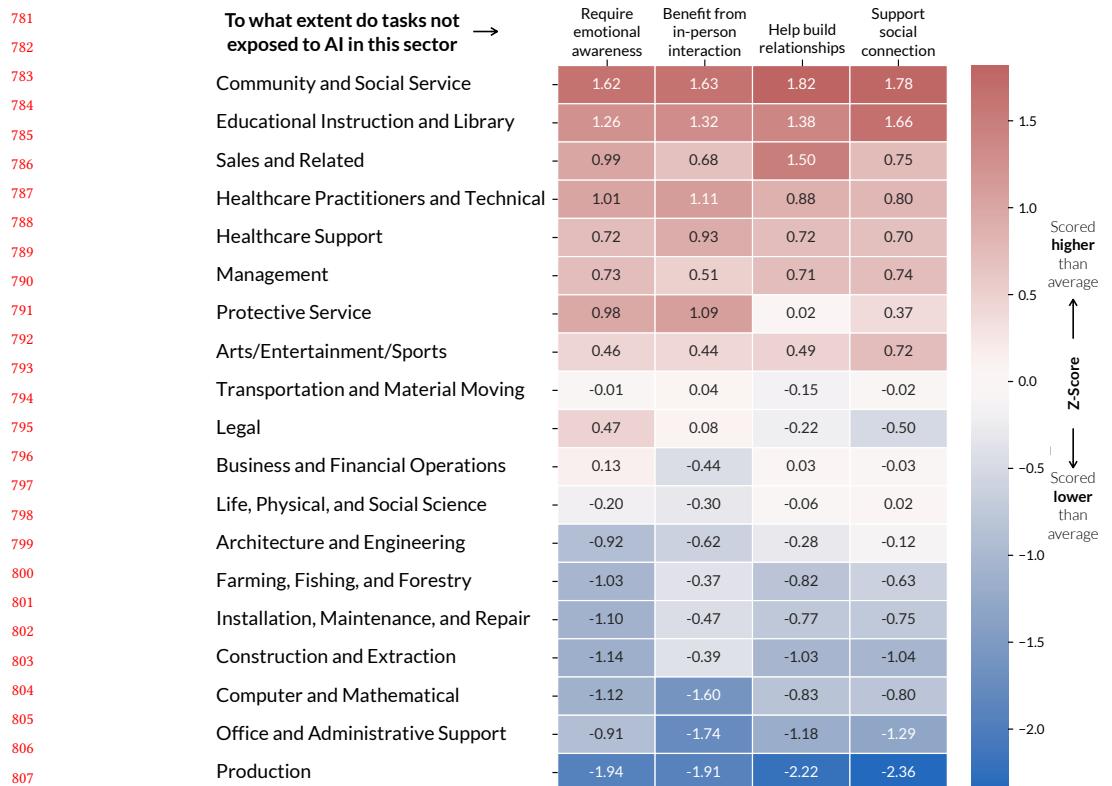


Fig. 5. Association of tasks not exposed to AI in each of the sectors (in the *rows*) with subset of four dimensions of meaningful work (emotional awareness, in-person interaction, relationship building, and social connections in the *columns*). Sectors are sorted by the average z-score across the subset 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,  $p_{LR} < 0.05$ ).

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  
 842 (3) *Tasks that remain less exposed to AI are those that rely on relationships and sensitivity to context, with their value*  
 843 *derived from human attention and judgment.* In Education, Sales, Community & Social Services, and Healthcare,  
 844 core activities (e.g., “counseling students through intertwined academic and personal issues”, “presenting  
 845 offers while preserving relationships”) depend on real-time, co-constructed meaning, and nuanced perception  
 846 that resists codification (Figure 5, and Appendix Table 12). Consistent with this pattern, clusters emphasizing  
 847 emotional awareness and relationship building are predominantly human-centered (Appendix Table 16).  
 848  
 849

#### 850 4.2 Do teams design AI systems with traits that align with the traits workers want? (RQ2)

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

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

$$859 \Delta_{t,q} = \text{workers rating}_{t,q} - \text{developers rating}_{t,q}.$$

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

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

885 Table 1. Worker–developer misalignment by AI traits. Misalignment is defined as the average absolute difference between worker  
 886 and developer ratings (Q34–Q45) of the traits they believe AI systems should possess. Differences ( $\Delta_{t,q}$ ) are calculated as worker  
 887 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  
 888 values are aggregated over sectors and traits are grouped into high, mixed, or aligned categories based on percentile thresholds of  
 889 average absolute misalignment. # Sig. Sectors refers to the number of sectors that had statistically significant *differences* in ratings  
 890 between workers and developers. The largest gaps appear for Straightforward vs. Polite, Tolerant/Open-minded vs. Strict, Practical  
 891 vs. Imaginative, and Flexible vs. Determined, whereas traits such as Generalized vs. Personalized, Simple vs. Comprehensive, and  
 892 Business-like vs. Warm/caring show little to no misalignment.

Trait	# Sig. Sectors	$\Sigma \Delta_{t,q} $	$\mu \Delta_{t,q} $
<b>High misalignment</b>			
(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
<b>Mixed misalignment</b>			
(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
<b>Aligned</b>			
(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

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

923 Also, to surface broad patterns of misalignment, for each trait, we identified tasks in the extreme percentiles of  
 924 misalignment (top 99<sup>th</sup>, and bottom 1<sup>st</sup>), clustered these tasks using MPNet<sup>5</sup> embeddings and K-Means clustering, and  
 925 labeled the resulting clusters (Appendix Tables 19–24). To interpret these aggregate results, we distilled three recurring,  
 926 salient design tensions:

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

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<sup>5</sup><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  
 1137

1138 1139 1140 1141 1142 1143 1144

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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  
 1149 **5.3 Limitations**  
 1150

1151 This work has several broad limitations:

1152  
 1153 (1) *Representativeness of tasks and participants.* We have focused on U.S. occupational tasks. Results may differ in  
 1154 other regions or settings with other norms or tools [16]. Our worker and developer samples were recruited  
 1155 through Prolific, where participants tend to be more technologically literate. As a result, perspectives from  
 1156 low-wage, non-digital, or less AI-exposed occupations may be underrepresented. Although our pre-screening  
 1157 procedure ensured that participants were highly familiar with the tasks they evaluated, future work should  
 1158 expand to other recruitment channels (e.g., industry partnerships, unions, vocational training programs) to  
 1159 capture a wider diversity of workplace contexts and skill levels. Although the distribution of technical roles,  
 1160 AI usage, and work functions in our sample indicates that developers were actively engaged in building or  
 1161 maintaining AI-driven systems across diverse sectors (Figure 7), we acknowledge that our samples may not  
 1162 fully capture the breadth of industry roles.  
 1163  
 1164 (2) *Modeling assumptions.* Our mixed-effects regression models assume linear relationships between AI exposure  
 1165 likelihood and each dimension of meaningful work. While this framework is appropriate for estimating average  
 1166 effects across occupations and sectors, relationships among meaningfulness dimensions may be non-linear or  
 1167 interactive. For example, creativity and autonomy may jointly shape how a task is exposed to AI. Exploring  
 1168 non-linearities, higher-order interactions, and potentially hierarchical or multivariate modeling structures is an  
 1169 important direction for future work.  
 1170  
 1171 (3) *Measurement bias in LM-assisted scaling.* We used an LM to scale ratings to roughly 10K tasks, which raises  
 1172 concerns about whether it reflects worker and developer perspectives or simply produces plausible responses.  
 1173 We therefore treat LM ratings as approximating the distribution of human responses rather than as ground truth,  
 1174 and use the term “agreement” to avoid implying a correct answer. To justify LM-assisted scaling, we compared  
 1175 empirical findings from LM vs. human ratings and observed that LM-simulated patterns of worker-developer  
 1176 misalignment closely matched human-only results (Appendix Figure 9, and Appendix Tables 17 and 18).  
 1177 Robustness checks further confirmed that ICC gains cannot be explained by LM stability alone, indicating  
 1178 substantive alignment between LM and human judgments. However, LM ratings are more uniform and optimistic  
 1179 in some sectors, and qualitative divergences remain (Appendix Table 8, and Appendix Figure 8). These findings  
 1180 support using LMs for scaling, but should be interpreted cautiously, as they may miss fine-grained nuances  
 1181 present in human judgments.  
 1182  
 1183 (4) *Task filtering and indices of exposure.* Our task-selection pipeline reduced the full O\*NET task universe to a  
 1184 subset most relevant for AI exposure, which may introduce task mix bias. Although we used established filters  
 1185 and impact scores [8, 79, 80], this process inevitably excludes tasks that matter in practice, especially specialized  
 1186 or licensed work that participants reported low familiarity with. We restored a targeted set of tasks from  
 1187 domains such as healthcare and education, and our final sample aligns with the U.S. Bureau of Labor Statistics  
 1188 employment distributions, but finer-grained gaps within sectors may remain. Future work with domain experts  
 1189 or professional organizations could help validate task coverage and identify activities that should be included.  
 1190  
 1191

