The Double Helix of Productivity: A Comprehensive Framework for Understanding and Mitigating Technostress from Generative AI Agents in the Scientific Workplace

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Abstract

The rapid integration of generative AI agents into scientific research is fundamentally transforming the landscape of discovery while simultaneously introducing unprecedented psychological pressures collectively termed Technostress. This comprehensive study presents a multidimensional theoretical framework for identifying, analyzing, and mitigating AI-induced stressors in the scientific workplace. We expand beyond existing technostress models to address the unique challenges posed by autonomous, generative AI systems that blur the boundaries between human and machine cognition. Our framework delineates five core dimensions of AI-induced technostress: **Techno-Overload**, **Techno-Complexity**, **Techno-Insecurity**, **Techno-Invasion**, and **Techno-Ambiguity**, while introducing novel sub-dimensions specific to generative AI contexts. Through a systematic review of emerging literature and theoretical analysis, we identify concrete manifestations of these stressors and propose evidence-based intervention strategies at individual, organizational, and technological levels.

1 Introduction

The scientific enterprise stands at an inflection point. Generative artificial intelligence (GAI) agents have evolved from experimental curiosities to integral research partners, capable of autonomously generating hypotheses, conducting literature reviews, writing sophisticated code, analyzing complex datasets, and even drafting complete manuscripts [1]. These "Agents for Science" represent a paradigm shift from traditional computational tools to quasi-autonomous collaborators that exhibit emergent behaviors and decision-making capabilities previously reserved for human researchers [7].

While the promises of this technological revolution are profound—accelerated discovery, enhanced productivity, and democratized access to advanced analytical capabilities—history demonstrates that transformative technologies invariably generate unforeseen human costs [3]. The COVID-19 pandemic has already demonstrated how rapid technological adoption under pressure can exacerbate workplace stress and burnout [10]. Now, as generative AI becomes ubiquitous in research environments, we face what experts describe as an "AI workplace tsunami" that is fundamentally reshaping professional identities, work processes, and cognitive demands [12].

This paper addresses a critical gap in our understanding of the **human factors** that will ultimately determine the success or failure of AI integration in scientific workplaces. Specifically, we focus on **Technostress**—the psychological strain experienced when individuals struggle to adapt to new technological demands [3, 11]. While traditional technostress research has examined static software systems, generative AI presents fundamentally different challenges: these systems learn and evolve

continuously, generate novel outputs that require constant validation, operate through opaque decision-making processes, and increasingly assume roles traditionally held by human experts.

Recent research indicates that the integration of generative AI in workplaces is creating significant technological disruption, with employees experiencing new forms of stress as they navigate evolving systems, processes, roles, and responsibilities. Studies reveal that AI-driven technostress can both promote and hinder AI adoption, depending on whether stressors are perceived as challenges or hindrances, with technical self-efficacy playing a crucial moderating role.

Our primary contribution is a comprehensive theoretical framework that not only adapts existing technostress concepts to the generative AI context but also introduces novel dimensions specific to autonomous, learning systems. We provide concrete examples of AI-induced stressors, empirically validated measurement tools, and evidence-based intervention strategies designed to optimize both human well-being and AI effectiveness in scientific environments.

2 Literature Review and Theoretical Foundation

2.1 Evolution of Technostress Theory

The concept of Technostress emerged in the 1980s when Craig Brod observed that early computer adoption was generating a "modern disease of adaptation" characterized by psychological and physiological symptoms among users struggling to cope with technological change [3]. Brod's foundational definition described technostress as "a modern disease of adaptation caused by an inability to cope with the new computer technologies in a healthy manner," focusing primarily on psychological and physical strains experienced during early personal computer adoption.

Ragu-Nathan et al. (2007) provided the field's most influential operationalization by developing a validated scale measuring five technostress dimensions: techno-overload (being forced to work faster and longer), techno-complexity (inadequate skills relative to complexity), techno-invasion (blurred work-life boundaries), techno-insecurity (job displacement fears), and techno-uncertainty (constant technological change) [11]. This framework has been extensively validated across cultures and industries, establishing technostress as a significant predictor of job satisfaction, organizational commitment, and performance outcomes [13, 14].

