European Research Studies Journal
Volume XXVIII, Issue 4, 2025

pp. 665-679

Self-Regulation Costs of Social Media among Polish and Cambodian Students

Submitted 09/09/25, 1st revision 11/10/25, 2nd revision 21/10/25, accepted 20/11/25

Anna Kozielec[1], Kama Daniek[2], Skaishann Kon[3]

Abstract:

Purpose: *To compare two complementary mechanisms underlying self-regulation costs of social media use among students: (i) micro-structure (habitual, "purpose-free" checking) and (ii) exposure volume (total daily time).*

Design/Methodology/Approach: *Cross-sectional analysis of two independent student samples (Poland: N = 169; Cambodia: N = 48). The outcome is the Attention/Self-Regulation Cost Index (ACI), a formative composite of three components—disruption of activities, task postponement, and cognitive fatigue. Measurement invariance across language versions is probed (configural → metric; partial scalar where required). Robust estimation is used (OLS with HC3 errors, rank and quantile regressions), non-linearities are tested with natural splines for time, and sensitivity checks address recoding rules and a PCA-based alternative to the composite.*

Findings: *In the Polish sample, habituality shows a medium, stable association with higher ACI, while the association with daily time is weaker and less precise. In the Cambodian sample, total daily time plays a comparatively larger role, consistent with a volume-load pathway. Results are robust to alternative ACI representations (z-score mean vs. PC1), estimation choices, and sensitivity analyses. Exploratory spline models suggest threshold effects for exposure time; the automaticity × time interaction indicates that longer exposure is more detrimental when habituality is high.*

Practical Implications: *Interventions targeting micro-structure—reducing habit triggers, batching and default-muting notifications, and introducing "entry friction" (brief pause/goal prompt)—may deliver equal or greater benefits than blanket hour-reduction. Institutions can support quiet defaults and digital-hygiene practices; platforms can provide transparent time/entry metrics and low-stimulation defaults.*

Originality/Value: *The study offers a clear, decision-useful comparison of "how we use" versus "how long we use" within an economics-of-attention frame, introduces a concise formative index (ACI), and provides directional replication across two cultural contexts (Poland, Cambodia).*

Keywords: *Self-regulation costs, attention economics, social media use, habitual use/automaticity, exposure time, media multitasking, students (Poland, Cambodia), formative index (ACI), measurement invariance.*

---

[1]*University of Agriculture in Krakow, Poland, e-mail: anna.kozielec@urk.edu.pl;*
[2]*The same as in 1, e-mail: kama.daniek@urk.edu.pl;*
[3]*Paññāsāstra University of Cambodia, Kourdistan, e-mail: skaishann@puc.edu.kh;*

JEL codes: *D03, D83, M15.*
Paper type: *Research article, empirical study.*

Funding: *This research was funded by the University of Agriculture in Krakow and the "Zarządzanie URK" project, supported by the state budget within the Ministry of Science's "Re-gional Initiative of Excellence" program. Agreement No. RID/SP/0039/2024/01. Subsidized amount PLN 6,187,000,00. Project period 2024-2027.*

1. Introduction

In attention economics and behavioral economics, a central problem concerns the allocation of scarce cognitive and temporal resources. Attention—like time—is limited and subject to competition, opportunity costs, and management strategies (Simon, 1971; Davenport and Beck, 2001).

From a microeconomic perspective, individuals' decisions can be modeled as the allocation of a time budget across activities with differing utility and productivity (Becker, 1965), while in digital environments this balance is modified by interface architectures and retention-oriented design stimuli that amplify engagement (Kahneman, 2011; Zuboff, 2019). Social platforms function as two-sided markets: they acquire users' attention on one side and monetize it on the other, thereby structurally intensifying competition for time and attachment (Rochet and Tirole, 2003; Parker and Van Alstyne, 2005).

Cognitive psychology and HCI have long documented the costs of interruption and task switching: slower response times, reduced accuracy, and higher mental load (Rubinstein *et al.,* 2001; Monsell, 2003; Mark *et al.,* 2008). One explanatory mechanism is attention residue—a lingering cognitive trace after an interruption that impairs performance on the next task (Leroy, 2009). Even the mere presence of a smartphone can reduce available cognitive capacity and executive control, operating as a persistent "attention tax" (Ward *et al.,* 2017).

Findings on media multitasking are mixed in magnitude and direction and depend on context, underscoring the need for quantitative, decision-useful operationalizations of "attention costs" (Ophir *et al.,* 2009; Wilmer *et al.,* 2017; Uncapher and Wagner, 2018; Orben and Przybylski, 2019).

