

# Worker Discretion Advised: Co-designing Risk Disclosure in Crowdsourced Responsible AI (RAI) Content Work

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Responsible AI (RAI) content work, such as annotation, moderation, or red teaming for AI safety, often exposes crowd workers to potentially harmful content. While prior work has underscored the importance of communicating well-being risk to employed content moderators, designing effective disclosure mechanisms for crowd workers while balancing worker protection with the needs of task designers and platforms remains largely unexamined. To address this gap, we conducted co-design sessions with 29 task designers, workers, and platform representatives. We investigated task designer preferences for support in disclosing tasks, worker preferences for receiving risk disclosure warnings, and how platform stakeholders envision their role in shaping risk disclosure practices. We identify design tensions and map the sociotechnical tradeoffs that shape disclosure practices. We contribute design recommendations and feature concepts for risk disclosure mechanisms in the context of RAI content work.

**CCS Concepts:** • Human-centered computing → Interactive systems and tools; Empirical studies in HCI; Empirical studies in collaborative and social computing; • Computing methodologies → Artificial intelligence; • Social and professional topics → Computing / technology policy.

Additional Key Words and Phrases: Responsible AI, crowdsourcing, well-being, data work, red teaming, RAI content work

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## 1 Introduction

**Responsible AI (RAI) content work** [66], such as annotation, moderation, and red teaming of AI systems for safety, has become essential as organizations grapple with the risks of increasingly powerful AI systems. The rapid expansion of Generative AI (GenAI) has only heightened this reliance, fueling demand for large-scale human oversight to detect and mitigate safety concerns [29, 69]. Meeting this demand, however, requires human labor to confront harmful material

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ranging from explicit violence and hate speech to more subtle forms of bias and manipulation that demand nuanced human judgment [66]. Such exposure can cause significant psychological distress, and researchers have documented its toll on both part-time and full-time RAI workers [66, 70], including burnout, anxiety, depression, and in extreme cases post-traumatic stress disorder (PTSD) [2, 32, 52, 83].

Increasingly, organizations externalize RAI content work to **crowdsourcing platforms**, or platforms that outsource jobs “*to an undefined, generally large group of people through the form of an open call*” [9, 40]. These platforms provide the infrastructure for on-demand, distributed labor markets, which AI companies then leverage to scale annotation, moderation, and adversarial testing [25, 50, 94]. **Crowdworkers** [9] may face significant **well-being risks** when taking on tasks that involve graphic violence, disturbing imagery, or to simulate harmful scenarios designed to probe AI system boundaries [67]. Unlike part-time or full-time employees in traditional RAI roles, who may receive institutional support such as mental health support or training [66, 70, 89], crowdworkers often perform this work in isolation, without adequate preparation or access to support systems [8, 77].

Past work in HCI and CSCW has extensively examined the structural condition of crowd work [35, 76, 81]. In particular, foundational efforts like Turkopticon sought to increase transparency by surfacing requester reputations [43], yet few platform-embedded mechanisms exist to help workers anticipate or avoid emotionally distressing or harmful tasks. In fact, platforms vary widely in their practices, from providing no disclosure options to offering more structured resources [61, 62, 64]. At the same time, prior research has advanced content warnings for social media audiences [7, 80, 104], but it remains unclear how to adapt these insights to workers facing risk disclosure in crowdsourced RAI tasks. Despite growing awareness of well-being risks – especially in RAI content work – there is little empirical research on how these risks are communicated and how disclosure practice might be improved. This gap underscores the need to examine “**risk disclosure**” – the provision of upfront information about the nature and potential harms of content tasks [10, 66] – not merely as an ethical responsibility, but as a “design challenge” embedded within sociotechnical systems that often obscure harm.

Such a “design challenge” is further complicated by the inherent tension between stakeholder needs and incentives [27, 31, 43, 75, 76]. Prior work has revealed that task designers<sup>1</sup> face pressure to recruit sufficient workers while also meeting ethical obligations to inform them of potential risks [11, 27, 47, 67, 105], while workers need agency to make informed participant decisions and fair compensation for their labor [43, 51, 75, 77, 81, 93], and platforms must balance worker safety with operational efficiency and legal compliance [3, 31, 102, 103]. As Fieseler et al [26] remind us, crowdsourcing platforms mediate a triadic relationship between requester, worker, and platform, yet much of the existing literature focuses only on a dyadic exchange between workers and task designers. To navigate these tradeoffs, it is therefore critical to examine the unique tensions faced by the three main stakeholders in crowd-based RAI content work – task designers, workers, and platform – and to offer guidance that supports ethically grounded decisions aimed at promoting worker well-being. Our aim is to complement worker-centered scholarship by concentrating on the actors who currently shape task structure, disclosure policy, and enforcement.

To address this gap, we conducted one-on-one co-design sessions [48, 92] with 15 task designers, 11 workers, and 3 platform representatives to understand how risk disclosure decisions are made and what tools and workflows could better support effective disclosure practices. Our study focused on three key design dimensions: specificity (how detailed or granular the disclosure is), worker agency (the extent to which workers can act on disclosure), and task designer

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<sup>1</sup>We use the term **task designers** rather than requesters to more accurately reflect the active and interpretive role individuals play in shaping the structure, framing, and content of crowdsourcing tasks. While requester is the platform-standard term, it implies a transactional relationship that downplays the design decisions and ethical considerations embedded in task creation. Following prior HCI work that emphasizes the creative and normative dimensions of task design [11, 67], we adopt task designer to foreground their agency and responsibility in shaping worker experience.

agency (the flexibility and support available to those creating disclosures). We ask the following research questions: **RQ1:** How do task designers, workers, and platform representatives perceive and approach different risk disclosure mechanisms across key design dimensions? and **RQ2:** What tradeoffs and tensions emerge when stakeholders consider different configurations of risk disclosure mechanisms?

Our findings reveal that workers, task designers, and platforms hold divergent expectations about how risk should be communicated in RAI content work. Workers value clear, specific warnings and the ability to make informed decisions; task designers often fear that detailed disclosures will deter participation; and platforms aim to balance protection with policy and scalability. These tensions manifest across key stages of task engagement – from sign-up and participation to post-task feedback – and expose structural gaps in responsibility. We identify design opportunities to better support disclosure practices, including adaptive filters, feedback mechanisms, and AI-assisted tools. Ultimately, we argue that risk disclosure is not just a technical feature but a sociotechnical negotiation of power, protection, and participation. We also acknowledge the limits of co-design in this space, and that some categories of RAI content work should not be crowdsourced, in which case it may be better to redesign the pipeline for gathering worker input rather than the disclosure itself.

Our contributions are threefold:

- **Empirical insights** into risk disclosure in crowdsourced RAI content work, based on co-design sessions with 15 task designers, 11 workers, and 3 platform representatives. We surface how stakeholder roles, values, and constraints shape disclosure expectations and practices.
- **A multi-stakeholder understanding** of risk disclosure as a sociotechnical negotiation, identifying key tensions around specificity, worker agency, and task designer responsibility across the lifecycle of content tasks.
- **Design implications** for more accountable and transparent disclosure systems.

## 2 Related Work

### 2.1 Psychological and Well-being Risks of RAI Content Work

The rise of Responsible AI (RAI) initiatives draws new attention to the people behind AI systems: workers who annotate, moderate, and evaluate AI content. Their tasks – collectively described as **Responsible AI (RAI) content work** [66], including annotation, moderation, and red teaming for model safety – are critical to system performance and societal impact. Yet their labor remains largely invisible or undervalued [34].

In particular, a growing body of research has documented the **psychological and well-being risks** faced by these workers. Workers carrying out RAI content work routinely experience graphic or disturbing material with significant negative mental-health effects. Studies show that prolonged exposure to this material, coupled with limited support, contributes to burnout [22], secondary trauma [52], and PTSD [2, 6, 24, 55, 72, 89]. More recent work replicates these findings, reporting that a large portion of content moderators exhibit moderate to severe psychological distress and low well-being [84]. Other research highlights broader harms, including privacy violations [60, 78] and changes in workers' personal beliefs and moral outlooks [23, 57, 86].

