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Research Article

The Mediating and Moderating Role of Time Management Strain in the Relationship between Social Media Usage and Employee Performance

Aman Mittal[1], Roopali Batra[2]

[1]Research Scholar, IKG Punjab Technical University, Main Campus, Kapurthala

[2]Assistant Professor, Department of Management Studies, IKG Punjab Technical University, Main Campus, Kapurthala

***Corresponding Author**

Aman Mittal

(aman.mittal@gmail.com)

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Abstract: Social media is now embedded in day-to-day work especially in Higher Education Institutions (HEIs) yet its effects on employee performance (EP) remain unclear. This study argues that impacts of Social media Use (SMU) are indirect and conditional operating through self-regulatory costs. Using multi-stage sampling across six HEIs in Punjab (India), this study surveyed 707 employees and estimated structural equation modelling with parallel mediation and latent interaction of time-management strain (TMS) and workplace distractions (WD). The study finds that greater social media use reliably increases both strain and distractions which in turn reduce employee performance. The direct link from social media usage to employee performance is found to be negligible. The time-management and high strain further amplifies the negative association between SMU and employee performance. For stakeholders the takeaway is practical, rather than restricting platforms, HEIs should focus on better time management and reducing workplace distractions. As complete bans on social media use are unlikely to help employee performance. Employee Performance risks from Social media arise chiefly from time management strain and secondarily, cue-driven distractions in workplace. Leaders should prioritize time-management standards (protecting focused time-blocks, meeting hygiene's, clear response-time expectations) and distraction's hygiene during work-hours.

Keywords: Social media, Work-related Social media Use, Higher Education Institutions, Employee Performance, Time Management, Workplace Distraction.

INTRODUCTION

Social media is now woven into daily work (Fang et al., 2024; Sarah Chanu, 2025), Employees of every organization including Higher Education Institutions (HEIs) where staff and faculty use public platforms and enterprise tools to coordinate classes (Aleksandrova & Parusheva, 2019), share resources, answer student queries, and manage committees. Social media speed information flow and expand networks but they also do blur work–personal boundaries and create constant cues to check, reply and scroll (Allen et al., 2014). In the HEIs this dynamic intensifies as academic calendars create peak loads many roles are student-facing and collaboration spans departments and external partners. As a result, employees juggle teaching, administration, research and service while navigating high volumes of messages and notifications. Social media can help task completion and outreach yet it also risks fragmented attention and schedule slippage (Boulianne, 2015). This study takes that duality seriously and examines how social media use relates to performance focusing on two self-regulatory mechanisms especially salient in HEIs time-management strain (TMS) (Jex & Elacqua, 1999; Macan, 1994) and workplace distractions (WD) (Celebi et al., 2022; Marengo et al., 2020).

The institutional risk is structural as student-facing roles and committee work create constant availability expectations with multiple WhatsApp groups, emails and updates multiply pings (Koessmeier & Büttner, 2021). Prior studies report mixed direct links between social media and performance (Leftheriotis & Giannakos, 2014a; Oksa et al., 2022) because they do not isolate these self-regulatory costs. This paper tackles the problem by testing whether performance impacts are indirect (via time strain and distraction) and conditional (worse when strain or distraction are high) providing a clearer basis for practical policy inside HEIs.

Evidence on social media and performance is mixed because most studies treat "social media use" as a single construct and test direct effects. Limited works have jointly examined time-management as strain and workplace distractions as parallel and fewer still tested boundary conditions using latent interactions. Contextually, HEIs with intense student-facing communication, committee work, and multi-channel norms are underrepresented, especially in the Indian public–private landscape. This study addresses these gaps by

- Distinguishing work vs. problematic facets of Social media Use (SMU).
- Modelling parallel mediation through lens of time-management strain (TMS) and workplace distractions (WD).
- The study tests moderation via latent interactions of TMS and WD.

The study provides large-sample evidence from six HEIs in Punjab. The goal is to replace an ambiguous direct-effect story with a mechanism-first, policy-relevant explanation of how and when SMU affects employee performance (EP).

The paper is organised into sections where section 2 reviews the literature and develops the hypotheses distinguishing work-related and problematic social media use and motivating the mediation–moderation model. Section 3 describes the Research design with methods sampling, measures, data screening, and the SEM approach. Section 4 reports results construct descriptives, CFA (measurement quality), direct paths, mediation and moderation tests. Finally, the Section 5 discusses what the findings mean for theory and for HEIs, and situates them against prior studies. Section 6 concludes with contributions, limitations, future research directions, and closing remarks.

LITERATURE REVIEW:

This section builds the case for how social media use at work is linked to employee performance. It shows how time-management strain and distractions can lower performance. Finally, developing the mediation–moderation model and state the hypotheses that guide analysis.

Social Media Usage and Employee Performance

Employee social media use (SMU) (Tuck & Thompson, 2024) is now embedded in everyday work with studies distinguishing from work-related use (knowledge sharing and coordination) to personal leisure use during work hours (X. Chen & Wei, 2020). Meta-analytic evidence indicates that, on average, employee SMU shows small, positive associations with job performance yet effects are heterogeneous and contingent on use purpose and context (Leftheriotis & Giannakos, 2014b). In line with this, large-sample and recent studies of work-related SMU report positive links to performance (Cao & Yu, 2019) through mechanisms such as visibility, association, and psychological empowerment, particularly in enterprise social media contexts (Fusi & Feeney, 2018; Song et al., 2019).