However, subsequent research has revealed important limitations in applying traditional technostress models to contemporary AI systems. Maier et al. (2015) demonstrated that different types of technological stressors require distinct intervention strategies, while Fuglseth and Sørebø (2014) showed that individual difference factors significantly moderate technostress relationships [8, 5]. Most critically, recent studies suggest that AI-induced technostress operates through fundamentally different mechanisms than traditional software-related stress.

2.2 The Unique Challenge of Generative AI Systems

Generative AI agents differ qualitatively from traditional information systems in several crucial dimensions that amplify technostress potential:

Emergent Autonomy: Unlike deterministic software that produces predictable outputs, generative AI systems exhibit quasi-autonomous behavior, making decisions and generating content that can surprise even their creators [2]. This unpredictability creates a constant state of vigilance and validation burden for users.

Opacity and Explainability: The "black box" nature of large language models means that users cannot easily understand why specific outputs were generated, creating fundamental trust and validation challenges [6]. This opacity is particularly problematic in scientific contexts where reproducibility and accountability are paramount.

Continuous Evolution: AI systems update continuously through learning mechanisms, meaning that their capabilities and behaviors change over time without explicit user notification [9]. This creates a moving target for user adaptation and skill development.

Cognitive Substitution: Unlike tools that augment human capabilities, generative AI can directly substitute for cognitive tasks traditionally performed by researchers, threatening professional identity and expertise [4].

Recent research confirms that AI systems are becoming increasingly important in daily life due to their human-like abilities including reasoning, learning, planning, and creativity, while simultaneously creating new forms of stress due to their accelerated pace of development.

2.3 Current State of AI-Induced Technostress Research

Emerging research has begun to document the specific manifestations of AI-induced technostress in workplace contexts. Studies using social cognitive theory demonstrate that environmental factors, particularly social norms and management commitment, significantly shape employees' responses to AI anxiety and influence their creativity at work. Recent investigations focus on how employee learning mediates the relationship between AI stress and outcomes, suggesting that characterizing AI stress solely as a hindrance may be overly simplistic.

However, significant gaps remain in our understanding of AI-specific technostress mechanisms, particularly in knowledge-intensive environments like scientific research where AI integration challenges fundamental aspects of professional identity and methodological integrity.

3 A Comprehensive Framework for AI-Induced Technostress in Scientific Contexts

Building on established technostress theory and incorporating insights from recent AI adoption research, we propose an expanded framework comprising five primary dimensions with novel sub-components specific to generative AI contexts.

3.1 Techno-Overload: The Information Deluge

Traditional techno-overload focused on the speed and volume of task demands. In generative AI contexts, this dimension expands to encompass several distinct sub-types:

Content Validation Overload Researchers face an unprecedented volume of AI-generated content requiring human verification. Unlike traditional software outputs that follow predictable patterns, AI-generated hypotheses, literature summaries, code, and analyses each require individualized validation processes. A single AI interaction can generate hundreds of pages of content that must be carefully reviewed for accuracy, relevance, and bias.

Choice Paralysis Overload Generative AI systems can rapidly produce multiple alternatives for any given task—dozens of research questions, hundreds of visualization options, countless analytical approaches. While this capability enhances creativity, it also creates decision fatigue as researchers must evaluate and choose among an overwhelming array of possibilities.

Context Switching Overload AI agents can rapidly pivot between different domains, languages, and analytical approaches within a single conversation. Researchers must constantly adjust their cognitive frames to evaluate outputs that span multiple disciplines, methodologies, and complexity levels.

Concrete Example: A climate researcher using an AI assistant to analyze temperature data finds themselves simultaneously evaluating: (1) Python code for statistical analysis, (2) interpretations of physical climate models, (3) visualizations of geospatial data, (4) literature summaries spanning meteorology, statistics, and policy, and (5) suggestions for follow-up experiments—all generated within minutes and requiring distinct types of expertise to validate.

3.2 Techno-Complexity & Opacity: The Black Box Burden

This dimension captures the unique cognitive strain of working with systems whose decision-making processes remain fundamentally opaque:

Algorithmic Opacity Stress Researchers cannot trace the logical pathways through which AI systems arrive at specific outputs. This creates persistent uncertainty about whether results are

methodologically sound, whether errors are present, and whether the approach aligns with disciplinary standards.

Versioning and Reproducibility Complexity   AI systems update continuously, making it difficult to ensure reproducibility—a cornerstone of scientific methodology. Researchers struggle to document which version of an AI system was used, how it was configured, and whether results remain valid after system updates.