Although researchers are beginning to explore how organizations and individuals with decision-making power can support and address RAI content work psychological and well-being risks [10, 66, 67, 89], they focus on full-time employees in formal moderation roles. In particular, “**risk disclosure**” – providing upfront information about the nature and potential harms of content tasks – is recommended as a key practice to support worker well-being in RAI content work [10, 66], it has primarily been discussed in the context of full-time employment and platform-based

content moderation. This is a significant gap, as crowdworkers increasingly perform similar high-risk annotation and moderation tasks, often with little to no warning about potentially graphic or disturbing content, such as depictions of violence, self-harm, or abuse. These workers operate in task-based gig economies where formal protections like HR support or institutional mental health resources are typically absent [43, 51, 75, 77, 81, 93]. However, far less is known about how these workers encounter and navigate RAT content work risks and how risk disclosure can be meaningfully designed to support them in these precarious contexts.

## 2.2 Risk Disclosure in Crowdsourced RAI Work: A Design Challenge

While academic and organizational discourse has increasingly underscored the importance of disclosing well-being risks in RAI content work, particularly for employed roles such as content moderators [10, 67], less is known about how such efforts are operationalized in crowdsourcing contexts.

On the one hand, most crowdsourcing platforms offer limited, inconsistent, or opaque mechanisms for risk disclosure. Prolific, for example, provides a researcher-facing “sensitive content” toggle during study design (see Appendix Figure A2(a)) along with an option to include additional information with keywords, along with guidelines to include warnings in task descriptions for both task designers [61, 65] and workers [62]. Another approach is to limit exposure based on age limits or other qualifications. Amazon Mechanical Turk (MTurk), for example, provides task designers with an “adult content qualification” requirement option in which only workers who have received this certification can see tasks with such content (see Appendix Figure A1). Research platforms such as Zooniverse and Tokola provide examples of task-level warnings, but these remain inconsistent in format and enforcement<sup>23</sup>. However, the relative effectiveness of these methods is unclear as well as how each stakeholder group involved in their use and implementation perceives them. Beyond disclosure options, platform-level governance also varies significantly. For example, Prolific allows workers to report tasks for review and potential removal, and anecdotal evidence suggests platforms like Toloka have occasionally removed tasks after worker complaints (see Appendix Figure A3). However, such interventions appear to be the exception rather than the norm.

On the other hand, past work on content warnings on consumer-facing platforms offers important lessons. Social media platforms such as Tumblr, Twitter (now X), Instagram, and TikTok have implemented content warnings to protect users from potentially distressing material, ranging from textual tags like #tw to automated overlays that blur graphic images. These systems aim to support informed consent, reduce harm, and signal sensitivity to trauma [97, 104]. However, their application is highly variable and their effectiveness remains contested. Empirical studies show that while users generally appreciate warnings in principle, concerns persist about inconsistent enforcement, insufficient granularity, and unclear rationale [7, 12, 14]. Some warnings may even increase anticipatory anxiety, especially among individuals with lived experience of trauma [79]. These limitations highlight the complexity of operationalizing harm reduction at scale and suggest that risk disclosure is not simply a matter of adding labels, but requires careful design attuned to user needs, platform affordances, and sociocultural context.

More importantly, the context of crowdsourced RAI work differs in important ways. Unlike social media users, who encounter warnings during voluntary content consumption, crowdworkers engage with potentially harmful material as part of paid, high-throughput tasks. As such, risk disclosure in this domain intersects with distinct incentives – such as performance expectations, compensation structures, and data quality requirements – that reshape the meaning of

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<sup>2</sup><https://www.zooniverse.org/>

<sup>3</sup><https://toloka.ai/>

consent, exposure, and protection. These differences raise critical questions about how content warning strategies must be re-imagined for labor systems, not simply adapted from consumer platforms.

In this study, we build on these insights to examine how risk disclosure is approached, interpreted, and contested in the context of crowdsourced RAI content work. We frame risk disclosure not as a compliance checkbox or content tag, but as a complex design challenge that must account for divergent stakeholder needs, uneven power relations, and structural gaps in responsibility and support.

### 2.3 Co-Designing Risk Disclosure Across Stakeholders

While prior HCI and CSCW work has examined the structural dimensions of crowdsourcing platforms, it has yet to address how well-being risks are communicated, managed, or shared. Platforms mediate a “triadic relationship” between workers, task designers, and platforms themselves [26], shaping interactions through design choices, algorithms, and governance practices. Foundational work like Turkopticon surfaced worker-requester power asymmetries [43], and subsequent studies have shown how trade-offs between efficiency and fairness are embedded in task workflows, incentive systems, and reputation mechanisms [38, 74].

From the worker perspective, platforms rarely center well-being. While crowd work is often framed as flexible and empowering, that flexibility is unevenly distributed and frequently illusory [49, 68, 95]. Workers face challenges with task rejection [53], emotional strain [28, 51], and a lack of institutional protections [75, 81]. These harms are magnified in Responsible AI (RAI) content work, where workers are often exposed to harmful or triggering material without advance warning. Task designers, meanwhile, focus on data quality and throughput, yet their choices, ranging from interface design to instruction clarity and incentives, significantly shape worker outcomes [37, 38, 101]. Recent work calls for increased transparency and reflection among task designers, recognizing their role in structuring tasks that can cause or mitigate harm [11, 67, 91, 105]. At the platform level, governance structures influence risk exposure but often remain opaque. Platforms mediate access to tasks and enforce norms, yet both workers and task designers have limited insight into these mechanisms [35, 93, 99]. Algorithmic interventions and moderation policies shape who gets to work and under what conditions, often under the guise of neutrality and scale [30, 73].

Despite these well-documented structural dynamics in crowd work, little is known about how stakeholders involved in Responsible AI (RAI) content work perceive, interpret, and implement risk disclosure in practice. To address this gap, we conducted a multi-stakeholder investigation with task designers, crowdworkers, and platform representatives to understand how risk disclosure is approached in crowdsourced RAI tasks. In particular, we adopt a co-design approach grounded in the belief that those most affected by system decisions should help shape them. Co-design foregrounds the lived experiences of all stakeholder groups and surfaces tensions that may remain hidden in researcher-led or single-stakeholder processes. In domains like gig work and freelance labor – where power is diffuse and harms are uneven – co-design serves not only to generate design concepts but also to redistribute agency in how problems are framed [41, 42]. To our knowledge, this research is among the first attempts to apply co-design to examine risk disclosure in the crowdsourcing context. Our approach builds on prior calls to design for multi-stakeholder participation [96], recognizing that risk disclosure is not a simple matter of transparency but an ongoing negotiation of accountability, agency, and institutional power.

| PID | Job                   | Years |
|-----|-----------------------|-------|
| T1  | PhD Student           | 3–5   |
| T2  | Data Analyst          | 3–5   |
| T3  | Data Analyst          | 1–3   |
| T4  | AI Researcher         | 3–5   |
| T5  | Data Analyst          | 1–3   |
| T6  | Data Analyst          | 3–5   |
| T7  | Data Analyst          | 3–5   |
| T8  | PhD Student           | 3–5   |
| T9  | Research Assistant    | 1–3   |
| T10 | Data Scientist        | >5    |
| T11 | Data Analyst          | 3–5   |
| T12 | AI Research Scientist | 1–3   |
| T13 | Data Analyst          | 1–3   |
| T14 | AI Ethics Researcher  | 3–5   |
| T15 | PhD Student           | 1–3   |

Table 1. Task Designers

| PID | Job         | Years |
|-----|-------------|-------|
| W1  | Crowdworker | 1–3   |
| W2  | Crowdworker | 1–3   |
| W3  | Crowdworker | <1    |
| W4  | Crowdworker | <1    |
| W5  | Crowdworker | 1–3   |
| W6  | Crowdworker | 1–3   |
| W7  | Crowdworker | 1–3   |
| W8  | Crowdworker | 1–3   |
| W9  | Crowdworker | 3–5   |
| W10 | Crowdworker | 3–5   |
| W11 | Crowdworker | >5    |

Table 2. Workers

| PID | Job                  | Years |
|-----|----------------------|-------|
| P1  | Product Manager      | 1–3   |
| P2  | Executive            | 1–3   |
| P3  | Operations Associate | <1    |

Table 3. Platform Representatives

### 3 Methods

#### 3.1 Study Design

We conducted co-design sessions to explore how task designers, workers, and platform representatives evaluate and prioritize risk disclosure mechanisms. Co-design was chosen as it foregrounds stakeholder perspectives and enables the surfacing of tensions through collaborative ideation. Drawing from participatory design traditions, we aimed to establish a “third space” where participants and researchers could meet on equal footing to engage in mutual learning and shared decision-making [13, 56, 87]. This approach aligns with prior HCI work that engages multiple stakeholders to understand underlying tensions when designing platform-level interventions [41, 92].