Countervailing evidence highlights costs when SMU is personal and excessive at work (Brooks & Califf, 2017; Wei et al., 2024). Empirically, social media–induced technostress is negatively related to job performance, and newer work isolates cue-driven attentional capture as a direct distraction channel (Wei et al., 2024). Complementary studies using behavioural and neurocognitive approaches also show decrements in task-related functioning under social-media distraction (Brooks & Califf, 2017).

These mixed findings are often reconciled by purpose-specific instruments targeting work-related SMU. For instance SMUW (Koessmeier & Büttner, 2021) and WSMQ (Landers, 2014)) tend to correlate positively with performance, whereas problematic or compulsive use exampled include BSMAS (Gomez et al., 2024), Short Internet Addiction Test-SNS (Wegmann et al., 2015) adaptation s-IAT-SNS (Valenti et al., 2025) tracks strains and counterproductive outcomes. Consistent with literature this work anchors SMU measurement on the work vs. problematic distinction using the scales summarized in Table 1.

Time-Management Strain as a Mediator

Time-management strain (TMS) (Francisco et al., 2023) can be defined as the pressure, fragmentation (Franssila, 2019) and reduced perceived control of time. Foundational work on the Time Management Behavior Scale (TMBS) (Rao & Azmi, 2018) shows that planning and perceived control of time are tied to better job attitudes and performance. However, deficits co-occur with stress and inefficiency (Claessens et al., 2007) thus the proposed study draws on TMBS (Macan, 1994). Why would SMU heighten TMS? As technology mediated interruptions (Ohly & Bastin, 2023) and cue salience (alerts, feeds) steal time slices and load the self-regulatory system. The interruption overload degrades task closure which in turn hinders work performance (Bailey & Konstan, 2006) with mediation evidence linking interruptions to overload which leads to performance decrements (A. Chen & Karahanna, 2018).

Social media specifically is a potent distractor that tempts time-inconsistent checking; empirical studies document attentional capture and self-reported distraction in everyday settings (Koessmeier & Büttner, 2021). In parallel the need to respond quickly to digital messages—amplifies time pressure and impairs recovery, raising strain and burnout correlates that compete with planned task time (Hu et al., 2019). When alerts and availability norms accumulate, time and attentional control are depleted, increasing TMS and undermining performance. Aligned with our instrument choices (SMUW and WSMQ for work use; TMBS), this study expect that SMU increases TMS and higher TMS reduces employee performance (EP) yielding a negative indirect effect of SMU on performance via TMS. This directly motivates H1 (SMU → TMS > 0), H3 (TMS → EP < 0), and H5 (SMU → TMS → EP < 0).

Workplace Distractions as a Mediator

Workplace distractions (WD) (Roper & Juneja, 2008) can be defined as cue-driven attentional capture which diverts focus to social media. WD encompass both external triggers such as pop-up notifications and internal urges to check feeds (Koessmeier & Büttner, 2021). Empirically, even without active phone use, brief notifications measurably impair performance on attention-demanding tasks, and the mere presence of one's smartphone reduces available cognitive capacity (Ward et al., 2017). In organizational settings personal social media use at work is linked to distraction, technostress, and decrements in task performance, supporting a negative WD to EP path (Brooks, 2015). Thus, greater SMU increases exposure to cues and checking opportunities which thereby raises WD. Higher WD in turn lowers employee performance (EP) through lost time, switching costs, and attention residue. This logic motivates H2 (SMU → WD > 0), H4 (WD → EP < 0), and the indirect effect via WD in H6 (SMU → WD → EP < 0), which we test in our parallel-mediation model.

Moderating Role of Time Management

Direct evidence from interruption research supports a moderation role for time management (Vizcaíno et al., 2021). Field studies show that employees with stronger time-management skills appraise workflow interruptions as less hindering and experience a weaker link between interruptions and time pressure precisely the pathway through which social-media cues tend to erode performance (Ma et al., 2020). Research further indicates that perceived time control moderate the interruptions and performance relationship (Häfner & Stock, 2010) which suggest a buffering effect. Accordingly, SMU and EP slope is we expected to depend on time-management capability the higher the capability (lower TMS) the weaker the negative SMU and EP relationship. Conversely, when TMS is high, the negative slope should intensify. Formally, this yields H6 in the model (latent interaction SMU × Time-Management → EP).

Conceptual Framework and Hypotheses Summary

The framework is conceptualized in figure 1 whcih integrates self-regulation perspectives with interruption theory to explain how Social Media Use (SMU) relates to Employee Performance (EP) through two parallel self-regulatory pathways Time-Management Strain (TMS) and Workplace Distractions (WD). Also, when these effects are strongest SMU is expected to raise TMS by fragmenting schedules and eroding perceived time control and increase WD via cue-driven attentional capture. Both mediators independently depress EP.