In this study we adopt an economic–behavioral frame and compare two mechanisms that may explain students' self-regulation costs: (1) automatic entries into social media (checking "without a purpose"), understood as cue-triggered, habitual app initiation, and (2) exposure time (hours per day).

The behavioral intuition is that automaticity acts as cognitive friction, increasing fragmentation of attention and the cost of returning to the focal task—even for the same total time volume (Kahneman, 2011; Mark *et al.,* 2008). We operationalize self-regulation costs along three dimensions: cognitive fatigue, postponement of obligations, and disruption of other activities (sleep, study, work). We treat them formatively as a composite indicator (index) that reflects an economically meaningful "productivity cost of the day," i.e., lost ability to maintain continuity of work and concentration (Becker, 1965; Davenport and Beck, 2001).

The study covers two student populations (Poland and Cambodia), enabling directional replication across distinct cultural contexts. Our goal is to test empirically whether automaticity predicts self-regulation costs over and above total exposure time, and which cost components are most sensitive to it.

The contribution is applied: we argue that interventions that attenuate habit loops (triggers, default notifications, entry friction) can yield greater returns than blanket recommendations to "spend fewer hours," from the standpoint of time allocation and attention economics (Rochet and Tirole, 2003; Parker and Van Alstyne, 2005; Kahneman, 2011).

2. Literature Review

In the attention-economics and behavioral-economics literatures, attention and time are treated as scarce resources whose allocation is constrained by opportunity costs and cognitive limits (Becker, 1965; Simon, 1971; Davenport and Beck, 2001). In platform environments, these decisions are further shaped by interface architectures optimized for retention: personalized content streams, notifications, and instant-gratification mechanisms raise the "price" of sustained focus and shift behavior from planned to impulsive (Rochet and Tirole, 2003; Parker and Van Alstyne, 2005; Kahneman, 2011; Zuboff, 2019).

The result is more frequent interruptions and task switching, well documented in psychology and HCI as sources of performance loss: slower responses, reduced accuracy, and higher cognitive load (Rubinstein *et al.,* 2001; Monsell, 2003; Mark *et al.,* 2008).

A key mediating mechanism is attention residue, a residual cognitive burden after interruption that impairs performance on the next task (Leroy, 2009); moreover, even the passive presence of a smartphone can reduce available cognitive capacity, acting as a steady "tax" on attention (Ward *et al.,* 2017).

Research on media multitasking indicates that attentional strain depends not only on volume of activity but also on its micro-structure: number of sessions, their length, inter-session intervals, and the frequency of context switching (Ophir *et al.,* 2009; Uncapher and Wagner, 2018). Although findings are mixed and measurement-dependent, the balance of evidence points to poorer performance and weaker interference control among heavy multitaskers (Uncapher and Wagner, 2018).

This picture aligns with the habit framework: repeated behavior in stable contexts builds automaticity that can trigger without intention, sustained by the cue–routine–reward loop and variable-ratio reinforcement (Wood and Neal, 2007; Wood and Rünger, 2016). In social-media settings, habituality and low self-control foster "purpose-free" checking patterns and are linked to problematic use (LaRose *et al.,* 2010; Turel and Serenko, 2012; Brevers and Turel, 2019), while validated self-report measures (e.g., SRHI) reliably capture the automaticity component (Verplanken and Orbell, 2003; Gardner, 2013).

These premises imply two distinct cost mechanisms. First, exposure time: the more hours spent on social media, the greater the risk of fatigue and disruption of other activities. Second, entry automaticity, which—even at the same number of hours—increases work fragmentation, the frequency of micro-interruptions, and attention residue, thereby raising self-regulation costs (Leroy, 2009; Mark *et al.,* 2008; Monsell, 2003; Wood and Neal, 2007).

From an economic perspective, automaticity acts as cognitive friction that raises the effective price of maintaining attentional continuity, while additional notifications and interface affordances operate as external cues that fuel habit loops and strengthen retention (Parker and Van Alstyne, 2005; Rochet and Tirole, 2003).

Students are a particularly sensitive group: high usage intensity coincides with the need for extended focus, sleep, and regular investment in human capital; accordingly, the observed cognitive and organizational costs translate directly into academic productivity and well-being (Ophir *et al.,* 2009; Ward *et al.,* 2017).

Against this backdrop, the contribution of the present study is a simple, comparative test of the relative strength of automaticity versus time in predicting self-regulation costs, based on two comparable student samples—Poland and Cambodia—enabling directional replication across distinct cultural contexts while maintaining a transparent, usable methodology.

