The Bot Made Me Do It: AI Usage Enhances the Penalty for Making Mistakes at Work

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Abstract

Workers are increasingly using AI to assist the performance of work tasks. Although the self-directed benefits and drawbacks of AI usage have received scholarly attention, less is known about how co-workers react to a focal worker's usage of AI, especially when such worker produces low quality outputs and makes mistakes. Interestingly, the impact of AI usage on the effect of poor performance could go either way: When using AI, one may be perceived either *less* responsible for the outputs, because part of the work is performed by another agent (i.e., the AI), or *more* responsible, because AI is known to hallucinate and AI users are expected to ensure that, when they use AI outputs, such outputs are truthful and correct. On a sample of 341 business school students, we tested our hypotheses in a co-working scenario where a colleague (i.e., peer) provided inputs necessary to one's work performance. In support of the latter argument, we found that the negative effect of the peer's poor work quality on peer evaluation by participants was amplified when the peer used AI. We identified perceived responsibility as a mediating mechanism of the moderation. Moreover, we found that more negative affect mediated the moderated effect of low work quality on peer evaluation. Thus, a peer's poor performance has a more negative effect on peer evaluation through an affective mechanism when the peer uses AI, because the peer is deemed more responsible for the work quality. This holds important implications for work collaboration under AI usage.

Keywords: artificial intelligence, peer evaluation, responsibility, positive emotions, negative emotions

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Introduction

The integration of Artificial Intelligence (AI) into work processes is fundamentally restructuring how people work alone and together. Although a burgeoning literature has been examining how AI is integrated in work practices (Jia et al., 2024; Raisch & Fomina, 2024) and how it is automating process or augmenting workers (Raisch & Krakowski, 2021), we know much less about how the AI wave (Magni, Yang, et al., 2024) is affecting the social and psychological contracts that govern workplace interactions. Initial evidence showed that when coworkers perceive a focal employee's AI usage as a way to slack off, they perceive such employee as less ethical, and are less likely to help him/her (Zhou et al., 2025). Yet, such findings are limited to helping behaviors and rely on coworkers' assumptions; they do not assess whether AI usage has a generalized effect that does not depend on coworkers' attributions of it, nor do they study relevant consequences of the focal employee using AI, such as how coworkers evaluate the AI user and their intentions to work together with that person in the future.

We specifically study coworker reactions in the context of workplace errors. Making mistakes at work is unavoidable, when working alone, with other humans, or with AI (Bell & Kozlowski, 2011; Frese & Keith, 2015; Qin et al., 2025). Indeed, on the one hand, humans are imperfect and make mistakes because of cognitive biases, incomplete information and miscommunication, and stressors (Frese & Keith, 2015). On the other hand, AI tools are intrinsically probabilistic and are prone to "hallucinations"—the generation of plausible but factually incorrect information (Sun et al., 2024). Because modern organizational work is highly interdependent (Puranam et al., 2014), one person's mistakes can have substantial consequences on coworkers' wellbeing and on the quality of downstream work outcomes (Winning et al., 2018), and thus give rise to negative coworker reactions. Yet, we do not know whether such reactions are impacted by AI usage. Hence, we study whether utilizing AI affects how coworkers react when an employee produces poor-quality output through attributions of the coworker's responsibility. Because coworkers' reactions to error often involve negative emotions, blaming, and conflict (Van Dyck et al., 2005), we further look at affective reactions as mechanisms linking the moderated effect of low quality performance on appraisals of the focal worker.

The Accountability Paradox

Theoretical considerations on the moderating effect of AI usage on the relationship between low quality output and appraisals of the focal worker reveal a possible *accountability paradox*. Indeed, the literature presents two competing theoretical directions of the moderation. On one hand, the use of AI facilitates a diffusion of responsibility and accountability. Because AI takes over tasks such as gathering information and making decisions based on such information, workers using AI may be perceived *less* responsible for errors just because errors may stem from parts of the process they were not first-hand involved in. Indeed, it may be difficult for a coworker to assess whether the poor quality is due to the focal worker or to the AI. Such attribution may be further substantiated by the black-box nature of AI: Not only do users often lack control over the specific features of AI, which could suggest a shift of accountability attributions towards developers (Grote et al., 2024), but they also lack knowledge of what specific decision-making pathways led to the AI output, generating process- and outcome-related uncertainty (Magni, Yang, et al., 2024). Hence, we posit that AI usage will lead to lower perceptions of the focal worker's responsibility for output quality, which will in turn weaken the negative effect of low-work quality on attributions of the focal worker.