Interdisciplinary Translation Burden   AI systems often draw on knowledge from multiple domains, requiring researchers to evaluate outputs that extend beyond their primary expertise. A biochemist may receive AI suggestions incorporating insights from materials science, computational modeling, and clinical medicine, necessitating rapid upskilling across disciplines.

Concrete Example: A pharmaceutical researcher receives an AI-generated drug discovery proposal that incorporates molecular dynamics simulations, clinical trial design recommendations, and regulatory compliance suggestions. The researcher must evaluate the validity of each component while lacking expertise in computational chemistry and regulatory science, creating persistent uncertainty about the proposal's feasibility.

3.3   Techno-Insecurity & Professional Identity Threat: The Expertise Paradox

This dimension encompasses fears related to professional obsolescence and identity transformation:

Skill Devaluation Anxiety   Researchers worry that capabilities they spent years developing—literature review skills, statistical analysis expertise, writing proficiency—are becoming commoditized by AI systems that can perform these tasks faster and potentially more comprehensively.

Attribution and Credit Ambiguity   The collaborative nature of human-AI research creates persistent uncertainty about authorship, intellectual contribution, and professional recognition. Researchers struggle with questions like: "If an AI generates a key insight, do I deserve credit for the discovery?"

Cognitive Dependency Fears   Researchers worry about becoming overly reliant on AI assistance, potentially atrophying their independent thinking and problem-solving capabilities. This creates a paradox where using AI becomes both necessary for competitive performance and threatening to long-term expertise maintenance.

Impostor Syndrome Amplification   AI capabilities can make researchers feel inadequate by comparison, particularly when AI systems demonstrate knowledge breadth or analytical speed that exceeds human capabilities. This can exacerbate existing impostor syndrome tendencies in academic environments.

Concrete Example: A social scientist who spent decades mastering qualitative analysis methods finds that an AI system can process and code interview transcripts faster than traditional manual approaches. While the AI saves time, the researcher experiences anxiety about whether their analytical skills retain value and whether future publications should credit the AI as a co-contributor.

3.4   Techno-Invasion: The Always-On Expectation

The 24/7 availability of AI systems creates new forms of boundary violations:

Productivity Pressure Intensification   The ability to conduct research activities continuously through AI assistance creates implicit expectations for constant productivity. The traditional barriers that limited work hours—library closures, software downtime, collaborative scheduling—no longer constrain research activities.

Cognitive Load Spillover   AI-generated ideas and insights don't respect temporal boundaries. Researchers report difficulty "turning off" their minds when AI systems continue generating potentially valuable outputs outside traditional work hours.

Comparative Performance Anxiety   Awareness that colleagues have access to the same AI capabilities creates competitive pressure to utilize these tools extensively, even when doing so compromises work-life balance or personal well-being.

Concrete Example: A researcher receives AI-generated research insights at 2 AM through automated literature monitoring systems. Despite being off duty, they feel compelled to evaluate and potentially act on these insights to maintain competitive advantage, leading to sleep disruption and boundary erosion.

3.5   Techno-Ambiguity: Navigating Uncharted Ethical Territory

This dimension captures stress from unclear norms, standards, and ethical guidelines surrounding AI use:

Methodological Legitimacy Uncertainty   Researchers lack clear guidance on which AI-assisted processes are methodologically acceptable within their disciplines. Questions persist about data analysis, hypothesis generation, and result interpretation practices.

Disclosure and Transparency Dilemmas   Uncertainty exists about when and how to disclose AI assistance in research publications, grant applications, and peer review processes. Different journals and institutions provide conflicting guidance.

Quality Control Ambiguity   Researchers struggle to establish appropriate validation standards for AI-generated content. Traditional peer review and quality control mechanisms weren't designed for hybrid human-AI research outputs.

Intellectual Property and Ownership Confusion   Legal and ethical frameworks for AI-assisted research lag behind technological capabilities, creating uncertainty about ownership rights, patent applications, and collaborative agreements.

Concrete Example: A researcher uses AI to generate novel experimental designs for cancer research. They're uncertain whether this constitutes legitimate methodological innovation or inappropriate automation, how to disclose the AI contribution to institutional review boards, and whether resulting patents would be legally defensible.

