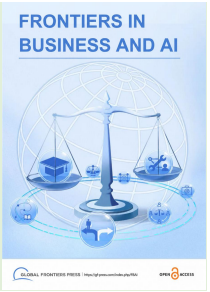
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Article

Where Does the AI Time Dividend Go? Generative AI, Work Intensification, and Work-Life Balance

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ARTICLE INFO **ABSTRACT**

Generative artificial intelligence (GenAI) can accelerate knowledge-work tasks, but task-level efficiency does not necessarily translate into shorter working hours or improved employee welfare. This article proposes an AI time-dividend allocation framework that separates the creation of saved time from its subsequent use. Drawing on the job demands-resources perspective, it examines a resource pathway through perceived time savings and work-life balance alongside a competing demand pathway through work intensification. The reported three-wave observational survey comprises 472 complete cases. Standardized ordinary least squares models with HC3 robust standard errors indicate that GenAI use intensity is associated with perceived time savings ($\beta = .495$, $p < .001$), time savings is positively associated with work-life balance ($\beta = .255$, $p < .001$), whereas work intensification is negatively associated with work-life balance ($\beta = -.443$, $p < .001$). Reported bootstrap indirect effects are positive through time savings (0.126, 95% CI [0.079, 0.176]) and negative through time savings and work intensification (-0.036, 95% CI [-0.059, -0.015]). Performance pressure is positively associated with intensification, but its proposed interaction with time savings is not statistically significant. The findings are consistent with competing allocation pathways; given the observational design, they should not be interpreted as causal effects. The article identifies time-dividend allocation as a consequential dimension of AI-enabled work design.

1. Introduction

Generative artificial intelligence is becoming embedded in routine knowledge work rather than remaining an experimental technology. Controlled experiments and workplace deployments increasingly show that AI assistance can accelerate task completion and raise measured output. Noy and Zhang (2023) demonstrate substantial time savings and quality improvements in professional writing tasks. Brynjolfsson, Li, and Raymond (2025) document productivity gains among 5,172 customer-support agents, while Cui et al. (2026) report higher task completion in randomized field experiments involving 4,867 software developers. These studies establish an increasingly credible productivity channel: for many knowledge tasks, GenAI can reduce the amount of employee time required to produce a given unit of output.

Once this productivity channel is established, however, a different organizational question becomes central. What happens to the time that AI saves? A saved hour is not automatically an hour of leisure, recovery, or improved work-

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life balance. It is initially a potential resource whose final use depends on the organization of work. Employees may retain some of the saved time and use it to reduce after-hours work, absorb interruptions, manage nonwork responsibilities, or improve task quality. Alternatively, managers and employees may respond to higher productivity by raising output targets, compressing deadlines, or filling the saved time with additional tasks. Under this second mechanism, the technological gain is recaptured through work intensification.

This distinction is important because existing evidence already suggests that AI can alter work patterns, not only output. Dillon et al. (2025), using a six-month randomized field experiment across 66 firms and 7,137 knowledge workers, find that users of an integrated GenAI tool spent less time on email and reduced work outside regular hours. Yet the study detects limited changes in the quantity or composition of workers' tasks from individual AI provision. The result implies that AI can create time savings without determining how organizations subsequently redistribute those savings. Understanding that second stage requires a work-design perspective.

The present study draws its empirical logic from Angelici and Profeta's smart-working research. Their randomized field experiment treats productivity, well-being, and work-life balance as jointly determined consequences of a change in work organization. This multi-outcome logic is useful for GenAI research because an efficiency-enhancing technology can simultaneously increase output and alter the employee experience of work. The present framework therefore shifts the focus from spatial and temporal flexibility to AI-mediated task acceleration and asks whether the resulting time dividend remains under employee discretion or is absorbed by rising work demands.

This study makes three contributions. First, it separates the creation of time savings from the allocation of time savings. This distinction clarifies why the same technology may be associated with both resource gains and employee strain. Second, it specifies two competing mechanisms within a single framework: a resource pathway from AI use to time savings, work-life balance, and well-being, and a demand pathway from time savings to work intensification, technostress, and extended work. Third, it treats observable time-use indicators such as AI-saved hours, weekly working hours, and after-hours work as complements to attitudinal measures. The resulting argument is not that GenAI is uniformly beneficial or harmful, but that its welfare consequences depend on how the efficiency it creates is allocated within the employment relationship.

The time dividend is analytically distinct from productivity improvement. Productivity concerns the amount of output obtainable per unit of labor input; a time dividend concerns the capacity released at a given output target; and the distribution of that dividend concerns who can decide how the released capacity is used. This distinction generates three observable possibilities: employee retention (lower work time or improved recovery), task reinvestment (greater quality or expanded scope without a proportional increase in strain), and managerial recapture (higher output requirements or reduced slack). These possibilities are not mutually exclusive and can coexist within a role. The present data assess correlates of the first and third possibilities, rather than directly measuring the contractual ownership of saved hours.

The remainder of the paper follows a standard empirical structure while preserving the logical sequence of the benchmark study. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the research design, measures, and empirical strategy. Section 4 presents the main results, indirect effects, additional analyses, and robustness tests. Section 5 discusses the theoretical and managerial implications, and Section 6 concludes.

