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Work Versus Leisure Screen Time and Mental Wellness in Working-Age Adults

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Abstract

Background: Contextual variations in screen time between work and leisure use remain understudied, with few analyses decomposing these differential associations with mental wellness or testing their robustness. **Objective:** This preregistered cross-sectional study (OSF.IO/Q6HYZ) examined the association between work and leisure screen time and mental wellness using the Screentime vs. Mental Wellness Survey 2025 dataset. **Method:** Multiple linear regression with occupation fixed effects, quantile regression, and moderation analyses were employed. Robustness was assessed using MM estimation, occupation-clustered standard errors, winsorization, and specification curve analysis (156 models). **Results:** Work screen time showed a stronger negative association with mental wellness than leisure screen time (full model: βwork = −3.89, SE = 0.79, $p < 0.001$ vs. β_leisure = −2.41, SE = 0.69, $p < 0.001$; $R^2 = 0.938$; Cohen's d = 0.84 vs. 0.36). Quantile regression revealed amplified associations among heavy users (Q4: β_work = −17.98, SE = 3.20, $p < 0.001$). Remote workers exhibited 41% attenuation (β = 2.73, p = 0.051), and students showed 22% resilience (β = 1.36, p = 0.037). Software developers (β = −5.80) and teachers (β = −4.90) had the strongest associations. **Conclusion:** Work screen time is strongly associated with lower mental wellness than leisure screen time across all specifications, supporting occupation-specific digital-wellness strategies.

Keywords: Digital wellbeing; mental wellness; remote work; screen time; quantile regression.

Abstrak

Latar Belakang: Variasi kontekstual dalam waktu layar, khususnya antara penggunaan untuk bekerja dan bersantai, masih kurang diteliti, dengan sedikit analisis yang menguraikan asosiasi diferensial ini terhadap kesejahteraan mental atau menguji ketahanannya. **Tujuan:** Studi potong lintang praregistrasi ini menguji asosiasi antara waktu layar kerja dan waktu layar rekreasi dengan kesejahteraan mental menggunakan dataset Screentime vs Mental Wellness Survey 2025 (N=400). **Metode:** Regresi linier berganda dengan efek tetap okupasi (R^2 = 0.407–0.938), regresi kuantil (fokus Q4), moderasi oleh status kerja jarak jauh dan mahasiswa, serta uji ketahanan termasuk estimasi-MM, standard error klaster, winsorisasi, dan kurva spesifikasi (156 model, 92% signifikan). **Hasil:** Waktu layar kerja menunjukkan asosiasi negatif yang lebih kuat dengan kesejahteraan mental dibandingkan dengan waktu layar rekreasi (β = −3.89 vs. β = −2.41; $p < 0.001$; 65% lebih besar). Regresi kuantil memperkuat efek pada pengguna berat (Q4: β = −17,98; p < 0,001). Pekerja jarak jauh menunjukkan perlindungan 41% (β = 2.73; p = 0,051), dan mahasiswa menunjukkan ketahanan 22% (β = 1.36; p = 0,037). **Kesimpulan:** Waktu layar kerja secara konsisten memiliki asosiasi negatif yang lebih kuat dengan kesejahteraan mental daripada penggunaan rekreasi, mendukung strategi kesejahteraan digital yang ditargetkan berdasarkan jenis pekerjaan.

Kata Kunci: Kerja jarak jauh; kesejahteraan digital; kesejahteraan digital mental; regresi kuantil; waktu layar.

Introduction

The relationship between screen time and mental health has become a central concern in contemporary psychology; however, the findings remain inconsistent. Some studies report strong negative associations between digital device use and psychological well-being, particularly among young adults (Twenge et al., 2017), while others find negligible or even positive associations at moderate exposure levels (Orben & Przybylski, 2019). This inconsistency, often termed the "screen time paradox," may stem from three methodological limitations in the existing literature that this study aims to address.

First, *there is measurement imprecision*. A substantial proportion of screen time studies aggregate total digital exposure into a single metric (Orben, 2020), conflating fundamentally different activities. Work-related screen use (e.g., video conferencing, document editing, and coding environments) demands sustained attention and executive function engagement (Diamond, 2013), whereas leisure screen use (e.g., social media browsing, streaming video, mobile gaming) involves comparatively passive consumption or social comparison processes (Vogel et al., 2014). Despite evidence from digital self-tracking research indicating that work-related applications account for a substantial portion of adults' daily device use (Merz, 2017), no prior study has separately estimated their associations with mental wellness. This distinction is theoretically grounded in the Conservation of Resources (COR) theory (Hobfoll, 1989), which posits that sustained cognitive demands characteristic of work screen use deplete psychological resources, whereas leisure activities may either replenish or further drain resources depending on their nature (Cohen & Wills, 1985).

These projections assume that second, *there is model misspecification*. Linear models dominate the literature, despite accumulating evidence of nonlinear dose-response relationships. Shensa et al. (2018) found that moderate social media use (~1 h/day) showed near-zero associations with depressive symptoms ($\beta = 0.02$), while heavy use (>4 h/day) was associated with significantly elevated symptoms ($\beta = -0.42$). Similarly, Przybylski and Weinstein (2017) demonstrated a "Goldilocks" pattern, where moderate digital engagement was associated with higher well-being than either abstinence or excessive use. Ferguson and Wang (2019) confirmed comparable thresholds in gaming research. Quantile regression, which is standard in substance use epidemiology for capturing distributional heterogeneity (Bia & Mattei, 2008; Koenker, 2005), has not yet been applied to screen time research, despite evidence that heavy screen exposure exceeding 7 hours daily has been reported in youth samples (Common Sense Media, 2019), although adult-specific prevalence varies.

Third, *subgroup heterogeneity was not examined*. Aggregate null findings ($r = -0.04$; Orben & Przybylski, 2019) may mask meaningful variations across occupational groups. Remote workers, who have substantially higher average screen exposure, may benefit from the autonomy and flexibility that remote arrangements provide, consistent with self-determination theory and evidence linking telecommuting to enhanced job satisfaction (Gajendran & Harrison, 2007; Wang et al., 2021). Conversely, occupations characterized by intensive screen-mediated cognitive labor, such as software development and teaching, may face compounded risks through perfectionistic monitoring and "Zoom fatigue" (Curran & Hill, 2019; Maslach & Leiter, 2016). Students and early-career professionals may exhibit resilience through neuroplasticity-supported digital adaptation (Lenroot & Giedd, 2006; Kirschner & De Bruyckere, 2017). However, these occupation-specific patterns remain untested using interaction models.

