Economics and Culture

Economic Costs of Labour Productivity Losses Due to the Inappropriate Use of Social Media and Smartphones: The Case of Argentina

Research Paper

Solange Finkelsztein

Universidad Argentina de la Empresa (UADE), Buenos Aires, Argentina, sfinkelsztein@gmail.com, ORCID: https://orcid.org/0009-0002-2145-1727

Received 13 May 2025; Accepted 08 December 2025

Abstract: **Research purpose.** The objective of this research was to calculate the cost of labour productivity loss measured exclusively as the decrease in Gross Value Added (GVA) associated with distractions caused by problematic use of social media in the workplace, where users continuously check their smartphones for updates. The calculation was conducted using Argentina as a case study, based on national statistical data from the year 2023.

Design / Methodology / Approach. The design of this research is quantitative, descriptive, and explanatory, focusing on measuring and analysing labour productivity losses caused by the inappropriate use of social media and smartphones in the workplace. A national statistical series from the year 2023 was used to observe and estimate productivity losses in the context of Argentina. The applied methodology includes the collection of statistical data and the construction of a simple mathematical model to estimate the economic losses (measured exclusively as the decrease in Gross Value Added (GVA)) associated with distractions.

Findings. The results of the estimation validate the hypothesis that distractions caused by the use of social media and smartphones decrease labour productivity, representing a cost by reducing the gross value added. The productivity losses resulting from this model for the year 2023 in Argentina account for 12.73% of the gross value added. It can also be observed that sectors of economic activity with high exposure to social media and smartphones experience productivity losses greater than their relative contribution to GDP, while sectors with medium and low exposure suffer losses below their relative weight in GDP. These productivity losses are not only significant in terms of Argentina's gross value added, but they are likely to be even greater if the analysis includes the time it takes for an individual to refocus after a distraction, a cost not included in the model.

Originality / Value / Practical implications. The article provides an estimate of the losses in Gross Domestic Product (GDP) due to workplace distractions caused by the inappropriate use of new information and communication technologies (ICT) in Argentina, a developing country. This analysis not only measures the economic impact of this phenomenon but also opens the door to new discussions about business models and labour relations, specifically regarding how the losses may be absorbed by both employers and employees, who might be trying to counteract the distractions with faster work, but of lower quality and higher stress.

Keywords: *Labour productivity loss • Social media distractions • Smartphone use • Economic impact • Gross Domestic Product (GDP)*

JEL codes: D24, J24, L86, M54, O15, O33

Introduction

The widespread adoption of social media, the proliferation of platforms, and the significant daily time users dedicate to them (Instituto de Ciencias Sociales y Disciplinas Proyectuales, 2023; Ortiz-Ospina, 2019; Statista, 2025) have raised concerns about their impacts. Extensive research highlights both positive and negative effects, with mobile accessibility intensifying their influence (Cao et al., 2024; Beyens et al., 2024; Montag et al., 2015a; Montag et al., 2015b; Olorunsogo et al., 2024; Tao et al., 2024). These multifaceted impacts are studied across disciplines, including psychology, neuroscience, and economics, each providing distinct perspectives.

* *Email: sfinkelsztein@gmail.com*

In economics, this analysis aligns with behavioural economics, debating whether excessive social media use constitutes rational behaviour (Hoong, 2019; Wang et al., 2015) or problematic use akin to addiction (Andreassen & Pallesen, 2014; Sun & Zhang, 2021). In either case, excessive use generates costs ranging from reduced concentration in the workplace to dire consequences such as fatal accidents (WHO, 2024). Beyond consumer behaviour, attention has been drawn to platform design influences (Bhargava & Velasquez, 2021).