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.  
 1206  
 1207

1209 **6 Conclusion**

1210 Our results suggest that the tasks most likely to be exposed to AI are disproportionately those that workers associate  
 1211 with joy and agency: novelty and creativity, feeling happy, and having freedom in how to do the work. Yet current  
 1212 design choices often appear not to match what workers say they want from AI, raising concerns that such systems may  
 1213 affect how meaningful work feels. This outcome is shaped by design choices, which can, in principle, be revised. As  
 1214 HCI researchers, we propose a five-part agenda detailed in Table 2.  
 1215

1216 We argue that a central risk of AI exposure is not mass unemployment but “mass demoralization”: a loss of meaning  
 1217 and ownership in day-to-day work. As models generate more early-stage outputs, the visible creative steps can  
 1218 feel machine-made, while human contributions can become rushed, under-resourced, and hard to recognize. The  
 1219 corresponding promise, if systems are designed and governed accordingly, is a clearer and more humane division of  
 1220 labor: systems that accelerate exploration and drafting, and people who retain authorship, make final judgments, and  
 1221 sustain the relationships that define meaningful work.  
 1222

1223 **7 Ethical Considerations**

1224 This study received approval through our institution’s research ethics review process. In recruiting workers and  
 1225 developers on Prolific, we did not collect personally identifiable information, and participants could withdraw at any  
 1226 time.  
 1227

1228 Beyond procedural safeguards, the study raised three broader ethical considerations. First, surveying both workers  
 1229 and developers about task-level evaluations of work and AI traits risks reinforcing stereotypes about either group’s  
 1230 perspectives. For instance, developers may be framed as indifferent to meaningful work, or workers as resistant to  
 1231 technology, while aggregate analyses can mask the diversity of individual viewpoints. To mitigate this, we reported  
 1232 results in the aggregate but emphasized the diversity of participant perspectives. We also encourage future work to  
 1233 analyze individual-level differences, including how socio-demographic characteristics shape experiences of meaningful  
 1234 work.  
 1235

1236 Second, our use of LMs to scale annotations introduces the risk of amplifying biases. LMs may underrepresent  
 1237 perspectives from marginalized groups or impose normative judgments about what constitutes meaningful work.  
 1238 To address this, we benchmarked model outputs against human responses, reported intra-class correlation metrics,  
 1239 and included parallel analyses based on human-only ratings to contrast with LM-scaled analyses. We caution that  
 1240 model-based scaling is an approximation, not a replacement, for direct human judgment.  
 1241

1249 Table 2. From empirical observations to research questions and developer/designer heuristics for worker-aligned AI. Each row links  
 1250 our findings to specific HCI research questions, example workflows, and design heuristics aimed at preserving creativity, autonomy,  
 1251 and meaning in day-to-day work.

1252	Empirical Observation + Example Workflow	Research Questions and Developer/Designer Heuristics
1253	<b>High-agency tasks appear heavily exposed to AI.</b> 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).	<p><b>Research questions.</b> (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?</p>
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.	<p><b>Heuristics for developers/designers.</b> (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”.</p>
1255		<p><b>Where in the workflow.</b> Ideation, outlining, first-draft generation, early revision.</p>
1256		<p><b>What success looks like.</b> 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.</p>
1257		
1258		
1259		
1260		
1261		
1262		
1263	<b>Joyful and creative parts of work often fall in high-exposure categories.</b> 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).	<p><b>Research questions.</b> (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)?</p>
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.	<p><b>Heuristics for developers/designers.</b> (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.</p>
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1268		
1269		
1270		
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1272		
1273	<b>Relational work appears less exposed to AI.</b> In our data, work that supports social connection and relationships tends to appear in the lower-exposure-to-AI group (Section 4.1).	<p><b>Research questions.</b> (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?</p>
1274		
1275		
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.	<p><b>Heuristics for developers/designers.</b> (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.</p>
1277		
1278		
1279		
1280		
1281		
1282		
1283	<b>Workers and developers differ in reported preferences for AI assistant traits.</b> 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).	<p><b>Research questions.</b> (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?</p>
1284		
1285		
1286		
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.	<p><b>Heuristics for developers/designers.</b> (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.</p>
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1289		
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1293		
1294		
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.	
1296		
1297		
1298	To minimize potential harm, we framed survey items in neutral and respectful language, and piloted them for clarity before deployment.	
1299		
1300		

1301 These considerations highlight the importance of protecting participants' dignity and avoiding overgeneralization  
 1302 when studying misalignment between workers and developers. Our aim is not to prescribe what should count as  
 1303 meaningful work, but to inform AI design choices that respect and align with workers' values.  
 1304

## 1305 8 Author Positionality Statement

1308 Our research team consists of two women and two men from the United States, Asia and Southern Europe representing  
 1309 diverse ethnic, linguistic, and religious backgrounds. All authors have lived and worked in multiple countries, including  
 1310 the United States, giving us direct experience with the cultural, economic, and policy contexts relevant our study. Our  
 1311 combined expertise spans natural language processing, Responsible AI, computational social science, human-computer  
 1312 interaction, and AI ethics. One author works primarily in academia, while others have experience in both academic and  
 1313 applied research settings.  
 1314

1315 Our positionalities shaped how we framed the research problem, selected sectors and occupations for analysis, and  
 1316 interpreted findings on worker/developer perspectives to AI exposure. Having worked across different cultural and  
 1317 labor market contexts informed our awareness of how occupational values and AI impacts can vary across sectors,  
 1318 regions, and professional identities. We recognize that our perspectives are influenced by our own academic and  
 1319 research experiences, which may limit the range of viewpoints represented. To support more inclusive and contextually  
 1320 grounded research on AI and the future of work, we encourage future studies to incorporate perspectives from workers,  
 1321 developers, and policymakers in regions and sectors beyond those examined here.  
 1322

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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
1522 Account Management	New Accounts Clerks
1523 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
1524 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
1525 CX / Customer Experience / Support	Computer User Support Specialists, Customer Service Representatives
1526 Data Analysis	Business Intelligence Analysts, Data Scientists, Statistical Assistants, Statisticians
1527 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
1528 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
1529 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
1530 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
1531 Fundraising	Fundraisers, Fundraising Managers
1532 Human Resources	Compensation and Benefits Managers, Human Resources Assistants, Except Payroll and Timekeeping, Human Resources Managers, Human Resources Specialists

1533 Continued on next page

Table 3. Prolific functions and their associated jobs.