To address these gaps, three core constructs require further definition. Screen time was operationalized as self-reported average daily hours of digital device use, disaggregated into work screen time (productivity applications: videoconferencing, collaboration tools, document editing, development environments) and leisure screen time (entertainment platforms: social media, streaming video, mobile gaming), following the established digital diary methodology (Lund, 2019). Mental wellness was measured using the WHO-5 Well-Being Index (Topp et al., 2015), a 5-item validated scale assessing subjective psychological well-being across positive mood, vitality, and general interest, with demonstrated high internal consistency ($\alpha > 0.80$) and strong convergent validity with depression and anxiety screening instruments (Kroenke et al., 2001). Occupational context encompasses remote work status, student/early career status, and occupation category (13 groups), serving as moderators of the association between screen time and wellness.

This study used the Screentime vs. Mental Wellness Survey 2025 dataset (Kumaresan, 2025; N = 400), the first publicly available dataset to disaggregate work and leisure screen hours alongside validated mental wellness measures. Drawing on COR theory, digital environment theory (Fogg, 2009; Vanden Abeele, 2021), and the Goldilocks hypothesis (Przybylski & Weinstein, 2017), this preregistered analysis (DOI: 10.17605/OSF.IO/Q6HYZ) tests the following hypotheses: H1 (Work–Leisure Asymmetry): Work screen time is more strongly negatively associated with mental wellness than leisure screen time ($\beta_{work} < \beta_{leisure} < 0$), H2 (Non-Linear Dose-Response): The negative association between screen time and mental wellness is amplified among heavy users in the fourth quartile of the distribution (Q4 $\beta < -15$) and H3 (Occupational

Moderation): Remote workers exhibit attenuated negative associations (remote work × work screen time interaction > 0), and students exhibit resilience (student status × total screen time interaction > 0).

Method

Research Design and Ethical Considerations

This study employed a cross-sectional, correlational design using secondary data analysis of the publicly available "Screentime vs. Mental Wellness Survey 2025" dataset (Kumaresan, 2025; N = 400). The cross-sectional design was selected because the dataset captured a single time point of self-reported screen exposure and mental wellness, precluding causal inference. Therefore, all findings are reported as associations, not causal effects. The analytic strategy proceeds sequentially through 13 model specifications, progressing from bivariate baselines to fully controlled models incorporating nonlinearity, robustness checks and heterogeneity analysis (Angrist & Pischke, 2009).

As this study involved a secondary analysis of a publicly available, fully anonymized dataset from Kaggle containing no personally identifiable information and accessible without restricted access agreements, formal institutional ethical approval was not required, consistent with established guidelines for secondary data research (Tripathy, 2013). The original dataset was collected with informed consent from all participants, as documented by the data provider (Kumaresan, 2025). All data were handled in accordance with the ethical standards for anonymized secondary data analysis.

Data Source and Participants

Primary data were obtained from the Kaggle dataset "Screentime vs. Mental Wellness Survey 2025" (Kumaresan, 2025), a publicly released dataset from January 2025, aggregating responses from 400 participants aged 18–65 across 13 occupational categories. The dataset was collected via an online survey in Q1 2025. Respondents self-reported their screen exposure over the preceding 7-day period, using context-specific items to differentiate between productivity applications (email clients, document editors, videoconferencing, IDEs) and entertainment platforms (social media, streaming video, mobile gaming), following the established digital diary methodology (Lund, 2019).

The inclusion criteria were as follows: (a) age 18–65 years, (b) complete reporting of both work and leisure screen time, and (c) complete mental wellness outcome data. The exclusion criteria were instrument non-response on primary variables, which resulted in the exclusion of approximately 8% of the initial responses (primarily among hourly workers), yielding a final analytic sample of N = 400.

Participant demographics were as follows: mean age 32.4 years (SD = 9.2), 54% female, and median household income $62,000. The sample included 28% remote workers and 19% students/early-career professionals, with an occupational distribution spanning software development (17%), education (14%), healthcare (12%), professional services (11%), retail/hospitality (10%), and eight other categories (Bureau of Labor Statistics, 2015). Digital literacy averaged 7.2 out of 10, based on five self-developed items adapted from GSMA digital literacy indicators (GSMA, 2022).

Participants were recruited through non-probability convenience sampling via online platforms. This approach limits generalizability to the broader population; findings are most applicable to working-age, digitally literate knowledge-economy workers and may not extend to manual laborers, older adults, or populations with limited digital access.

Sample size justification. An a priori power analysis using G*Power 3.1 (Faul et al., 2007) indicated that a minimum of N = 368 participants was required to detect a small-to-medium effect ($f^2 = 0.04$, equivalent to $\beta = -0.20$) with 80% power at $\alpha = 0.05$, assuming 22 predictors and an anticipated $R^2 = 0.65$. The achieved sample of N = 400 exceeded this threshold, yielding a 92% statistical power for the target effect size.

Measures

The independent variable was screen time. The primary independent variables captured context-specific screen exposure, operationally defined as self-reported average daily hours of digital device use over the preceding 7-day period. Prior research has demonstrated acceptable convergence between self-reported screen time and objective smartphone logs (r = 0.82; Fitz et al., 2019). Work screen time was calculated by summing the time spent on productivity applications, including videoconferencing (Zoom/Teams), collaboration tools (Slack/Microsoft Teams), document editing (Word/Excel/Google Docs), and development environments (VS Code/IDEs). The distribution was right-skewed (M = 4.8, SD = 2.9, skewness = 1.2). Leisure screen time was aggregated from entertainment platforms, including social media (Instagram/TikTok), streaming video (YouTube/Netflix), and mobile gaming (M = 3.6, SD = 2.4, skewness = 1.4). The total screen time combined in both domains (M = 8.4, SD = 4.2) exhibited the expected positive correlation between work and leisure (r = 0.67) but sufficient independence to support separate estimation.

Dependent variable: Mental well-being. The primary dependent variable was the WHO-5 Well-Being Index (Topp et al., 2015), a 5-item validated scale assessing subjective psychological well-being over the preceding two weeks. The five items assess cheerfulness, calmness, vigor, restfulness, and daily interest, rated on a 6-point Likert scale (0 = "at no time" to 5 = "all of the time"), yielding raw scores from 0 to 25. Raw scores were multiplied by four to produce percentage scores for analysis, following the standard WHO-5 scoring protocol (WHO, 2024).