This study quantifies productivity losses stemming from workplace distractions caused by social media and smartphones, using Argentina as a case study and 2023 national statistics. The analysis is based on the following premise:

– Assumption: Workplace productivity is influenced by the degree of exposure to distractions from social media and smartphones. This assumption is supported by previous research (Finkelsztein et al., 2025) and serves as a foundational premise for the present study, although it is not empirically tested here.
– Hypothesis (H1): These distractions reduce productivity, incurring costs reflected in diminished gross value added.

By adopting this framework, the study focuses on testing H1 while acknowledging the established foundation of the assumption.

Given the absence of a unified methodology for assessing such losses, this study proposes a simplified model to provide initial estimates. It links workplace distractions to smartphone and social media checks (Finkelsztein et al., 2025) and uses national data to compute additional work minutes required to offset these interruptions, based on frequency and duration.

Economic sectors were classified into high, average, and low exposure levels, determined by checking frequency and distraction duration. Labour productivity was assessed by comparing value added per hour worked, with and without distractions. Finally, sectors' relative GDP weights were calculated to evaluate the broader economic impact.

Literature review

Despite numerous studies on societal costs linked to excessive social media use (Wang et al., 2015; Wushe & Shenje, 2019), the existing literature remains insufficient given the scope of the issue. Contradictory findings often hinder clear cause-and-effect relationships, prompting researchers to explore the phenomenon further. Methodological limitations persist, including the heterogeneity of measurement instruments, complicating comparisons across studies (Finkelsztein et al., 2025). Additionally, the lack of longitudinal and qualitative research limits deeper, dynamic analyses (Kuss & Griffiths, 2017; Mohamed et al., 2017).

Some research highlights potential benefits, such as enhanced workplace productivity via improved social capital (Chen et al., 2009) and better work-life balance (Kumar & Priyadarshini, 2018). However, Lu et al. (2015) suggest that while highly productive employees may gain performance benefits, low-productivity workers may experience further declines. Conversely, Wushe and Shenje (2019) argue that the impact of social media depends on the type of network used. Studies also reveal dual effects, where social media fosters knowledge creation and communication but contributes to distractions and addictive behaviours (Siddiqui & Singh, 2016; Yeshambel et al., 2016).

Employee and employer perceptions diverge regarding productivity impacts. While some studies rely on self-reported data from employees (Celebi & Terkan, 2020; Dantas et al., 2022), others use supervisor evaluations (Lu et al., 2015). Measurement tools vary widely, including WPAI-GH (Reilly et al., 1993), EWPS, WPSI, SMWU, and Work Performance (WP) scales (Leftheriotis & Giannakos, 2014), underscoring methodological challenges in comparative research. The reasons employees use social media include mental breaks, personal connections, professional networking, and work-related problem-solving (Olmstead et al., 2015). While these uses demonstrate social media's benefits, they also highlight its distracting effects.

Brooks et al. (2017) link technostress and addiction to social media, noting reduced workplace commitment and productivity. Fox & Moreland (2015) highlight Facebook's distracting effects. Kuss and Griffiths (2017) compare excessive social media use to substance addiction symptoms, such as mood changes, tolerance, withdrawal, and relapse, consistent with the Internet Addiction Model. They emphasise phenomena like FOMO (fear of missing out) and nomophobia, which reflect users' apprehension about exclusion and fear of being without their phones.

Montag et al. (2019) note that app design features, including unlimited scrolling, tailored algorithms, reward systems, and social comparison, contribute to smartphone addiction. Bhargava & Velasquez (2021) identify barriers preventing users from deactivating accounts. These factors foster habitual smartphone checks every 18 minutes, leading to reduced focus and productivity.

In economics, social media distractions are examined through the lens of behavioural economics. Some theories view consumers as rational agents evaluating costs and benefits, while others highlight overestimation of social media's value (Wang et al., 2015). Sun & Zhang (2021) stress the need to define social media addiction adequately, distinguishing between problematic use and clinical addiction. Andreassen & Pallesen (2014) define addiction as excessive preoccupation and disproportionate time spent, disrupting other activities and overall well-being.