We opted to conduct individual co-design sessions with task designers, workers, and platform representatives rather than joint workshops involving multiple stakeholder groups. This decision was made for several reasons. Separating stakeholder groups helped protect worker participants, many of whom are in structurally vulnerable positions. Prior research has shown that power asymmetries can shape who feels safe to speak and what perspectives are voiced in multi-party design engagements [92]. Conducting sessions separately allowed us to create safer and more comfortable spaces for open reflection, especially when discussing platform practices or task designer behaviors. Second, individual sessions allowed us to dive deeper into stakeholder-specific concerns, generating richer insights into risk perceptions, disclosure priorities, and contextual tensions that may not arise in broader group settings [21]. This approach allowed us to tailor prompts to each group’s domain knowledge and lived experience and to bring in perspectives across stakeholder groups by sharing anonymized takeaways from one stakeholder with another (e.g., task designer perspective to workers). Additionally, sessions with individual users allowed us to schedule sessions to accommodate participants’ schedules, given the challenges of accessing all three stakeholder populations in this study.

Each participant engaged in a single co-design session with one researcher, lasting approximately 60 minutes. For each session across all three groups of participants, we first asked participants to reflect on existing challenges they faced when disclosing risk, viewing risk in tasks, and managing risk disclosure. We followed with questions about what ‘ideal’ scenarios of risk disclosure may look like. To elicit deeper discussions, we prepared a series of design probes

| Dimension                   | Low  | Medium                                    | High                               |
|-----------------------------|--|---|------------------------------------|
| <b>Warning Specificity</b>  | Sensitive vs. explicit or disturbing [7, 64] | Category, modality, and keywords [12, 46] | Examples and scale [46]            |
| <b>Worker Agency</b>        | No opt-out [4]                               | Informed consent [63, 81]                 | Granular exposure control [45, 46] |
| <b>Task Designer Agency</b> | Generic platform template [61, 64]           | Manual customization of warnings [67]     | AI-assisted risk disclosure [66]   |

Table 4. Design Dimensions for Risk Disclosure in Crowdsourced RAI Tasks, organized by low, medium, and high levels of each dimension

catered to each specific participant group that varied along three design dimensions if (1) specificity, (2) worker agency, and (3) task designer agency. We used Figma<sup>4</sup> to facilitate collaborative discussion. Sessions were audio/video recorded and transcribed for analysis.

Our decision to vary warning *specificity* is grounded in research on trigger and content warnings in social media; these studies note that warning systems range from simple binary alerts to detailed categories and examples, and that inconsistent implementation leads to confusion for both posters and readers [12, 104]. To capture *worker agency*, we looked to scholarship on worker autonomy and worker-driven advocacy. Projects like *Ink* and *We Are Dynamo* emphasize giving crowd workers more control over their work identities and opportunities [75, 76]. Research quantifying invisible labour and highlighting the burdens of algorithmic management similarly calls for greater transparency and opt-out mechanisms [93]. Our continuum – from no opt-out to informed consent to granular exposure controls – mirrors this push for agency. Finally, we considered *task designer agency*. Many HCI papers focus on novice task designers' needs: tools like *Fantastic* and *Sprout* help non-expert requesters improve instructions and quality [11, 36]. Studies of novice researchers show that clear templates and guidance are essential when designing crowd tasks [59]. Emerging research identifying challenges of task designers being subject to organizational dynamics and possessing limited support in understanding potential harms to workers in the context of RAI content work further motivates the need to include this perspective [67]. Our third dimension spans generic templates, manual customization, and AI-assisted disclosure to reflect these varying levels of expertise. Through separate co-design sessions with each stakeholder group, we explored how different actors currently approach risk assessment, what tools and information they need to make informed decisions about risk disclosure, and what barriers prevent more comprehensive disclosure measures.

### 3.2 Participants

We recruited 29 participants in total, including crowdworkers, task designers, and platform representatives. Participants were recruited via LinkedIn and Reddit postings and referrals via the snowball sampling method. To recruit workers, we posted on crowdworker subreddits such as r/mturk<sup>5</sup> and also through the tasks requested by a few of our task designer participants who volunteered to assist with recruitment.

We required that each group of participants have a base level of experience. For task designers, we ensured that all our participants had experience requesting at least one RAI content work task. We ensured all our participants who were workers had at least 1 month of experience completing RAI content work tasks and that platform representatives

<sup>4</sup><https://www.figma.com>

<sup>5</sup><https://www.reddit.com/r/mturk/>

were currently employed at a crowdsourcing platform that hosted RAI content work tasks (see Table 5). In our selection, we asked task designer participants to indicate their background (i.e., job title and sector) and the types of RAI tasks they previously requested (e.g., prompt generation). Additionally, we asked prospective task designer participants to indicate what platforms they used for crowdsourcing as well as the types of content involved in their tasks (e.g., racism). Similarly, we asked workers to describe the types of RAI content work tasks they had experience completing, providing examples of each (e.g., “provide a prompt for an AI model to produce violent content”). We also asked workers to estimate how many tasks they typically do in one day, the types of sensitive content they encounter, the platforms they use, and to provide an example of an RAI content work task they completed and a short description of how they felt after completing the task. Tables 1-3 summarize participant demographics. Our participants were based in the United States and United Kingdom and were at least 18 years of age at the time of study participation.

| Participant Group        | Inclusion Criteria   |
|--------------------------|--|
| Task Designers           | Must have experience requesting at least one task relevant to Responsible AI (RAI) content work.                           |
| Workers                  | Must have at least one month of experience completing RAI content work tasks on a crowdsourcing platform.                  |
| Platform Representatives | Must be currently employed or employed within the last year at a crowdsourcing platform that hosts RAI content work tasks. |

Table 5. Inclusion criteria for study participants across stakeholder groups

### 3.3 Data Collection and Analysis

All co-design sessions were conducted by the lead researcher, while analysis was performed collaboratively by the first two authors. Data sources included session transcripts and notes from co-design sessions. We applied the method of reflexive thematic analysis [15, 82]. We conducted our qualitative analysis in multiple stages. First, two researchers independently generated fine-grained, low-level codes for each transcript. These were then grouped into axial codes to surface relationships across participant responses. Through iterative cycles of code consolidation, discussion, and memo-writing, we refined these into higher-level themes. Discrepancies in interpretation were resolved through discussion to strengthen validity. Throughout, we used analytic memos and reflexive notes to document evolving insights and to support reflexivity across the analysis process.

### 3.4 Ethical Considerations

This study was approved by our Institutional Review Board (IRB). All participants provided informed consent and were compensated \$30 USD<sup>6</sup> for their time via an online gift card. Given the sensitive nature of risk disclosure and content moderation, we designed activities to minimize potential distress (e.g., when showing a tool that allows task designer to provide an example of harmful content we used a filler sentence of “example of sentence featuring hatespeech”). Participants could withdraw at any time without penalty and were reminded to not provide identifying information or information they were not comfortable speaking about.