1561	Prolific Function	Jobs
1562		
1563		
1564	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
1565		
1566	Legal	Law Teachers, Postsecondary, Lawyers, Paralegals and Legal Assistants
1567	Marketing	Advertising and Promotions Managers, Market Research Analysts and Marketing Specialists, Marketing Managers, Search Marketing Strategists
1568		
1569	Operations	General and Operations Managers
1570	Product or Product Management	
1571	Project or Program Management	Information Technology Project Managers, Management Analysts, Project Management Specialists
1572	Public Relations / Communications	Communications Teachers, Postsecondary, Public Relations Managers, Public Relations Specialists
1573	Research	Bioinformatics Scientists, Computer and Information Research Scientists, Operations Research Analysts, Social Science Research Assistants, Survey Researchers
1574		
1575	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
1576		
1577		
1578	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
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Table 4. Representative examples of occupations not filtered out from O\*NET database.

1613	<b>Occupations</b>
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, Zoolologists and Wildlife Biologists
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1638	<b>B Scoping Review on Meaningfulness of Work</b>
1639	We reviewed 21 articles (as shown in Table 5 across psychology, sociology, anthropology, and ethics on what work
1640	means to people and to society as a part of our scoping review on meaningfulness of work. The studies show how
1641	people judge their own work, how organizations shape those judgments, and how societies value different kinds of
1642	work.
1643	
1644	
1645	<b>C Worker and Developer Survey</b>
1646	We provide our full survey items for meaningfulness of work and AI traits in Table 6. We also include several follow up
1647	questions related to human intervention preferences based on Shao et al. [80]. We provide a detailed overview of the
1648	demographics of our recruited Prolific participants in Table 7.
1649	
1650	
1651	Table 6. Survey items used in the study.
1652	
1653	
1654	
1655	<b>ID Survey Item</b>
1656	
1657	<b>Perceived Bullshitness (Q1–Q5)</b>
1658	
1659	Q1 The task feels pointless.
1660	Q2 If I stopped doing this task, nothing important would change.
1661	Q3 I perform this task only to satisfy bureaucracy or appearances.
1662	Q4 This task does not contribute to the goals of my organization.
1663	Q5 I would be embarrassed to explain this task to someone outside my field.
1664	

1665	ID	Survey Item
1666		
1667		<b>Perceived Value (Q6–Q10)</b>
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.
1673		
1674		<b>Status Maintenance (Q11–Q16)</b>
1675	Q11	Not doing this task might make me look less competent to others.
1676	Q12	If I stopped doing this task, others might question my role or importance.
1677	Q13	This task helps reinforce my standing in the organization.
1678	Q14	I worry that letting go of this task could reduce my influence or visibility.
1679	Q15	Even if the task feels unimportant, I feel pressure to keep doing it to maintain status.
1680	Q16	I feel this task signals to others that I am busy or valuable.
1681		
1682		<b>EPOCH (Q17–Q21)</b>
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.
1688		
1689		<b>Human Flourishing (Q22–Q33)</b>
1690	Q22	This task makes me feel satisfied and content with my work.
1691	Q23	This task makes me feel happy and positive.
1692	Q24	This task supports my physical well-being (e.g., energy, comfort).
1693	Q25	This task supports my mental health (e.g., reduced stress, clarity, peace of mind).
1694	Q26	This task feels meaningful and worthwhile.
1695	Q27	This task helps me connect with my personal or professional purpose.
1696	Q28	This task allows me to act in accordance with my values and integrity.
1697	Q29	This task challenges me to exercise discipline, patience, or courage.
1698	Q30	This task helps me build or strengthen relationships with colleagues or clients.
1699	Q31	This task makes me feel supported and connected socially.
1700	Q32	This task contributes to my sense of job or financial security.
1701	Q33	This task helps me feel that my work has tangible value and reward.
1702		
1703		<b>AI Trait Preferences (Q34–Q45)</b>
1704	Q34	Handle more complex work rather than routine work.
1705	Q35	Focus more on addressing human needs and emotions rather than just data handling.
1706	Q36	Make fast, automatic decisions without explanation rather than decisions that are easy for people to understand.
1707	Q37	Be open to challenge or treat the decision as final.
1708	Q38	Adjust based on the individual it's helping rather than treat everyone the same.
1709	Q39	Show warmth and care rather than remain neutral and business-like.
1710	Q40	Be polite even if that means not being fully honest, rather than being sincere and straightforward.

1717	ID	Survey Item
1718		Q41 Be strict and follow the rules exactly rather than be tolerant and open-minded.
1719		Q42 Be fast and simple even if less perfect, rather than highly skilled and precise.
1720		Q43 Be determined and persistent rather than flexible and willing to change course.
1721		Q44 Show comprehensiveness, deep understanding and insight rather than keep things simple and straightforward.
1722		Q45 Be imaginative and bring new ideas rather than stay practical and follow familiar approaches.
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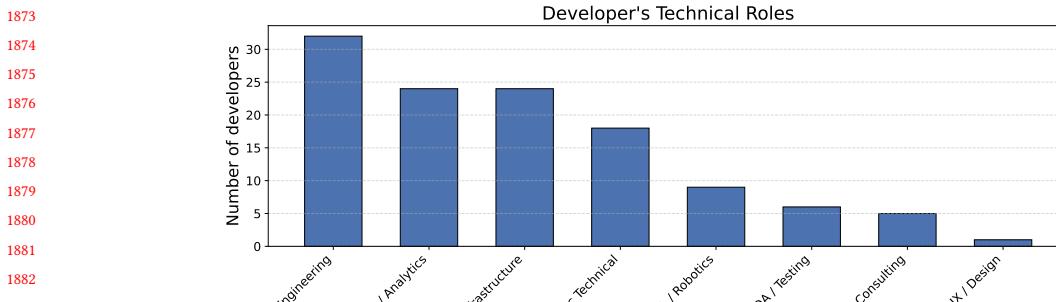
1768