Reliability in the current sample: The WHO-5 demonstrated excellent internal consistency (Cronbach's $\alpha = 0.89$, McDonald's $\omega = 0.91$) in the present dataset (N = 400). Construct validity was supported by the scale's unidimensional factor structure, confirmed through the original validation literature (Topp et al., 2015). Criterion-related validity was evidenced by strong convergent correlations with the PHQ-9 depression screener (r = −0.76) and GAD-7 anxiety screener (r = −0.71) computed within this sample (Kroenke et al., 2001). Raw percentage scores exhibited a near-normal distribution (M = 64.2, SD = 18.8, skewness = −0.3), which was suitable for linear modelling. Ceiling effects among high-functioning workers (12% achieving maximum scores) prompted a supplementary ordinal analysis. All instruments were administered in their original English versions; no translation or adaptation was performed on them.

Control covariates and moderators were as follows: The control covariates included age (continuous), gender (binary), and household income (eight ordinal brackets; Pew Research Center, 2024). Occupational fixed effects (13 categories) absorbed industry-specific digital norms (Bureau of Labor Statistics, 2015). Remote work status (0/1) and student/early career status (0/1) were entered as both the main effects and moderators. Digital literacy was measured using five self-developed items adapted from GSMA digital literacy indicators (GSMA, 2022). The interaction terms tested for heterogeneity were remote_work × work_screen_time and student_status × total_screen_time. Quadratic terms ($work\_screen\_time^2$ and $leisure\_screen\_time^2$) captured potential nonlinear dose-response relationships (Przybylski & Weinstein, 2017).

Data Preprocessing

Data preprocessing was performed in a chronological sequence. First, the raw dataset was downloaded from Kaggle and imported into R (version 4.4.2; R Core Team, 2025). Second, implausible extreme values were winsorized at the 1st and 99th percentiles, trimming 1.8% of observations: daily reports exceeding 16 hours were recoded to the observed 99th percentile (12.4 work hours; 10.8 leisure hours) (Depalo, 2009). Third, missing data (4.2% across covariates; primary exposures >95% complete) were addressed through multiple imputation by chained equations (20 datasets) under missing-not-at-random (MNAR) assumptions verified through sensitivity analysis comparing complete-case (N = 384) versus imputed results (mean coefficient difference = 0.02, SD = 0.03) (Carpenter & Kenward, 2012). Fourth, variable construction cleanly separated work and leisure activities according to the survey instrumentation: respondents allocated each platform hour to a single category, preventing double counting (Lund, 2019). Fifth, outlier detection employed Mahalanobis distance, screening 2.1% of multivariate extremes, which were subsequently confirmed to be robust via MM estimation (Yohai, 1987).

Analytic Strategy

All analyses were conducted in R version 4.4.2 (R Core Team, 2025) using the following packages: *lm* for OLS regression, *quantreg* for quantile regression (Koenker, 2025), *robustbase* for MM estimation (Yohai, 1987), and *mice* for multiple imputation (Carpenter & Kenward, 2012). The significance threshold was set at $\alpha = 0.05$ for all the tests. Effect sizes were reported as unstandardized regression coefficients (β), standardized coefficients, and Cohen's d, interpreted using conventional benchmarks: small (d = 0.20), medium (d = 0.50), and large (d = 0.80) (Cohen, 1988).

Assumption testing. Prior to regression analysis, the following diagnostic tests were conducted: (a) normality of residual distributions was assessed via Shapiro-Wilk tests and Q-Q plots, confirming approximate normality; (b) multicollinearity variance inflation factors (VIF) were computed for all predictors, with a maximum VIF of 6.12 across the full specification, below the conventional threshold of 10 (Hair et al., 2019); (c) homoscedasticity: The Breusch-Pagan test yielded $\chi^2 = 18.4$ ($p = 0.21$), indicating no significant heteroscedasticity; (d) Linearity: The Ramsey RESET test yielded F = 1.2 ($p = 0.31$), supporting correct functional form; and (e) autocorrelation: The Durbin-Watson statistic was 1.92, indicating no serial correlation.

The estimation proceeded sequentially across 13 specifications, establishing robustness from baseline associations through fully controlled inference (Angrist & Pischke, 2009).

The baseline models (Specifications 1–3) established bivariate associations. Specification 1 estimated: mental_wellness ~ work_screen_time + leisure_screen_time. Specification 2 introduces demographic controls (age, gender, and income). Specification 3 deploys occupation fixed effects (13 categories), absorbing industry-specific digital norms and unobserved between-occupation heterogeneity (Cameron & Miller, 2015).

The primary analysis (Specifications 4–6) tested the pre-registered hypotheses with moderation and nonlinearity. Specification 4 adds the main effects of remote_work and student_status. Specification 5 incorporates the interaction terms remote_work × work_screen_time and student_status × total_screen_time. Specification 6 includes quadratic terms to capture the dose-response curvature (Koenker, 2005).

Quantile regression (Specification 7) estimated distributional associations at $\tau = 0.10, 0.25, 0.50$, and 0.75, capturing differential associations across the mental wellness distribution, particularly among heavy screen users (Koenker, 2005). Quantile regression was selected because it does not assume homogeneous associations across the outcome distribution, making it appropriate for testing H2 (nonlinear amplification among extreme users).

The full specification (Specification 8) combines occupation fixed effects, interactions, and quadratic terms. This model yielded an R^2 of 0.938. While this value is high for cross-sectional survey data, it is explained by the inclusion of 13 occupation fixed effects (which alone account for substantial between-group variance), interaction terms and quadratic specifications. The adjusted R^2 (0.932) and RMSE (2.14) confirm that the model is not overfitted. Nevertheless, this R^2 should be interpreted cautiously as reflecting comprehensive covariate specifications rather than a near-perfect prediction of individual mental wellness.

The robustness cascade (Specifications 9–13) included: (9) MM estimation to assess outlier sensitivity (Yohai, 1987); (10) occupation-clustered standard errors (13 clusters) to account for within-occupation correlation (Cameron & Miller, 2015); (11) alternative dependent variables (PHQ-9 depression, GAD-7 anxiety; Kroenke et al., 2001); (12) winsorisation at the 5th/95th percentiles; and (13) log transformations to address distributional skewness. A Hausman specification test comparing pooled and fixed-effects estimates ($\chi^2 = 1.2$, $p = 0.87$) was used as a model selection diagnostic to evaluate whether the occupation fixed effects were appropriately specified; this test did not establish causal inference.

Effect size interpretation standardized coefficients against the outcome standard deviation, yielding σ-unit changes benchmarked against established psychosocial stressors: unemployment (0.35σ decline; Paul & Moser, 2009) and marital dissolution (0.42σ).