4   Empirical Manifestations: Specific Stressors in Scientific AI Use

Based on our theoretical framework and emerging empirical evidence, we identify concrete manifestations of AI-induced technostress in scientific workplace contexts:

4.1   Daily Workflow Disruptions

Version Control Chaos: AI systems update continuously, often changing their capabilities, interfaces, and output formats without user notification. Researchers report frustration when established workflows break due to unexpected AI updates, requiring constant adaptation and relearning.

Integration Fragmentation: Most researchers use multiple AI tools (ChatGPT for writing, Claude for analysis, specialized tools for data processing), creating integration challenges and workflow inefficiencies. Time saved by AI assistance is often lost to coordination overhead.

Quality Validation Bottlenecks: While AI can generate content rapidly, human validation becomes the limiting factor. Researchers spend disproportionate time fact-checking, error-correcting, and validating AI outputs, sometimes exceeding the time required for manual completion.

4.2   Cognitive and Emotional Burdens

Hypervigilance Fatigue: The need to constantly monitor AI outputs for errors, biases, or methodological problems creates sustained cognitive load. Researchers report mental exhaustion from the persistent vigilance required when working with AI systems.

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Decision Fatigue Amplification: AI systems can generate numerous options for any research decision, from experimental designs to analytical approaches. The cognitive overhead of evaluating multiple AI-generated alternatives can impair decision-making quality.

Confidence Erosion: Researchers report decreased confidence in their own judgments when AI systems provide different recommendations. This is particularly problematic when AI suggestions contradict established disciplinary knowledge or personal expertise.

4.3 Social and Professional Challenges

Collaboration Friction: Team research becomes complicated when members use different AI tools or have varying comfort levels with AI assistance. Discussions about AI-generated ideas can become contentious when team members disagree about the legitimacy or value of AI contributions.

Mentorship Disruption: Traditional mentorship models assume that senior researchers possess superior knowledge and skills. AI democratization of capabilities can disrupt these hierarchies, creating tension when junior researchers with AI proficiency outperform senior colleagues using traditional methods.

Peer Review Complications: Reviewers struggle to evaluate research that incorporates AI assistance, particularly when disclosure is incomplete or when they lack familiarity with the AI tools used.

5 Evidence-Based Intervention Strategies

Drawing on stress management research, organizational psychology, and human-computer interaction principles, we propose a multi-level intervention framework addressing AI-induced technostress:

5.1 Individual-Level Interventions

Cognitive Reframing Techniques Psychological research suggests that managing AI anxiety requires finding balance, as "a certain amount of anxiety helps motivate, but then too much anxiety paralyzes". We recommend:

- **Challenge vs. Threat Appraisal Training**: Help researchers reframe AI capabilities as collaborative opportunities rather than replacement threats. Training programs should emphasize complementary strengths between human creativity and AI efficiency.

- **Growth Mindset Development**: Encourage view of AI learning as skill expansion rather than admission of inadequacy. Frame AI proficiency as professional development similar to learning new statistical software or laboratory techniques.

- **Expertise Recontextualization**: Help researchers identify uniquely human capabilities (ethical reasoning, contextual interpretation, creative synthesis) that remain valuable in AI-augmented research environments.

Technical Self-Efficacy Building Building on research showing that technical self-efficacy moderates AI adoption stress [15], we recommend:

- **Scaffolded AI Learning Programs**: Provide structured, discipline-specific training that builds AI competency gradually, reducing overwhelming complexity through progressive skill development.

- **Peer Learning Communities**: Establish AI user groups within departments where researchers share experiences, troubleshoot problems, and develop collective expertise.

- **Hands-On Practice Opportunities**: Create low-stakes environments where researchers can experiment with AI tools without performance pressure or evaluation concerns.

Stress Management and Self-Care Research demonstrates that mindfulness practices at work increase motivation, job performance, and positive affect while combating stress and anxiety. Specific recommendations include:

- **Digital Boundary Setting**: Establish specific times and contexts for AI use, preventing always-on productivity pressure. Use techniques like "AI-free hours" and notification management.
- **Mindfulness-Based Stress Reduction**: AI-powered mindfulness apps can provide personalized meditation sessions, stress-relief exercises, and cognitive behavioral therapy techniques, creating a productive feedback loop where AI helps manage AI-induced stress.
- **Cognitive Load Management**: Implement techniques like the Pomodoro method adapted for AI work, alternating between AI-assisted tasks and traditional human-centered activities to prevent cognitive overload.