Table 5. Foundational citations on the personal and the social meaning of work

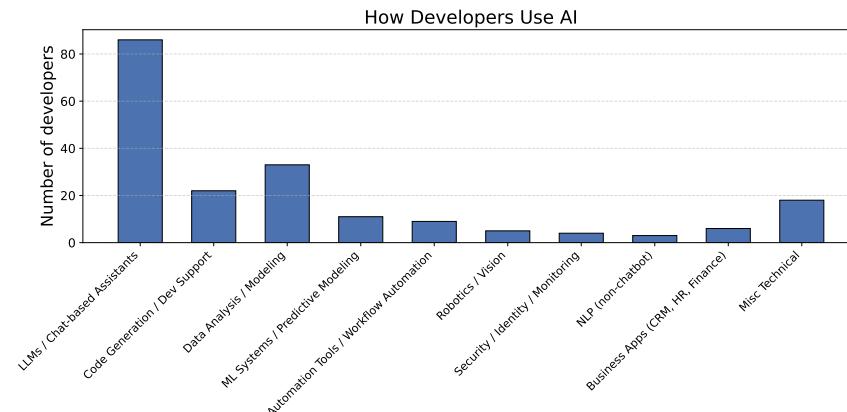
1769	Theme	Foundational Work and Description
1770	<b>Bullshit Jobs, Task Meaning &amp; Worthwhile Contributions</b>	<p>Graeber (2018): Introduce the concept of 'bullshit jobs,' emphasizing tasks perceived as socially useless or performative [37].</p> <p>Hackman &amp; Oldham (1976, 1980): specify which 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>
1771		<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>
1772		<p>Steiger <i>et al.</i> (2012): Provide the Work and Meaning Inventory (WAMI) to measure perceived meaningfulness of work [83].</p>
1773		<p>Rostain and Clarke (2025): Identify three ways factory workers in France created meaning in low-skilled jobs often seen as meaningless: (i) using hidden skills beyond their usual tasks, (ii) finding small opportunities to do the work in their own way, and (iii) demonstrating skills that earned respect from coworkers and supervisors [77].</p>
1774		<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>
1775		<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) the person's own belief that their work matters, (ii) recognition from others, and (iii) confidence that they can do the work well [10].</p>
1776	<b>Task Status, Impression Management, Identity Formation &amp; Symbolic Work</b>	<p>Meyer &amp; 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>
1777		<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>
1778		<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>
1779		<p>Tomlinson and Souto-Otero (2025): Explore how recent UK graduates defined meaningful work. Identified three dimensions: meaning in work (i) as self-expression and self-actualization, (ii) through relationships and social relatedness, and (iii) as societal contribution [85].</p>
1780		<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>
1781		<p>Bellezza <i>et al.</i> (2017): Argue that busyness serves as a modern status symbol [12].</p>
1782		<p>Rafaeli &amp; Pratt (2006): Discuss identity and symbolic expression in work settings [69].</p>
1783	<b>Status Threat in Social Psychology</b>	<p>Pettit <i>et al.</i> (2010): Examine reactions to the threat of losing status within groups [68].</p>
1784		<p>Anderson <i>et al.</i> (2012): Explore conditions under which individuals prefer lower-status roles to maintain group dynamics [4].</p>
1785	<b>Work Motivation &amp; Utility Theory</b>	<p>Eccles &amp; Wigfield (2002): Outline expectancy-value theory as a foundation for understanding task utility and motivation [27].</p>

1821 Table 7. Demographic characteristics of participants recruited from Prolific.  
1822

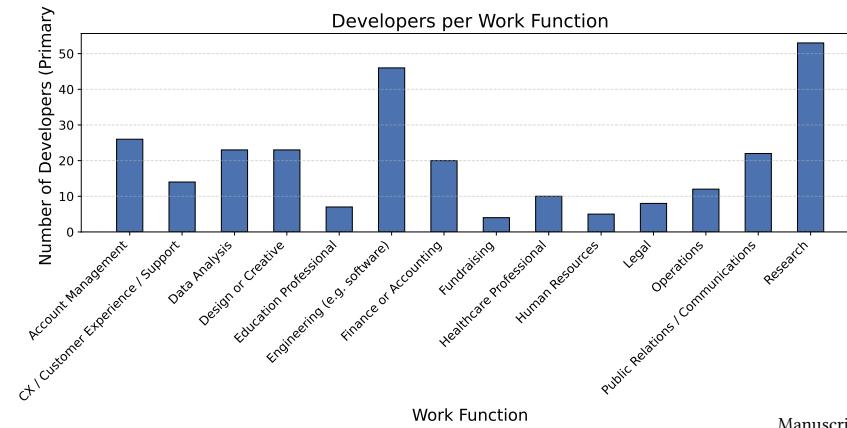
1823 <b>Demographics</b>	1824 <b>Workers (N=202)</b>	1825 <b>Developers (N=197)</b>
1826 Mean age (SD)	1827 42.63 (13.05)	1828 36.68 (10.29)
1829 Gender		
1830 Male	34.03%	64.46%
1831 Female	61.94%	28.42%
1832 Non-binary / Other	0%	0%
1833 Consent Revoked	4.03%	7.11%
1834 Employment status		
1835 Full-time	46.94%	69.54%
1836 Part-time	16.29%	13.71%
1837 Unemployed/Other	4.03%	1.52%
1838 Consent Revoked/No data avail- 1839 able	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

1937 Table 8 provides several examples where LM annotations deviate from human annotations. For *perceived bullshitness*,  
 1938 LM rated legal tasks such as drafting wills or contracts by Lawyers as entirely non-pointless (0.0), emphasizing their  
 1939 essential and substantive nature, while humans reported moderate meaningfulness (1.93), reflecting their perception of  
 1940 some bureaucratic routine. For *perceived value*, planning projects for Poets, Lyricists, and Creative Writers was rated  
 1941 higher by LM (3.8) than humans (2.0), highlighting LM’s focus on tangible outcomes, autonomy, and team contribution.  
 1942 For *status maintenance*, managerial tasks like setting prices as General and Operations Managers received higher LM  
 1943 ratings (3.83) than human ratings (1.89), reflecting LM’s weighting of visibility, authority, and organizational standing.  
 1944 In contrast, for *EPOCH*, Survey Researchers reviewing and recording data were rated very low by LM (0.40) but high by  
 1945 humans (3.20), indicating that humans derive well-being and satisfaction from task completion, whereas LM views these  
 1946 tasks as routine and procedural. For *human flourishing*, conducting new employee orientations as Human Resources  
 1947 Specialists was rated higher by LM (3.50) than humans (1.69), reflecting LM’s emphasis on purpose, social connection,  
 1948 and personal growth. Finally, for *psychological trait of AI behavior*, recruiting sponsors or volunteers for Fundraisers  
 1949 was rated higher by LM (3.08) than humans (0.94), highlighting LM’s prioritization of emotional engagement, tailored  
 1950 reasoning, and insight, while humans perceive the task primarily as functional.  
 1951

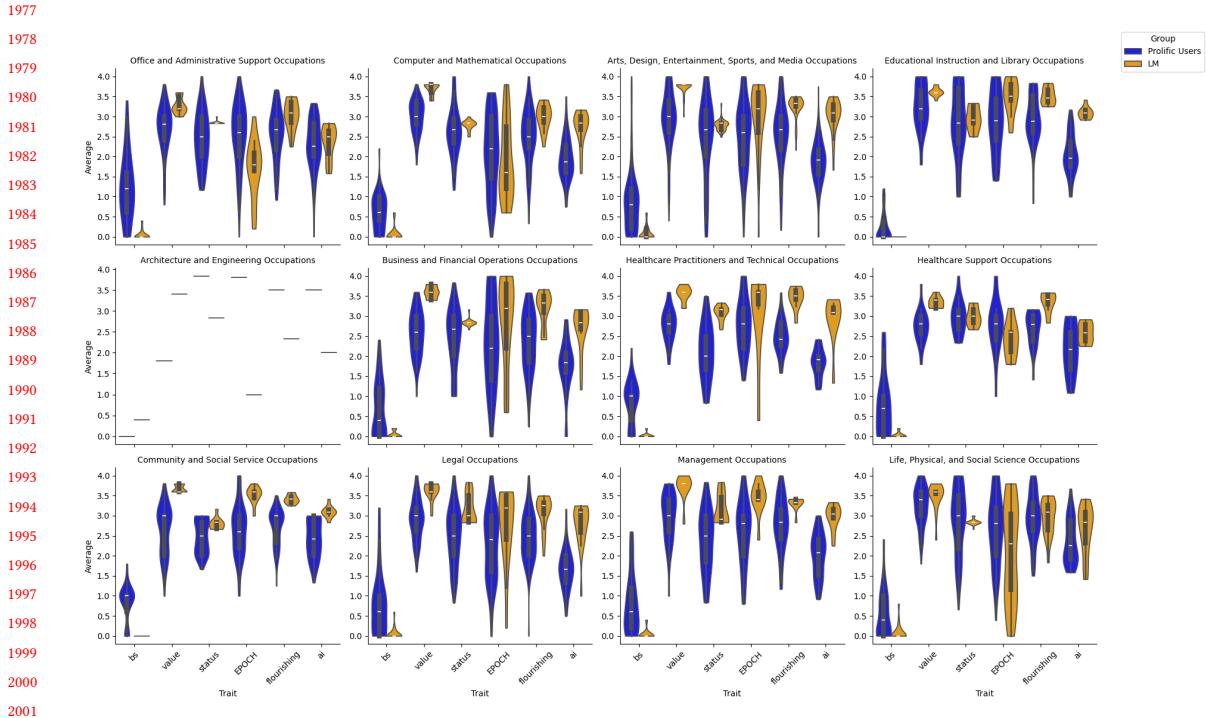


Fig. 8. Distribution comparison of dimensions of meaningful work between the LM and Prolific users across different sectors.