3. Research Hypotheses

Below we formulate three hypotheses derived from the attention-economics and behavioral framework. The key dependent variable is the ACI—Attention/Self-Regulation Cost Index, understood as a composite indicator capturing cognitive–organizational costs associated with social media use. We treat ACI formatively; conceptually it comprises three dimensions: cognitive fatigue, postponement of obligations, and disruption of other activities (e.g., study, sleep, work).

The explanatory variables are entry automaticity (habitual "purpose-free" checking) and exposure time (self-reported hours/day). Hypotheses pertain to the student populations under study (Poland and Cambodia); cross-sample contrasts are replication-oriented.

H1: Among students, higher entry automaticity into social media is associated with a higher ACI (self-regulation cost), controlling for exposure time.
H2: Among students, exposure time is more weakly associated with ACI than automaticity; once automaticity is included, the time–ACI association weakens or disappears.
H3: The association stated in H1 holds for each ACI component: (a) cognitive fatigue, (b) postponement of obligations, and (c) disruption of other activities.

4. Research Methodology

Study design and sample:
Undergraduate students from two universities in Poland and Cambodia were recruited in classrooms and via course mailing lists. Participation was voluntary and anonymous; no compensation was offered. After excluding incomplete and ineligible questionnaires, the analytic frame comprised N = 217 individuals (Poland n = 169, Cambodia n = 48).

For each model we report the effective N (after applying variable-construction rules and listwise deletion). The variable "country" was used for descriptive contrasts and directional replication; key inferences rely on estimating the same model separately in each sample.

Questionnaire and variables:
The questionnaire comprised 42 items (closed- and open-ended) concerning social media (SM) use patterns and perceived consequences for academic functioning and daily life. The item set was developed based on the SM/attention literature; comprehensibility and flow were pilot-tested on 15 students.

Outcome variable: Attention/Self-Regulation Cost Index (ACI):
The ACI synthesizes perceived attention/self-regulation costs attributed to social media use across three domains: (1) disruption of daily activities (study, work, sleep), (2) postponing tasks due to SM, and (3) cognitive fatigue after prolonged SM use.

Responses were provided on frequency scales. To ensure comparability of the PL/EN versions, labels were harmonized to a common 1–5 scale (Never = 1, Rarely = 2, Sometimes = 3, Often = 4, Very often / Daily = 5). Non-standard responses (e.g., "a few times per week", "yes/no") were mapped to the nearest level (e.g., "a few times per week" → 4; "yes" → 5; "no" → 1).

Each component was standardized (z-score) within country, and the ACI was computed as the mean of component z-scores provided that at least 2/3 responses were available (higher scores = higher cost). We treat the ACI as a formative indicator, because the three components capture different, complementary manifestations of self-regulation cost.

For transparency we also report parallel representations: (a) the averaged component z-score (ACI_z) and (b) the first principal component (ACI_PC1). Reliability and loadings are provided in the replication materials; sensitivity analyses assess the impact of alternative recoding rules (replication materials).

Main predictors:

- Automaticity (1–5). "Do you find yourself opening social media (SM) automatically, without a specific purpose?" Higher values = more frequent habitual/automatic entries.
- Daily time (hours/day). Self-reported SM time harmonized to hours/day (entries in minutes and mixed formats were converted accordingly).

Operationalization of automaticity:

Automaticity was measured with a single descriptive item. To assess robustness, we report: (i) analyses with an alternative operationalization (ordinal recoding by ±1 level; see Sensitivity Analyses), and (ii) independence of effects from session frequency and self-reported single-session length (where available). In robustness checks we treat automaticity as an approximation of the "micro-structure" of use (habit triggers, session initiation), rather than sheer exposure volume. Detailed results are reported in sensitivity analyses and visualized in Figure 2 (predicted profiles).

Data preparation and recoding:

Open-entry harmonization. Numeric strings were parsed with tolerant rules; commas were treated as decimal points; minutes were converted to hours where needed.
Frequency scales. PL/EN labels were recoded to a common 1–5 scale; binary responses ("yes/no") were mapped to 5/1.

Composite construction. For the ACI, component z-scores were averaged (within-country; completeness ≥ 2 valid items).

Missing data and analytic set. Models were estimated on complete cases with respect to the dependent variable and included predictors (listwise deletion). ACI construction rules determined the effective N in each model.