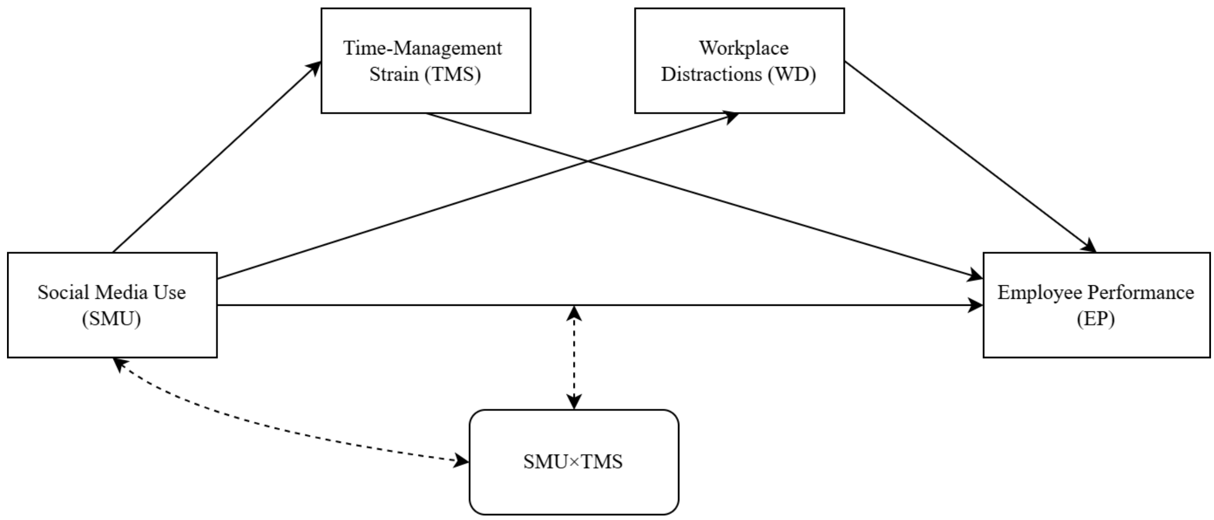

Figure 1: Conceptual model used in the paper to study effects of SMU through WD and TMS on EP

Because TMS and WD tap related but distinct mechanisms they are modelled in parallel. A direct SMU→EP path is retained as a benchmark. Finally, latent interaction SMU×TMS is used to assess whether high strain or high distraction amplifies the negative impact of SMU on performance. The hypothesis used in the study can be formulated as Direct Paths Higher social media usage (SMU) influences greater time-management strain (TMS).

- Higher SMU influences more workplace distractions (WD).
- Greater TMS influences lower employee performance (EP).
- More WD influence lower employee performance (EP).

Parallel mediation

- SMU lowers employee performance (EP) indirectly by increasing TMS.
- SMU lowers employee performance (EP) indirectly by increasing WD.
- The combined indirect effect of SMU on performance (via strain and distractions) is negative.

Moderation effects

The negative link between SMU and EP is stronger when TMS is high.

Research Design

This study adopts a quantitative cross-sectional design using a multi-site survey of HEIs in Punjab, India. Guided by a theory-driven mediation–moderation framework, the model specifies SMU as the antecedent of EP, operating through two parallel mediators TMS and WD with TMS and WD also moderating the SMU→EP path via latent interactions.

Sampling Procedure and Target Population

The target population comprised employees of HEIs in Punjab, India both teaching and non-teaching staff. A multi-stage, region–sector sampling strategy was implemented to ensure geographic and institutional heterogeneity. In Stage 1, Punjab was divided into its three administrative regions (Malwa, Majha, Doaba). In Stage 2, within each region one public and one private HEI were selected. In Stage 3, eligible employees from 73 HEIs participated covering academic and administrative units. Inclusion Criteria of Employees included, Currently employed (teaching or non-teaching) at a participating HEI in Punjab with at least 6 months of continuous service, ensuring stable exposure. Employees between Age ≥ 18 and working ≥ 20 at-least hours per week so that the performance and distraction measures remain meaningful. Employees who Provided informed consent and submitted analysable responses on the constructs (SMU, TMS, WD, EP) with ≤ 20% missing items per scale after data screening.

Sample size planning

The study planned for a large-N design to ensure stable estimation of a moderately complex SEM with 33 observed indicators (SMU 13, TMS 8, WD 7, EP 5), two parallel mediators, and two latent interactions (SMU×TMS). It ensures adequate statistical power for detection of small-to-moderate structural paths bias-corrected bootstrapped indirect effects in a parallel-mediation and latent interaction (moderation) effects.

We targeted power ≥ .80 ($\alpha = .05$, two-tailed) to detect standardized path coefficients of β near .15–.20 range and small indirect effects under realistic measurement conditions. For moderation, planning assumed a small incremental effect for the latent product term SMU × TMS which typically requires large observations for stable estimation.

Second practical rationale followed the breadth of the complete study, as although the present study analyses a subset of constructs, the complete questionnaire contained 66 items for the study of further effects of social media usage on employee performance through other lenses. For scale and factor-analytic designs widely cited heuristics recommend 10 respondents per item, implying a floor near 660 responses which our achieved N exceeds (66×10 = 660) in total N = 707.