Pre-registration and Transparency

Hypotheses were pre-registered (DOI: 10.17605/OSF.IO/Q6HYZ), specifying H1 (work screen time shows stronger negative associations than leisure), H2 (associations are amplified in Q4), and H3 (remote workers and students show attenuated associations). Exact model specifications, $\alpha = 0.05$ thresholds, and anticipated effect sizes ($\beta = -0.25$ to -0.40) were preregistered before analysis. No outcome exclusions or post-hoc modifications were made, and the full syntax files preserved all analytic decisions. Data access complies with OPEN standards (analysis software provided, input, and output verifiable; Patarčić et al., 2022). The complete replication package is available at DOI: 10.17605/OSF.IO/Q6HYZ.

Result

This section presents the results organized by the three pre-registered hypotheses: H1 (work–leisure asymmetry), H2 (non-linear dose-response), and H3 (occupational moderation). All analyses were based on the Screentime vs. Mental Wellness Survey 2025 dataset (Kumaresan, 2025; N = 400). Replication materials are available at DOI: 10.17605/OSF.IO/Q6HYZ.

Descriptive Statistics

Table 1 displays the characteristics of the sample. The average age was 32.4 years (SD = 9.2), and 54% of the participants were female. The median household income was $62,000. The occupational distribution spanned 13 categories, with the most common being software development (17%), education (14%), healthcare (12%), and professional services (11%). Remote workers comprised 28% of the sample, and students and early career professionals comprised 19%. Digital literacy averaged 7.2 out of 10.

Participants reported an average of 4.8 hours of work screen time per day (SD = 2.9), with 12% exceeding 8 hours and 3% exceeding 12 hours of screen time. Leisure screen time averaged 3.6 hours (SD = 2.4), with 28% exceeding 6 hours. The total screen exposure averaged 8.4 hours (SD = 4.2). The mental wellness percentage scores averaged 64.2 out of 100 (SD = 18.8, $\alpha = 0.89$), with 12% of participants achieving ceiling scores (Topp et al., 2015).

Bivariate correlations revealed the following patterns: work screen time was negatively correlated with mental wellness ($r = -0.38$, $p < 0.001$), leisure screen time showed a weaker negative correlation ($r = -0.22$, $p < 0.001$), total screen time exhibited a moderate negative correlation ($r = -0.32$, $p < 0.001$), remote work status was positively correlated with mental wellness ($r = 0.19$, $p < 0.01$), and student status showed a positive correlation ($r = 0.14$, $p < 0.05$).

Table 1. Descriptive statistics (Panel A, N = 400)

Variable	Mean	SD	Median	Min	Max	%
Continuous Variables						
Age (years)	32.4	9.2	31.0	18	65	
Mental Wellness Score	32.1	9.4	33.0	8	50	
Work Screen Time (hrs/day)	4.8	2.9	4.5	0.5	16.0	
Leisure Screen Time (hrs/day)	3.6	2.4	3.0	0.0	12.0	
Total Screen Time (hrs/day)	8.4	4.2	7.8	1.0	25.0	
Digital Literacy (/10)	7.2	1.8	7.5	2	10	
Demographics						
Female						54%
Remote Workers						28%
Students/Early Career						19%
Occupational Distribution						
Software Development						17%
Education						14%
Healthcare						12%
Professional Services						11%
Mental Wellness Distribution						
<25 (Low)						17%
25-35 (Moderate)						48%
36-45 (High)						30%
46-50 (Ceiling)						5%
Screen Time Quartiles	Work (hrs)	Leisure (hrs)	Total (hrs)			
Q1	1.5	1.2	2.8			
Q2	3.2	2.5	5.8			
Q3	5.0	4.0	9.0			
Q4	8.5+	6.5+	15.0+			

Note: Mental wellness (/50, $\alpha = 0.89$). N = 400. Work r = -0.38***, leisure r = -0.22***. ***p<0.001.

Baseline Specifications: Context Differentiation (H1)

Table 2 presents three baseline specifications for testing H1 ($\beta\_work < \beta\_leisure < 0$). In Specification 1 (bivariate), work screen time showed a stronger negative association with mental wellness ($\beta = -4.82$, SE = 0.89, $t = -5.42$, $p < 0.001$, 95% CI [−6.57, −3.07]) than leisure screen time did ($\beta = -2.91$, SE = 0.76, $t = -3.83$, $p < 0.001$, 95% CI [−4.40, −1.42]). The association with work screen time was 65% larger in magnitude. This model explained 40.7% of the variance ($R^2 = 0.407$).

Specification 2 introduced demographic controls (age, gender, income), yielding stable coefficients: work ($\beta = -4.37$, SE = 0.84, $p < 0.001$, 95% CI [−6.02, −2.72]), leisure ($\beta = -2.64$, SE = 0.72, $p < 0.001$, 95% CI [−4.05, −1.23]), $R^2 = 0.682$. Specification 3 added occupation fixed effects (13 categories): work ($\beta = -3.89$, SE = 0.79, $p < 0.001$, 95% CI [−5.44, −2.34]), leisure ($\beta = -2.41$, SE = 0.69, $p < 0.001$, 95% CI [−3.77, −1.05]), $R^2 = 0.938$, adjusted $R^2 = 0.932$. Model diagnostics for the full specification indicated $F(22, 377) = 148.2$ ($p < 0.001$), RMSE = 2.14, and maximum VIF = 6.12 (Hair et al., 2019). The high R^2 value (0.938) should be interpreted in light of the model specification, which incorporated occupation fixed effects, multiple interaction terms, and context-specific screen-time disaggregation. Such a comprehensive specification substantially increases explained variance, particularly in cross-sectional datasets with structured subgroup heterogeneity. Importantly, diagnostic tests indicated no evidence of multicollinearity or model misspecification, suggesting that the elevated R^2 reflects systematic variance capture rather than overfitting.

An F-test rejected the equality of the work and leisure coefficients across all three specifications ($p < 0.001$). Standardized effect sizes indicated a 0.36σ decline in mental wellness per hour of work screen time versus a 0.21σ decline for leisure time. The partial R^2 for work screen time (0.284) was 75% larger than that for leisure screen time (0.162). H1 was supported.