H_{1a}: *AI usage, through perceived responsibility, moderates the negative effect of low-quality work on (peer) worker evaluation, such that when the focal worker uses AI, (s)he is perceived as less responsible, and the effect of work quality on evaluation is weaker.*

On the other hand, when a human worker uses AI and the output is flawed, the resulting failure is a social event that triggers a complex cascade of attributional judgments and behavioral consequences. Indeed, another perspective suggests that workers using AI will be perceived as *more* responsible. This is because human workers using AI have a duty to verify the correctness of AI output, and failure to do so can cause blame because it may imply carelessness, poor professionalism, and laziness—especially because knowledge that AI can hallucinate is widespread (Custers et al., 2025; Verdicchio & Perin, 2022; Zhou et al., 2025). Indeed, because AI is perceived to exert less effort in the performance of tasks and because lower effort is indicative of lower quality (Kruger et al., 2004; Magni, Park, et al., 2024), reliance on AI at work can be interpreted as slacking off and insufficient professionalism. This is exemplified in sectors such as law and healthcare, where professionals carrying over AI mistakes are considered liable (Appel, 2025; Gunder, 2023). Based on this reasoning, we advance a competing hypothesis that workers using AI will be perceived more responsible for work outputs, and this will amplify the effect of low-quality work on negative attributions.

H_{1b}: *AI usage, through perceived responsibility, moderates the negative effect of low-quality work on (peer) worker evaluation, such that when the focal worker uses AI, (s)he is perceived as more responsible, and the effect of work quality on evaluation is stronger.*

Finally, we argue that affective reactions mediate the (moderated) effect of low-quality output on focal worker evaluations. Mistakes generate blame, negative emotions, and conflict among coworkers (Frese & Keith, 2015). Hence, when a focal worker shares low quality work with a coworker, the coworker is likely to experience both a reduction in positive emotions (e.g., contentment) and an increase in negative emotions (e.g., frustration) (Qin et al., 2025; Van Den Ouweland et al., 2019). These emotional reactions would then likely convert into a more negative evaluation of the focal worker's performance (Antonioni & Park, 2001; Tsui & Barry, 1986). Thus, we posit that emotional reactions towards the focal worker's output mediate the effect of low-quality work on evaluations of the focal worker, with this indirect effect moderated by the AI usage-perceived responsibility chain.

H_2: *Low-quality work reduces coworker positive emotions, which leads to lower (peer) worker evaluation.*

H_3: *Low-quality work increases coworker negative emotions, which leads to lower (peer) worker evaluation.*

H_4: *AI usage, through perceived responsibility, moderates the indirect negative effect of low-quality work on (peer) worker evaluation via positive emotions, such that when the focal worker uses AI, (s)he is perceived as [(a) less / (b) more] responsible, and the effect of work quality on evaluation is [weaker / stronger].*

H_5: *AI usage, through perceived responsibility, moderates the indirect negative effect of low-quality work on (peer) worker evaluation via negative emotions, such that when the focal worker uses AI, (s)he is perceived as [(a) less / (b) more] responsible, and the effect of work quality on evaluation is [weaker / stronger].*