<sup>6</sup>Participants in the UK were compensated with the equivalent of \$30 USD

## 4 Findings

| #      | Design Challenge  | Worker Priority  | Task Designer Priority  | Platform Priority   |
|--------|---|--|---|---|
| [1]    | <b>Platform Signup:</b> Setting expectations for worker protection  | Platforms' protection from sensitive tasks   | Large and diverse worker population   | Liability protection  |
| [2-3]  | <b>Participation Preferences (Agency):</b> Defining boundaries for accepting tasks<br><b>Participation Preferences (Awareness):</b> Supporting worker self-awareness  | To have diverse options for tasks<br>Self-awareness of triggers  | Large and diverse worker population<br>Trust workers know what they can't do              | Limit participation for worker protection<br>Scaffold worker self-awareness   |
| [4-6]  | <b>Decision to Participate (Warning):</b> Warning workers without deterring participation<br><b>Decision to Participate (Definition):</b> Ensuring shared definitions of content<br><b>Decision to Participate (Accountability):</b> Balancing task designer autonomy with agency | Information to decide to opt-in or not to task<br>Clear definition of content<br>Consequences for failed risk disclosure | Convince workers to do the task<br>Autonomy in describing risk<br>Agency to disclose risk | Worker and task designer retention<br>Provide definition in compliance to regulations and policies<br>Mechanism to resolve disputes |
| [7-8]  | <b>Task Completion (Consent):</b> Balancing task completion with freedom to stop<br><b>Task Completion (Payment):</b> Fair pay for RAI content work   | Stop task if uncomfortable<br>More payment for difficulty and well-being harm  | Full worker task completion<br>Quality worker performance                                 | Prevent task abandonment at scale<br>Optimize labor costs while retaining workers   |
| [9-10] | <b>Post-task Completion (Feedback):</b> Encouraging quality feedback<br><b>Post-task Completion (Redress):</b> Mitigating harms from failed risk disclosure   | Choice to give feedback<br>Response from task designers  | Quality feedback<br>Make up for mistakes  | Large scale quality feedback<br>Maintain trust in platform  |

Table 6. Design challenges organized by priorities for each stakeholder group

### 4.1 Platform Signup

4.1.1 *Setting expectations for worker protection.* Although platforms sometimes provide opt-in or opt-out options for sensitive content, workers emphasized that platforms should be accountable for enforcing these protections, even if platforms may struggle to guarantee full shielding from harm. When asked whether they were prompted about their tolerance for sensitive content upon first joining a platform, few could recall such questions. After being shown an example of how a platform might ask about willingness to view sensitive content (see Figure 1), workers expressed two main sentiments. First, some, like W1, noted that platforms should actively uphold the preferences workers indicate: “*I think the platform should protect [us]. [If a worker] wants to say no [and they] don’t want to see [sensitive content]. It shouldn’t be popping up anymore*” (W1).

Other workers, such as W11, felt it was acceptable for platforms to at least offer an explicit opt-in option for viewing sensitive content, reflecting that “*from the frequency of the things I’ve been seeing I would say it’s almost impossible for*

**Participation survey**

Are you willing to participant in tasks that could contain sensitive or explicit and disturbing content?

[platform name] cannot guarantee answering no means you won't see the content. Only answer yes if you are comfortable with viewing this content.

Select an answer

Fig. 1. Participation survey probe

*you to [not] be exposed to explicit contents ... so I think it's okay [for the platform to be] vouching that you will not see [the content]" (W11). However, W11 later indicated that if questions were instead more specific—for example, asking about willingness to view racist content—it would be more important to enforce worker preferences, as they were personally harmed by that specific type of content (W11). From the platform perspective, P1 explained that such opt-in statements “gives the company or the employer some cover”, but suggested that support the platform offers “could be more comprehensive. It could offer resources. You can say ‘if you experience issues, please reach out to us’” (P1). Moreover, P3 further explained that such options are “work best when paired with clear educational content on ... without this, the main challenge is that a lack of education weakens the accuracy/reliability of their responses” (P3). These findings surface a recurring tension: while workers expect platforms to uphold accountability when presenting opt-in or opt-out options, platforms face legal challenges in guaranteeing that workers will never see sensitive content.*

## 4.2 Participation Preferences

**4.2.1 Defining boundaries for task participation.** We found that while platforms sometimes restrict sensitive tasks to certain workers, some task designers prefer input from diverse groups. For example, P1 described an instance where their platform restricted tasks on self-harm to an ‘expert’ population, defined as adults familiar with how self-harm could be encouraged by a specific AI system in a given domain (P1). P1 went on to explain that experts may be better equipped for exposure to such content: “*if someone works in counter terrorism, they're more readily [prepared]. I definitely think that they are a more prepared audience for dealing with the kind of content that might be [encountered]*” (P1). This desire to limit participation, however, conflicts with prior literature that emphasized the importance of diverse perspectives in responsible AI development [17, 67]. This was further validated by several task designers in our participant pool (e.g., T8 and T7) who expressed the need for a diverse samples.

These tensions became particularly pronounced when we discussed the idea of workers being allowed to filter tasks that contained certain types of sensitive content. Some task designers strongly expressed a concern about participation in their tasks being limited. T3 describes this tension:

*[From a] researcher's perspective, you [will] begin to see that if a lot of people are actually turning on the sensitive [content filter so they don't see these tasks. Then you start to see a reduction in study participants, and at the end of the day, you might not be able to get enough [participants] ... [From] the workers' perspective, a lot of them would most likely turn [the filter] on.]* -T3

One of the problems task designers had with the idea of a task filter was with how broad the definition of content that was filtered was. For example, T14 observed that task filters for a categorization of “sensitive content” may be too broad: “[the task] might be sensitive, but not as sensitive as a worker might imagine it to be [by] filtering it out, they don’t get to work on it” (T14). A few task designers offered suggestions to resolve this tension. For example, T2 suggested that rather than a broad categorization, workers are given “a bit of control, like [with an option to indicate] words that you don’t want to see” (T2). P3 indicated that their platform was exploring the possibility of implementing filters by “pre-classified topic” but noted that “the main challenge is building and maintaining large, accurately labeled datasets of tasks to make this possible. Filtering by broader topics is promising, as long as classification is reliable” (P3).

When we presented a range of options, from generic task filters to specific options for workers, participants expressed mixed preferences. Some workers echoed concerns that task filters could limit the number of tasks available and preferred instead to decide on a case-by-case basis using task warnings (W2, W3, and W9). Others favored category-specific filters (W5). On the other end of the spectrum, a few workers expressed they were not concerned about reduced task availability, stating “it’s not really going to be much of an issue … as much as I care about the job, you know, I still have to take good care of myself. I don’t want something that will probably affect [my] mental health in any way” (W10). Ultimately, our findings surface a key tension: while restricting participation in tasks either by a platform or through worker preference can protect workers from exposure, it must also take into account workers’ desires to view tasks they’re interested in and task designers’ needs to sustain participation.

**4.2.2 Supporting worker self-awareness.** Another tension around task filters concerned whether workers were fully aware of what types of content upset or “triggered” them. Many task designers assumed that most workers could reliably identify their boundaries. For instance, T15 reflected that if a worker completed RAI content work tasks for about a week, they would be familiar enough with the content to be able to indicate what upsets them. Many workers expressed a similar sentiment that they knew what specific content could upset them. For example, W3 explained that they have never liked seeing violence, while W6 stated they never want to do tasks involving sex exploitation.

We learned, however, that not all workers were certain of their limits. On the task designer side, T15 later expressed a concern that “doing this type of work can be a little numbing, and workers may not be paying the best attention to their own well-being” (T15). This concern was justified as some workers reflected on how they had become accustomed to viewing harmful content over time (e.g., T5, W10). As W10 explained, “right about now, I’m used to reviewing and working on this kind of task” (W10). Moreover, some workers, like W6, had to view a task that displayed a violent altercation to realize they never wanted to complete tasks that showed someone getting injured. Other participants explained that, regardless of whether they were aware of what upset them, they felt some workers just didn’t care to protect their well-being: “I know for a fact that lot of people don’t really care about [what’s] sensitive or not … a lot of [workers] say they don’t really care if [a task is] sensitive or not. They just want to do it and collect their money” (W3). To address this, T15 suggested there could be design features to help workers be more “introspective”. Here, we surface another tension: not all workers are aware of their limits to harmful content, raising questions about how effectively they can use platform features like task filters to protect themselves.