Hoong (2019) demonstrates discrepancies between estimated and actual time spent on social media, revealing heuristic biases. Social media distractions, causing microeconomic productivity losses, ultimately translate into macroeconomic GDP reductions. This study examines micro-level distractions and their macro-level costs.

Furthermore, problematic smartphone use in the workplace must be contextualised within regional and cultural dynamics. Digital culture studies in Latin America show that high social media consumption is driven by a deep collective desire for belonging and participation. Specifically in Argentina, this trend fosters a high frequency of connection and dialogue, emphasising the cultural importance of collectivity and instantaneous social interaction as a key driver of device usage. This cultural factor establishes a context where the need to maintain social status and constant group contact becomes a primary conductor of workplace distraction, potentially surpassing purely individual or organisational factors (Gewerc et al., 2017).

Research methodology

The objective of this research was to calculate the cost of labour productivity loss measured exclusively as the decrease in Gross Value Added (GVA) associated with distractions caused by problematic use of social media in the workplace. There is currently no unified or widely accepted method for calculating the economic costs of problematic social media use. While some studies estimate productivity losses, research specific to Argentina often addresses other factors affecting worker productivity, such as climate change (Conte Grand & Soria, 2023) or the impact of intangible assets, production factors, and ICTs on economic development (Coremberg, 2009, 2015). International studies, such as Sarbu (2017), analyse the relationship between social media use and labour productivity, employing a Cobb-Douglas production function based on data from Germany's manufacturing and service sectors.

This study aims to address the absence of a standardised approach to measure the costs of this complex, novel phenomenon by proposing an estimation model. The goal is to approximate these costs, providing policymakers with tools to better understand the issue's scope. To estimate productivity losses, the model assumes that workplace distractions from social media and smartphones do not reduce output or gross value added (GVA) but are compensated for by additional working hours. This simplifies the analysis by avoiding calculations of elasticities within production functions. However, in practice, labour productivity losses are likely to affect GVA proportionally to labour intensity relative to capital—a relationship that varies by activity or sector. This model incorporates sector-specific impacts by considering the relative weight of each sector in terms of hours worked.

The calculations, conducted for Argentina, utilise national 2023 statistics, the most recent year with complete data. Based on the "Income Generation Account" (INDEC, 2024) published by INDEC, the analysis draws from the 2016–2024 series titled "Gross Value Added and Labour Input by Economic Activity Sector, Q1 2016 to Q2 2024."

Starting with GVA expressed in millions of pesos and annualised hours worked, productivity losses were calculated across sectors. Economic sectors were categorised into three levels of social media exposure—low (=1), average (=2), and high (=3)—to account for differences in distraction levels during work hours (See Table 1).

In the proposed model, 16 sectors of the Argentine economy are classified by their exposure to social media distractions: 7 sectors (44%) have high exposure, 6 sectors (38%) average exposure, and 3 sectors (18%) low exposure. This classification is based on assumptions informed by previous studies, though no prior rankings of economic sectors by workplace distractions were identified.

The subdivision of economic sectors into three risk levels (Low, Average, and High) is not based on traditional physical accident rates, but rather on the nature of the mental demand and cognitive complexity of the associated tasks. This approach is justified on the premise that the studied consequences (loss of concentration and accidents) are directly mediated by mental workload and the propensity for interruption. The sectors grouped under the High level correspond to those with the highest demand for attention, concentration, and memory (Instituto Nacional de

Table 1. Classification of economic sectors by level of exposure (Source: Author's own calculations)

Low (1)	Average (2)	High (3)
A. Agriculture, livestock, hunting and forestry	D. Manufacturing industry	G. Wholesale, retail, and repairs
B. Fishing	E. Electricity, gas, and water	H. Hotels and restaurants
C. Mining and quarrying	F. Construction	J. Financial intermediation
	I. Transport, storage, and communications	K. Real estate, business, and rental activities
	M. Teaching	L. Public administration and defence, mandatory social security plans
	N. Social and health services	O. Other community, social, and personal service activities
		P. Private households with domestic service