Methods

Participants and Procedure

We recruited a sample of 346 business school students at a large university in Singapore (61% female, M_{age} = 20.23, SD_{age} = 1.67), who completed an online survey in exchange for course credit. At the beginning of the survey, participants were asked to imagine they were in the following scenario: They had to prepare presentation slides about the financial performance of their organization, and a colleague named Alex was going to provide them with a spreadsheet containing the financial data necessary for the presentation. Participants were randomly assigned to one of four conditions in a 2 (Work quality: high vs. low) × 2 (AI usage: yes vs. no) design. Participants in the AI usage (non-AI usage) conditions were told that Alex relied on ChatGPT (a friend) to help with the calculation functions in the spreadsheet. Work quality was manipulated with the inclusion of evident mistakes, such as misspelled months, unrealistic values, and faulty calculations in the low-quality spreadsheet, whereas values and formatting were correct in the high-quality spreadsheet (see Figure 1). After reading the instructions, participants were asked to compute some simple financial ratios (for which they were provided equations, such as *equity = assets – liabilities*) as a manipulation reinforcement and attention check: In doing so, they would discover that data in the low-quality conditions were faulty and mistaken. Five participants failed to compute the ratios correctly and were excluded from analyses. Afterwards, participants reported the quality of Alex's work (a manipulation check), mediators, moderators, control variables, and peer evaluation.

Figure 1
Work Quality Manipulation (Low Quality: Left Panel; High Quality: Right Panel)

Month	Revenue ($M)	Operating Costs ($M)	Profit ($M)	Assets ($M)	Liabilities ($M)	Equity ($M)
2023.09	80	50	130	1000	500	500
2023.1	85	52	137	1010	502	508
2023.11	90	54	144	1020	504	516
2023.12	95	56	151	10030	506	524
2024.01	100	58	158	1040	508	532
2024.02	105	60	165	1050	510	540
2024.03	110	62	172	1060	512	548
2024.04	115	64	179	1070	514	556
2024.04	120	66	186	1080	516	564
2024.04	125	68	193	10090	518	572
2024.07	130	70	200	1100	520	580
2024.08	135	72	207	1110	522	588

Month	Revenue ($M)	Operating Costs ($M)	Profit ($M)	Assets ($M)	Liabilities ($M)	Equity ($M)
Sep 2023	80	50	30	1000	500	500
Oct 2023	85	52	33	1010	502	508
Nov 2023	90	54	36	1020	504	516
Dec 2023	95	56	39	1030	506	524
Jan 2024	100	58	42	1040	508	532
Feb 2024	105	60	45	1050	510	540
Mar 2024	110	62	48	1060	512	548
Apr 2024	115	64	51	1070	514	556
May 2024	120	66	54	1080	516	564
Jun 2024	125	68	57	1090	518	572
Jul 2024	130	70	60	1100	520	580
Aug 2024	135	72	63	1110	522	588

Measures

Participants rated their emotional reactions towards the Alex's work with a six-item scale adapted from Lee (2018), with three items (*happy*, *joyful*, and *proud*, Cronbach's α = 0.95) assessing positive emotions and three items (*disappointed*, *angry*, and *frustrated*, Cronbach's α = 0.89) assessing negative emotions. Alex's perceived responsibility was measured with a three-item scale taken from Botti and McGill (2006), with sample item *"Alex is responsible for the presentation's outcome*" (Cronbach's α = 0.85). Participants reported their peer evaluation of Alex based on the instructions "*Your and Alex's boss is preparing performance evaluations and would like to hear your feedback on your coworkers anonymously, given that you have better knowledge of each other's performance. Based on your interaction with Alex regarding the data described before, what peer evaluation would you give Alex*?", and provided their rating on a seven-point Likert scale ranging from *1 = Way below expectations* to *7 = Way above expectations*. Additionally, participants rated their own extraversion and conscientiousness with the two-item scales from the Big Five TIPI (Gosling et al., 2003). We included these as controls because these two personality traits may affect how people feel and how they evaluate others' work (Kmicinska et al., 2016; McNiel et al., 2010). We included gender as a control

(Female = 1, non-female = 0), because it is known to affect social evaluations (Taylor & Hood, 2011).

We used SPSS 29 for correlations and ANOVA, R lavaan (Rosseel, 2012) to conduct regression-based path-analyses, and R semTools (Jorgensen et al., 2019) to estimate Monte Carlo 5,000-bootstrap confidence interval to test our hypotheses.