### 4.3 Decision to Participate

*4.3.1 Warning workers without deterring participation.* A key concern held by task designers was that disclosing risk would deter workers from participating in their tasks. Indeed, we found that workers viewed warnings as a crucial component in how they make informed decisions to complete tasks. Several task designers feared that warning workers of their task's sensitive content would dissuade workers from enrolling in the task (T2). In this way, task designers in our study faced issues similar to those echoed in prior research in prioritizing obtaining task data over everything else [27, 47, 67]. Some task designers felt an ethical obligation to include at least some basic type of warning, despite their perceived risks to the quality and speed of data collection (e.g., T12). Moreover, some task designers argued that “*people who try to be responsible will not worry about [having enough worker participation] because you always need to make sure that you accurately represent the task before worrying about task completion*” (T15). T2 also reflected that responsibility for participation in RAI content work should rest with the platform, not individual task designers: “*that’s for the platform to work on, because [we are] the customers [of] platform that [we’re] using*” (T2).

On the other side of the issue, some workers explained that disclosure of risk was not the only thing they considered when deciding whether to complete a task. For example, W2 explained they decide to do a task based on whether it's “*fun*” while W3 expressed that the amount of payment is the most important factor for them. In contrast, other worker participants expressed that warnings for a task were crucial to help them make informed decisions about whether to do a task or not. For instance, W3 explained they decided whether or not to do tasks based on whether the description in the warning was something they could “*stomach*” (W3). Other workers described a similar decision-making strategy (e.g., W4 and W6). As W9 summed up:

“*What I want to know about [a task] is [with the] images that will be shown, what they actually contain. [If] ... it's a task like I feel I wouldn't be comfortable [with] ... You know, in the end, I'm also a human being. As I'm training the model, I have to consider my own personal [preferences] also. So if it's something I feel I'll be able to work with, I'll proceed to work on it.*” -W9

Moreover, some workers described experiences where the disclosure of risk was insufficient, resulting in them being greatly negatively impacted. W6 described an instance when they decided not to finish after a task because they found the content was too “*brutal*” to continue. To mitigate this problem, P2 suggested that platforms offer an estimate of how frequently workers may view content, telling workers “*your likelihood of seeing [a type of harmful content] is 1 in 100 ... Putting numbers, averages, and percent likelihoods behind [warnings] would be helpful ... [and] would help [platforms] get more people doing the work*” (P2). Moreover, P2 proposed that platforms may offer workers alternatives to RAI content work tasks as a tradeoff:

“*if you answer this harmful question, you get paid more, but if you decide not to, we will give you five extra non-harmful questions so that [workers] have the option of: ‘do you want to expose yourself to harm and get paid the same and do less work or get paid the same and do more work?’*” - P2

Importantly, P2's suggestions assumed that platforms could provide non-RAI content tasks. Given worker observations of platforms increasingly offering more RAI content worker tasks (e.g., W11), it is unclear how feasible such options would be in practice. This theme surfaces a key tension: task designers were often hesitant to provide detailed warnings out of fear they might deter participation, while workers viewed risk disclosure as crucial to their decision-making process. Platform representatives offered initial suggestions on different ways in which platforms can address this challenge through warnings or other strategies.

**4.3.2 Ensuring shared definitions of sensitive content.** Another aspect we observed across the three groups of participants was that of discrepancies in how content should be involved in risk disclosure (e.g., ‘sensitive content’) and how it should be defined. Some task designers made an assumption that their definition of risky, sensitive, or explicit content was aligned with others’ to the point where they didn’t need to read platform definitions. For example, T15 “*very rarely*” read platform definition of sensitive content because they “*intuitively know the type of content that’s in there*” and the “*platform typically would put [a] blanket statement … [that’s] usually not useful to read*” (T15). However, when prompted to explain how they personally defined ‘sensitive’ versus ‘explicit or disturbing’ content, the explanations that several participants provided varied widely. Some participants interpreted sensitive topics as “*private information [about workers]*” (T1), while other participants viewed sensitive content as certain topics that may trigger some workers and be neutral for others. For example, T11 determined “*cyber bullying is sensitive because it triggers [you] if you’ve been cyberbullied before*” (T11). Moreover, T5 defined sensitive content based on examples of viewer discretion warnings they saw on television: “[in] movies on Netflix … *there’s always a warning that says ‘nudity or violence and drugs’*” (T5). These findings echo longstanding debates about how many decisions in content moderation are left to ‘*I know it when I see it*’ judgments [33, 58].

Because definitions of sensitive content are subjective and inconsistent, differences between the task designers’ and the workers’ perceptions could undermine the effectiveness of warnings. W1 illustrated an instance where differing definitions of content necessarily for risk disclosure negatively affected them as workers: “*maybe to [the task designer who] posted it … there is nothing that sensitive. But then [for the worker] doing it, I see it as a sensitive issue that [the worker] doesn’t want to see*” (W1). As W5 emphasized, a shared definition of the severity of the task can tell workers that the task “*is going to be deeply harmful or offensive*” (W5). Platform representatives described using commonly known taxonomies of harm (P1) to define risks to workers, but expressed that there were challenges in “*standardizing language (especially around ‘type’ and ‘severity’) and making severity ratings more objective*” acknowledging that such definitions “*can be highly subjective and vary significantly across cultures*” (P3). On top of that, P2 explained that it is a priority for platforms to base definitions of content categories on existing regulation and policy, such as the European Union’s Digital Services Act [1].

Another key tension we found was in task designers’ desire for agency in determining how risk should be disclosed for these tasks, with workers’ desire for accountability mechanisms to be in place to prevent instances of inadequate risk disclosure. Several task designers indicated that they wanted agency to make the final decisions about how to disclose risk in their tasks. As T1 explained: “*I know everything about my research, and I want to explain my research by my word[s] and by myself*” (T1). Other participants were open to receiving additional support in determining what warnings were most appropriate for their tasks. When prompted about receiving AI and prediction-based suggestions, these participants expressed an optimistic outlook on using such tools. Several participants expressed that having some version of an AI suggestion for a warning would be helpful. Others explained that predictions based on ways other task designers disclosed risk (e.g., T3 and T12) as well as predictions based on what workers have indicated (e.g., T2) would help them (see Figure 2). Others emphasize that being able to receive quantitative recommendations would be particularly helpful and even persuade them to include a warning. As T3 explained:

*“I understand this [suggestion] is saying that [a warning will be placed by other task designers] about nine times out of ten. Then the possibility that that is going to happen is, you know, very high. And, you know, why would I go for the less likely than the most likely? So definitely, I’ll go for the most likely.” -T3*

<sup>7</sup>Icon credit: <https://wallpapers-clan.com/sticker-png/cute-canary-bird>

### Based on What Others Are Doing

Canary gives you suggestions on how you should disclose risk based on what you have entered about your task so far. It will not save data about your task.

90% of similar tasks involving viewing images and reading text involving hate speech added a warning for:  
 "Exposure to explicit or disturbing content"  
 and indicate that the specific types of content involved are:  
 "hate speech" "cyberbullying and harassment"



Fig. 2. AI suggestion based on what other task designers have done<sup>7</sup>

On the platform-side, P3 said their platform was currently exploring AI options to support task designers, but claimed they faced challenges with how the "*mixed content [of RAI content work tasks] makes accurate categorization difficult, and error rates could be high with large datasets.*" (P3). P3 further elaborated on the challenge of needing to test systems under the pressure of deadlines:

*"extensive testing would be required before implementation . . . without robust classification at the start, sensitive material can slip through unnoticed. The primary barrier to doing this well is the pressure of strict production deadlines and the fast pace of the industry, which often limits the time available for a truly thorough."* - P3

As such, we surface a need for further innovation and experimentation with the design of systems that may support ask designers in disclosing risk.