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	
2009	In {function}, consider the task: {task}
2010	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.
2011	Q1. The task feels pointless.
2012	Q2. If I stopped doing this task, nothing important would change.
2013	Q3. I perform this task only to satisfy bureaucracy or appearances.
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	

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.)
2041	Before answering, provide a reasoning of one or two sentences, with a maximum of 50 words. Name the reasoning as "Reason_49".
2042	Q49. Why would collaboration be needed for this task? Do not check any boxes if you don't think collaboration is needed.
2043	a. This task requires physical actions.
2044	b. This task involves making high-stake decisions which I would like to control.
2045	c. This task requires specific domain knowledge.
2046	d. The task involves nuanced communication or interpersonal skills.
2047	e. The task needs validation or oversight to ensure quality
2048	f. The task is dynamic and requires adapting to changing circumstances
2049	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
2053 In {function}, consider the task: {task}
2054 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.
2055 Q34. Handle more complex work rather than routine work.
2056 Q35. Focus more on addressing human needs and emotions rather than just data handling.
2057 Q36. Make fast, automatic decisions without explanation rather than decisions that are easy for people to understand?
2058 Q37. Be open to challenge or treat the decision as final?
2059 Q38. Adjust based on the individual it's helping rather than treat everyone the same?
2060 Q39. Show warmth and care rather than remain neutral and business-like?
2061 Q40. Be polite even if that means not being fully honest, rather than being sincere and straightforward?
2062 Q41. Be strict and follow the rules exactly rather than be tolerant and open-minded?
2063 Q42. Be fast and simple even if less perfect, rather than highly skilled and precise?
2064 Q43. Be determined and persistent rather than flexible and willing to change course?
2065 Q44. Show deep understanding and insight rather than keep things simple and straightforward?
2066 Q45. Be imaginative and bring new ideas rather than stay practical and follow familiar approaches?
2067 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.
2068 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?
2069 a. Not at all (I would not want the AI to do this task for the user)
2070 b. Slightly (I'd want the AI to do only small parts of the task)
2071 c. Moderately (I'd want the AI to do about half the task)
2072 d. A lot (I'd want the AI to do most of the task)
2073 e. Entirely (I'd want the AI to do the entire task)
2074 Q48 (Required Human Agency Scale). If AI were to assist in this task, how much collaboration would be needed to complete this task effectively?
2075 H1. AI handles the task entirely on its own.
2076 H2. AI needs minimal human input for optimal performance.
2077 H3. AI and human form equal partnership, outperforming either alone
2078 H4. AI requires human input to successfully complete the task.
2079 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  
2089 f. The task is dynamic and requires adapting to changing circumstances  
2090 g. The task has ethical, sensitive, or subjective aspects.

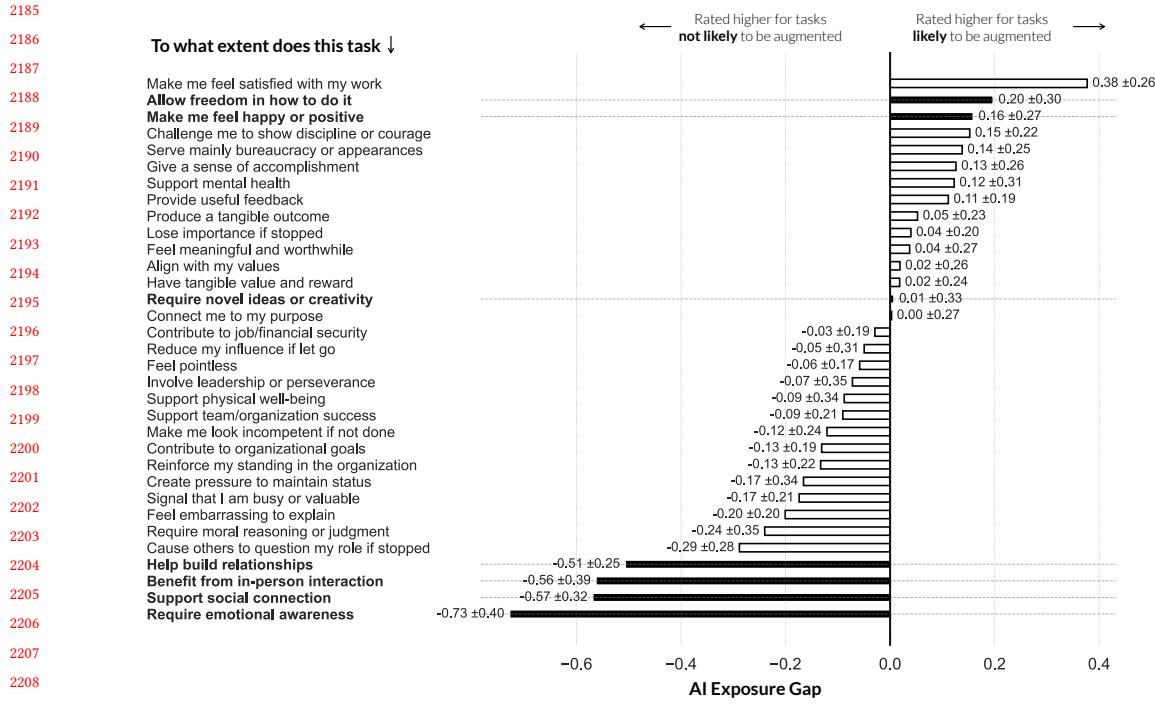
2091 Received 20 February 2007; revised 12 March 2009; accepted 5 June 2009

2133 Table 8. Example tasks with the largest differences between LM and human ratings across survey items, using a Likert scale ranging  
 2134 from 0 (strongly disagree) to 4 (strongly agree). The largest gaps occur when LMs emphasize functional or procedural aspects (e.g.,  
 2135 legal drafting, survey coding), while humans evaluate tasks in terms of social, emotional, or organizational meaning (e.g., status  
 2136 maintenance, employee orientation). We found both LM and human interpretations can be valid in different contexts. For instance,  
 2137 the LM perceived the task ‘review, classify, and record survey data in preparation for computer analysis’ as a routine procedure with  
 2138 minimal emotional demands, whereas a human annotator emphasized its creative and moral dimensions. Such divergences reflect  
 2139 subjective differences that are difficult to resolve.