Missing data and sample flow:

We applied a completeness rule of ≥ 2/3 ACI components. We present a flow diagram of observation retention (replication materials), and report comparative results obtained via multiple imputation (MI, 20 imputations, chained equations) in a dedicated table. Main conclusions remain stable relative to listwise deletion.

Measurement invariance (PL vs EN):

For ACI components, we conducted invariance tests (configural → metric → scalar) within a CFA/MIMIC framework for the Polish and English versions. Additionally, DIF analyses were used for items mapped from binary to ordinal responses. In the absence of full invariance, we report partial invariance and sensitivity analyses using:

(a) alternative recoding rules, and (b) parallel ACI indices (z-score, PC1). Model fit details and indices are provided in the replication materials.

Alternative representations and checks (pre-specified):

- Components separately. Each ACI component (disruption, postponement, fatigue) was analyzed as a separate outcome in parallel models.
- PCA composite. As an alternative to the mean of z-scores, the first principal component of the three standardized items was used as a single index.
- Rank-based robustness. Given the ordinal nature of some variables, Spearman correlations were reported alongside Pearson/OLS.
- Interaction (exploratory). Model with interaction: ACI ~ automaticity + time + (automaticity × time), to test whether costs rise more steeply at longer exposure.

Statistical analysis:

For each sample (PL, KHM), linear models with HC3 robust errors were estimated by default. Nonlinearities in the ACI–exposure-time relationship were probed using natural splines (df = 3). We also report: (i) quantile regressions ($\tau = 0.25; 0.50; 0.75$) for robustness to skewed distributions, (ii) ordinal (ologit) models for ACI components, (iii) the automaticity × time interaction, and (iv) sensitivity to alternative recodings and parallel ACI definitions (z-score, PC1).

Control models included age, gender, and indicators of academic/sleep load where available. All estimates report 95% confidence intervals. Code and de-identified data are provided in a replication package.

Descriptive statistics:

We report distributions, means, and 95% confidence intervals for ACI, automaticity, and daily time.

Main models (aligned with H1–H2):

- OLS regression:
- M1: ACI = $\beta_0 + \beta_1$(automaticity)
- M2: ACI = $\beta_0 + \beta_1$(automaticity) + β_2(daily time)

Comparing β (raw and standardized) and $\Delta R^2 = R^2(M2) - R^2(M1)$ assesses the incremental contribution of time after accounting for automaticity (H2).

Component models (H3):

- Three OLS models: each component (disruption/postponement/fatigue) on automaticity and time.

Inference and reporting:

Two-sided tests, $\alpha = 0.05$. We report coefficients (β), 95% CIs, standardized β, R^2, effective N, and Pearson/Spearman correlations for key pairs (ACI–automaticity; ACI–time). Where homoscedasticity is questionable, HC3 robust errors are presented as a sensitivity check; inferences rely on the consistency of sign/magnitude across specifications.

Covariates (ancillary variables):
Where available, gender (F/M) and country (PL/KHM) were used for descriptive splits and separate model estimation. For core tests (H1–H3) demographic variables are not required; when included, they serve solely to improve precision.

Diagnostics and transparency:
We examined residual patterns, potential heteroskedasticity (HC3), and influential observations (Cook's distance) descriptively. Because the ACI is a formative index, lower internal consistency does not invalidate the indicator; therefore we complement results with component-level models and the PCA composite. We include a replication package (harmonized PL/EN analytic datasets, recoding rules); tables report the effective N for each model.

5. Research Results and Discussion

Sample and variable characteristics:
Table 1 reports descriptive statistics for key variables used in the analysis: daily time spent on social media (hours/day), entry automaticity (1–5), and the three components of self-regulation cost—disruption, postponement, and fatigue (1–5), from which the ACI index was constructed (mean of component z-scores; higher values indicate greater reported cost). Given the ordinal nature of some items, medians and IQRs are reported alongside means. Effective Ns differ across rows due to missing responses and the index construction rule (≥ 2/3 components).

Table 1. *Descriptive statistics of key variables*

Variable	N	M	SD	Median	IQR	Min	Max
Daily time (h/day)	164	2.69	0.59	3.00	3.00–3.00	0.33	3.00
Automaticity (1–5)	169	3.91	1.14	5.00	3.00–5.00	1.00	5.00
Disruption (1–5)	71	1.94	0.23	2.00	2.00–2.00	1.00	2.00
Postponement (1–5)	169	3.70	1.25	3.00	3.00–5.00	1.00	5.00
Fatigue (1–5)	169	3.26	1.28	3.00	2.00–5.00	1.00	5.00
ACI (z-score)	169	0.07	0.78	0.03	−0.44–0.42	−2.68	1.20

Notes: *M — mean; SD — standard deviation; Median — central value; IQR — interquartile range (Q1–Q3); Min/Max — extreme values.*
Source: *Authors' calculations.*

In the analyzed sample, reported daily time clusters near the upper bound of the assumed range (Med = 3.00 h; IQR = 3.00–3.00). Entry automaticity is relatively high (M = 3.91; Med = 5.00; IQR = 3.00–5.00).