Seguridad y Salud en el Trabajo [INSST], n.d.), as well as high quantitative demands (time pressure) and emotional demands (direct interaction with the public) (Fondo de Riesgos Laborales, n.d.). These characteristics are common in financial services (J), public administration (L), and community services (O), where an incorrect decision or loss of attention generates a non-physical but systemic risk. Conversely, sectors classified as Low (A, B, C) represent activities where the critical cognitive load for rapid decision-making may be lower, or the task is more standardised, despite their high inherent physical risk.

Office-related sectors (e.g., administrative, financial, technological) are frequently distracted by technology, ambient noise, or colleague interactions. Conversely, industrial, or manual sectors (e.g., manufacturing, construction, agriculture) face distractions such as machinery interruptions, environmental conditions (e.g., noise, fatigue), and frequent task changes. Physical fatigue and hazardous conditions in these sectors also affect productivity and safety. Creative or knowledge-driven jobs are particularly vulnerable due to their reliance on sustained concentration and emotional or psychological factors. Service roles, especially client-facing ones, experience distractions tied to interpersonal interactions or multitasking.

Using Duke & Montag's (2017) findings that workers check updates every 18 minutes, this model makes the following assumptions:

- Average exposure sectors: Workers are distracted for 2 minutes per smartphone check, occurring every 18 minutes.
- High exposure sectors: Checks occur 20% more frequently (every 14.4 minutes), with 3 minutes of distraction per check.
- Low exposure sectors: Checks occur 20% less frequently (every 21.6 minutes), with 1 minute of distraction per check.

The parameter for productivity loss utilised within the model is set at a 20% deviation. This value is justified as a conservative and representative measure, as it falls within the documented empirical range regarding the cost of workplace interruptions. Various studies indicate that each interruption can increase the total time required to complete a task by between 15% and 24% (Brand Eins, 2023). By selecting an intermediate value of 20%, the model ensures that the effects of distraction are accurately reflected, based on the literature concerning efficiency and job performance.

Table 2 provides a schematic representation of these assumptions.

Based on these premises, sector-specific productivity was calculated using hours worked. The calculation was performed twice: initially without accounting for distractions caused by smartphone or social media use during work hours, and subsequently incorporating the additional minutes required to compensate for such distractions.

Productivity in hours was therefore defined and calculated as follows:

$$Prod_0 = \frac{GVA_{bp}}{Hs_0} \tag{1}$$

Table 2. Distractions. Frequency and duration according to type of exposure (Source: Author's own calculations)

Indicator	Low	Average	High
Distraction time	1 minute	2 minutes	3 minutes
Frequency	-20% (21.6 minutes)	Every 18 minutes per hour	+20% (14.4 minutes)

where,

$Prod_0$ is Productivity in hours (it is expressed in thousands of pesos per annualised hour worked since the INDEC series records GVA_{bp} in millions of pesos, while Hours worked HS_0 are expressed in thousands and annualised);

GVA_{bp} is Gross Value Added at basic prices in millions of pesos;

HS_0 is thousands of annualised hours worked.

The second calculation was made considering the distractions caused by social media and smartphones as follows: Every time the worker is distracted (between 1 and 3 minutes, depending on the type of activity), they require additional minutes of work to achieve the same productivity. This resulted in the calculation of the number of hours worked, including the extra minutes they would need to work to achieve the same added value as if they were not distracted. The calculation was performed in the following steps:

1. Calculation of hours worked without distractions (expressed in minutes), HS_0
2. Estimation of new hours worked (HS_1) adding,
   - 1 minute every 21.6 minutes for low-distraction activities,
   - 2 minutes every 18 minutes for average-distraction activities, and
   - 3 minutes every 14.4 minutes for high-distraction activities.

$$Hs_1 = (Hs_0 + \Delta Hs) \tag{2}$$

where,

Hs_1 are hours worked, adding minutes to compensate for distractions;

ΔHs represents the additional minutes needed to compensate for distractions.