2140 Dimensions of Mean- 2141 ingful Work	2142 Occupation	2143 Task Description	2144 LM Annota- 2145 tion	2146 Human Annota- 2147 tion	2148 Reasoning by LM and Humans
2149 <b>Perceived</b> 2150 <b>Bullsh*tness</b> (e.g., 2151 the task feels pointless)	2152 Lawyers	2153 Prepare, draft, and review legal doc- 2154 uments, such as wills, deeds, patent 2155 applications, mortgages, leases, and 2156 contracts.	2157 0.00 2158 (Strongly 2159 disagree)	2160 1.93 2161 (Neutral)	2162 <i>LM</i> : Essential, substantive, impacts clients' rights, cen- 2163 tral to organizational goals. <i>Humans</i> : Moderate meaningfulness, some bureau- 2164 cratic perception.
2165 <b>Perceived Value</b> (e.g., I 2166 have the freedom to de- 2167 cide how to carry out 2168 this task)	2169 Poets, Lyricists, Cre- 2170 ative Writers	2171 Plan project arrangements or out- 2172 lines, and organize material accord- 2173 ingly.	2174 3.80 2175 (Strongly 2176 agree)	2177 2.00 2178 (Neutral)	2179 <i>LM</i> : Tangible outcomes, autonomy, team contribution. <i>Humans</i> : Recognize value but lower perceived impact.
2180 <b>Status Maintenance</b> 2181 (e.g., This task helps re- 2182 inforce my standing in 2183 the organization)	2184 General & Operations 2185 Managers	2186 Set prices or credit terms for goods 2187 or services, based on forecasts of 2188 customer demand.	2189 3.83 2190 (Strongly 2191 agree)	2192 1.89 2193 (Neutral)	2194 <i>LM</i> : Visibility, authority, organizational standing. <i>Humans</i> : Less tied to status perception.
2195 <b>EPOCH</b> (e.g., This task 2196 requires recognizing 2197 and responding appro- 2198 priately to the emotions 2199 of others)	2200 Survey Researchers	2201 Review, classify, and record survey 2202 data in preparation for computer 2203 analysis.	2204 0.40 2205 (Strongly 2206 disagree)	2207 3.20 2208 (Agree)	2209 <i>LM</i> : Technical, routine, procedural, minimal emo- 2210 tional/moral impact. <i>Humans</i> : Requires some novel ideas and sometimes 2211 requires emotional and moral judgments.
2212 <b>Human Flourishing</b> 2213 (e.g., This task helps 2214 me build or strengthen 2215 relationships with col- 2216 leagues or clients)	2217 HR Specialists	2218 Schedule or conduct new employee 2219 orientations.	2220 3.50 2221 (Agree)	2222 1.69 2223 (Neutral)	2224 <i>LM</i> : Purpose, social connection, growth-oriented. <i>Humans</i> : Perceived as routine or standard procedure.
2225 <b>Psychological Traits</b> 2226 of <b>AI Behavior</b> (e.g., 2227 Show warmth and care 2228 rather than remain neu- 2229 tral and business-like)	2230 Fundraisers	2231 Recruit sponsors, participants, or 2232 volunteers for fundraising events.	2233 3.08 2234 (Agree)	2235 0.94 (Dis- 2236 agree)	2237 <i>LM</i> : Emotional engagement, tailored reasoning, in- 2238 sight, creativity. <i>Humans</i> : Functional, minimal AI-alignment traits per- 2239 ceived.

2163 Table 11. RQ1: Significant task dimensions (FDR < 0.05 and  $|\Delta| \geq 0.10$ ). Estimates from nested RE models;  $\Delta$  is the back-transformed  
 2164 Likert difference (likely – not-likely) where (+) means that the dimension was more exposed to AI augmentation and (-) it was less  
 2165 exposed to AI augmentation

2166 Task Characteristic	2167 $\beta$ (95% CI)	2168 $\Delta$ (95% CI)
2169 Novel ideas/creativity (+)	2170 0.22698 [0.17405, 0.27991]	2171 0.29298 [0.22466, 0.36131]
2172 Happy/Positive (+)	2173 0.19965 [0.13789, 0.26143]	2174 0.12675 [0.08753, 0.16596]
2175 Freedom in how to do it (+)	2176 0.18587 [0.12659, 0.24516]	2177 0.11487 [0.07823, 0.15151]
2178 In-person interaction (-)	2179 $-0.17564 [-0.23024, -0.12035]$	2180 $-0.23429 [-0.30713, -0.16145]$
2181 Emotional Awareness (-)	2182 $-0.13643 [-0.19021, -0.08259]$	2183 $-0.20635 [-0.28781, -0.12492]$
2184 Build relationships (-)	2185 $-0.13422 [-0.19249, -0.07594]$	2186 $-0.15360 [-0.22028, -0.08692]$
2187 Socially supported (-)	2188 $-0.10393 [-0.16434, -0.04352]$	2189 $-0.10683 [-0.16893, -0.04473]$



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 <b>Cluster (size)</b>	2293 <b>Label</b>	2294 <b>Exemplar task (Occupation   Sector)</b>
2295 2 (n=148)	2296 Automated Task Management	2297 Plan or coordinate investigation and resolution of customers' re- 2298 ports of technical problems with aircraft or aerospace vehicles. 2299 ( <i>Aerospace Engineers / Architecture and Engineering</i> )
2300 6 (n=140)	2301 Policy Development	2302 Conduct educational programs that provide farmers or farm co- 2303 operative members with information that can help them improve 2304 agricultural prod... ( <i>Agricultural Engineers / Architecture and Engi-    2305 neering</i> )
2306 5 (n=128)	2307 Innovative Solutions Evaluation	2308 Analyze project requests, proposals, or engineering data to deter- 2309 mine feasibility, productibility, cost, or production time of aerospace 2310 or... ( <i>Aerospace Engineers / Architecture and Engineering</i> )
2311 3 (n=124)	2312 Sustainable Project Planning	2313 Design environmentally sound structural upgrades to existing 2314 buildings, such as natural lighting systems, green roofs, or rainwa- 2315 ter collect... ( <i>Architects, Except Landscape and Naval / Architecture    2316 and Engineering</i> )
2317 8 (n=112)	2318 Creative Engineering Tasks	2319 Plan or conduct experimental, environmental, operational, or stress 2320 tests on models or prototypes of aircraft or aerospace systems or 2321 equip... ( <i>Aerospace Engineers / Architecture and Engineering</i> )
2322 9 (n=107)	2323 Design and Planning Tasks	2324 Prepare scale drawings or architectural designs, using computer- 2325 aided design or other tools. ( <i>Architects, Except Landscape and    2326 Naval / Architecture and Engineering</i> )
2327 0 (n=96)	2328 Logistics and Market Analysis	2329 Analyze new medical procedures to forecast likely outcomes. ( <i>Bio-    2330 engineers and Biomedical Engineers / Architecture and Engineering</i> )
2331 4 (n=95)	2332 Biofuels Research and Development	2333 Design sensing, measuring, and recording devices, and other in- 2334 strumentation used to study plant or animal life. ( <i>Agricultural En-    2335 gineers / Architecture and Engineering</i> )
2336 7 (n=81)	2337 Creative Visual Production	2338 Create custom illustrations or other graphic elements. ( <i>Art Direc-    2339 tors / Arts, Design, Entertainment, Sports, and Media</i> )
2340 1 (n=79)	2341 Marketing and Promotion	2342 Confer with customers to assess customer needs or obtain feedback. 2343 ( <i>Craft Artists / Arts, Design, Entertainment, Sports, and Media</i> )