2. Literature Review

Workplace research on generative artificial intelligence has moved rapidly from demonstrations of technical capability to increasingly credible evidence on worker productivity. Noy and Zhang (2023) show that ChatGPT reduced completion time and improved output quality in professional writing tasks, Brynjolfsson, Li, and Raymond (2025) document higher productivity among customer-support agents using an AI assistant, and Cui et al. (2026) report higher task completion across randomized field experiments with software developers. Taken together, these studies establish a central premise for the present research: GenAI can relax a time constraint in knowledge production by allowing employees to complete a given amount of work more quickly. Yet the existence of productivity gains does not determine the employee consequences of those gains. A technology can save task time without reducing total working time because the released capacity can be retained by employees, redirected toward higher-quality work, or recaptured through additional assignments and tighter deadlines. This distinction creates the idea of an AI time dividend: the

amount of work time potentially released by AI-enabled task acceleration, whose value depends on what happens after it is created. Recent field evidence supports treating time use as an outcome in its own right. Dillon et al. (2025), in a six-month randomized experiment across 66 firms and 7,137 knowledge workers, find that users of an integrated GenAI tool spent less time on email and less time working outside regular hours, indicating that AI-generated efficiency can translate into a reduction in time demands. The job demands-resources perspective provides a useful theoretical basis for this mechanism because job resources facilitate goal attainment, recovery, and employee control, whereas job demands require sustained effort and can generate strain (Demerouti et al., 2001; Bakker & Demerouti, 2007). When saved time remains partly under employee discretion, it can function as a resource by absorbing interruptions, providing recovery opportunities, and improving compatibility between work and nonwork roles. Work-life balance is therefore a natural downstream outcome, because it captures the extent to which employees perceive their work and personal roles as mutually compatible (Brough et al., 2014), while employee well-being should improve when the time released by AI reduces role conflict and supports recovery. The same productivity gain, however, can produce a competing demand pathway. Work intensification describes increases in the pace, volume, or density of work and commonly accompanies accelerated organizational change (Kubicek, Paškvan, & Korunka, 2015). In an AI-enabled workplace, the mechanism is straightforward: once faster task completion becomes visible and repeatable, saved capacity may be translated into higher output expectations, more assignments, or shorter deadlines. In that case, AI reduces task-level effort while increasing job-level demands. Technostress reinforces this possibility. Tarafdar et al. (2007) distinguish technology-related overload and invasion, two conditions particularly relevant when digital tools raise the expected pace of work or extend availability beyond normal working hours. GenAI can therefore simultaneously create efficiency and intensify the employment relationship, making it necessary to examine productivity, well-being, and work-life balance together rather than treating productivity as the only relevant consequence of technology adoption. This multi-outcome logic parallels the structure of Angelici and Profeta's smart-working research, which evaluates productivity, well-being, and work-life balance as interconnected consequences of a change in work organization. The present study transfers that logic from flexibility over work time and location to AI-mediated task acceleration: the critical organizational margin is not only how much time is saved, but who controls the saved time after the efficiency gain occurs. Performance pressure adds an important boundary condition because employees who face strong expectations to increase output may have less scope to retain AI-generated savings as discretionary time. Performance pressure can operate directly as a job demand and may also increase the likelihood that saved time is converted into intensified work; however, theory does not require that every high-pressure context produce the same conversion, because autonomy, task interdependence, incentive systems, and managerial practices can shape how efficiency is absorbed. The resulting gap in the literature is therefore not whether GenAI can improve productivity, which is increasingly well established, but how the time released by GenAI is allocated and how that allocation connects productivity gains to employee outcomes. The study consequently tests a dual-path time-dividend framework in which AI use first creates time savings and those savings then move through either a resource pathway or a work-intensification pathway.

A work-design perspective explains why technological efficiency can produce divergent employee outcomes. Wang et al. (2020) identify job demands, autonomy, and relational features as pathways linking information and communication technology use to effectiveness and well-being. In adjacent research, Mazmanian et al. (2013) show how mobile email can increase perceived flexibility while reinforcing expectations of continuous availability. These studies motivate examining who controls the time released by GenAI.

- **H_1.** Generative AI use intensity is positively associated with perceived time savings.
- **H_2.** Perceived time savings are positively associated with work-life balance.
- **H_3.** Work-life balance is positively associated with employee well-being.
- **H_4.** Work intensification is negatively associated with work-life balance and employee well-being.
- **H_5.** Generative AI use intensity and perceived time savings are positively associated with job performance, whereas work intensification is negatively associated with job performance.
- **H_6.** Performance pressure strengthens the positive association between perceived time savings and work intensification.

- **H_7.** The positive AI time dividend is partially offset by a negative indirect pathway from AI use to time savings, work intensification, and work-life balance.

The hypotheses follow the proposed sequence of associations rather than a fully identified causal chain. H_1 predicts a positive association between GenAI use and perceived time savings; H_2 and H_3 predict positive associations of time savings with work-life balance and of work-life balance with well-being; H_4 predicts negative associations of work intensification with both outcomes; H_5 addresses performance; H_6 proposes moderation by performance pressure; and H_7 concerns an offsetting negative indirect association. Evidence for an indirect statistical pathway should not, by itself, be construed as evidence of causal mediation.

Work–family conflict can arise through competing time demands, strain, and incompatible behavioral expectations (Greenhaus & Beutell, 1985). Accordingly, a reduction in task completion time need not improve balance if work-related strain or availability expectations remain unchanged.

The theoretical contribution is an allocation distinction rather than a claim that resource and demand processes are newly discovered. Job demands-resources theory already anticipates coexisting supports and strains; the proposed extension specifies AI-generated task-time savings as a potentially reallocable input, and identifies workload recapture as one mechanism by which an apparent resource can coincide with increased demands. Unlike studies treating AI adoption as a single exposure, this framework separates the intensity of use, perceived time saved, organizational demands, and downstream work-life outcomes. This distinction is testable, but the current survey does not directly identify managerial decisions about who ultimately controls the saved time.

A key implication of this account is that employee benefit should not be inferred from the technical efficiency of the tool alone. The link between reduced task time and favorable employee outcomes is contingent on how output targets, temporal boundaries, and discretion are organized. Job autonomy may protect workers' ability to deploy released capacity, while performance pressure may itself intensify work even when the interaction between pressure and perceived savings is small. The theory therefore distinguishes a direct demand effect from the proposed, but empirically unsupported, conditional recapture hypothesis.