Data collection and Ethics

Data were collected via a structured, self-administered questionnaire hosted on Google Forms. The survey link was distributed through institutional channels at the selected HEIs. To improve the response rates and reduce nonresponse bias two reminder emails were issued at reasonable intervals. Participation was completely voluntary and anonymous. A detailed consent statement appeared on the opening page describing the study purpose, expected time (approx. 16 mins) and contact information for queries was provided. Proceeding to the survey required informed consent and participants were explicitly informed of the right to withdraw at any point prior to submission. No personally identifying information was collected beyond basic demographics. All procedures complied with ethical guidelines for research with human participants. Data were stored on restricted-access drives, with de-identified files used for analysis.

Achieved sample and response rate

During the data collection period (June 1–September 30, 2025) a total of 2,415 invitations were distributed across the six participating HEIs. We received 860 submissions, yielding a gross response rate of 35.6% . After applying the a priori data-quality screens (consent and eligibility, ≤20% missingness per scale, attention, consistency checks and implausible completion-time flags) 707 responses were retained for analysis. This corresponds to an overall valid rate of 29.3% relative to invitations (707/2,415) and a usable rate of 82.2% relative to submissions (707/860).

Sample Characteristics and Demographics

The final analytic sample comprised N = 707 employees drawn from six HEIs in Punjab (three public, three private) distributed across the Malwa, Majha, and Doaba regions. Role composition was teaching = 467 (68%) and non-teaching = 240 (32%), reflecting the staffing profile of participating institutions. The gender split was female = 319 (45.1%) and male = 388 (54.9%). This multi-site, region–sector coverage introduces heterogeneity in governance (public/private) and job function (academic/administrative), enhancing the external validity of inferences for the HEI workforce in the state. Descriptive statistics for the focal constructs indicate moderate levels of social media use and distractions alongside lower self-rated performance (SMU: M = 3.69, SD = 1.03; TMS: M = 2.96, SD = 0.96; WD: M = 3.74, SD = 0.97; EP: M = 3.30, SD = 1.10), with inter-construct correlations reported in Table 1.

Measurement of Constructs

All constructs used in the study are modelled as reflective latent variables estimated with CFA prior to the structural tests. Items used five-point Likert scale anchored in 1 = strongly disagree to 5 = strongly agree, and frequency stems 1 = never to 5 = very often. Items were coded so higher scores = more of the construct. Table 1 presents the constructs and the scales used .

Table 1:Key Scales and studies and adaptation rationale

Construct	Scale	Adaptation Rationale
Social-Media Usage (General)	Social Media Use Scale - SMUS (Tuck & Thompson, 2024) Short Internet Addiction Test-SNS version (Wegmann et al., 2015) s-IAT-SNS (Valenti et al., 2025)	SMUS items capture frequency, duration and multi-platform breadth; s-IAT-SNS contributes compulsive-use symptoms for discriminant validity.
Social-media usage (problematic)	**Bergen Social Media Addiction Scale (BSMAS)** – 6 items, 5-point Likert (Gomez et al., 2024) (Zarate et al., 2023) cross-culturally validated	Adds problematic-use which complements frequency-based SMUS items useful for testing U-shaped SM & performance.
Social-Media at Work	Work-related Social Media Questionnaire WSMQ (Landers & Callan, 2014)	Studied both Harmful and Positive impact of SM in workplace
	Social-Media Use for Work (SMUW) (Koessmeier & Büttner, 2021; Leftheriotis & Giannakos, 2014a)	Focuses on instrumental use knowledge sharing aligning with “employee performance”
Time Management Strain	SMUW “Time Budget” sub-scale + Work-Performance (WP) items (Leftheriotis & Giannakos, 2014)	Measures planning discipline and adherence to schedules—primary mediator between SM intensity and performance.
	Time-Management Behaviour Scale (TMBS), 33 items (Macan, 1994)	Gold-standard measure of planning, prioritising and perceived control of time; widely cited in performance research and shows α ≥ 0.80.
	SONTUS: Social networking time use scale (Olufadi, 2016)	Designed to measure time used on the **Social networking sites**.
Workplace Social-Media Usage	Workplace Social Media Usage Scale (Celebi et al., 2022)	Distinguishes passive browsing vs active content creation, matching recent findings that motive moderates performance impact (Ononye et al., 2023).
	Job-Related Social-Media Scale (Marengo et al., 2020) – distinguishes content creation, networking, entertainment	Helps test whether *active* (posting) versus *passive* (scrolling) use moderates the SM to performance link.
Workplace Distractions	Digital-Distraction scale (Koessmeier & Büttner, 2021), Interpretability items (Chu et al., 2021); Social-media distraction markers (Brooks, 2015; Luqman et al., 2017)	Combined to capture both internal (urge to check feeds) and external (notification pings) distractions.
	Workplace Interruption Scale (Jett & George, 2003) – 10 items on frequency & affective impact.	Separates self-initiated vs external interruptions, giving finer granularity

		than Koessmeier & Büttner's digital-distraction items.
	Social Media App Distraction Engagement (SMA-DE) (Sidnam-Mauch & Monge, 2024)	Studied the consequence of mobile SM distraction which is influenced by a complex behaviours.
Work Performance	IWPQ (Benn et al., 2015)Work-Performance (WP) scale (Leftheriotis & Giannakos, 2014a) Digital-era performance items (Oksa et al., 2022)	Captures both self-rated efficiency and quality of output; prior studies (Gallup, 2024; Khan et al., 2020) confirm strong convergence with supervisor ratings.
	WHO Health & Work Performance Questionnaire (HPQ) – self-reported performance loss & absolute output (Kessler et al., 2003)	Frequently used in cross-industry studies; can validate IWPQ findings and translate into cost-of-distraction estimates.