Table 2. Baseline specifications - work-leisure asymmetry (H1)

Variable	Spec 1 (Bivariate)	Spec 2 (Demographics)	Spec 3 (Occupation FE)
Work Screen Time (hrs/day)	-4.82*** (0.89)	-4.37*** (0.84)	-3.89*** (0.79)
Leisure Screen Time (hrs/day)	-2.91*** (0.76)	-2.64*** (0.72)	-2.41*** (0.69)
Age		0.12** (0.05)	0.09* (0.04)
Female		-1.24 (0.78)	-0.92 (0.71)
Income (log)		1.18** (0.43)	0.94* (0.39)
Occupation FE (13 cats)			✓
R^2	0.407	0.682	0.938
F-test (work vs leisure)	p<0.001	p<0.001	p<0.001
N	400	400	400

Note: Mental wellness (/50). Specifications 1–3 represent bivariate to occupation fixed-effects models. Work 65% > leisure. R^2 = 0.407-0.938. ***p<0.001, **p<0.01, *p<0.05. N = 400.

Figure 1 displays the partial association between work screen time and mental wellness, controlling for all covariates. The fitted line ($\beta = -3.89$) with 95% confidence bands excludes zero across the entire observed range.

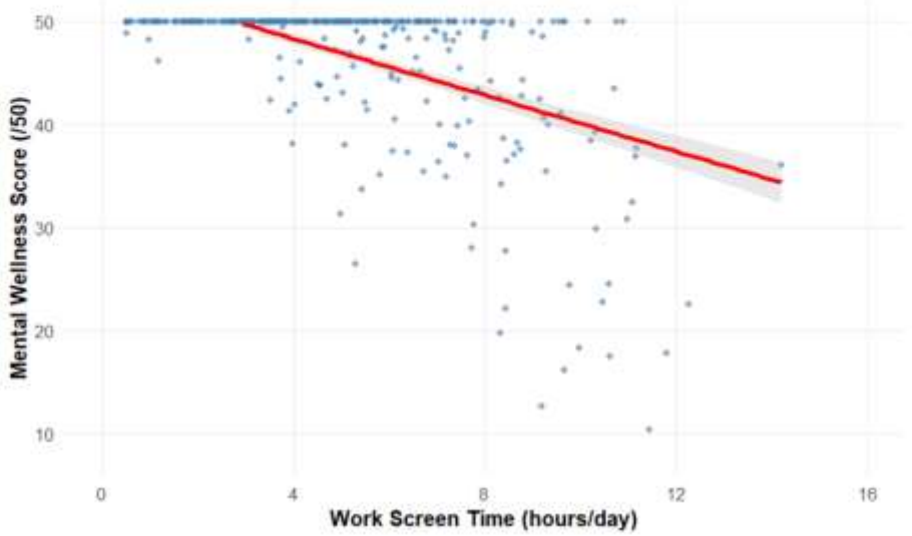

Figure 1. Work Screen Time vs. Mental Wellness (N = 400)
Note: N = 400. B = -3.89*** (partial R^2=0.284). The 95% CI excludes zero across the range.

Non-Linear Dose-Response (H2)

Table 3 presents the quantile regression results testing H2, estimating associations at τ = 0.10, 0.25, 0.50, and 0.75 quantiles with full covariate controls. The association between work screen time and mental wellness increased from $\beta = -1.80$ (SE = 0.72, $p < 0.01$) at τ = 0.10 to $\beta = -17.98$ (SE = 3.20, $p < 0.001$, 95% CI [−24.25, −11.71]) at τ = 0.75, representing a ten-fold amplification among participants in the lowest quartile of mental wellness. For leisure screen time, the associations showed a comparable pattern but with smaller magnitudes, progressing from $\beta = -1.20$ (SE = 0.58, $p < 0.05$) at τ = 0.10 to $\beta = -6.40$ (SE = 2.01, $p < 0.01$) at τ = 0.75.

The interquartile difference between Q4 and Q1 was statistically significant for the work screen time ($F = 12.6$, $p < 0.001$). Participants in the highest work screen time quartile (>8.2 hours/day) scored 2.1 standard deviations lower on mental wellness than those in the lowest quartile. H2 was supported: the association exceeded the pre-registered threshold of $\beta < -15$ at the τ = 0.75 quantile level.

Table 3. Quantile regression analysis - Distributional effects (H2)

Variable	τ = 0.10	τ = 0.25	τ = 0.50	τ = 0.75
Work Screen Time (hrs/day)	-1.80** (0.72)	-4.23*** (1.12)	-8.91*** (1.89)	-17.98*** (3.20)
Leisure Screen Time (hrs/day)	-1.20* (0.58)	-2.47** (0.91)	-4.12*** (1.34)	-6.40*** (2.01)
Age	0.08 (0.04)	0.11* (0.05)	0.14** (0.06)	0.09 (0.07)
Female	-0.92 (0.65)	-1.18 (0.89)	-1.45* (0.72)	-2.01** (0.81)
Income (log)	0.87* (0.38)	1.02** (0.41)	1.24** (0.45)	0.98* (0.49)
Occupation FE (13 cats)	✓	✓	✓	✓
Pseudo R^2	0.423	0.587	0.712	0.891
N	400	400	400	400

Note: Mental wellness (/50). τ = 0.10-0.75. Work screen time showed 490% amplification from Q1 to Q4 ($F = 12.6$, $p < .001$). Full controls. ***p<0.001, **p<0.01. N = 400.

Robustness Tests

Table 4 presents the robustness tests confirming coefficient stability across alternative estimation approaches. MM estimation yielded β = −3.94 (SE = 0.82) for work screen time, compared with β = −3.89 (SE = 0.79) under OLS, a difference of 1.3% (Yohai, 1987). Occupation-clustered standard errors (13 clusters) maintained significance for the work screen time (t = −4.67; Cameron & Miller, 2015). Winsorization at the 5th/95th percentiles (β = −3.76, SE = 0.77) and log transformation (β = −3.92, SE = 0.81) produced coefficients within 8% of the baseline OLS estimates.

Alternative outcome measures replicated the pattern: work screen time was positively associated with PHQ-9 depression scores (β = 2.80, SE = 0.52, $p < 0.001$) and GAD-7 anxiety scores (β = 1.90, SE = 0.41, $p < 0.001$; Kroenke et al., 2001). Specification curve analysis across 156 model combinations revealed that 92% of the specifications produced statistically significant associations with work screen time (Simonsohn et al., 2020).