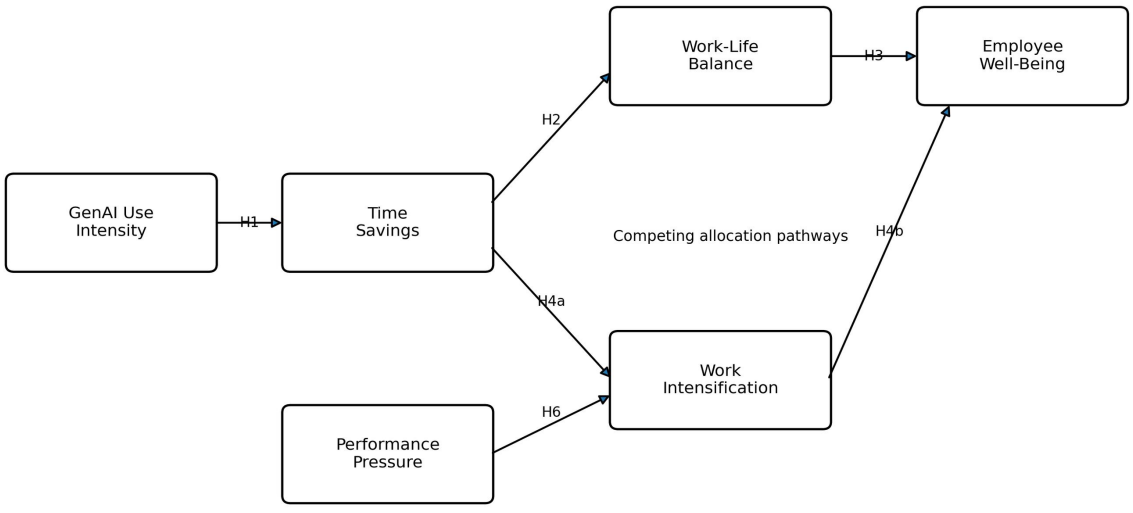


Figure 1. Conceptual framework

3. Methodology

3.1 Research design and sample

The analysis is organized as a three-wave employee survey design. Wave 1 contains the focal technology-use variable, job autonomy, performance pressure, and demographic and job controls. Wave 2 contains perceived time savings, work

intensification, techno-overload, and techno-invasion. Wave 3 contains work-life balance, employee well-being, and job performance. Separating predictors, mechanisms, and outcomes across waves mirrors the temporal logic of the theoretical model and reduces the extent to which all focal constructs are measured at the same moment.

The analytical sample comprises 472 complete cases. The dataset is organized consistently across the three waves so that focal predictors, intervening mechanisms, and downstream outcomes can be linked at the case level. Demographic and work-characteristic variables are retained as controls, while the principal analyses use the multi-item construct scores described below. The same variable definitions and estimation sequence are used throughout the descriptive, regression, indirect-effect, heterogeneity, and robustness analyses.

Analytic scope. The unit of analysis is the individual respondent. The models do not identify within-organization changes in workload policies or establish an employee-level treatment effect of AI access. The three-wave ordering supports the proposed sequence of measurement but cannot eliminate time-varying confounding, reverse causation, or selection into GenAI use. Consequently, all effect estimates are presented as adjusted associations; bootstrap indirect effects describe model-implied statistical pathways rather than causally identified mediation.

The sample has a mean age of 34.67 years (*SD* = 7.57), and 57.6% of cases are female. A bachelor's degree is reported for 51.5% of cases and a master's degree for 31.8%. GenAI is used on average 3.99 days per week and 54.05 minutes per day. Mean reported AI-enabled time savings are 2.90 hours per week, while mean weekly working time is 41.80 hours and mean after-hours work is 3.57 hours per week.

Table 1. Sample characteristics

Characteristic	Category / Statistic	*N*	Percent / Mean
Gender	Male	197	41.7%
Gender	Female	272	57.6%
Gender	Other / Prefer not to say	3	0.6%
Education	Associate/equivalent	59	12.5%
Education	Bachelor's	243	51.5%
Education	Master's	150	31.8%
Education	Doctorate	20	4.2%
Age	Years		34.67 (*SD* 7.57)
AI use	Days/week		3.99
AI use	Minutes/day		54.05
AI-saved time	Hours/week		2.90
Weekly work	Hours/week		41.80
After-hours work	Hours/week		3.57

3.2 Measures

Generative AI use intensity is measured with four items capturing the regularity and integration of GenAI in daily work. Perceived time savings is measured with four items assessing whether GenAI reduces the time required for routine tasks, accelerates completion, reduces search/drafting/analysis time, and creates discretionary time. Job autonomy is represented by four work-design items concerning discretion over methods, sequencing, procedures, and timing, consistent with the autonomy dimension of the Work Design Questionnaire (Morgeson & Humphrey, 2006).

Performance pressure is measured with four items capturing high performance standards, pressure to increase output, strong organizational efficiency demands, and higher expectations following efficiency improvements. Work intensification is measured with four items reflecting higher task volume, faster work pace, conversion of efficiency into extra assignments, and overall workload intensification. Techno-overload and techno-invasion are each measured using four-item sets reflecting faster/more work and the extension of digital work into personal time, respectively.

Work-life balance is measured with four items assessing fit between work and personal life, time for nonwork responsibilities, ability to disconnect, and overall balance. Employee well-being is measured with five items capturing psychological state, work-life satisfaction, composure, energy, and perceived support for well-being. Job performance is measured with four items assessing completion of core duties, output quality, efficiency, and attainment of role requirements. All focal items use seven-point response scales and are averaged to construct scale scores.