2341 Table 14. K-means clustering ( $k = 10$ ) of tasks in the 99th percentile for ‘happy/positive’ restricted to tasks judged likely to be  
 2342 augmented. Cluster labels were assigned using GPT-4o, and exemplar tasks come from sectors with the strongest heatmap z-scores.  
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2344 Cluster (size)	2345 Cluster label	2346 Exemplar task (Occupation   Sector)
2347 6 (n=124)	2348 Client Support and Training	2349 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> )
2350 7 (n=79)	2351 Positive Media Production	2352 Use computers, audio-visual aids, and other equipment and materials to supplement presentations. ( <i>Kindergarten Teachers, Except Special Education / Educational Instruction and Library</i> )
2353 9 (n=72)	2354 Patient Eligibility Assessment	2355 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> )
2356 5 (n=70)	2357 Client Rehabilitation Plans	2358 Modify treatment plans to comply with changes in client status. ( <i>Substance Abuse and Behavioral Disorder Counselors / Community and Social Service</i> )
2359 1 (n=50)	2360 Training and Development	2361 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> )
2362 4 (n=44)	2363 Robotics and Mechatronics	2364 Design advanced precision equipment for accurate or controlled applications. ( <i>Mechatronics Engineers / Architecture and Engineering</i> )
2365 0 (n=41)	2366 Emergency Response Tasks	2367 Provide assistive devices, supportive technology, or assistance accessing facilities, such as restrooms. ( <i>Special Education Teachers, Preschool / Educational Instruction and Library</i> )
2368 3 (n=37)	2369 Creative Performance Tasks	2370 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> )
2371 2 (n=35)	2372 Biofuels Innovation	2373 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> )
2374 8 (n=28)	2375 Speech and Language Therapy	2376 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 Cluster label	2399 Exemplar task (Occupation   Sector)
2398 2399 3 (n=188)	2400 Automated Security Systems	2401 Develop computer information resources, providing for data security and control, strategic computing, and disaster recovery. ( <i>Computer and Information Systems Managers/Management</i> )
2400 2401 4 (n=141)	2402 Marketing and Strategy Evaluation	2403 Identify, develop, or evaluate marketing strategy, based on knowledge of establishment objectives, market characteristics, and cost and mar... ( <i>Marketing Managers/Management</i> )
2401 2402 2403 0 (n=136)	2404 Sustainability Strategies	2405 Develop or execute strategies to address issues such as energy use, resource conservation, recycling, pollution reduction, waste eliminatio... ( <i>Chief Sustainability Officers/Management</i> )
2402 2403 2404 7 (n=124)	2405 Engineering Design Tasks	2406 Identify opportunities to improve plant electrical equipment, controls, or process control methodologies. ( <i>Geothermal Production Managers/Management</i> )
2403 2404 2405 1 (n=123)	2406 Health Program Management	2407 Maintain awareness of advances in medicine, computerized diagnostic and treatment equipment, data processing technology, government regulat... ( <i>Medical and Health Services Managers/Management</i> )
2404 2405 2406 6 (n=102)	2407 Design and Layout Tasks	2408 Plan store layouts or design displays. ( <i>General and Operations Managers/Management</i> )
2405 2406 2407 5 (n=71)	2408 Environmental Planning Tasks	2409 Manage site assessments or environmental studies for wind fields. ( <i>Wind Energy Development Managers/Management</i> )
2406 2407 2408 2 (n=71)	2409 Marketing and Promotion Tasks	2410 Develop or implement product-marketing strategies, including advertising campaigns or sales promotions. ( <i>General and Operations Managers/Management</i> )
2407 2408 2409 9 (n=69)	2410 Biofuels Research and Development	2411 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> )
2408 2409 2410 8 (n=44)	2411 Training Program Development	2412 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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2450 <b>Cluster (size)</b>	2451 <b>Cluster label</b>	2452 <b>Exemplar task (Occupation   Sector)</b>
2453 2 (n=185)	2454 Emotion Awareness in Leadership	2455 Testify in depositions or trials as an expert witness. ( <i>Physicians, Pathologists/Healthcare Practitioners and Technical</i> )
2456 7 (n=171)	2457 Crisis Intervention and Support	2458 Perform crisis interventions to help ensure the safety of the patients and others. ( <i>Mental Health Counselors/Community and Social Service</i> )
2459 1 (n=165)	2460 Emotion Awareness Tasks	2461 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> )
2462 3 (n=140)	2463 Emotion Awareness Tasks	2464 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> )
2465 6 (n=129)	2466 Personnel Management	2467 Direct the operations of short stay or specialty units. ( <i>Hospitalists/Healthcare Practitioners and Technical</i> )
2468 8 (n=115)	2469 Emotion Awareness Tasks	2470 Attend meetings, educational conferences, and training workshops, and serve on committees. ( <i>Educational, Guidance, and Career Counselors and Advisors/Community and Social Service</i> )
2471 4 (n=105)	2472 Networking and Representation	2473 Deliver presentations to lay or professional audiences. ( <i>Preventive Medicine Physicians/Healthcare Practitioners and Technical</i> )
2474 0 (n=104)	2475 Emotion Awareness Counseling	2476 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> )
2477 5 (n=60)	2478 Professional Development	2479 Teach pharmacy students serving as interns in preparation for their graduation or licensure. ( <i>Pharmacists/Healthcare Practitioners and Technical</i> )
2480 9 (n=40)	2481 Student Behavior Management	2482 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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2497 Table 17. *RQ2*: Worker–developer misalignment by AI traits with human ratings on 171 tasks. Misalignment is defined as the average  
 2498 absolute difference between worker and developer ratings (Q34–Q45) of the traits they believe AI systems should possess when  
 2499 augmenting tasks. Differences ( $\Delta$ ) are calculated as worker minus developer ratings, with the magnitude ( $|\Delta|$ ) reflecting the size  
 2500 of the misalignment. Reported values aggregate over sectors and traits are grouped into high, mixed, or aligned categories based on  
 2501 percentile thresholds of average absolute misalignment. The bolded traits are those classified into the same categories based on  
 2502 human and LM ratings (Table 18) on the same set of 171 tasks. As with LM rating–based results, the highest misalignments in human  
 2503 ratings occur for Explainable vs Fast/automatic, Straightforward vs. Polite, and Emotional vs. Apathetic. However, for the for the  
 2504 highly misaligned traits, discrepancies emerge: Handle complex vs. Routine work are highly misaligned in human ratings but fall only  
 2505 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 $
<b>High misalignment</b>	
<i>(Q36) Explainable vs. Fast/automatic</i>	1.367
<i>(Q40) Straightforward vs. Polite</i>	1.211
<i>(Q34) Handle complex vs. Routine work</i>	1.165
<i>(Q35) Address emotions vs. Apathetic</i>	1.165
<b>Mixed misalignment</b>	
<i>(Q43) Flexible vs. Determined</i>	1.0917
<i>(Q39) Business-like vs. Warm/caring</i>	1.073
<i>(Q41) Tolerant/Open-minded vs. Strict</i>	1.064
<i>(Q38) Generalized vs. Personalized</i>	0.936
<b>Aligned</b>	
<i>(Q42) Precise vs. Simple</i>	0.936
<i>(Q45) Practical vs. Imaginative</i>	0.872
<i>(Q37) Definitive vs. Open to challenge</i>	0.853
<i>(Q44) Simple vs. Comprehensive</i>	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 $
<b>High misalignment</b>	
<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
<b>Mixed misalignment</b>	
<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
<b>Aligned</b>	
<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