Results

Descriptives and correlations are shown in Table 1, and the regression results are shown in Table 2. Participants in the high-quality work conditions (M = 3.54, SD = 0.98) reported significantly higher work quality ($F(339)$ = 114.72, p < .001), than those in the low-quality work conditions (M = 2.34, SD = 1.09), supporting the effectiveness of the manipulation. Interestingly, and in line with H_{1b} (against H_{1a}), participants rated Alex are *more* responsible ($F(339)$ = 8.34, p < .001) when Alex used AI (M = 5.20, SD = 1.12) compared to when Alex did not (M = 4.87, SD = 1.05).

Table 1
Means, Standard Deviations and Correlations

Variables	*M*	*SD*	1	2	3	4	5	6	7	8
1. Gender	0.62	0.49								
2. Extraversion	3.82	1.50	.02							
3. Conscientiousness	4.59	1.19	-.05	.02						
4. AI usage	0.50	0.50	-.05	-.08	-.13*					
5. Low work quality	0.50	0.50	.05	.10	.05	.00				
6. Positive emotions	3.52	1.38	-.10	.01	-.04	.00	-.38***			
7. Negative emotions	4.20	1.33	-.07	.05	-.01	.06	.44***	-.53***		
8. Perceived responsibility	5.03	1.09	-.09	.04	.03	.16**	.07	-.03	.10	
9. Peer evaluation	4.02	1.36	.00	.04	-.00	-.05	-.41***	.64***	-.56***	.04

Note. n = 341. Gender: Non-Female = 0, Female = 1. AI usage: no = 0, yes = 1. Low work quality: no = 0 (high), yes = 1 (low).
* = p < 0.05
** = p < 0.01
*** = p < 0.001

In line with the ANOVA results, linear regression results showed that AI usage positively predicted perceived responsibility (b = .35, p = .003). In turn, responsibility moderated the effect of low work quality on peer evaluation (b = –.27, p < .001) and the mediated moderation index was significant (b = –.10, CI: [–0.163, –0.033]), supporting H_{1b}.

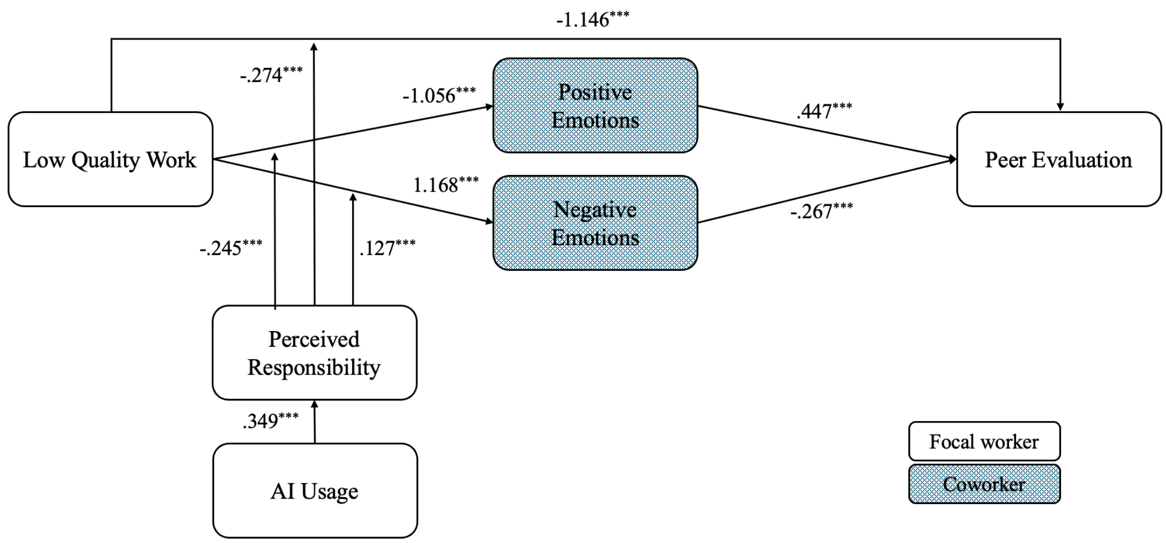
The effect of low-quality work on peer evaluation was significantly mediated by both positive (b = –.47, CI: [–0.630, –0.329]) and negative (b = –.31, CI: [–0.444, –0.198]) emotions, supporting H_2 and H_3. Moreover, the interaction of low-quality work and perceived responsibility significantly impacted both positive (b = –.25, p < .001) and negative (b = .13, p < .001) emotions. Accordingly, the mediated-moderated-mediation indices for both the pathways through positive (b = –.08, CI: [–0.132, –0.025]) and negative (b = –.01, CI: [–0.024, –0.004]) emotions were significant and supporting H_{4b} and H_{5b}, against H_{4a} and H_{5a}. The full theoretical model and path analysis results are shown in Figure 2.