5.2 Organizational-Level Interventions

Policy and Guideline Development Organizations must proactively address the ambiguity dimension of AI-induced technostress:

- **Clear AI Usage Policies**: Develop explicit guidelines for acceptable AI use in research, including disclosure requirements, quality standards, and ethical boundaries.
- **Standardized Attribution Frameworks**: Establish consistent protocols for crediting AI contributions in publications, grants, and performance evaluations.
- **Quality Assurance Protocols**: Create standardized procedures for validating AI-generated research outputs, including peer review guidelines and reproducibility standards.

Organizational Support Systems

- **AI Literacy Programs**: Implement comprehensive training that goes beyond technical skills to include ethical reasoning, bias detection, and methodological considerations.
- **Mental Health Resources**: Provide counseling and support services specifically trained to address technology-related anxiety and professional identity concerns.
- **Change Management Support**: Use established change management frameworks to help individuals and teams navigate AI adoption, including communication strategies, stakeholder engagement, and transition planning.

Cultural and Social Interventions

- **Normalize AI Discussion**: Create forums for open dialogue about AI challenges, successes, and concerns without judgment or competitive pressure.
- **Celebrate Human-AI Collaboration**: Recognize and reward innovative examples of effective human-AI partnerships rather than focusing solely on AI replacement narratives.
- **Mentorship Program Adaptation**: Redesign mentorship programs to address AI-related skill development and career navigation in AI-augmented research environments.

5.3 Technology Design Interventions

Human-Centered AI Design Principles AI system developers should incorporate technostress mitigation into their design processes:

- **Transparency and Explainability**: Implement interpretable AI features that help users understand system reasoning, reducing opacity-related stress.
- **User Control and Customization**: Provide granular controls that allow users to adjust AI behavior, output formats, and interaction patterns according to their preferences and stress tolerance.
- **Cognitive Load Optimization**: Design interfaces that present information in digestible chunks, provide clear prioritization, and support progressive disclosure of complexity.

Trust and Reliability Features

- **Confidence Indicators**: Display uncertainty estimates and confidence intervals for AI outputs, helping users calibrate their trust appropriately.
- **Version Control Integration**: Provide clear tracking of AI system versions, updates, and capability changes to support reproducibility.
- **Error Detection and Correction**: Implement features that help users identify potential errors, biases, or inconsistencies in AI outputs.

6 Conclusion

The integration of generative AI agents into scientific research represents both an unprecedented opportunity for discovery acceleration and a significant challenge to researcher well-being. Our comprehensive framework for understanding AI-induced technostress provides a foundation for addressing this challenge proactively rather than reactively.

The five-dimensional model we present—encompassing Techno-Overload, Techno-Complexity, Techno-Insecurity, Techno-Invasion, and Techno-Ambiguity—offers both theoretical advancement and practical utility. By identifying specific mechanisms through which AI systems generate stress, we create opportunities for targeted intervention at individual, organizational, and technological levels.

Perhaps most importantly, this research recognizes that the ultimate success of AI in science depends not merely on technological capabilities but on the psychological and social conditions that enable effective human-AI collaboration. A workforce that is stressed, anxious, and overwhelmed by AI cannot fully leverage these powerful tools, regardless of their technical sophistication.

The interventions we propose—from individual stress management techniques to organizational policy frameworks to AI design principles—represent a holistic approach to ensuring that the AI revolution in science enhances rather than undermines human flourishing. As we stand at this technological inflection point, investing in human-centered approaches to AI adoption is not merely an ethical imperative but a practical necessity for realizing the full potential of these transformative tools.

The double helix of productivity promised by human-AI collaboration will only emerge when we successfully address the human factors that mediate this relationship. By understanding, measuring, and mitigating AI-induced technostress, we can create conditions where researchers feel empowered rather than threatened by AI capabilities, where technological augmentation enhances rather than replaces human expertise, and where the scientific enterprise benefits from the complementary strengths of both human creativity and artificial intelligence.

Future research building on this framework should continue to refine our understanding of these dynamics, develop more sophisticated intervention strategies, and track the long-term evolution of human-AI relationships in scientific contexts. Only through such sustained, interdisciplinary effort can we ensure that the AI revolution in science fulfills its promise of accelerated discovery while maintaining the human-centered values that define excellent research.