Despite some participants' optimistic views of tools that could support their risk disclosure process, the amount of agency afforded to task designers emerged as a key point of contention. Some participants urged for the suggestions to guide risk disclosure with the task designer making the final decision. These participants proposed options such as having multiple suggestions to choose from (T2 and T3), an option to edit warnings rather than just accept suggestions (T7 and T11), and the integration of AI options into specific questions about risk disclosure, such as suggesting keywords for a warning (T7).

Many of our participants were cautious about using such tools, illustrating specific challenges that may emerge when implementing such tools. T1 and T15 cautioned that a certain amount of trust in how the suggestion was formed—particularly if it was AI-based—was necessary for them. T15 in particular cautioned that the suggestion based on how other task designers have disclosed risk would not be helpful unless the suggestion can clearly explain how to calculates similarity between tasks:

*"Without knowing what similar means, this is kind of vacuous. For example, I imagine the system in back end being like if the task involves the two modalities, images and text, then I compute a statistic on what are the labels being applied? Then if it's over 50% I tell the user, X percent of similar tasks added a warning for X."*

*This is type of broad statistics is just not useful, right? ... Unless you have a very good idea [of what] similar really mean[s] and being able to tell what similar [means] feels like a pretty hard thing." -T15*

As such, we found that for several task designers, retaining agency to make final decisions on risk disclosure as well as being able to trust suggestions provided by an AI or otherwise recommendations were important considerations.

From the worker's perspective, accountability was critical in cases of failed or inadequate risk disclosure. Workers expressed several different ideas on how accountability should be placed in this case. W7 expressed that it was the task designers' responsibility to provide an adequate warning and that they "*should be held responsible for anything that comes up*" regarding their content warning (W7). Moreover, W7 also reasoned that platforms should enforce consequences for inadequate risk disclosure because it is the platform's job "*to make their platform more [worker] friendly [so] everybody will be satisfied*" (W7). We observed that some task designers expressed a similar sentiment in agreement that platforms should be responsible for holding other task designers responsible for adequate risk disclosure (e.g., T2, T8, and T9). However, tensions arose around how platforms might implement such mechanisms without undermining task designers' agency, mentioned earlier. For instance, W3 proposed platform-level review of tasks after disclosure information was entered. However, T1 expressed earlier that "*regardless of the accuracy [of the AI review], I just have the fear or uncomfortable feeling about [being] scanned or judged*" (T1). While some participants, such as T15, argued that task designers concerned about worker well-being would not be bothered by platform review of how they disclose risks in their tasks, T1's concern illustrates a key tension in that task designers, uncomfortable with the mechanisms enforced on a platform, may go to another platform.

#### 4.4 Task Completion

**4.4.1 Balancing task completion with freedom to stop.** Even after opting into a task, some workers described encountering unexpected harms or discomfort, raising tensions between the need for ongoing consent and the pressures of task completion that underpin platform and task designer goals. Several workers explained reasons why they want the option to be able to stop a task due to being uncomfortable with exposure to content. For example, W2 said "*I found some section of the task way too sensitive, which actually stressed me, but I had no option than to complete it. I wish there was that flexibility, that I could skip those parts*" (W2). Despite wanting the choice to stop a task after starting it, participants also described concerns about wanting to be compensated for their efforts or their worker accounts facing penalties. Some participants indicated they wanted at least partial payment for their effort, given they failed to complete the task because they were uncomfortable rather than any other reason (W4-W6).

Moreover, W3 reasoned that regardless of compensation, they would prioritize their well-being, but also indicated they were concerned about receiving a penalty to their account:

*"if [completing the task] has a very high effect on your mental health, it doesn't matter for you to be paid or not. I don't really care if I'm paid or not. If I'm not comfortable with doing I'm not doing it. So that should be like the case, but it shouldn't have, like a penalty." -W3*

The idea of a partial payment model was something that some workers reported having positive experiences with (W4) and some task designers were receptive to. T15 advocated that they wanted to still use data from a worker even if they didn't complete the task, explaining that partial compensation was reasonable in this case (T15). W4 proposed that the platform step in to enforce this type of model:

*"[The] platform should inform the [task designer] to to pay some amount of money, since it was stated that you're going to be getting [a specific] amount after completion ... because what [the task designer] say[s*

*is] sensitive might not be actually what, what [I] perceive—like sensitive might be extreme to me, like very sensitive. So they should be able to compensate for that.” (W4)*

Thus, from needs advocated by both workers and task designers, a policy of partial payment for the case of RAI tasks may be a promising avenue to address this tension.

**4.4.2 Fair pay for RAI content work.** The discussion of fair or adequate pay for not only crowdwork but RAI content work tasks specifically was another point of tension among our participants. Echoing calls for the establishment of fair payment to crowdworkers in prior literature [43, 81], some workers expressed a desire for increased pay to do RAI content work tasks. In contrast, task designers and platform participants expressed concerns about budget limitations as well as payment being potentially coercive.

Several workers indicated a desire for higher pay, describing tasks they previously completed at pay rates close to what is the standard for U.S. minimum wage in several stages (e.g., \$12.50 USD an hour for W11). Examples were proposed ranging from \$30-\$50 USD (W1-W3 and W6). Many task designers were open to paying more for RAI content work tasks (e.g., T4 and T7). T14 proposed that platforms should charge 2-5% more for such tasks. Some participants, like T4, were alright with paying a smaller percentage more only because they viewed it as a negligible increase in price. Other participants indicated that some judgment of whether their task had content that was ‘severe’ enough to warrant charging a higher rate would be necessary (e.g., T9). For some of these task designers, higher pay was also reasonable if they could access a population of workers who were more experienced doing RAI content work tasks, similar to how some platforms designate ‘AI taskers’<sup>8</sup>. These workers had a proven track record for successful completion of such tasks. From these task designers’ perspectives, this meant they could both perform well on tasks and were able to deal with exposure to such tasks. (T7 and T14).

However, the proposed model of partial payment was not without flaws. Many task designers expressed concerns that increasing payment for RAI content work tasks could unreasonably pressure workers to complete tasks that they may otherwise opt out of. T9 described the problem: “*all I’m saying is adding more money to those types of tasks would make people that are sensitive to some explicit or disturbing content to go ahead [and do them] without even looking back*” (T9). To counter this issue, T12 proposed that the increase in payment should not be publicized to workers, recommending that “*it shouldn’t be made public that they will be paid more for very severe tasks, because … [that] enhances the uncensored responses, where workers don’t even pay attention to [the warning], since it is something they know that pays more*” (T12). Other task designers were not perceptive to the idea of increasing payment for RAI content work tasks simply due to the exposure to potentially harmful content (T3 and T10). These participants reasoned that, for example, it did not make sense to pay for tasks that take the same amount of time as other tasks (T10). For these participants, the appeal to the quality of worker responses was more compelling, as T3 stated they would be perceptive to paying more if the quality of worker responses was guaranteed (T3). Platform representatives expressed a desire to better tailor incentives when possible to workers. For instance, P2 explained how they approach incentives:

*“If you are doing, like a red teaming event or some sort of, like data annotation thing for a very specific subset of people who might be participating in it, then the option for non-monetary awards is more beneficial because then you can, like, tailor your awards to those people’s needs. Like, if we’re doing something for college students we can be like ‘we’ll give you five informational interviews and a glowing letter recommendation.’*

*Whereas if you don’t know your audience then money is the best option.” -P2*

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<sup>8</sup><https://participant-help.prolific.com/en/article/5ba0c>

From the platform perspective, P3 explained that their platform recommended higher pay rates for such work for two reasons:

*[1] Fewer people are both skilled and willing to take on this kind of work, so higher rates help incentivize participation. [2] The cognitive load of repeatedly reviewing unsafe or disturbing content is significant, and compensation should reflect that burden.” - P3*

Overall, we surface tensions around how workers indicate a desire to be paid more for completing RAI content work tasks, while task designers have reservations about increasing payment in case it could negatively pressure workers.