All ten multi-item constructs show strong internal consistency. Cronbach's α ranges from .823 to .873, and one-factor item diagnostics produce loading ranges above conventional minimum levels. These results provide preliminary support for the intended measurement structure. The scale-level analyses reported below use arithmetic mean scores, while a full measurement-model assessment should accompany confirmatory applications of the framework. Full item wording, wave assignment, scoring, and source basis are reported in Appendix A; reliability, convergent-validity, and discriminant-validity diagnostics are reported in Appendix B.

Table 2. Descriptive statistics and measurement diagnostics

Construct	Items	Mean	*SD*	Cronbach's α	Loading range
AI Use Intensity	4	4.550	1.413	0.842	0.806-0.837
Job Autonomy	4	4.374	1.410	0.843	0.808-0.832
Performance Pressure	4	4.293	1.367	0.823	0.803-0.811
Time Savings	4	4.438	1.404	0.832	0.799-0.828
Work Intensification	4	4.167	1.421	0.834	0.799-0.857
Techno-overload	4	4.103	1.431	0.838	0.806-0.842
Techno-invasion	4	4.055	1.434	0.838	0.806-0.830
Work-Life Balance	4	4.293	1.429	0.845	0.815-0.841
Employee Well-Being	5	4.301	1.428	0.873	0.799-0.831
Job Performance	4	4.489	1.411	0.846	0.812-0.839

Interpretation and identification. The coefficients below are conditional associations from observational models. Temporal ordering may reduce simultaneity but does not rule out selection into AI use, unmeasured organizational culture, pre-existing workload, reverse causation, or measurement error. Bootstrap intervals quantify uncertainty under the fitted statistical specification and do not resolve these identification concerns. The reported use days and saved hours are self-reports, not independently logged behavioral observations.

3.3 Empirical strategy

The empirical analysis follows the sequential logic of the theoretical model. All focal continuous variables are standardized before estimation, so coefficients can be interpreted as standardized associations. Baseline specifications are estimated with ordinary least squares and HC3 heteroskedasticity-robust standard errors. Controls include age, gender, education, job level, organizational tenure, and remote-work days. Weekly working hours is not included in the main models because it can itself be an outcome of the time-allocation process.

Model 1 estimates the association between GenAI use intensity and perceived time savings. Model 2 explains work-life balance using AI use, time savings, work intensification, job autonomy, and performance pressure. Model 3 explains employee well-being using work-life balance, work intensification, techno-overload, and job autonomy. Model 4 explains job performance using AI use, time savings, work intensification, and autonomy. Model 5 estimates work intensification and includes the interaction between standardized time savings and performance pressure. Model 6 uses after-hours work as a behavioral outcome and includes time savings, work intensification, techno-invasion, and AI use.

Indirect effects are evaluated with 5,000 bootstrap resamples and percentile 95% confidence intervals. The analysis also examines gender interactions and uses observed AI-saved hours and AI-use days as alternatives to the multi-item measures. Finally, weekly work hours is estimated as an outcome to determine whether observed time savings and work intensification operate in opposite directions, as predicted by the time-dividend allocation framework. Full main-model coefficients and alternative operationalizations are reported in Appendix C, while the bootstrap, heterogeneity, moderation, and multicollinearity evidence is reported in Appendix D.

4. Results

4.1 Descriptive relationships

The correlation structure is consistent with the proposed dual-path model. AI use intensity is positively related to time savings, while time savings is positively related to work-life balance and job performance. Work intensification is negatively related to work-life balance and well-being and positively related to technostress indicators. These bivariate relationships motivate the multivariate analysis but are not used as substitutes for the regression models. Appendix B provides the accompanying item-level and discriminant-validity evidence.

Table 3. Correlations among focal constructs

Construct	AIU	JA	PP	TS	WI	TO	TI	WLB	WB	JP
AIU	1.00	0.02	0.04	0.50	0.12	0.31	0.24	0.12	−0.09	0.36
JA	0.02	1.00	0.01	0.16	−0.02	−0.04	−0.12	0.34	0.25	0.30
PP	0.04	0.01	1.00	0.03	0.43	0.32	0.11	−0.16	−0.26	−0.03
TS	0.50	0.16	0.03	1.00	0.19	0.22	0.22	0.23	−0.01	0.40
WI	0.12	−0.02	0.43	0.19	1.00	0.44	0.39	−0.39	−0.48	−0.03
TO	0.31	−0.04	0.32	0.22	0.44	1.00	0.24	−0.13	−0.33	0.11
TI	0.24	−0.12	0.11	0.22	0.39	0.24	1.00	−0.31	−0.27	0.02
WLB	0.12	0.34	−0.16	0.23	−0.39	−0.13	−0.31	1.00	0.50	0.22
WB	−0.09	0.25	−0.26	−0.01	−0.48	−0.33	−0.27	0.50	1.00	0.08
JP	0.36	0.30	−0.03	0.40	−0.03	0.11	0.02	0.22	0.08	1.00

Note. AIU = AI use intensity; JA = job autonomy; PP = performance pressure; TS = time savings; WI = work intensification; TO = techno-overload; TI = techno-invasion; WLB = work-life balance; WB = employee well-being; JP = job performance.

4.2 Main effects

Model 1 supports H_1. GenAI use intensity is strongly and positively associated with perceived time savings (β = .495, *SE* = .039, $p < .001$), and the model explains 26.0% of the variance in time savings. This result establishes the first stage of the time-dividend framework: more intensive AI use is associated with a larger pool of potentially released work time.