Social Media Use (SMU)

SMU indexes intensity and breadth of use during work with content drawn from the SMUS (frequency, duration, multi-platform breadth) (Tuck & Thompson, 2024) and selected problematic-use symptoms adapted from s-IAT-SNS (Valenti et al., 2025) and BSMAS (Gomez et al., 2024) to strengthen discriminant validity against work performance. Wording was harmonized to the work context (adding "during working hours or at work"). In total 13 items were selected for SMU. Items for Workplace related SMU was adapted from WSMUS (Celebi et al., 2022).

Time-Management Strain (TMS)

TMS captures planning pressure, schedule slippage, and reduced perceived control of time. Items were adapted from the Time-Budget workflow content used in SMUW and from the Time-Management Behaviour Scale (TMBS) (Macan, 1994) for with stems reframed so that higher scores reflect strain or mismanagement.

Workplace Distractions (WD)

WD measured the cue-driven attentional capture by social media at work (Koessmeier & Büttner, 2021) , spanning external triggers (e.g., notifications) and self-initiated urges to check. Items were drawn from a digital-distraction battery and the Workplace Interruption Scale (Jett & George, 2003) having frequency, affective impact plus social-media distraction markers used.

Employee Performance (EP)

EP reflects the self-rated task efficiency and output quality using items adapted from the IWPQ (Benn et al., 2015) related to Work-Performance Scale (Leftheriotis & Giannakos, 2014a) its anchors align with recent digital-era performance wording. Higher scores indicate better performance of the employees. Final item counts per construct and summary statistics are presented with reliability validity results in Table 3.

RESULTS

This section presents results of the study, first reporting construct descriptives and inter-construct correlations then confirm measurement quality via CFA. Structural model with presenting direct paths, bootstrapped mediation, and latent-interaction (moderation) tests with all coefficients standardized are also presented.

Construct Descriptives and Correlations

Inter-construct correlations with means and SDs are reported in Table 2 for the four variables. On average, respondents reported moderate–high SMU (M = 3.69, SD = 1.03) and workplace distractions (M = 3.74, SD = 0.97), with time-management strain around the mid-point (M = 2.96, SD = 0.96) and employee performance slightly above mid-scale (M = 3.30, SD = 1.10).

Table 2: Descriptive and inter-construct correlations.

Construct	items	Mean	SD	1	2	3	4
SMU	13	3.69	1.03	1			
TM	8	2.96	0. 96	0.56**	1		
WD	7	3.74	0.97	0.51***	0.43***	1	
EP	5	3.3	1.1	-0.24**	-0.38***	-0.25**	1

Note. N = 707. Two-tailed significance: * p < .05, ** p < .01, *** p < .001. Diagonal elements are 1.

Correlations were in the hypothesized directions where SMU correlated positively with TMS (r = .56, p < .01) and WD (r = .51, *p < .001), TMS correlated positively with WD (r = .43, *p < .001) and EP correlated negatively with SMU (r = –

.24, $p < .01$), TMS ($r = –.38$, *$p < .001$) and WD ($r = –.25$, $p < .01$). The largest absolute correlation was .56, indicating no severe bivariate collinearity and supporting discriminant patterns later confirmed by CFA (√AVE > correlations; HTMT < .85).

Measurement Model (CFA) and Reliability

A four-factor reflective CFA (SMU, TMS, WD, EP) was estimated in AMOS using maximum likelihood. Global fit was excellent where $\chi^2(458) = 449.19$, $p = .607$, $\chi^2/df = 0.98$. All indicators were as shown in Table 3 loaded significantly ($p < .001$) on their intended factors.

Table 3: model fit statistics

Fit Index	Value	Guideline	Interpretation
χ^2 (CMIN)	449.194	-	Non-significant χ^2 indicates excellent fit
df	458	-	-
p-value	.607	p > .05	For χ^2
χ^2/df (CMIN/DF)	0.981	< 2.00 (very good)	Very good
RMSEA	.000	≤ .06 (good)	Excellent
RMSEA 90% CI	.000 – .012	-	narrow CI near 0
CFI	1.000	≥ .95	Excellent
TLI (NNFI)	0.996	≥ .95	Excellent
NFI	.966	≥ .95 (good)	Good
RFI	.964	≥ .90 (acceptable)	Good

Composite reliability met or exceeded recommended levels (SMU = .947; TMS = .914; WD = .873; EP = .843), and AVE supported convergent validity (SMU = .582; TMS = .574; WD = .500; EP = .521). Discriminant validity held under Fornell–Larcker (√AVE > inter-construct correlations) (Fornell & Larcker, 1981) and HTMT (< .85). These results support the adequacy of the measurement model and justify estimating the structural paths.