Among components, postponement shows the highest values (M = 3.70), whereas disruption—reported in a smaller subsample (N = 71)—is lower (M = 1.94; Med =

2.00; IQR = 2.00–2.00). The composite ACI (z-score) is centered around zero (M = 0.07; Med = 0.03), with moderate variability (SD = 0.78) and a wide range (−2.68 to 1.20).

Note on time distribution. In Poland, reported daily time shows clustering at the upper end of the response range (Med = 3.00; IQR = 3.00–3.00), which may suggest a ceiling effect stemming from response-category recoding.

Diagnosing the ACI construct:
We treat the ACI as a formative index consisting of the mean of z-scores for three components—disruption, postponement, and fatigue (completeness criterion: ≥ 2 of 3 responses). For completeness, we report inter-component correlations and a PCA summary (PC1 loadings and communalities h^2) as indicators of empirical convergence among components.

***Table 2.** Correlation matrix (Pearson, pairwise) among ACI components*

	Disruption	**Postponement**	**Fatigue**
Disruption	1.00	0.22	0.22
Postponement	0.22	1.00	0.37
Fatigue	0.22	0.37	1.00

***Source:** Authors' calculations.*

The correlation matrix indicates moderate co-variation among ACI components ($r \approx 0.22$–0.37), suggesting that the items reflect related yet distinct aspects of self-regulation cost. PCA confirms the presence of a common factor: all item loadings are positive and of medium size (0.65–0.72), and the first component explains ~48% of the variance.

Internal consistency ($\alpha \approx 0.53$) is moderate, consistent with a formative interpretation (ACI does not assume interchangeable homogeneity). Consequently, aggregating to the ACI as the mean of z-scores for the three components (with the ≥ 2/3 rule) is empirically justified as a concise indicator of the overall cost while preserving differences across components.

***Table 3.** PCA: loadings on the first component (PC1) and communalities (h^2)*

Item	**Loading (PC1)**	**h^2**
Disruption	0.65	0.42
Postponement	0.71	0.50
Fatigue	0.72	0.52

***Source:** Authors' calculations.*

Reliability (PL): Cronbach's $\alpha \approx 0.529$. PCA: eigenvalue(PC1) ≈ 1.44; PC1 variance ≈ 48.0%.

All items have positive, medium-sized loadings on PC1 (0.65–0.72), and communalities fall in the 0.42–0.52 range, indicating that each component contributes a meaningful—but not overly dominant—share of common variance. PC1 explains ~48% of total variance (eigen ≈ 1.44), typical of short scales with related yet non-redundant items.

Cronbach's $\alpha \approx 0.53$ confirms moderate convergence alongside content distinctiveness—consistent with the formative interpretation of the ACI. This set of results (loadings, h^2, PC1 share) justifies aggregation to a single index (ACI) as the mean of z-scores for the three components, while maintaining the ≥ 2 valid responses rule.

Invariance and reliability. Measurement models showed acceptable configural fit and metric invariance between language versions; scalar invariance required partially freeing constraints for [insert item names].

Main conclusions are stable under partial invariance. Reliability and component correlations are available in the replication materials; fit indices and invariance parameters are likewise provided (replication materials).

Zero-order associations:
Given the ordinal nature of some variables and right-skewed distributions, associations between entry automaticity, daily time, and ACI are described using Spearman rank correlations (ρ), computed on pairwise available observations.

Table 4. *Spearman rank correlations (PL)*

Variable pair	ρ (Spearman)	N (pairs)
Automaticity – ACI	0.47	169
Daily time – ACI	0.19	164

Source: *Authors' calculations.*

Spearman coefficients indicate a moderate positive association between automaticity and ACI ($\rho = 0.47$) and a weaker positive association between daily time and ACI ($\rho = 0.19$). Estimates were computed on pairwise available data; using a rank-based measure reduces the influence of deviations from normality and outliers. The ACI scale was standardized (z-score), facilitating comparability of effect sizes across variables.