Table 2
Hierarchical Regression Results

	PR	Positive emotions		Negative emotions		Peer evaluation		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Gender	-.19	-.24	-.27	-.25	-.23	.07	.10	.12
	(.12)	(.14)	(.14)	(.13)	(.13)	(.14)	(.11)	(.11)
Extraversion	.03	.05	.06	.01	.01	.08	.05	.05
	(.04)	(.05)	(.05)	(.04)	(.04)	(.04)	(.04)	(.04)
Conscientiousness	.04	-.03	-.02	-.03	-.03	.01	.02	.01
	(.05)	(.06)	(.06)	(.06)	(.05)	(.06)	(.04)	(.04)
AI usage	$.35^{**}$	-.00	.02	.15	.12	-.15	-.08	-.12
	(.12)	(.14)	(.14)	(.13)	(.13)	(.14)	(.11)	(.11)
Low work quality	.16	-1.06^{***}	1.42^{***}	1.17^{***}	$.52^{***}$	.22	$-.36^{**}$	-.02
	(.12)	(.14)	(.14)	(.13)	(.13)	(.13)	(.13)	(.03)
Positive emotions							$.45^{***}$	$.44^{***}$
							(.04)	(.04)
Negative emotions							$-.27^{***}$	$-.28^{***}$
							(.04)	(.04)
PR			$.25^{***}$		.00	$.25^{***}$		$.14^{**}$
			(.06)		(.06)	(.06)		(.05)
Low work quality × PR			$-.49^{***}$		$.13^{***}$	$-.27^{***}$		-.02
			(.03)		(.02)	(.03)		(.03)

Note. n = 341. Unstandardized coefficients, with standard errors in parentheses. PR = Perceived responsibility. Gender: Non-Female = 0, Female = 1. AI usage: no = 0, yes = 1. Low work quality: no = 0 (high), yes = 1 (low).
$^{*} = p < 0.05$
$^{**} = p < 0.01$
$^{***} = p < 0.001$

Figure 2
Theoretical Model and Path Analysis Results



Note. $^{***} = p < 0.001$

Conclusion

With these results, we provide timely evidence on how coworkers react when the focal worker produces low-quality work when using AI. Importantly, we discover that using AI accentuates (rather than mitigate) workers' responsibility for work outcomes in the eyes of coworkers, which increases the penalty for mistakes and generally poor work outputs. Coworkers' emotions are a critical mechanism through which AI-supported faulty work leads to poor peer evaluations.

These findings hold important implications for workers and organizations. Because using AI to assist in the performance of work tasks is becoming normalized (Magni, Yang, et al., 2024), it is important to keep into account that coworkers may react more negatively to mistakes, which could deteriorate social interactions at work and generate conflict. Our work also informs attribution and accountability theories (Feldman, 1981; Grote et al., 2024), providing crucial evidence that outsourcing part of one's work to AI does not diminish one's responsibility, but rather increases it in the eyes of external evaluators. Hence, workers need to pay extra attention when producing work artifacts, especially in situations of high interdependence and when AI usage is self-evident or known to coworkers. Organizations may also take action to address this issue, training workers on how to assess their colleagues' production as well as on how to adequately verify AI-generated outputs, and also by enforcing clear guidelines on how and when AI can and should be used.

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