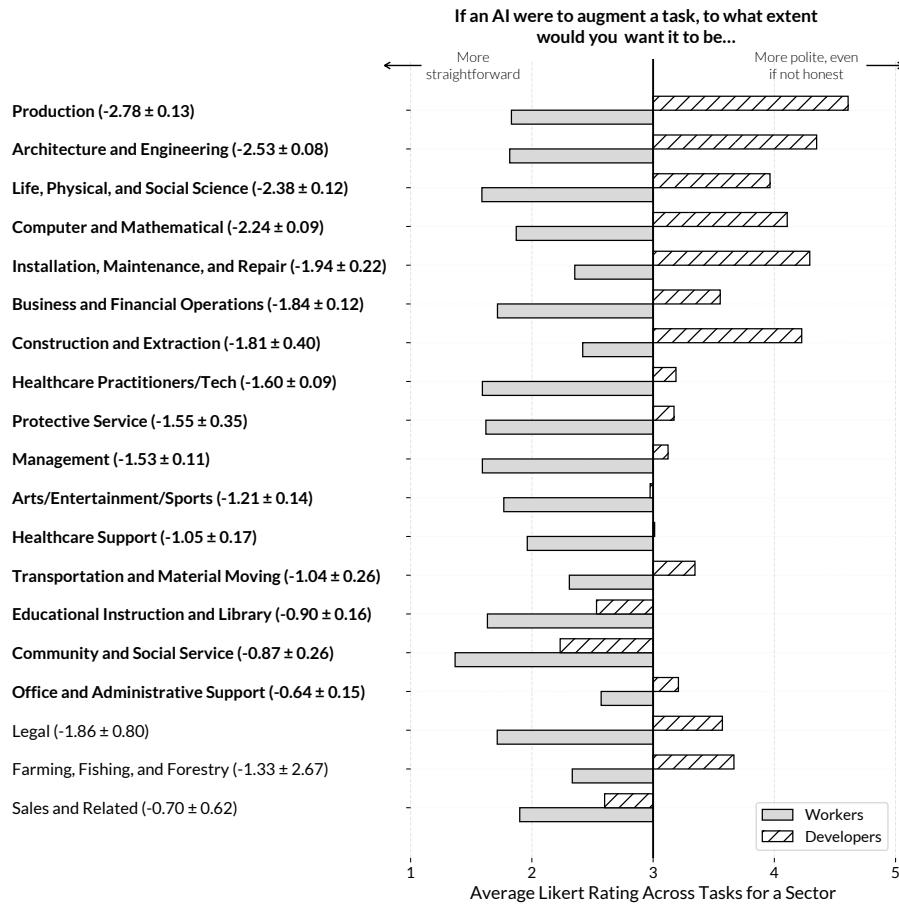


Fig. 10. Worker vs. developer preferences for AI to be straightforward or polite, by sector. Paired bars show mean Likert ratings for each group. Greater distance between bars indicates stronger misalignment; misalignment scores with standard errors are shown on the y-axis.

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 <b>Cluster (size)</b>	2813 <b>Cluster label</b>	2814 <b>Exemplar task (Occupation   Sector)</b>
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> )

2861 Table 23. Clusters of tasks with the highest worker-developer misalignment on the trait tolerant/open-minded vs. strict, identified  
 2862 using MPNet embeddings and K-means clustering. Cluster labels were generated using GPT-4o.

2864 Cluster (size)	2865 Cluster label	2866 Exemplar task (Occupation   Sector)
2865 2 (n=20)	2866 Strict Process Improvement	2867 Identify opportunities to improve plant electrical equipment, controls, or process control methodologies. ( <i>Geothermal Production Managers / Management</i> )
2866 0 (n=15)	2867 Strict Monitoring and Planning	2868 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> )
2867 4 (n=11)	2868 Data Analysis and Evaluation	2869 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> )
2868 8 (n=7)	2869 Strict Budget Management	2870 Develop or review budgets, annual plans, power contracts, power rates, standing operating procedures, power reviews, or engineering studies. ( <i>Hydroelectric Production Managers / Management</i> )
2869 1 (n=6)	2870 Research and Evaluation Tasks	2871 Conduct research to develop methodologies, instrumentation, and procedures for medical application, analyzing data and presenting findings. ( <i>Epidemiologists / Life, Physical, and Social Science</i> )
2870 9 (n=5)	2872 Data Analysis and Marketing	2873 Monitor and analyze sales promotion results to determine cost effectiveness of promotion campaigns. ( <i>Advertising and Promotions Managers / Management</i> )
2871 5 (n=5)	2874 Strict Risk Management	2875 Create scenarios to reestablish operations from various types of business disruptions. ( <i>Business Continuity Planners / Business and Financial Operations</i> )
2872 3 (n=5)	2876 Environmental Stewardship Analysis	2877 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> )
2873 6 (n=4)	2878 Strict Supply Chain Oversight	2879 Establish or monitor specific supply chain-based performance measurement systems. ( <i>Transportation, Storage, and Distribution Managers / Management</i> )
2874 7 (n=4)	2880 Rigid Web Development Guidelines	2881 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
<b>Installation, Maintenance, and Repair</b>	<b>-0.6</b>	<b>0.072</b>	<b>[-0.744, -0.456]</b>	<b>65</b>
<b>Architecture and Engineering</b>	<b>-0.567</b>	<b>0.024</b>	<b>[-0.614, -0.520]</b>	<b>476</b>
<b>Transportation and Material Moving</b>	<b>-0.545</b>	<b>0.077</b>	<b>[-0.700, -0.391]</b>	<b>55</b>
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
<b>Production</b>	-2.777	0.135	[-3.044, -2.511]	166
<b>Architecture and Engineering</b>	-2.532	0.085	[-2.698, -2.365]	476
<b>Life, Physical, and Social Science</b>	-2.376	0.116	[-2.604, -2.149]	279
<b>Computer and Mathematical</b>	-2.235	0.086	[-2.404, -2.067]	574
<b>Installation, Maintenance, and Repair</b>	-1.938	0.218	[-2.374, -1.503]	65
<b>Business and Financial Operations</b>	-1.837	0.118	[-2.069, -1.605]	289
<b>Construction and Extraction</b>	-1.806	0.403	[-2.629, -0.984]	31
<b>Healthcare Practitioners and Technical</b>	-1.597	0.088	[-1.770, -1.424]	392
<b>Protective Service</b>	-1.552	0.353	[-2.275, -0.829]	29
<b>Management</b>	-1.525	0.113	[-1.748, -1.303]	217
<b>Arts, Design, Entertainment, Sports, and Media</b>	-1.207	0.137	[-1.476, -0.938]	203
<b>Healthcare Support</b>	-1.051	0.169	[-1.387, -0.714]	79
<b>Transportation and Material Moving</b>	-1.036	0.262	[-1.562, -0.511]	55
<b>Educational Instruction and Library</b>	-0.9	0.156	[-1.211, -0.589]	90
<b>Community and Social Service</b>	-0.867	0.257	[-1.392, -0.341]	30
<b>Office and Administrative Support</b>	-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
<b>Community and Social Service</b>	<b>1.267</b>	<b>0.106</b>	<b>[1.049, 1.484]</b>	<b>30</b>
<b>Educational Instruction and Library</b>	<b>1.067</b>	<b>0.077</b>	<b>[0.913, 1.220]</b>	<b>90</b>
<b>Management</b>	<b>0.76</b>	<b>0.072</b>	<b>[0.618, 0.902]</b>	<b>217</b>
<b>Sales and Related</b>	<b>0.7</b>	<b>0.213</b>	<b>[0.217, 1.183]</b>	<b>10</b>
<b>Arts, Design, Entertainment, Sports, and Media</b>	<b>0.655</b>	<b>0.059</b>	<b>[0.538, 0.772]</b>	<b>203</b>
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
<b>Production</b>	<b>-1.09</b>	<b>0.077</b>	<b>[-1.243, -0.938]</b>	<b>166</b>
<b>Transportation and Material Moving</b>	<b>-0.6</b>	<b>0.146</b>	<b>[-0.892, -0.308]</b>	<b>55</b>
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