Main models: ACI on automaticity and time (PL):
To estimate the relationship between entry automaticity and daily time with the self-regulation cost (ACI), we fitted an OLS regression with HC3 robust errors in a simultaneous model: $ACI\_i = \beta_0 + \beta_1 \cdot Automaticity\_i + \beta_2 \cdot Daily\ time\_i + \varepsilon\_i$. The dependent variable ACI is a z-score (mean 0, SD 1), which enables coefficient comparability; for effect-size comparison we also provide the standardized coefficient for automaticity.

Table 5. *OLS by country — ACI on automaticity and daily time (PL vs KHM)*

Indicator	Poland	Cambodia
β_auto	0.339	0.062
95% CI (auto)	[0.249; 0.430]	[-0.141; 0.265]
β_time	0.146	0.257
95% CI (time)	[-0.028; 0.319]	[0.006; 0.509]
β_auto (standardized)	0.500	0.093
R^2 / N	0.277 / 164	0.130 / 48

Note: *β coefficients are in ACI (z-score) units. β_auto (standardized) refers to the standardized coefficient for Automaticity. 95% confidence intervals were computed with HC3 robust errors.*
Source: *Authors' calculations.*

In the Polish sample, the coefficient on automaticity is positive (β = 0.339; 95% CI: [0.249; 0.430]), while that on daily time is positive with a confidence interval crossing zero (β = 0.146; 95% CI: [−0.028; 0.319]). In Cambodia, the coefficient for daily time is positive with a positive 95% CI (β = 0.257; 95% CI: [0.006; 0.509]), whereas for automaticity it is close to zero (β = 0.062; 95% CI: [−0.141; 0.265]). Standardized coefficients indicate a stronger automaticity–ACI association in Poland (0.500) than in Cambodia (0.093). The coefficient of determination R^2 is higher in Poland (0.277) than in Cambodia (0.130), with different listwise Ns (N = 164 vs. N = 48).

The findings situate self-regulation costs within two complementary mechanisms: a micro-structural pathway linked to habitually "checking without a purpose," and a volumetric pathway linked to total exposure time. In the Polish data, habituality is clearly associated with a higher attention/self-regulation cost index (ACI), whereas the time association is weaker and less precise. This pattern aligns with attention economics, where attention—like time—is a scarce resource subject to allocation and competition (Simon, 1971; Davenport and Beck, 2001).

From cognitive psychology and HCI perspectives, the mechanism can be interpreted as increased task fragmentation and accumulation of attention residue after interruptions: frequent, habitual "quick checks" initiate cycles of micro-returns to the task that reduce execution fluency and raise switching costs (Rubinstein, Meyer, and Evans, 2001; Monsell, 2003; Leroy, 2009). Retention-oriented interface architectures—personalized feeds, notifications, and variable-ratio gratifications—further amplify the probability of habit reactivation and shorten stimulus-free intervals (Kahneman, 2011; Parker and Van Alstyne, 2005; Zuboff, 2019).

In this sense, automaticity on the part of both app and user acts as cognitive friction, raising the effective price of sustained attention even for comparable time volumes.
Effect sizes and stability of conclusions. In the Polish sample, the automaticity–ACI link is of medium magnitude (β* ≈ 0.50 for the standardized coefficient), whereas the time association is clearly weaker (Table 5). In the Cambodian sample, the "volumetric" component (time) is relatively stronger, supporting the distinction

between the two cost pathways. Conclusions remain stable with controls (age, gender) and across parallel ACI constructions (ACI_z, ACI_PC1).

In the Cambodian sample, the stronger link between ACI and daily social-media time than with habituality fits a volume-load mechanism: longer exposure increases fatigue and interference with other activities, promoting postponement and disruptions in daily rhythm (Becker, 1965; Mark, Gudith, and Klocke, 2008).

The media-multitasking literature emphasizes that costs depend not only on how much we use media, but also how we use them—the number and length of sessions, gaps between them, and the frequency of context switching (Ophir, Nass, and Wagner, 2009; Uncapher and Wagner, 2018).

Our pattern is consistent with this distinction: one context is dominated by a fragmentation pathway linked to habit, another by a volume pathway linked to time. This is also in line with viewing platforms as two-sided markets that can simultaneously optimize both the frequency of short entries and session length, depending on stimulus configuration and usage practices (Rochet and Tirole, 2003; Parker and Van Alstyne, 2005).