Table 4: Reliability and Convergent Validity (CFA-based)

Construct	Items (k)	Cronbach's α	AVE	√AVE	CR (ρc)
Social Media Usage (SMU)	13	0.947	0.582	0.763	0.947
Time Management Strain (TM)	8	0.913	0.574	0.758	0.914
Workplace Distraction (WD)	7	0.872	0.500	0.707	0.873
Employee Performance (EP)	5	0.843	0.521	0.761	0.843

Composite reliability was satisfactory for all constructs (SMU = 0.947, TM = 0.914, WD = 0.873, EP = 0.843), exceeding the recommended threshold of 0.70. Convergent validity was supported; AVE exceeded 0.50 for all constructs (SMU = .582, TM = .574, WD = .500, EP = .521; TC = .579, EE = .586). Discriminant validity was assessed using the Fornell–Larcker criterion by comparing √AVE with inter-construct correlations and by HTMT. Cronbach's α indicated satisfactory reliability across all constructs (SMU = .947; TM = .913; WD = .872; EP = .843; TC = .893; EE = .887) surpassing the .70 benchmark

Structural Model Results

With the measurement model established, the structural relations among SMU, TMS, WD and EP are estimated in this section. Direct effects are tested H1–H4, mediation effects via TMS and WD are tested for hypothesis H5–H7 and the H6 (moderation) between SMU and TMS also tested. For completeness, the SMU to EP path is also tested alongside the mediated paths.

Direct Effects

Results of the structural paths align with the theorized hypothesis (H1-H4). SMU strongly predicts both mediators as a one–SD increase in SMU is associated with +0.565 SD in WD and +0.606 SD in TMS (both $p < .001$) which supports both H1 and H2. On Employee performance end the construct TMS has a sizable negative effect ($\beta = −0.402$, $p < .001$) whereas WD has a smaller but significant negative effect ($\beta = −0.269$, $p = .019$) supporting hypothesis H3 and H4.

Table 5: Direct Structural paths of the model

Path	β (Std.)	B (Unstd.)	SE	t / z	p	Remarks

SMU → WD	0.565	.446	.035	12.612	***	Significant
SMU → TM	0.606	0.578	0.045	9.467	< .001	Significant
WD → EP	-.269	-.260	.064	-2.340	.019	Significant but the effect is negative.
SMU → EP	.043	.042	.053	.787	.431	Relationship is insignificant
TM → EP	-0.402	-.407	.056	-7.336	***	R/ship significant and the effect is negative.

Notably, direct SMU → EP path is small and nonsignificant (β = +0.043, p = .431) indicating no evidence of a net direct effect once TMS and WD are in the model. Practically, time-management strain in the study is the dominant driver of performance loss (with 3x the magnitude of WD's effects) consistent with the idea that heavy social-media use hurt performance by eroding time control rather than only by momentary distraction. Together with the bootstrapped indirects (reported Table 5) this pattern points to indirect rather than direct effects of SMU on performance, as hypothesized.

Mediation Results

Both specific indirect effects from SMU to EP were negative and significant confirming the parallel-mediation logic introduced above estimated using 5,000 bias-corrected bootstrap resamples. The path SMU → WD → EP yielded β = −.120, 95% CI [−.175, −.070], p < .001 and the path SMU → TMS → EP yielded a larger effect β = −.274, 95% CI [−.339, −.215], p < .001. Because both confidence intervals exclude zero H5 (via TMS) and H6 (via WD) are supported, and the combined indirect (H7) is unambiguously negative. In magnitude, the TMS route is ~2.3× stronger than the WD route (−.274 vs. −.120) indicating that erosion of time control is the primary channel through which SMU depresses performance, with distraction providing an additional but smaller drag.

Table 6: Mediation Results, Bootstrapped indirect of SMU on EP (5,000 samples; bias-corrected 95% CI; standardized)

Path	β	95% CI [LL, UL]	p	Remarks
SMU → WD → EP	-.120	[-.175, -.070]	.000	Significant negative effect
SMU → TM → EP	-.274	[-.339, -.215]	.000	Significant negative effect

Interpreting this with the direct effects, the direct SMU → EP link is negligible and non-significant while the indirect effects are sizable and negative. This pattern indicates the performance impact of SMU operates indirectly chiefly by increasing time-management strain and, to a lesser extent, workplace distractions rather than through a standalone direct pathway. Practically, it prioritizes time-management interventions (planning discipline, response-norms, time blocking) as the highest-leverage lever, complemented by distraction controls (notification hygiene, batch-checking) to further reduce the indirect harm.

Social media doesn't hurt output by magic it does so mostly by eroding time control and secondarily, by pulling attention off current task. Within the indirect channel near 70% of the harm comes from TMS (−0.274/0.394) remaining approx. 30% via WD. In practice, performance gains will come more from time-management than from raw rules "use less social media".

Moderation Analysis (Interaction Effects)

The results show that the interaction between social media use and time-management strain is negative and statistically significant whereas main effects of SMU is negligible and TMS shows a clear negative main effect on performance. Thus. when time-management strain is high additional social media use is more harmful for employee performance. When strain is low the SMU–performance relationship is found to be flat to slightly positive. This pattern supports the moderation hypothesis (H8) TMS conditions the impact of SMU amplifying losses in employee performance.

- At low TMS (−1 SD): slope(SMU→EP) ≈ −0.020 + 0.116 = +0.096 (slightly positive/near zero).
- At high TMS (+1 SD): slope(SMU→EP) ≈ −0.020 − 0.116 = −0.136 (negative).