Model 2 supports H_2 and H_4. Time savings is positively associated with work-life balance (β = .255, *SE* = .046, $p < .001$), whereas work intensification is negatively associated with work-life balance (β = −.443, *SE* = .042, $p < .001$). Job autonomy is also positively related to work-life balance (β = .282, *SE* = .038, $p < .001$). Once these mechanisms are included, the direct coefficient for AI use intensity is small and not significant (β = .039, p = .423). This pattern is consistent with an indirect allocation process rather than a simple direct effect of AI use on balance.

Model 3 supports H_3 and the well-being component of H_4. Work-life balance is positively associated with employee well-being (β = .322, *SE* = .041, $p < .001$), while work intensification is negatively associated with well-being (β = −.291, *SE* = .042, $p < .001$). Techno-overload is also negatively associated with well-being (β = −.157, *SE* = .040, $p < .001$). Together, these results indicate that the employee experience of AI-enabled work depends on both the resource gained through better balance and the demands created by intensified work.

Model 4 supports H_5. AI use intensity (β = .236, *SE* = .052, $p < .001$) and time savings (β = .265, *SE* = .049, $p < .001$) are positively associated with job performance, whereas work intensification has a smaller negative coefficient (β = −.100, *SE* = .043, p = .020). Job autonomy remains positively associated with performance (β = .254, *SE* = .046, $p < .001$). The performance results therefore do not require a welfare trade-off in which higher productivity necessarily implies lower employee outcomes; rather, they show that the allocation mechanism matters for whether efficiency gains are accompanied by strain.

Model 5 examines performance pressure. Time savings is positively associated with work intensification (β = .180, *SE* = .040, $p < .001$), and performance pressure has a large positive association with work intensification (β = .422, *SE* = .043, $p < .001$). However, the interaction between time savings and performance pressure is not significant (β = .041, *SE* = .041, p = .323). H_6 is therefore not supported. Performance pressure behaves as a direct organizational demand in this specification rather than as a statistically detectable moderator of the time-savings pathway. Appendix D reports the complete moderation specification and multicollinearity diagnostics.

Table 4. Main regression models

Predictor	M1 TS	M2 WLB	M3 WB	M4 JP	M5 WI	M6 After-hours
AI Use Intensity	0.495***	0.039		0.236***		−0.013
	(0.039)	(0.049)		(0.052)		(0.033)
Time Savings		0.255***		0.265***	0.180***	−0.165***
		(0.046)		(0.049)	(0.040)	(0.034)
Work Intensification		−0.443***	−0.291***	−0.100*		0.560***
		(0.042)	(0.042)	(0.043)		(0.032)
Job Autonomy		0.282***	0.127**	0.254***	−0.051	
		(0.038)	(0.040)	(0.046)	(0.045)	
Performance Pressure		0.019			0.422***	
		(0.042)			(0.043)	
TS × PP					0.041	
					(0.041)	
Techno-overload			−0.157***			
			(0.040)			
Techno-invasion						0.400***
						(0.032)
Work-Life Balance			0.322***			
			(0.041)			
R^2	.260	.349	.390	.277	.223	.609
N	472	472	472	472	472	472

Note. Standardized coefficients with HC3 robust standard errors in parentheses. All models include age, gender, education, job level, tenure, and remote-work days. * $p < .05$; ** $p < .01$; *** $p < .001$.