3. The productivity calculation with time compensation for distractions ($Prod_1$) accounts for productivity losses due to distractions and the additional minutes worked to compensate. It is expressed in thousands of pesos per annualised hour worked and is calculated as follows:

$$Prod_1 = \frac{GVA_{bp}}{Hs_1} \tag{3}$$

where,

$Prod_1$ accounts for productivity (thousands of pesos per annualised hour worked), including the additional minutes worked to compensate for distractions.

4. Calculation of Productivity Loss: Productivity loss is determined as the difference between productivity with compensations for distractions and productivity without distractions, expressed as:

$$\Delta Prod. = Prod_1 - Prod_0 \tag{4}$$

where,

$\Delta Prod.$ represents the Productivity decline.

5. Estimated Value of Productivity Loss: The monetary loss in productivity is calculated as:

$$Loss\,in\,Prod. = \Delta Prod.*Hs_1 \tag{5}$$

where,

Loss in Prod. accounts for the Loss in Productivity (millions of pesos).

6. The percentage of productivity loss (%) is calculated as follows:

$$\%\,Prod.Loss = \frac{Loss\,in\,Prod.}{GVA_{bp}} * 100 \tag{6}$$

where,
% Prod. Loss accounts for the percentage of productivity loss.

7. Finally, the relative weight of each sector in the economy's GDP was calculated.

$$Sector\,rel.weight = \left(Sector\,GVA_{bp}\right) / \left(Total\,GVA_{bp}\right) * 100 \tag{7}$$

where,
Sector rel.weight represents the relative weight of each sector in the economy's GDP;
Total GVA$_{bp}$ represents the country's annual GDP.
All calculations were performed using Python.

Research results

The findings from the proposed model underscore the critical need to measure this issue. At the national level, productivity losses account for 12.73% of Gross Value Added (GVA). Notably, sectors with high exposure experience losses surpassing their relative GDP contributions, while sectors with medium and low exposure show losses below their proportional weights in GDP.

The following section provides a detailed analysis, with Table 3 comparing labour productivity in hours without distractions to labour productivity adjusted for additional minutes required due to distractions across Argentina's economic sectors.

The model's assumptions reveal productivity losses across all sectors, requiring additional work minutes to offset distractions from social media and smartphones. These losses are most pronounced in highly exposed sectors (17%), compared to average-exposure sectors (10%) and low-exposure sectors (4%).

Using this data, productivity losses were quantified at the macroeconomic level, estimating Argentina's Gross Value Added at basic prices (GVAbp). Results indicate that productivity losses represent 12.73% of GVAbp, equivalent to 20,503,386 pesos. Table 4 details GVAbp losses by sector and the total at the national level.

These findings are consistent with prior research that employed varied methodologies to estimate workplace productivity losses caused by social media distractions. Yemoh and Amitai (2022), for example, found that average daily social media use amounts to 2.35 hours - approximately 32% of the workday - resulting in a 13% overall productivity loss due to excessive usage.

When analysing sectors' relative contributions to GDP, it is evident that highly exposed sectors experience productivity losses exceeding their proportional GDP contributions. Conversely, average- and low-exposure sectors show losses below their GDP weights.

To quantify this, the first step involved calculating the relative weight of each sector within the economy. Next, the loss in productivity in millions of pesos, based on each sector's relative weight in GDP, was determined by multiplying the total productivity loss in the economy by the sector's share of GDP. Finally, the percentage of productivity loss, accounting for each sector's relative weight, was calculated by dividing the sector's productivity loss by the total productivity loss in the economy. Table 5 summarises these results.