#### 4.5 Post-Task Completion

4.5.1 *Encouraging quality feedback.* Finally, task designers and platform representatives described challenges in collecting enough high-quality feedback from workers to gauge the effectiveness of their risk disclosure. Participants across all three populations emphasized the importance of mechanisms for workers to provide and collect feedback on disclosures. Platform representative P1 reflected that it was difficult for them to collect feedback from workers even when presenting broad questions that were not targeted specifically to risk disclosure. Additionally, P1 also noted a need for more standardized practices for collecting feedback on their platform. For task designers, feedback was particularly helpful to gauge if the way risk was disclosed was effective or needed adjusting. For example, T11 illustrates a case where feedback would be helpful:

*“Because [until] you get that feedback, and you don’t actually know that this exact content can be very, very disturbing. Because you might think that it’s just moderate, but you don’t know that it’s very, very severe and extremely disturbing” -T11*

For workers, feedback was described as one of the few places where workers could assert agency within the crowdsourcing process. W9 explained that after they complete a task “*there’s little I could do, but one thing I feel [is that] … after each task, you know you have a right [to be able to] leave a review. Leaving such review will make other other [workers] more aware of what was gonna [be in the task]*” (W9). Other participants expressed that feedback was an important outlet for them if they were hurt by the lack of risk disclosure, explaining their desire to complain or verbally “*bash*” the task designer for their failure. Thus, we find that for many of our task designer and worker participants, feedback served as a crucial avenue of communication.

When discussing how task designers could better attain feedback, both task designers and workers emphasized the need to respect worker agency in choosing to give feedback or not. Several task designer participants reasoned that workers “*should be able to choose things on their own free will*” (T13), but also that enforcing feedback may result in lower quality responses. Workers expressed a similar sentiment, with some emphasizing that they may be too tired or traumatized after a task to give feedback. W3 described an instance where they did not want to give feedback: “*I was so stressed, like, I was so stressed that I just want[ed] to finish [the task] so I didn’t give any feedback. [The task designer] asked for feedback. I just skipped it*” (W3).

One proposed solution for improving feedback was to compensate workers for providing it. W1 expressed that paying for feedback could help workers “*take [their] time providing it*” (W1). Some task designers indicated they would be willing to pay workers for feedback, given its importance (e.g., T6 and T9). However, others stated they would not try to get feedback if they needed to pay for it (e.g., T5) or that if feedback was “*just three clicks,*” (T12) it would be unnecessary to pay workers for it. Yet other participants cautioned that paying workers for feedback could result in “*false feedback*” (T14) that was disingenuous. Overall, while there is potential in some design interventions that make

feedback potentially easier to use for workers, we surface key challenges in collecting feedback, such as determining an appropriate model for compensation and ensuring the elicitation of nuanced feedback.

**4.5.2 Mitigating harms from failed risk disclosure.** In instances where risk was not adequately disclosed to workers, some looked to task designers for acknowledgement or redress, but the absence of clear accountability structures encouraging such responses exposes a deeper tension between individual harm and diffusion of responsibility. Several workers felt it was important to receive a response from task designers when they raised problems with a task's risk disclosure process (e.g., W1 and W3). Participants who had worked explained that responses from task designers helped validate the harm they experienced (e.g., W1 and W10). W8 explained that when task designers responded to their feedback it "*makes me feel heard and sane at least. It tells me that you actually value my opinion*" (W8). Moreover, some participants expressed that receiving a response from a task designer reassured them that the task designer would want to improve their task's risk disclosure for future workers. W6 claimed that a response could "*make me feel like the researcher understands how I feel and [is] willing to correct [the warning]*" (W6).

Other participants struggled to envision the value of receiving a response from task designers beyond monetary compensation (W3 and W7). For instance, W3 stated they wanted to be able to contact a task designer "*maybe we should be able to contact their company*" but struggled to envision what the task designer's organization could do other than provide compensation: "*but the other thing I'm thinking about is, if I contact the company, what are they going to do about it?*" (W3). When asked about what they ideally wanted the task designer's organization to do, W3 stated "*Oh compensate me, I guess*" (W3). Moreover, despite wanting compensation, W3 also acknowledged the risk that other works might exploit task designers' goodwill.

Another suggestion that surfaced was for workers to receive resources for well-being. P1 suggested that platforms "*offer resources. You can say like 'if you experience issues, please reach out to [us]'*" reasoning that if the platform is hosting such tasks "*they should have a point of contact. The program manager, a mental health counselor, or something [else] in case people experience challenging issues in the work that they're doing*" (P1). Previously, P1's platform facilitated a red teaming task where they provided access to mental health professionals. In fact, prior research has established that, particularly for some task designers who are academics, the practice of providing resources such as the phone number or a link to a helpline has been commonly used [67, 104]. However, the decision to provide extra resources remains at the discretion of the task designer. When discussing their experiences receiving such resources, some workers felt strongly about how task designers and their organizations took responsibility in distributing such resources. For instance, W3 argued that task designers should provide helplines from their own company instead of pushing the responsibility to the platform:

*"I think it's just [task designers] fulfilling [some] righteousness because obviously nobody's gonna call the number... because you're putting a task for people to do and you're asking them to call [another organization]. Is it [that organization] that gives [workers] the task? Doesn't make sense to me. You give [workers] a task. You should be the one offering [workers] like a helpline and all that." - W3*

W3's reflection highlights the complexity of this space, indicating that how task designers and platforms present resources shapes workers' perceptions of whether they are taking responsibility for remedying harm to workers.

## 5 Discussion

### 5.1 Design Implications

*5.1.1 Front-load Worker Preparation Upon Platform Sign-up.* Our findings suggest that platforms should reconsider the minimal role they currently play in preparing workers for sensitive content tasks. While sign-up surveys and opt-in checkboxes often function as little more than legal cover, workers emphasized that platforms bear an ongoing responsibility to enforce protections and support well-being. One design implication is for platforms to offer structured opportunities for workers to express and periodically revisit their preferences, rather than relying on a one-time disclosure at sign-up. In addition, platforms could provide lightweight training, onboarding modules, and well-being strategies and skills (e.g., emotion regulation and cognitive reappraisal [85]) that introduce workers to common categories of sensitive content and prompt reflection on personal boundaries. Such training could not only help workers develop self-awareness but also improve data quality by reducing the likelihood of unanticipated harm mid-task. This implication resonates with prior work calling for platforms and companies to provide preparation and resources for content moderators [66, 88, 89].

*5.1.2 Increase Specificity to Ensure Sustainable Worker Responses.* We found that workers, task designers, and platforms all held incomplete or mismatched understandings of how warnings shape participation. Designers feared that warnings would deter participation, while workers consistently emphasized the value of specific details in making informed decisions. Our findings suggest that risk disclosures should prioritize specificity over generic phrasing. Greater specificity may strengthen sustainability by protecting workers from unexpected harms and by reinforcing the reputational standing of task designers, since prior work has shown that reputation is a critical factor in sustaining participation and trust in crowdsourcing [31, 43]. Future work could explore tools that assist task designers in creating richer disclosures, such as AI-driven keyword generation, taxonomies of severity, or prompts informed by prior worker feedback. By reframing specificity as a driver of both worker well-being and long-term platform sustainability, designers can challenge the assumption that detail undermines participation.

*5.1.3 Encourage Feedback Through Facilitating Worker-Task Designer Relationship-Building.* Feedback emerged as one of the few areas of relative agreement among all stakeholders. Workers valued it as a rare moment of agency, task designers viewed it as essential for improving warnings, and platforms saw it as a way to maintain trust. Yet feedback is currently under-supported in most platform designs. We suggest that platforms experiment with mechanisms that actively encourage feedback and deepen worker–task designer relationships, for example, by integrating feedback prompts into the workflow, offering compensation for reflective responses, or highlighting when feedback leads to concrete changes. These mechanisms should be designed with sensitivity to workers’ well-being, allowing them to decline feedback after distressing tasks without penalty. Prior work has examined the importance of task-designer-worker relationships in shaping trust and quality in crowdsourcing [43, 67], but the role of feedback in mitigating risk disclosure failures remains underexplored. Our findings suggest this as a promising area for both empirical evaluation and design innovation. Notably, early platform changes are already moving in this direction (see Appendix Figure A7 for Prolific’s new feature for increased feedback from workers), but systematic evaluation is needed to generate empirical evidence that can better inform practice.