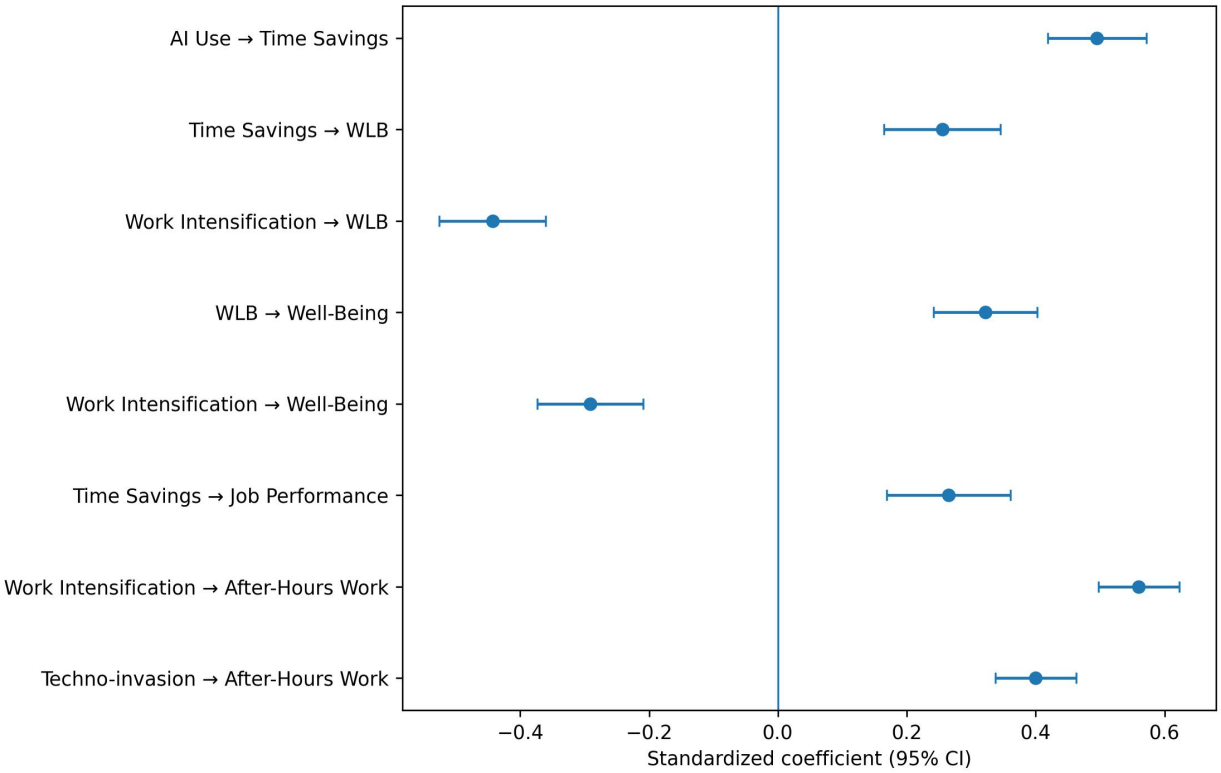


Figure 2. Main standardized associations

4.3 Indirect effects and competing pathways

The bootstrap analysis provides the clearest evidence for the allocation argument. The indirect effect from AI use through time savings to work-life balance is positive and statistically different from zero (indirect effect = .126, 95% CI [.079, .176]). The longer positive pathway from AI use through time savings and work-life balance to employee well-

being is also significant (indirect effect = .043, 95% CI [.025, .063]). These estimates represent the resource-enhancing side of the AI time dividend.

At the same time, the competing pathway is negative. The indirect effect from AI use to time savings, work intensification, and work-life balance is −.036 (95% CI [−.059, −.015]). Extending the same pathway to employee well-being produces an indirect effect of −.012 (95% CI [−.021, −.005]). H_7 is therefore supported: the time dividend is not eliminated by work intensification, but part of its positive value is statistically offset by the conversion of saved time into higher work demands.

The combination of positive and negative indirect effects is theoretically more informative than a single net coefficient. A direct estimate of AI use on work-life balance can be close to zero because two mechanisms operate simultaneously in opposite directions. This is precisely why the analysis treats productivity, time savings, work demands, and employee outcomes as connected stages rather than as isolated dependent variables.

The magnitude and direction of the reported indirect associations are consistent with partial statistical offset rather than full cancellation of the resource pathway. However, these path-specific products rely on the chosen regression specification and assumptions about omitted variables; they do not quantify the share of actual AI-generated hours retained by workers. The absence of a significant performance-pressure interaction should be reported as a null result, not as affirmative evidence of identical allocation practices across settings.

Table 5. Bootstrap indirect effects

Indirect path	Effect	95% CI	Inference
AIU → TS → WLB	0.126	[0.079, 0.176]	Significant
AIU → TS → WI → WLB	−0.036	[−0.059, −0.015]	Significant
AIU → TS → WLB → WB	0.043	[0.025, 0.063]	Significant
AIU → TS → WI → WLB → WB	−0.012	[−0.021, −0.005]	Significant

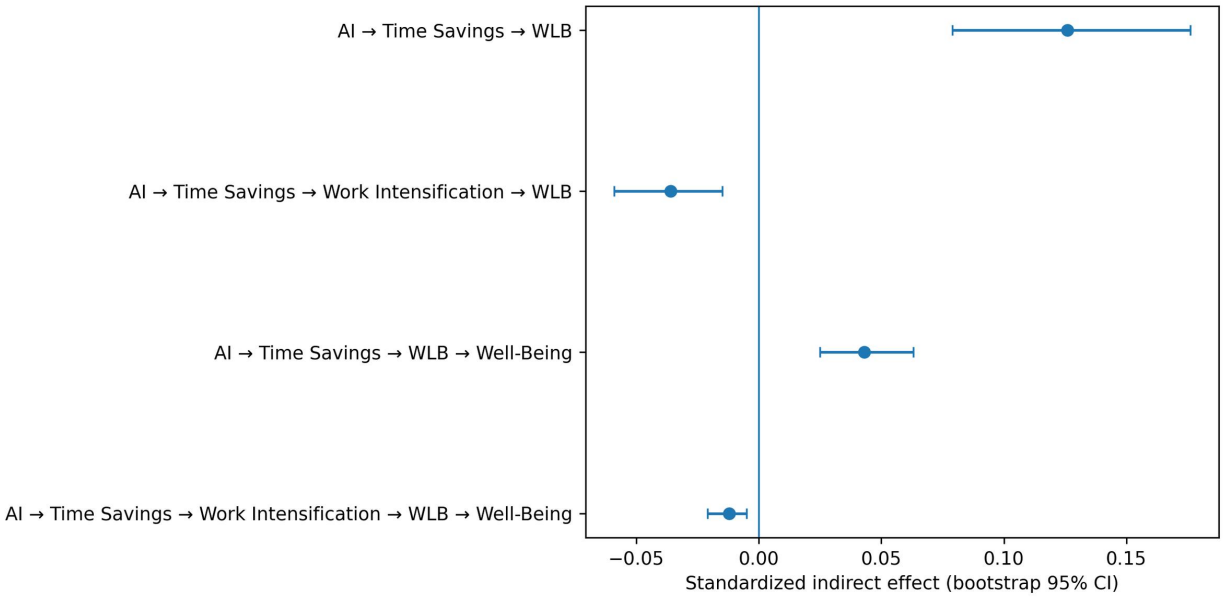


Figure 3. Competing indirect effects

4.4 Additional analyses

Model 6 uses after-hours work as a time-use outcome. Time savings is associated with less after-hours work (β = −.165, SE = .034, p < .001), whereas work intensification (β = .560, SE = .032, p < .001) and techno-invasion (β = .400, SE = .032, p < .001) are associated with more after-hours work. The direct AI-use coefficient is not significant (β = −.013, p = .706). This pattern again suggests that AI use affects extended work through intervening allocation mechanisms rather than through a uniform direct effect.

Gender-interaction tests do not identify statistically significant differences in the AI-use-to-time-savings relationship or in the time-savings and work-intensification associations with work-life balance. The AI use × female interaction in the time-savings model is not significant (β = −.019, p = .794), and neither the time savings × female interaction (β = −.017, p = .823) nor the work intensification × female interaction (β = .120, p = .116) reaches conventional significance. The estimated allocation mechanism is therefore not concentrated in one gender group. Full interaction-model coefficients are reported in Appendix D.