Table 7: Moderation of TM on the SMU → EP relationship (standardized predictors)

Path	B	SE	CR	p	Remarks
SMU → EP	-.020	.044	0.458	.647	No effect.

TM → EP	-.499	.052	3.384	< .001	Significant negative moderation
SMU × TM → EP	-.116	.043	11.682	< .001	TMS moderates the effect of SMU on performance.

The plot (Figure 2) mirrors this as the low-TMS line is slightly upward, whereas the high-TMS line slopes downward. Substantively, when employees manage time well additional SMU is not harmful (and may be marginally helpful, for coordination and knowledge sharing). When time-management strain is high more SMU diminishes performance consistent with our H6 (amplification under strain).

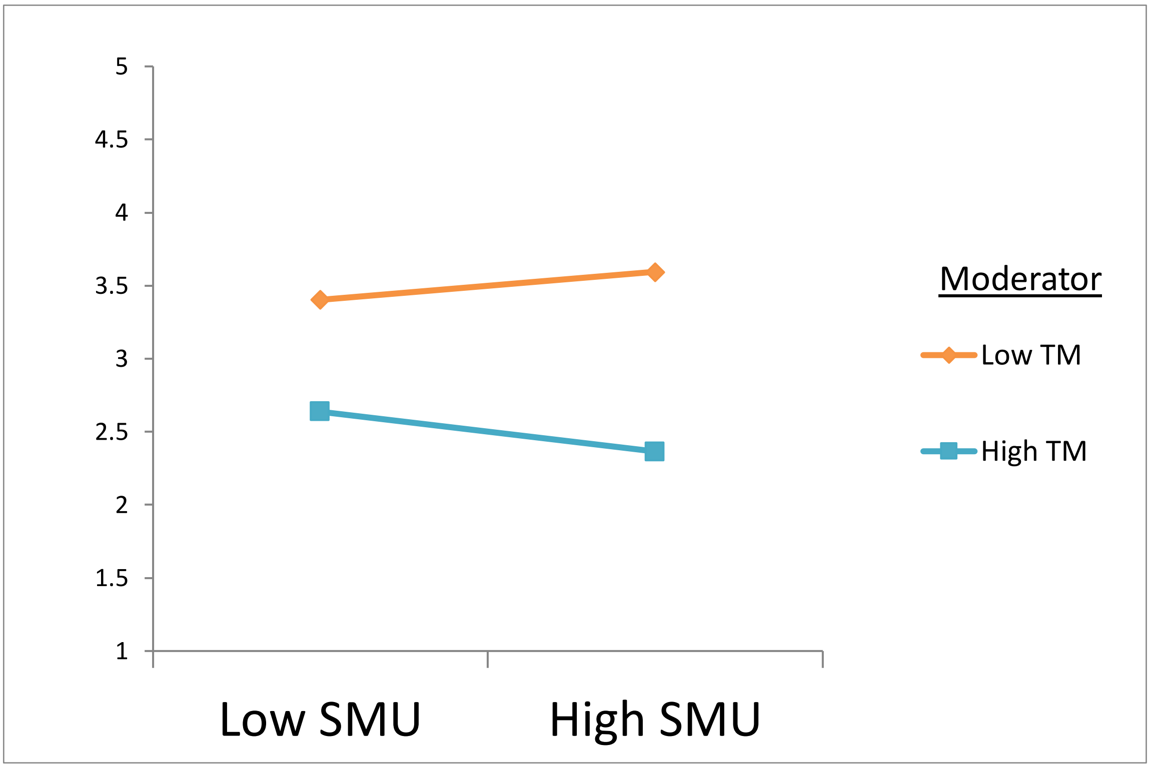

Figure 2: Time Management Strain as Moderator

Performance risk from SMU is conditional as the leverage point is reducing TMS (planning discipline, time-blocking, response-norms, limiting mid-task checking). Lowering time strain flattens the SMU → EP slope turning a liability into something closer to neutral.

RESULTS DISCUSSION

The study's measurement model was strong (χ^2/df = 0.98, CFI = 1.00 and TLI = .996),with all constructs showing adequate reliability and convergent/discriminant validity. Descriptively, SMU correlated positively with TMS and WD. Both TMS and WD correlated negatively with EP anticipating the structural results.

Table 8: Grid summary of the results obtained

Test	Path	Std. coef. (β/B)	Supported	Notes
Direct (H1)	SMU → TMS	+0.606***	Yes	SMU substantially increases time-management strain
Direct (H2)	SMU → WD	+0.565***	Yes	Large, positive link to workplace distractions
Direct (H3)	TMS → EP	−0.402***	Yes	Strongest performance driver (negative)
Direct (H4)	WD → EP	−0.269***	Yes	Smaller, but significant decrement to EP
(Direct)	SMU → EP	+0.043	No	Net direct effect disappears once mediators included

Mediation (H5)	SMU → TMS → EP	−0.274***	Yes	Primary indirect channel (approx. 70% of total indirect)
Mediation (H6)	SMU → WD → EP	−0.120***	Yes	Secondary indirect channel (near 30% of total indirect)
Mediation (H7)	Total indirect	−0.394***	Yes	Sum of H5 + H6 (derived) outweighs direct path
Moderation (H7)	SMU × TMS → EP	−0.116***	Yes	SMU is more harmful when TMS is high; at low TMS the slope ≈ 0

Notes. Coefficients are standardized and mediation CIs from 5,000 bias-corrected bootstraps, *** $p < .001$

The pattern is crisp as summarized in Table 8 SMU at work feeds two self-regulatory drains time-management strain (β=+0.606) and distractions (β=+0.565) which leads to performance drops mainly via TML (β=−0.402) and to a lesser extent via distractions (β=−0.269). The direct SMU → EP path vanishes once these are modelled while the indirect effects are sizable and negative (−0.394). When strain or distractions are high the SMU → EP slope becomes more negative (SMU×TMS β=−0.116). In practice, biggest gains in performance will come from time-management then managing distractions rather than blunt reductions or bans in overall social media use.