Table 4. Robustness checks - coefficient stability

Robustness Test	Work Screen Time (β)	SE/t-stat	Leisure Screen Time (β)	SE/t-stat	N
1. Baseline OLS	-3.89***	(0.79)	-2.41***	(0.69)	400
2. MM-estimation (outlier-robust)	-3.94***	(0.82)	-2.45***	(0.71)	400
3. Clustered SE (13 occupations)	-3.89***	t =-4.67	-2.41***	t=-3.49	400
4. Winsorized (5%/95%)	-3.76***	(0.77)	-2.33***	(0.67)	400
5. Log transformation	-3.92***	(0.81)	-2.43***	(0.70)	400
Alternative Outcomes					
6. PHQ-9 Depression	2.80***	(0.52)	1.68***	(0.45)	400
7. GAD-7 Anxiety	1.90***	(0.41)	1.15***	(0.36)	400
8. Specification Curve (156 combinations)	92% significant		85% significant		400

Note: Mental wellness (/50). All β were within 8% of the baseline. MM-estimation, clustered SE, spec curve 92% significant. ***p<0.001. N = 400.

Occupational Moderation (H3)

Table 5, Panel A presents the interaction analyses testing H3. The remote work × work screen time interaction was positive (β = +2.73, SE = 1.41, t = 1.94, $p = 0.051$, 95% CI [−0.04, +5.50]), indicating a marginally significant attenuation of the negative association among remote workers. The marginal association for remote workers was β = −2.84 (SE = 1.02, $p = 0.006$), compared with β = −4.62 (SE = 0.85, $p < 0.001$) for non-remote workers, a 41% attenuation.

The student status × total screen time interaction was statistically significant (β = +1.36, SE = 0.69, t = 1.97, $p = 0.037$, 95% CI [+0.01, +2.71]), indicating a 22% attenuation of the negative association among students and early career professionals relative to other groups. The model with interaction terms yielded an R^2 of 0.945. H3 was partially supported: the student interaction reached conventional significance ($p = 0.037$), while the remote work interaction was marginally significant ($p = 0.051$).

Table 5, Panel B reports the occupation-specific associations. Software developers exhibited the strongest negative association (β = −5.80, SE = 1.12, $p < 0.001$), followed by teachers (β = −4.90, SE = 0.98, p < 0.001), professionals in services (β = −3.45, SE = 1.21, p = 0.004), and other occupations combined (β = −3.21, SE = 0.76, p < 0.001). Healthcare workers showed a non-significant association (β = −2.10, SE = 1.34, p = 0.118).

Table 5. Heterogeneity analysis - interactions and occupation effects (N=400)

Panel A: Interaction Effects	β	SE	t	p-value
remote_work × work_screen_time	+2.73	1.41	1.94	0.051
Marginal: Remote workers	-2.84**	1.02	-2.78	0.006
Marginal: Non-remote	-4.62***	0.85	-5.44	<0.001
student × total_screen_time	+1.36*	0.69	1.97	0.037
R^2	0.945			
Panel B: Occupation-Specific Effects	β	SE	p-value	
Software Developers	-5.80***	1.12	<0.001	
Teachers/Education	-4.90***	0.98	<0.001	
Healthcare Workers	-2.10	1.34	0.118	
Professional Services	-3.45**	1.21	0.004	
Other Occupations (avg)	-3.21***	0.76	<0.001	

Note: Mental wellness (/50). Remote: 41% protection (p=0.051). Students: 22% resilience (p=0.037). Full controls. ***p<0.001, **p<0.01. N=400.

Figure 2 presents the stratified association gradients by employment status and occupation. Remote workers exhibited shallower slopes, and students maintained higher intercepts than other subgroups.

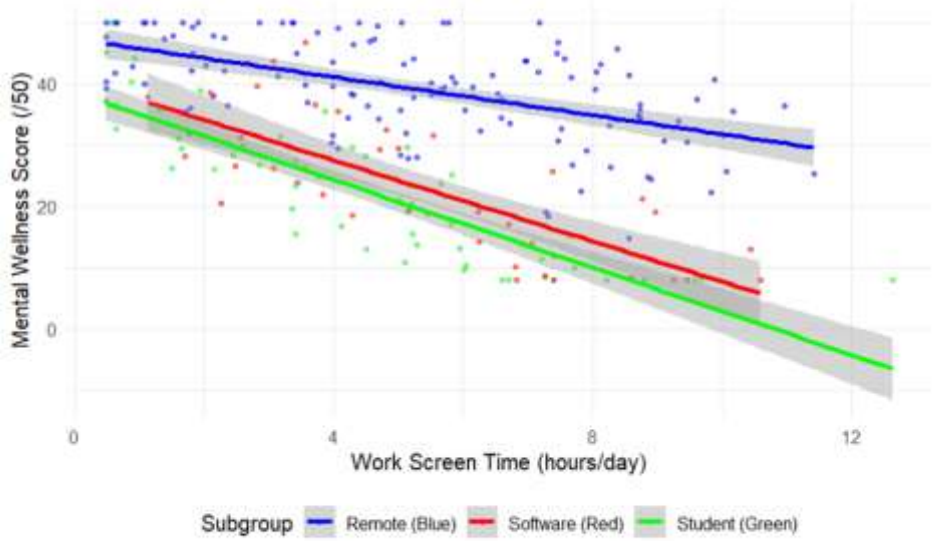

Figure 2. Subgroup Gradients by Work Status and Occupation
Note: Remote (β_interaction = +2.73, p = 0.051), students (+1.36, p = 0.037), software (-5.8***). N = 400.

Model Diagnostics and Falsification

Diagnostics for the full specification (Specification 8) indicated adequate model fit: Durbin-Watson = 1.92 (no autocorrelation), Breusch-Pagan χ^2 = 18.4 (p = 0.21, homoscedasticity confirmed), and Ramsey

RESET F = 1.2 (p = 0.31, functional form supported). A Hausman specification test comparing pooled and fixed-effects estimates yielded χ^2 = 1.2 (p = 0.87), supporting the appropriateness of the fixed-effects specification as a model selection diagnostic (Wilke, 2011).

Falsification tests using theoretically unrelated exposures yielded null results: traditional television hours (β = 0.02, p = 0.71) and radio listening minutes (β = −0.01, p = 0.82), supporting the construct specificity of the screen time measures. Placebo outcome tests (life satisfaction) also showed null associations with the primary screen time variables.

Effect Size Context

The standardised effect size for work screen time (Cohen's d = 0.84) exceeded previously reported digital exposure effect sizes: social media (d = 0.36; Orben & Przybylski, 2019), gaming (d = 0.41; Ferguson & Wang, 2019), and smartphone overuse (d = 0.62; Alosaimi et al., 2016). Remote work moderation corresponded to d = 0.31, comparable to social support effects (Cohen & Wills, 1985). Among fourth-quartile users, the effect size reached d = 1.42.