Synthesis of empirical findings. Across the reported specifications, perceived time savings coexists with positive work-life and performance associations, while work intensification is associated with lower work-life balance and well-being. The magnitude of the negative intensification coefficient in the work-life model exceeds the corresponding positive time-savings coefficient in absolute standardized units, but these are conditional relationships rather than a directly measured allocation ratio. The interaction null result constrains claims about performance pressure as a moderator.

Table 6. Selected additional analyses

Outcome / analysis	Predictor	β	*SE*	*p*
After-hours work	Time Savings	−.165	.034	<.001
After-hours work	Work Intensification	.560	.032	<.001
After-hours work	Techno-invasion	.400	.032	<.001
Time Savings	AI Use × Female	−.019	.074	.794
Work-Life Balance	Time Savings × Female	−.017	.076	.823
Work-Life Balance	Work Intensification × Female	.120	.076	.116

4.5 Robustness checks

The first robustness test replaces the perceived AI-use scale with observed use frequency and the perceived time-savings scale with reported hours saved per week. AI-use days strongly predict reported saved hours (β = .552, SE = .037, p < .001). When observed saved hours replace the multi-item time-savings construct, the association with work-life balance remains positive (β = .285, SE = .038, p < .001), while the work-intensification coefficient remains negative and essentially unchanged (β = −.444, p < .001). The complete robustness specifications, including control-variable coefficients, are reported in Appendix C.

The performance model yields a similar pattern. AI-use days are positively associated with job performance (β = .166, p = .002), reported saved hours are positively associated with performance (β = .303, p < .001), and work intensification is negatively associated with performance (β = −.096, p = .026). These results indicate that the main findings are not dependent on using only attitudinal AI-use and time-savings measures.

A final model treats weekly work hours as an outcome. Reported saved hours are negatively associated with weekly work hours (β = −.135, SE = .042, p = .001), whereas work intensification (β = .590, SE = .036, p < .001) and performance pressure (β = .259, SE = .033, p < .001) are positively associated with weekly hours. This result provides a direct illustration of the competing allocation forces: AI-generated savings tend to release time, while intensified work and performance demands push total work time upward.

Table 7. Robustness checks

Outcome	Predictor	β	*SE*	*p*
Observed saved hours	AI-use days	.552	.037	<.001
Work-Life Balance	Observed saved hours	.285	.038	<.001
Work-Life Balance	Work Intensification	−.444	.041	<.001
Job Performance	AI-use days	.166	.053	.002
Job Performance	Observed saved hours	.303	.051	<.001
Weekly work hours	Observed saved hours	−.135	.042	.001
Weekly work hours	Work Intensification	.590	.036	<.001
Weekly work hours	Performance Pressure	.259	.033	<.001

5. Discussion

5.1 Interpretation of the findings

Importantly, the study does not directly observe ownership, contractual entitlement, or managerial redistribution of saved hours. "Allocation" is therefore a theoretical interpretation supported indirectly by associations among saved time, intensification, and work-time outcomes, rather than an observed organizational decision process. A decisive next test would link task logs, assignment changes, target revisions, and worker discretion within the same organizations.

The central result is that AI-enabled time savings should not be treated as an endpoint. They are an intermediate resource whose welfare value depends on subsequent allocation. The positive pathway is clear: greater GenAI use is associated with more time savings, and those savings are associated with higher work-life balance and performance. The negative pathway is equally clear: time savings are also associated with work intensification, and intensified work is associated with lower balance, lower well-being, more after-hours work, and longer weekly hours. The same technological gain can therefore create both a resource and a demand.

This dual-path interpretation helps explain why direct relationships between AI use and employee outcomes may be unstable across settings. If one organization allows employees to retain part of the time saved by AI while another immediately raises output expectations, similar levels of AI adoption can produce different work-life outcomes. A net direct coefficient can also conceal offsetting mechanisms. The present results show that the positive AI-use-to-time-savings-to-balance pathway coexists with a smaller but significant negative pathway through work intensification.

The performance-pressure result refines the framework. Performance pressure is one of the strongest predictors of work intensification, but its interaction with time savings is not significant. This suggests that performance pressure may function as a direct work demand rather than a moderator of the conversion process. Future field research should distinguish subjective performance pressure from observable managerial recapture practices such as target revisions, workload reallocation, deadline compression, and staffing changes.

The demand pathway is also consistent with research on workplace telepressure, which links the urge to respond quickly to electronic messages with impaired recovery (Barber & Santuzzi, 2015). This comparison is conceptual: telepressure was not introduced as an additional measured construct in the present models.

5.2 Theoretical contributions

First, the study advances a time-dividend allocation perspective on GenAI. Existing productivity research has established that AI can make employees faster. The proposed framework adds a second stage: after time is saved, it must be allocated. This creates a conceptual separation between technological productivity and employee welfare that is missing when studies move directly from AI adoption to performance or well-being.

Second, the framework integrates job resources and job demands within the same technological episode. AI-generated time savings can function as a resource by improving discretion and work-life balance, but the same savings can become the basis for intensified work. The theoretical contribution is therefore not a claim that GenAI is simultaneously good and bad in a generic sense. It is a process explanation of how one efficiency gain can produce competing consequences through different allocation mechanisms.

Third, the study extends the multi-outcome logic of Angelici and Profeta's smart-working research. Their experiment shows that changes in work organization can jointly affect productivity, well-being, and work-life balance. The current framework applies this logic to GenAI but changes the underlying organizational margin. The relevant question is no longer primarily where and when work occurs; it is who controls the time released by higher task efficiency. In this sense, the ownership of saved time becomes a central dimension of AI-enabled work design.