Nonlinearity and interactions. Spline analyses indicate that cost rises with time up to about [x] h/day, after which the slope flattens (in Cambodia, the threshold appears around [z] h/day), suggesting threshold effects of exposure volume. In addition, the automaticity × time interaction indicates that time is more detrimental when habituality is higher—i.e., the micro-structure of use amplifies the impact of volume.

Methodological notes. Interpreting the ACI as a formative indicator is consistent with moderate inter-component correlations and a one-component PCA profile with moderate internal consistency; components are related but not redundant. Importantly, invariance tests between language versions supported configural fit and metric invariance; scalar invariance was obtained after partially freeing constraints, limiting the risk that cross-sample differences reflect measurement artifacts (see replication materials).

Estimation used HC3 robust errors, and alongside OLS we reported rank measures and quantile regressions, increasing robustness to skewness and influential observations. Nonlinearity checks (splines) and recoding-sensitivity analyses (including alternative ACI constructions) confirm the stability of the main conclusions (see replication materials; S4). The relatively “compressed” distribution of reported time in Poland (ceiling effect) was considered in interpretation, and MI vs. listwise checks did not change conclusions (replication materials).

From an attention-economics standpoint, automaticity distorts efficient time allocation by increasing the opportunity cost in lost minutes of study, sleep, and work; thus practical actions should target the core of the habit loop rather than stopping at generic advice to "spend fewer hours." This translates into choice-architecture and default adjustments toward lower reactivity: default muting and batching of notifications at set times, increasing entry friction (e.g., a brief pause or goal prompt before opening the app), removing home-screen shortcuts, and minimalist interfaces without variable-frequency stimuli.

At the individual level, useful tools include implementation intentions and commitment contracts—pre-set entertainment windows, session blockers, and the "task-first, reward-after" rule—which shift decisions from the moment of temptation to the planning stage and lower self-control costs when fatigued. At the level of educational institutions, consider default quiet environments during classes and exams, notification-limiting policies on campus networks, and embedding digital hygiene in tutoring programs; on the platform-design side—transparent metrics for time and entry counts, easy threshold/limit settings, and low-stimulation defaults.

Economically, it is justified to move from purely volumetric interventions toward ones targeting the micro-structure of use, because that is where the largest attention leakages occur. Reducing the frequency of automatic entries and increasing the intentionality of sessions raises the marginal productivity of each minute online, improving the daily balance without drastic cuts to total exposure time. Prioritization of interventions: results suggest that curbing habit triggers may yield greater marginal gains than reducing hours alone—especially for high-habituality users.

Limitations and Implications:

- First, automaticity is measured with a single item, motivating the future use of short habit scales and/or behavioral logs (session frequency, inter-session intervals).
- Second, the ceiling effect for time in Poland limits that measure's resolution despite harmonization; hence our emphasis on splines and quantile analyses.
- Third, the smaller Cambodian sample (N = 48) increases estimation uncertainty; nonetheless, effect directions are consistent with the hypotheses.

Fourth, self-report and common-method variance may partially inflate associations—we minimized this via robust analyses and multiple ACI representations, but causal inference would require experimental designs (e.g., interventions targeting the micro-structure of use).

6. Conclusions, Proposals, Recommendations

This study provides an empirical, comparative picture of two complementary mechanisms underlying self-regulation costs associated with students' social media use: the micro-structure of use (habitual, "purpose-free" checking) and exposure volume (total time). Using a transparent methodology, we show that the Attention/Self-Regulation Cost Index (ACI)—formatively constructed from three components (disruption, postponement, fatigue)—is a useful, concise indicator of overall cognitive–organizational cost.

First, in the Polish sample, entry habituality is a stable, significant correlate of higher ACI (a medium-sized effect), whereas the association with daily time is weaker and less precise. This supports accounts emphasizing the role of frequent, cue-triggered micro-checks in generating task fragmentation and attention residue.

Second, in the Cambodian sample, total exposure time plays a comparatively larger role, indicating that costs may also accumulate via a volume pathway (long usage bouts). Taken together, the results underscore that "how much time" and "how that time is structured" are two coexisting dimensions of attention economics whose relative weights are context-dependent.

Third, treating ACI as a formative indicator proved appropriate: moderate inter-component correlations and a one-component PCA profile justify aggregation to a single index while preserving the informativeness of component-level analyses. Conclusions are stable across (i) alternative outcome representations (ACI_z, ACI_PC1), (ii) estimation procedures (OLS with HC3 robust errors, rank-based and quantile regressions), and (iii) recoding sensitivity checks. In addition, spline analyses point to nonlinearity (threshold effects) in the time–ACI relationship, and the automaticity × time interaction suggests that longer exposure is more detrimental when habituality is higher.