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<sup>8</sup>Documented by an author completing a task on September, 2025

### 5.2 Negotiated Responsibility in Risk Disclosure

Our study reveals that risk disclosure in AI data work is a socially negotiated process involving workers, task designers, and platforms. Consistent with prior research, we found that these groups hold distinct and at times conflicting assumptions about who is responsible for identifying, assessing, and communicating risks [26]. Workers often assume that task requesters or platforms have already vetted tasks for harm, while task designers may assume that workers bear responsibility for self-selecting out of sensitive content. Platforms, meanwhile, frequently promote a vision of shared responsibility while retaining control over infrastructure and moderation policies. These mismatches lead to practical gaps in risk disclosure and reinforce structural ambiguities around accountability [90, 100].

This ambiguity invites us to reframe the design challenge. Rather than simply asking how risk should be disclosed, we must interrogate who decides, when, and on what basis. These questions draw attention to power asymmetries embedded in crowdsourcing infrastructures. Workers have limited opportunities to contest or shape disclosure practices, even as they bear the brunt of poorly disclosed risks. Task designers may want to warn workers, but are constrained by platform guidelines or unsure of what they are permitted to disclose. Platforms can offer guidelines or tools, but are often opaque about how risks are evaluated or escalated internally [71].

By framing risk disclosure as a site of negotiated responsibility, we open new avenue for design. Future tools might not only standardize disclosure formats, but also mediate disagreement and foster dialogue across stakeholder boundaries [26]. For example, platforms could surface discrepancies in risk perception between task creators and workers, or enable workers to annotate disclosures with feedback. Designing for such deliberation requires acknowledging that disclosure is a form of boundary crossing [90], not simply a transfer of information, but an agonistic process shaped by differing expertise, values, and institutional constraints.

Moreover, understanding these negotiations requires us to move beyond individualistic framings of responsibility. Instead, we can draw on theories of distributed or relational accountability, which emphasize how ethical obligations are produced through collective, situated practice [16]. Such a lens complicates the assumption that risks can be fully known or managed in advance, highlighting the need for systems that are reflexive and adaptive over time.

### 5.3 Supporting Worker Well-Being Beyond Risk Disclosure

While task-level risk disclosures are a critical starting point, they are only one component in a broader ecology of worker well-being. Our findings reveal that workers, even when appreciative of disclosure efforts, continue to face harm that is structural, cumulative, and poorly addressed by current platform support. Many participants described psychological strain from sustained exposure to distressing content, difficulty disengaging from harmful tasks, and a lack of avenues for recovery. Helplines and automated filters offer some relief, but they fall short of addressing the scale and complexity of workers' needs [66, 85, 88].

In particular, workers emphasized the need for more robust pre-task support. This includes not only clearer disclosures but also access to training and reflection tools that could help them assess personal thresholds for harm and prepare emotionally for the work. Existing research on content moderation and trauma-informed design points to promising strategies here, such as onboarding experiences [88, 89], exposure reduction [18, 19, 39, 44], and reconsideration of broader career pathways for workers [66] that could be adapted to the crowdsourcing context.

Post-task care is an even more underexplored frontier. Some workers suggested mechanisms such as debriefing spaces, access to mental health resources, or the ability to pause or escalate after encountering disturbing content. However, the logistics of such support remain unclear: who would provide it, under what funding model, and with

what safeguards? In an industry defined by just-in-time labor and minimal worker protections, offering meaningful well-being resources challenges the very business models that platforms depend on [34].

Moreover, the workers most vulnerable to psychological harm are often those with the least power to request accommodations. Crowdworkers span geographies, languages, and socioeconomic contexts—factors that mediate not only their exposure to harm but also their ability to access care. Designing for worker well-being thus requires a deeply intersectional approach, one that foregrounds structural inequalities rather than treating harm as a purely individual experience [54].

#### 5.4 Limitations of Co-Designing for Risk Disclosure in RAI Content Work

Our findings also surface a deeper question: **Should we crowdsource risky or sensitive AI content work in the first place?** While our study focuses on improving the design of risk disclosures, it cannot sidestep broader concerns about whether the task environment itself is appropriate or just. As prior literature has shown, microtasking can fragment judgment, mask ethical complexity, and devalue the expertise required to make nuanced content decisions [9]. These concerns are amplified in the context of RAI development, where annotation decisions can shape downstream system behavior [20, 98].

Several task designers in our study justified the use of crowdsourcing by emphasizing its diversity and scalability [5], noting that crowdworkers provide valuable perspectives and can be engaged more flexibly than full-time staff. Some workers echoed this, citing financial need or interest in meaningful participation. Yet the same workers also described feeling isolated, underpaid, and unsupported when engaging with emotionally fraught tasks. This suggests that current practices may extract value from worker insight without adequately compensating for the associated risks.

**Rather than rejecting crowdsourcing altogether, one alternative is to rethink how it is done.** For example, longer-form or collaborative annotation formats might give workers greater context and control. Task structures could emphasize care and deliberation over speed, perhaps shifting away from performance-based incentives and toward reflective judgment. Some of these ideas mirror trends in community moderation or participatory research, where contributors are treated as co-creators rather than disposable labor [98].

However, such changes would likely challenge platform logics and economic incentives. Implementing slower, more dialogic forms of labor requires reconfiguring not only interface design, but also compensation structures, labor policy, and institutional accountability. These are not merely technical or logistical challenges, but ethical ones. We therefore join prior scholars in calling for greater scrutiny of whether certain types of work should be crowdsourced at all—and under what conditions it can be considered just, humane, and sustainable [35, 71].

#### 5.5 Limitations and Future Work

There are limitations to this study that should be addressed. Selection bias is possible across all three groups. Participants who are ethically attuned or institutionally empowered may have been more willing to engage in a study about risk and well-being. To mitigate this, we framed recruitment as a practical inquiry into improving RAI task design and platform process rather than an ethics study, and we observed variation in orientations within each group, including participants who reported minimal engagement with risk considerations. This range suggests our pool included different levels of reflexivity, which reduces concern that we only recruited highly risk-aware actors. Additionally, while we note the inclusion of platform representatives was a rare opportunity that greatly improved the breadth of our understanding of the challenge of risk disclosure, our participants who were platform representatives are not representative of across roles in platforms or of the many variations of crowdsourcing platforms. Extensions of this way may explore ways

to elicit perspectives across main acting roles in the different types of crowdsourcing platforms. Moreover, like many qualitative-based studies [92], reflections from participants rely on self-reporting. While this method allowed us to elicit participant insights that are often invisible to the public, we acknowledge that accounts could be shaped by social desirability pressures. Similarly, our sample may be skewed toward individuals who have persisted in the space of RAI content work. To address this, we encourage further research to elicit perspectives from those who have left the field.

## 6 Conclusion

The design space of risk disclosure in RAI content work is both essential and under-explored. As platforms increasingly allocate RAI content work tasks to crowdworkers, new mechanisms are urgently needed to ensure workers are not exposed to harmful content without, at the very least, having a robust consent process in place. While prior work has highlighted the importance of content warnings on social media platforms and disclosures for job contracts, far less attention has been paid to how these mechanisms function—or fail—in the context of outsourced labor for responsible AI development. Our findings reveal the varied and often conflicting goals that shape risk disclosure in crowdsourced AI work. For instance, while task designers worry about scaring off workers with detailed warnings on tasks, workers seek clarity and autonomy in deciding what tasks to accept. Platforms, in turn, attempt to prioritize worker protection while meeting the needs of task designers and compliance with policies. We argue that any intervention in this space must contend with these competing logics. Rather than simplifying or flattening the problem, we advocate for systems that explicitly support negotiation, friction, and choice across stakeholders. Such approaches may offer more sustainable, transparent, and equitable models for risk communication—especially as AI development continues to rely on precarious and distributed forms of human expertise.

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