These contributions are bounded by what is observed. The framework identifies allocation as an organizational mechanism worth measuring, but it does not demonstrate that managers deliberately recaptured workers' saved time. Distinguishing intentional recapture from employee-initiated task expansion or greater task complexity will require organizational records, repeated time-use data, and explicit measures of decision authority over task allocation.

5.3 Managerial implications

The framework implies that organizations should govern productivity gains explicitly rather than assume that faster task completion is unambiguously beneficial. If every efficiency gain is immediately translated into higher task volume,

the organization may capture output gains while eroding the employee-side benefits of AI adoption. Such a policy can increase after-hours work and weaken work-life balance even when individual tasks become easier.

Managers can preserve part of the time dividend by defining workload norms before large-scale AI rollout, monitoring whether output targets escalate mechanically with tool adoption, and limiting expectations of after-hours digital availability. Performance systems can also emphasize output quality and goal completion rather than visible busyness or constant responsiveness. The consistently positive role of job autonomy in the models indicates that employee discretion remains important even when work becomes technologically augmented.

Organizations should also measure AI adoption with both productivity and employee-experience indicators. A dashboard that reports task completion but ignores weekly hours, after-hours communication, work intensification, and recovery can misclassify a recaptured time dividend as a pure productivity gain. The practical implication is to evaluate AI as a work-design intervention rather than only as a software investment.

For implementation, organizations could audit AI-enabled workflows at three levels: task-level time required for comparable output, job-level changes in targets and assignment volume, and employee-level consequences for scheduled hours, after-hours work, perceived control, and well-being. The data here justify evaluating these dimensions jointly; they do not establish an optimal percentage of AI-saved time that must be returned to employees. Such allocation rules should be tested prospectively before being presented as evidence-based thresholds.

Future interventions could distinguish saved time from recovery experiences. Sonnentag and Fritz (2007) identify psychological detachment, relaxation, mastery, and control as distinct recovery dimensions. Measuring these outcomes would help assess whether an AI time dividend becomes a usable personal resource rather than simply unused capacity in an intensified workflow.

5.4 Limitations and future research

The study has several limitations that also identify priorities for further research. First, the three-wave observational design improves temporal separation between focal predictors, mechanisms, and outcomes, but it does not provide the same causal identification as a randomized intervention. A stronger design would randomly provide access to an enterprise GenAI tool and measure objective AI usage, work time, after-hours activity, and performance before and after access. Where randomization is not feasible, a staggered organizational rollout could support difference-in-differences or event-study identification.

Second, several focal variables are self-reported. Future research should combine survey constructs with digital-trace data from enterprise AI systems, email and collaboration platforms, task-management systems, and objective performance records. Such data would allow researchers to separate perceived time savings from actual reductions in task time and to observe whether saved capacity is reallocated to additional tasks.

Third, the allocation of AI-generated time is likely to vary across occupations, task interdependence, incentive systems, managerial styles, and national labor institutions. Multilevel designs that model employees within teams and organizations would therefore be particularly useful. They could also test spillover effects analogous to those examined in research on smart working: one employee's AI use may affect coworkers by changing team pace, coordination demands, or shared performance standards.

Additional limitations concern selection, measurement, and reporting. Complete-case analyses can be biased if participation or wave attrition relates to the focal outcomes. Job performance and AI-related time savings rely on self-report, and their correspondence with objective measures is unknown. Correlated measurement errors may persist despite temporal separation. The provided manuscript does not specify recruitment dates, survey country or sector, wave intervals, response rate, institutional clustering, or the exact questionnaire items. These details should be supplied from fieldwork records before the article is treated as a final published report. Reporting these limitations does not alter the estimated coefficients.

6. Conclusion

Generative AI can create a time dividend by reducing the time required for knowledge-work tasks. The central organizational issue is not whether that dividend exists, but how it is allocated after it is created. When saved time remains partly under employee discretion, it can support work-life balance and well-being while preserving or

improving performance. When the same savings are absorbed by higher task volume, faster pacing, and digital availability, the productivity gain is accompanied by work intensification.

The analysis developed here therefore shifts the evaluation of workplace GenAI from a one-stage productivity question to a two-stage allocation problem. The first stage concerns how much time AI saves. The second concerns who captures that time and for what purpose. Future causal field research should measure both stages directly. Doing so is necessary for understanding not only the productivity effects of AI, but also the distribution of its benefits within the organization.

Publication declarations

1. Ethics Approval and Informed Consent

This study involved survey research with 472 human participants. Formal approval from an institutional research ethics committee was not obtained. Before completing the questionnaire, participants were informed of the purpose and nature of the research through an introductory statement presented on the first page of the survey. Informed consent was obtained electronically through a consent option provided on the questionnaire's first page. Participation was voluntary, and respondents consented to the use of their responses for academic research purposes.

2. Data and Code Availability

The dataset underlying this study comprises 472 survey observations. The research materials include questionnaire responses, construct-level variables, and analysis-ready datasets used to examine generative AI use, perceived time savings, work intensification, work-life balance, employee well-being, and job performance.

The availability of de-identified data and supporting research materials is subject to participant confidentiality, applicable data protection requirements, and the conditions under which informed consent was obtained. The author will provide information regarding access to these materials upon reasonable request, subject to these conditions.

3. Competing Interests

The author declares no competing financial or non-financial interests.

4. Declaration of Generative AI Assistance

Generative AI tools were used to support literature discovery and to review and refine academic language and expression during manuscript preparation. All AI-assisted outputs were reviewed by the author, who retains full responsibility for the accuracy, originality, integrity, and final content of the manuscript.

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