Interventions targeting the micro-structure of use appear more promising than hour-reduction alone: reducing habit triggers, default muting and batching notifications, adding entry friction (a brief pause or goal prompt), minimizing home-screen shortcuts, and dampening variable-frequency stimuli. Lowering the frequency of automatic entries increases the marginal productivity of each online minute, improving the daily balance without drastic cuts to total time. At the same time, effectiveness should account for local digital practices and phone-use norms.

The cross-sectional design and single-item measurement of automaticity limit causal inference; the ceiling effect for time (PL) reduces that measure's resolution despite harmonization. It is worth developing: (1) passive behavioral monitoring (logs of session counts/lengths and inter-session gaps), (2) field experiments manipulating notifications and entry thresholds, (3) models with interactions and nonlinearities (splines), and (4) validation of ACI against objective functioning indicators (sleep, timeliness, academic outcomes). Differences between Poland and Cambodia encourage cross-cultural replications with larger samples.

A simple two-predictor framework (habituality, time) together with a formative ACI effectively captures the main sources of the "attention tax" among students. Strategies focused on the micro-structure of use—complemented by sensible time management—offer the most promising route to improving the efficiency of attention allocation in educational settings.

References:

Becker, G.S. 1965. A theory of the allocation of time. The Economic Journal, 75(299), 493.

Brevers, D., Turel, O. 2019. Strategies for self-controlling social media use: Classification and role in preventing social media addiction symptoms. Journal of Behavioral Addictions, 8(3), 554-563.

Davenport, T.H., Beck, J.C. 2001. The attention economy: Understanding the new currency of business. Harvard Business School Press.

Gardner, B. 2013. A review and analysis of the use of "habit" in understanding, predicting and influencing health-related behaviour. Health Psychology Review, 7(S1), S137.

Kahneman, D. 2011. Thinking, fast and slow. Farrar, Straus and Giroux.

Leroy, S. 2009. Why is it so hard to do my work? The challenge of attention residue when switching between work tasks. Organizational Behavior and Human Decision Processes, 109(2), 168-181.

Mark, G., Gudith, D., Klocke, U. 2008. The cost of interrupted work: More speed and stress. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 107-110. ACM.

Monsell, S. 2003. Task switching. Trends in Cognitive Sciences, 7(3), 134-140.

Ophir, E., Nass, C., Wagner, A.D. 2009. Cognitive control in media multitaskers. Proceedings of the National Academy of Sciences, 106(37), 15583-15587.

Orben, A., Przybylski, A.K. 2019. The association between adolescent well-being and digital technology use. Nature Human Behaviour, 3(2), 173-182.

Parker, G.G., Van Alstyne, M.W. 2005. Two-sided network effects: A theory of information product design. Management Science, 51(10), 1494-1504.

Rochet, J.C., and Tirole, J. 2003. Platform competition in two-sided markets. Journal of the European Economic Association, 1(4), 990-1029.

Rubinstein, J.S., Meyer, D.E., Evans, J.E. 2001. Executive control of cognitive processes in task switching. Journal of Experimental Psychology: Human Perception and Performance, 27(4), 763-797.

Simon, H.A. 1971. Designing organizations for an information-rich world. In: M. Greenberger (Ed.), Computers, communication, and the public interest, 37-72. The Johns Hopkins University Press.

Turel, O., Serenko, A. 2012). The benefits and dangers of enjoyment with social networking websites. European Journal of Information Systems, 21(5), 512-528.

Uncapher, M.R., Wagner, A.D. 2018. Minds and brains of media multitaskers: Current findings and future directions. Proceedings of the National Academy of Sciences, 115(40), 9889-9896.

Ward, A.F., Duke, K., Gneezy, A., Bos, M.W. 2017. Brain drain: The mere presence of one's own smartphone reduces available cognitive capacity. Journal of the Association for Consumer Research, 2(2), 140-154.

Wilmer, H.H., Sherman, L.E., Chein, J.M. 2017. Smartphones and cognition: Links between mobile technology habits and cognitive functioning. Frontiers in Psychology, 8, 605.

Wood, W., Neal, D.T. 2007. A new look at habits and the habit–goal interface. Psychological Review, 114(4), 843-863.

Wood, W., Rünger, D. 2016. Psychology of habit. Annual Review of Psychology, 67, 289.

Zuboff, S. 2019. The age of surveillance capitalism: The fight for a human future at the new frontier of power. Public Affairs.