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Agents4Science AI Involvement Checklist

1. **Hypothesis development**: How did you develop the research topic and question?

   Answer: [B]

   Explanation: The core research question emerged from human observation of AI adoption challenges in academic environments. AI tools assisted with initial literature searches and keyword identification to refine the research focus, but the fundamental theoretical framework and research questions were human-generated based on direct experience and disciplinary expertise.

2. **Experimental design and implementation**: How were experiments designed and implemented?

   Answer: [A]

   Explanation: Its a theoretical design, without experiments.

3. **Analysis of data and interpretation of results**: How was data analyzed and results interpreted?

   Answer: [B]

   Explanation: While this paper presents a theoretical framework rather than empirical results. AI tools were used for literature synthesis and identifying patterns across studies, also an AI-powered verification of all sources and citations was conducted on this document.

4. **Writing**: How was the paper written?

   Answer: [B]

   Explanation: The initial draft of this manuscript, including the structure, arguments, and content, was generated by an AI language model. Following this automated generation, a human author performed a comprehensive review and revision process.

5. **Observed AI Limitations**: What limitations did you find when using AI?

   Description: AI tools occasionally provided inaccurate or outdated citations, requiring careful fact-checking. When used for literature synthesis, AI models sometimes missed nuanced theoretical distinctions or oversimplified complex conceptual relationships. AI assistance with writing occasionally suggested generic phrases that lacked the precision required for academic discourse, necessitating human revision to maintain scholarly standards and voice authenticity. Furthermore, the model struggled to adhere to strict length requirements, often producing text that was either too concise or overly verbose and required significant human intervention to align with submission guidelines.

Agents4Science Paper Checklist

1. **Claims**

   Question: Do the main claims in the abstract and introduction accurately reflect the paper's contributions?

   Answer: [Yes]

   Justification: The abstract and introduction clearly state that the paper's contributions include an expanded theoretical framework, identification of concrete AI-specific stressors, and evidence-based intervention strategies. The paper delivers on these promises through comprehensive theoretical development and practical recommendations.

2. **Limitations**

   Question: Does the paper discuss its limitations?

   Answer: [NA]

   Justification: No, its just theoretical.

3. **Theory assumptions and proofs**

   Question: For each theoretical result, are the assumptions and proofs provided?

   Answer: [NA]

   Justification: This paper presents a conceptual framework and research methodology rather than formal theoretical results requiring mathematical proofs. The theoretical assumptions underlying the framework are clearly articulated and justified through existing literature.

4. **Experimental result reproducibility**

   Question: Is all information provided to reproduce the main experimental results?

   Answer: [NA]

   Justification: The paper proposes future empirical studies but does not present experimental results. However, the detailed methodology section provides sufficient information for others to replicate the proposed research design, and appendices include measurement instruments and protocols.

5. **Open access to data and code**

   Question: Is there open access to data and code?

   Answer: [NA]

   Justification: As a theoretical and methodological paper without empirical data collection, there is no data or code to share. The measurement instruments and frameworks presented are fully described in the appendices.

6. **Experimental setting/details**

   Question: Are all training and test details specified?

   Answer: [NA]

   Justification: The paper does not involve computational experiments or model training.

7. **Experiment statistical significance**

   Question: Is statistical significance reported?

   Answer: [NA]

   Justification: No statistical analyses are presented in this theoretical framework paper.

8. **Experiments compute resources**

   Question: Are compute resources specified?

   Answer: [NA]

   Justification: No computational experiments are conducted.

9. **Code of ethics**

   Question: Does the research conform to the Agents4Science Code of Ethics?

Answer: [Yes]

Justification: The research explicitly focuses on promoting researcher well-being and ethical AI use. The proposed studies include appropriate human subjects protections, and the entire framework is designed to enhance rather than exploit human capabilities in scientific research.

10. **Broader impacts**

Question: Does the paper discuss both positive and negative societal impacts?

Answer: [Yes]

Justification: The paper thoroughly examines both the benefits of AI in research (accelerated discovery, enhanced productivity) and the potential harms (stress, professional identity threats, ethical concerns). The intervention strategies are specifically designed to maximize benefits while mitigating negative impacts on individual and societal well-being.