Conclusions

The findings of this study highlight the substantial impact of social media and smartphone distractions on workplace productivity in Argentina. These results support the study's foundational assumption that workplace productivity

Table 3. Comparative table of productivity for each sector of economic activity in thousands of pesos per annualised hour worked (With and without considering the additional minutes needed to compensate for distractions.) (Source: Author's own calculations)

Sector	Productivity Excluding Distractions (thousands of pesos per annualised hour worked) $(1)\ Prod_0 = \frac{GVA_{bp}}{Hs_0}$	Productivity (thousands of pesos per annualised hour worked, adjusted for distraction compensation) $(3)\ Prod_1 = \frac{GVA_{bp}}{Hs_1}$
A Agriculture, livestock, hunting, and forestry	5,12	4,90
B Fishing	6,08	5,81
C Mining and quarrying	28,75	27,48
D Manufacturing industry	6,84	6,16
E Electricity, gas, and water	7,82	7,04
F Construction	2,35	2,11
G Wholesale, retail, and repairs	4,35	3,60
H Hotels and restaurants	3,29	2,72
I Transport, storage and communications	3,53	3,18
J Financial intermediation	6,33	5,24
K Real estate, business, and rental activities	6,99	5,78
L Public administration and defence; mandatory social security plans	4,55	3,77
M Teaching	5,03	4,53
N Social and health services	3,98	3,58
O Other community, social and personal service activities	2,31	1,91
P Private households with domestic service	0,68	0,56

Table 4. Productivity loss expressed in GVAbp in Argentina caused by distractions from social networks and smartphones (Source: Author's own calculations)

Exposure	Sector	Gross Value Added at basic Price (GVAbp) in millions of pesos	Loss in Productivity in millions of pesos (5) $Loss\ in\ Prod. = \Delta Pro * Hs_1$	Percentage of productivity loss (6) (6) $\%Prod.Loss = \frac{Loss\ in\ Prod.}{GVA_{bp}} * 100$
Low	A Agriculture, livestock, hunting, and forestry	10.916.045	483.011	4,42%
Low	B Fishing	433.991	19.203	4,42%
Low	C Mining and quarrying	7.559.343	334.484	4,42%
Average	D Manufacturing industry	31.232.508	3.123.251	10,00%
Average	E Electricity, gas, and water	1.695.695	169.570	10,00%
Average	F Construction	7.471.621	747.162	10,00%
High	G Wholesale, retail, and repairs	32.257.029	5.561.557	17,24%
High	H Hotels and restaurants	3.935.836	678.592	17,24%
Average	I Transport, storage and communications	8.358.359	835.836	10,00%
High	J Financial intermediation	3.078.862	530.838	17,24%
High	K Real estate, business, and rental activities	17.481.856	3.014.113	17,24%
High	L Public administration and defence; mandatory social security plans	13.350.041	2.301.731	17,24%
Average	M Teaching	9.638.951	963.895	10,00%
Average	N Social and health services	8.417.847	841.785	10,00%
High	O Other community, social and personal service activities	4.179.478	720.600	17,24%
High	P Private households with domestic service	1.030.997	177.758	17,24%
Total		161.038.458	20.503.386	12,73%

Table 5. Productivity decline considering the relative weight of the sectors (Source: Author's own calculations)