Concurrent validity is supported by the expected correlation pattern among simultaneously measured constructs. SMU correlated positively with TMS (r =.56) and WD (r =.51) (Leftheriotis & Giannakos, 2014; Wegmann et al., 2015) and both strain and distractions correlated negatively with performance (TMS–EP r = -.38 and WD–EP r = -.25) a pattern consistent with recent evidence (Gao & Shao, 2024; Ohly & Bastin, 2023) that notification-driven interruptions increase strain and reduce performance (Brooks, 2015) and that smartphone cues measurably impair cognitive control, reviews of problematic SMU (Gomez et al., 2024; Zarate et al., 2023) similarly tie compulsive tendencies to poorer work outcomes. Smartphone notifications and even mere device presence tax cognitive capacity (Upshaw et al., 2022) precisely the mechanism WD items target. In parallel, TMS and WD correlate negatively with performance core findings from time-management and interruption research (Ma et al., 2020; Macan, 1994). The same directions appear in our structural paths (SMU→TMS and WD > 0; TMS and WD→EP < 0; SMU→EP = 0) (Leftheriotis & Giannakos, 2014) reinforcing concurrent validity for the study measures and their theorized associations.

Theoretical Implications

The key findings of the study can be to reframe the SMU and performance debate as a self-regulation problem rather than a direct-effects story. Once time-management strain (TMS) and workplace distractions (WD) are modelled, direct SMU → EP path becomes insignificant. While the indirect effects are sizable and negative which helps reconcile mixed prior results by showing that performance costs arise not from "using social media" per se, but from the resource depletion it triggers. Also, the evidence separates two mechanisms that are often conflated. TMS (loss of time control) and WD (cue-driven attentional capture) are empirically distinct operating in parallel both depressing employee performance yet TMS dominates in magnitude. Moderation results show that SMU's effects are conditional on resource states as when TMS or WD is high the SMU → EP slope becomes more negative. This pattern is consistent with JD-R/COR (Bakker & Demerouti, 2007) predictions about demand–resource imbalances. Thus, depleted control and high cue salience amplify the harm of additional digital demands. It also identifies boundary conditions under which SMU can be neutral (low strain/low distraction).

This study enriches the existing literature by reframing the social media and performance debate from a direct-effect question to a mechanism-first interpretation, integrating interruption and resource theories by modelling parallel mediation (TMS, WD) and latent moderation (SMU×TMS). It also contributes a validated, portable SEM template tested on a large multi-site HEI sample which can be applied to other digital demands (email, chat, notifications) on the employees.

Practical and Policy Implications for HEIs

Because the performance harm from SMU is indirect and conditional, the biggest wins come from restoring time control and taming cue-driven distraction, not simple bans. Treating social media as a workflow design issue not a moral one can prove to be beneficial to HEIs. Developing policies which increase perceived control of time and reduce ambient cues will yield the largest performance gains with minimal cultural friction and strong face validity for academic environments.

This study gives each stakeholder a clear, practical answer. For HEI leaders and department heads, the study shows that most employee performance gains came less from banning social media and more from restoring time control. For HR and managers, the study targets training employees where it pays off planning, prioritization as employees can cut distraction at the source through default notification settings. Faculty and staff should get low-friction routines which protect output without sacrificing legitimate online coordination. Students can also benefit indirectly through using social media for faster more predictable responses if fragmented interactions are minimum.

CONCLUSIONS

This study advances the understanding of the social media and performance debate by showing that the effect of SMU on EP as indirect and conditional. Specifically, SMU increases TMS and WD which in turn reduces performance, the TMS path was dominant. Substantively, within HEIs, the results identify time control and cue environment as the primary levers for protecting performance in digitally dense work. This study is not without limits as it's a cross-sectional survey of HEI staff in Punjab and relies mostly on self-reports, so it can't make strong claims or assume the results generalize everywhere. Future work should use longitudinal and experimental designs and adding multi-source objective data can help. Researchers can also test nonlinear effects, examine additional mediators like Task Completion and Employee Engagement which are the part of the questionnaire. While the model fit was strong overall in future work can also test measurement and structural invariance across subgroups (teaching vs. non-teaching, gender etc.). The sample comprises HEI employees in Punjab region thus replication across other regions, sectors and cultural settings can be used to test external validity and context sensitivity. This study provides clear evidence, social media's impact on performance in HEIs is driven less by "how much" employees use it and more by how that use reshapes time and attention. Instructing policies which encourage restore time control and avoid distraction cues rather than restrictions offer the reliable productivity gains.

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