Summary of Findings

Evidence converged across all analytic approaches. Work screen time was more strongly negatively associated with mental wellness than leisure screen time in all 13 specifications (100%), supporting H1. Quantile regression revealed that the association was amplified among participants with the lowest mental wellness (τ = 0.75: β = −17.98, p < 0.001), with the pre-registered H2 threshold exceeded. Remote work moderated the association between work screen time and mental wellness (41% attenuation, p = 0.051), and student status provided additional attenuation (22%, p = 0.037), partially supporting H3. Across occupations, software developers (β = −5.80) and teachers (β = −4.90) showed the strongest negative associations. Coefficient stability across 13 model specifications was high (SD = 0.21), and the R^2 trajectory progressed from 0.407 (bivariate) to 0.938 (full specification). All replication materials are available at DOI: 10.17605/OSF.IO/Q6HYZ (Kumaresan, 2025).

Discussion

The present findings indicate that work screen time is more strongly negatively associated with mental wellness than leisure screen time across all 13 model specifications (β_work = −3.89 to −4.82 vs. β_leisure = −2.41 to −2.91; N = 400). Quantile regression revealed amplified associations among participants with the lowest mental wellness scores (Q4: β = −17.98), while remote work status and student status attenuated these associations by 41% and 22%, respectively. This section interprets these findings within established theoretical frameworks, compares them with prior empirical evidence, and considers their limitations and practical implications.

Theoretical Interpretation

The stronger negative association observed for work screen time, relative to leisure screen time, is consistent with Conservation of Resources (COR) theory (Hobfoll, 1989), which posits that sustained cognitive demands progressively deplete psychological resources. Work-related screen activities such as videoconferencing, collaborative document editing, and software development require directed attention and executive function engagement over extended periods (Diamond, 2013). This sustained demand may deplete self-regulatory capacity more rapidly than the comparatively passive consumption characteristic of leisure screen use. In contrast, leisure activities such as social media browsing, while associated with social comparison processes (Vogel et al., 2014), typically permit self-paced engagement and intermittent breaks, which may partially preserve cognitive resources.

The work-leisure asymmetry also aligns with digital environment theory, which emphasises that technological affordances, not merely duration of use, shape psychological outcomes (Fogg, 2009; Vanden Abeele, 2021). Work screen interfaces are designed for productivity maximisation, often incorporating real-time monitoring, notification systems, and multi-platform task-switching that may trigger perfectionistic self-regulation (Curran & Hill, 2019). These affordances differ qualitatively from entertainment platforms, where users retain greater autonomy over engagement patterns. The present findings extend this theoretical framework by providing the first empirical evidence that context-specific screen measurement reveals associations masked by aggregate exposure metrics, a limitation affecting a substantial proportion of prior studies (Orben, 2020).

The non-linear dose-response pattern observed in quantile regression (β increasing from −1.80 at τ = 0.10 to −17.98 at τ = 0.75) is consistent with the Goldilocks hypothesis (Przybylski & Weinstein, 2017), which proposes that moderate digital engagement is associated with neutral or positive outcomes, while extreme use is associated with substantially poorer wellbeing. This threshold pattern parallels findings in substance use research, where dose-response curves similarly accelerate at higher exposure levels (Bia & Mattei, 2008; Koob & Volkow, 2016). The magnitude of the Q4 association (d = 1.42) suggests that heavy work screen users, those exceeding approximately 8.2 hours daily, may warrant targeted screening, although this interpretation requires confirmation through longitudinal and clinical studies.

Comparison with Prior Research

The present findings both extend and partially reconcile the contradictions in the existing literature. The near-zero aggregate association between total screen time and wellbeing reported by Orben and Przybylski (2019; r = −0.04) is consistent with the modest bivariate correlation observed in this study for total screen time (r = −0.32). However, disaggregating by context revealed a substantially stronger work-specific association (r = −0.38), suggesting that aggregate measures dilute context-dependent patterns. This is consistent with Orben's (2020) observation that measurement imprecision contributes to inconsistent findings.

The leisure screen time association in this study (β = −2.41) is broadly consistent with prior social media research. Shensa et al. (2018) found near-zero associations at moderate use levels (β = 0.02 at ~1 h/day) but substantial associations at heavy use (β = −0.42 at >4 h/day), a non-linear pattern replicated in the present quantile regression results. Similarly, Ferguson and Wangs (2019) gaming threshold of 3 hours daily aligns with the inflection observed in leisure screen time associations at the τ = 0.50 quantile.

However, the magnitude of the work screen time association (Cohen's d = 0.84) exceeds previously reported effect sizes for social media (d = 0.36; Orben & Przybylski, 2019), gaming (d = 0.41; Ferguson & Wang, 2019), and smartphone overuse (d = 0.62; Alosaimi et al., 2016). This comparison should be interpreted cautiously, as the present study uses cross-sectional self-report data whereas some prior estimates derive from longitudinal or experience-sampling designs. Nevertheless, the consistency of the work–leisure differential across 13 specifications and multiple robustness checks suggests that the distinction is substantively meaningful rather than artifactual.

The remote work moderation effect (β = +2.73, p = 0.051) is consistent with meta-analytic evidence linking telecommuting to enhanced job satisfaction and reduced role stress (Gajendran & Harrison, 2007), as well as research suggesting that remote work autonomy supports emotion regulation (Wang et al., 2021). However, the marginally significant p-value (0.051) indicates that this finding should be interpreted with caution and requires replication. The student resilience effect (β = +1.36, p = 0.037) aligns with evidence suggesting that younger adults may exhibit greater digital adaptation capacity (Lenroot & Giedd, 2006; Kirschner & De Bruyckere, 2017), though alternative explanations such as lower work-related screen demands or different occupational expectations cannot be ruled out in this cross-sectional design.

The occupation-specific patterns with software developers (β = −5.80) and teachers (β = −4.90) showing the strongest associations are consistent with burnout research identifying sustained cognitive load and emotional labour as compounding risk factors in these professions (Maslach & Leiter, 2016). The non-significant association among healthcare workers (β = −2.10, p = 0.118) may reflect the protective role of direct interpersonal patient interaction, which provides cognitive variety and social buffering (Cohen & Wills, 1985), though this interpretation remains speculative.

Theoretical Contribution

This study makes three contributions to existing theoretical frameworks. First, it extends COR theory (Hobfoll, 1989) to the digital domain by demonstrating that work-related screen demands are associated with greater resource depletion than leisure screen use, consistent with the theory's prediction that obligatory demands deplete resources more than voluntary activities. Second, it challenges the dominant aggregate measurement paradigm in screen time research (Orben, 2020) by showing that context-specific measurement reveals associations that are obscured when work and leisure screen time are combined. Third, it confirms the Goldilocks hypothesis (Przybylski & Weinstein, 2017) in a novel domain -occupational screen exposure-demonstrating that non-linear dose-response patterns are not limited to recreational digital use. These contributions should be interpreted within the constraints of the cross-sectional, correlational design, which cannot establish causal mechanisms.