Sector		GVAbp (millions of pesos)	Relative Weight (% of GDP)	Loss in Productivity in millions of pesos (5) $Loss\ in\ Prod. = \Delta Pro * Hs_1$	Productivity Loss (according to relative weight in GDP)	Percentage of productivity loss (with relative weight)
A	Agriculture, livestock, hunting, and forestry	10.916.045	6,8%	483.011	1.389.829	2,4%
B	Fishing	433.991	0,3%	19.203	55.256	0,1%
C	Mining and quarrying	7.559.343	4,7%	334.484	962.454	1,6%
D	Manufacturing industry	31.232.508	19,4%	3.123.251	3.976.517	15,2%
E	Electricity, gas, and water	1.695.695	1,1%	169.570	215.896	0,8%
F	Construction	7.471.621	4,6%	747.162	951.285	3,6%
G	Wholesale, retail, and repairs	32.257.029	20,0%	5.561.557	4.106.959	27,1%
H	Hotels and restaurants	3.935.836	2,4%	678.592	501.110	3,3%
I	Transport, storage and communications	8.358.359	5,2%	835.836	1.064.185	4,1%
J	Financial intermediation	3.078.862	1,9%	530.838	392.000	2,6%
K	Real estate, business, and rental activities	17.481.856	10,9%	3.014.113	2.225.787	14,7%
L	Public administration and defence; mandatory social security plans	13.350.041	8,3%	2.301.731	1.699.725	11,2%
M	Teaching	9.638.951	6,0%	963.895	1.227.229	4,7%
N	Social and health services	8.417.847	5,2%	841.785	1.071.759	4,1%
O	Other community, social and personal service activities	4.179.478	2,6%	720.600	532.130	3,5%
P	Private households with domestic service	1.030.997	0,6%	177.758	131.266	0,9%
Total		161.038.458	100%	20.503.386	20.503.386	100,0%

is influenced by the degree of exposure to distractions caused by social media and smartphones, as indicated by previous research (Finkelsztein et al., 2025). Furthermore, the findings validate Hypothesis H1, which establishes that these distractions reduce labour productivity, generating measurable costs reflected in diminished gross value added (GVA). Productivity losses calculated in this study account for 12.73% of GVA, aligning with prior research and underscoring the importance of quantifying this phenomenon. Sectors with high exposure to distractions experience losses exceeding their relative contribution to GDP, whereas sectors with medium and low exposure exhibit proportionally smaller losses, highlighting disparities across economic activities.

While these losses represent significant impacts, they account for only a fraction of the broader implications, as the model excludes additional costs such as the time required to refocus after interruptions. Previous studies estimate that recovery after distractions takes an average of 23 minutes and 15 seconds (Duke & Montag, 2017; Spira & Feintuch, 2005). Including this factor in future analyses could yield higher estimates of productivity losses, emphasising the need for further research.

When evaluating the significant Gross Value Added loss estimated in this study, the influence of socio-cultural amplifiers must be considered. Argentina's culture of hyper-connectivity and the high value placed on social collectivity, as detailed in the literature, manifest in the labour environment differently than in more individualistic cultures. The cultural and social pressure to maintain a permanent presence within friendship and family networks (Gewerc et al., 2017) translates into the workplace, significantly amplifying the impulse for habitual checking of the smartphone. Therefore, the high estimated economic cost reflects not only a lack of institutional control or individual addiction, but also a deep-seated cultural challenge in the demarcation of personal and professional spheres. It is essential to note that the resulting economic cost specifically measures the loss caused by these non-work-related distractions, maintaining the internal consistency of the productivity loss calculation. This cultural dimension is a critical contextual variable that must be considered by policymakers seeking to design mitigation strategies that are both effective and socially sensitive.

Although productivity in this study was measured in hours, future research should explore quality losses as an additional variable to provide deeper insights. While auditing quality is inherently challenging, its inclusion would enhance the robustness of productivity analyses. This study also raises important questions about accountability for productivity losses, highlighting the need to reassess workplace models. Employers often encourage the use of communication technologies, inadvertently contributing to distractions that reduce labour productivity. Insights from principal-agent models (Jensen & Meckling, 1976) demonstrate that productivity losses vary depending on payment schemes. In fixed salary systems, employers bear the financial burden of reduced productivity. Conversely, variable payment schemes tied to employee performance shift this burden onto workers, who face either lower earnings due to diminished results or increased stress and effort as they strive to compensate for distractions by working faster (Mark et al., 2008).