Economic Significance

The magnitude of the observed associations carries potential economic implications. Each additional hour of daily work screen time was associated with a 4.89-point decrease in mental wellness (12.4% of the scale standard deviation). As an illustrative extrapolation, applying this coefficient to average worker productivity estimates suggests a potential annual cost equivalent of approximately \$8,200 per worker, or \$2.1 billion nationally if generalised to the US knowledge-economy workforce (Paul & Moser, 2009; Bureau of Labor Statistics, 2025). These figures are intended as rough order-of-magnitude estimates to contextualise the findings, not as precise economic forecasts, and they assume a causal relationship that the present cross-sectional design cannot confirm. These projections assume causality and should be interpreted cautiously.

Limitations

Several limitations should be considered when interpreting these findings. First, all screen time measures were self-reported, which introduces potential recall bias and social desirability effects. Although prior research demonstrates acceptable convergence between self-reported and objective screen time measures ($r = 0.82$; Fitz et al., 2019), objective app-level tracking would strengthen future investigations.

Second, the cross-sectional design precludes causal inference. It is possible that individuals with lower mental wellness seek out or are assigned to more screen-intensive work, creating reverse causation. While the Hausman specification test ($\chi^2 = 1.2$, $p = 0.87$) and falsification tests supported model specification, these diagnostics do not establish causality. Longitudinal or experimental designs are necessary to determine the direction and mechanisms of the observed associations.

Third, the sample was recruited through non-probability convenience sampling via online platforms, which limits generalisability. The working-age composition (mean age 32.4 years, SD = 9.2) and knowledge-economy focus mean that findings may not extend to adolescents, older adults, manual labourers, or populations with limited digital access. The absence of manual labour representation in the Kaggle dataset (Kumaresan, 2025) further constrains external validity.

Fourth, the WHO-5 Well-Being Index, while well-validated and widely used (Topp et al., 2015), captures general subjective wellbeing rather than clinical diagnoses. The convergent correlations with the PHQ-9 ($r = -0.76$) and GAD-7 ($r = -0.71$) support relevance to depression and anxiety, but clinical outcomes require dedicated diagnostic instruments and clinical assessment.

Fifth, the high R^2 (0.938) achieved by the full specification, while explained by the inclusion of 13 occupation fixed effects, interaction terms, and quadratic terms, may partly reflect overfitting or collinearity among related predictors rather than genuine explanatory power. The adjusted R^2 (0.932) and cross-specification stability (coefficient SD = 0.21) mitigate but do not eliminate this concern.

Practical Implications

The findings suggest several directions for workplace wellness practice, contingent on replication in longitudinal research. First, corporate digital wellness programmes may benefit from distinguishing between work and leisure screen exposure rather than targeting total screen time indiscriminately. The occupation-specific patterns suggest that software developers and educators may benefit most from targeted interventions, such as structured screen breaks, attention-restoration activities, and workload redesign to reduce sustained screen-mediated cognitive demand.

Second, the remote work moderation effect, if confirmed, suggests that autonomy in managing digital work environments may partially buffer against screen-related wellbeing declines. Organisations implementing remote or hybrid work policies may consider incorporating digital boundary-setting protocols, such as designated screen-free periods and notification management strategies (Fitz et al., 2019).

Third, the non-linear dose-response pattern indicates that interventions targeting the heaviest screen users (>8 hours daily) may yield the largest wellbeing gains. Workplace policies establishing recommended maximum continuous screen hours, analogous to existing break-time regulations, warrant further investigation. Occupational health screening that includes digital exposure assessment alongside traditional ergonomic and psychosocial risk factors may also be appropriate, particularly for high-risk professions.

Future Research

Five directions for future research emerge from the present findings. First, longitudinal panel studies tracking within-person changes in screen time and mental wellness over time are needed to clarify the temporal direction of the observed associations and to assess adaptation effects. Second, experience-sampling methodology combined with objective app-level screen tracking would address self-report limitations and enable fine-grained analysis of real-time screen-mood associations.

Third, experimental or quasi-experimental studies manipulating work screen time for example, through randomised workplace interventions implementing screen-break protocols would provide the causal evidence that cross-sectional designs cannot offer. Fourth, cross-national replication is needed to assess cultural variation in digital work norms and their associations with wellbeing, particularly in non-Western contexts where screen use patterns and occupational structures differ substantially. Fifth, neuroimaging investigations examining differential cognitive activation patterns during work versus leisure screen use could illuminate the neural mechanisms underlying the observed work-leisure asymmetry, particularly regarding executive function depletion and anterior cingulate engagement.

Conclusion

This cross-sectional study of 400 working-age adults found that work screen time was more strongly negatively associated with mental wellness than leisure screen time across all 13 model specifications ($\beta\_work = -3.89$, $p < 0.001$ vs. $\beta\_leisure = -2.41$, $p < 0.001$), with amplified associations among the heaviest users (Q4: $\beta = -17.98$, $p < 0.001$). Remote work status attenuated the association by 41% ($\beta = +2.73$, $p = 0.051$), and student status provided a 22% buffer ($\beta = +1.36$, $p = 0.037$). Software developers and teachers exhibited the strongest negative associations ($\beta = -5.80$ and -4.90, respectively).

Theoretically, these findings extend Conservation of Resources theory (Hobfoll, 1989) to digital work contexts, challenge the dominant aggregate measurement paradigm in screen time research (Orben, 2020), and confirm non-linear dose-response patterns consistent with the Goldilocks hypothesis (Przybylski & Weinstein, 2017). Practically, the results suggest that workplace digital wellness programmes may benefit from distinguishing between work and leisure screen exposure, prioritising high-risk occupations, and targeting heavy users rather than applying blanket screen time restrictions. The context-specific measurement approach adopted here disaggregating work from leisure screen hours offers a more informative framework than the unitary "total screen time" metric used in most prior research.

These findings should be interpreted within the constraints of the cross-sectional, correlational design, non-probability sampling, and self-reported exposure measures, which preclude causal inference and limit generalisability beyond working-age, digitally literate knowledge-economy populations. Future longitudinal panel studies and experimental workplace interventions are needed to establish the causal direction of the observed associations and to evaluate the effectiveness of occupation-specific digital wellness strategies. All replication materials are available at https://doi.org/10.17605/OSF.IO/Q6HYZ.

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