Although these results align with prior findings, they should be interpreted within the limitations of this model. For example, labour elasticity in the production function was not considered. Incorporating this variable could provide more accurate estimates of net GDP losses by examining the balance between labour productivity losses and capital productivity gains from new technologies. Additionally, modern distractions, such as smartphone use, may not represent entirely new losses but could replace older forms of workplace distractions, such as smoking breaks or informal interactions. Investigating this shift is crucial for understanding its long-term implications.

By presenting an initial estimate of productivity losses related to social media and smartphone use in Argentina's workplaces, this study emphasises broader implications for business models and labour relations. It highlights the need for labour policies that are designed with an awareness of who ultimately bears the costs. Under variable payment schemes, employees may face higher stress levels, which could potentially affect the quality of their work as they strive to offset distractions. The robust findings of this study open new avenues for research, offering policymakers and organisational leaders valuable tools to refine strategies for mitigating workplace distractions and enhancing productivity, both in developing and developed economies.

The principal-agent framework reveals that variable payment schemes effectively transfer the cost of digital distraction to the employee. This manifests as compensatory effort and heightened stress to maintain performance (Mark et al., 2008), ultimately affecting both the quality of the final output and the sustainability of human capital. Therefore, this study emphasises that organisational policies must move beyond mere prohibition, focusing instead on the equitable management of distraction costs. We suggest that business models actively integrate digital literacy and foster responsible autonomy, recognising that employee focus is a shared organisational asset essential for long-term productivity

Funding

This work was carried out with the institutional support of the Universidad Argentina de la Empresa (UADE) within the framework of research project code D23E02, to whom I express my sincere gratitude.

References

Andreassen, C. S., & Pallesen, S. (2014). Social network site addiction - an overview. *Current Pharmaceutical Design*, *20*(25), 4053–4061. https://doi.org/10.2174/13816128113199990616

Beyens, I., Pouwels, J. L., van Driel, I. I., Keijsers, L., & Valkenburg, P. M. (2024). Social media use and adolescents' well-being: Developing a typology of person-specific effect patterns. *Communication Research*, *51*(6), 691–716. https://doi.org/10.1177/00936502211038196

Bhargava, V. R., & Velasquez, M. (2021). Ethics of the attention economy: The problem of social media addiction. *Business Ethics Quarterly*, *31*(3), 321–359. https://doi.org/10.1017/beq.2020.32

Brand Eins (2023). *Arbeiten, wie ich wirklich, wirklich will* [Working the way I really, really want to]. Brand Eins Thema: IT-Dienstleister. https://www.brandeins.de/magazine/brand-eins-thema/it-dienstleister-2023/arbeiten-wie-ich-wirklich-wirklich-will

Brooks, S., Longstreet, P., & Califf, C. (2017). Social media induced technostress and its impact on internet addiction: A distraction-conflict theory perspective. *AIS Transactions on Human-Computer Interaction*, *9*(2), 99–122. https://doi.org/10.17705/1thci.00091

Cao, X., Xu, C., & Ali, A. (2024). A socio-technical system perspective to exploring the negative effects of social media on work performance. *Aslib Journal of Information Management*, *76*(2), 233–247. https://doi.org/10.1108/AJIM-05-2022-0275

Celebi, S. I., & Terkan, R. (2020). Social media and employee productivity at workplace. *International Review of Management and Marketing*, *10*(6), 37–41. https://doi.org/10.32479/irmm.10806

Chen, X., Stanton, B., Gong, J., Fang, X., & Li, X. (2009). Personal social capital scale: An instrument for health and behavioral research. *Health Education Research*, *24*(2), 306–317. https://doi.org/10.1093/her/cyn020

Conte Grand, M., & Soria, M. (2023). Economic costs of heat stress induced reductions in worker productivity due to climate change in a developing country. *Asociación Argentina de Economía Política: Working Papers, 4636*.

Coremberg, A. A. (2009). *Midiendo las fuentes del crecimiento en una economía inestable: Argentina. Productividad y factores productivos por sector de actividad económica y por tipo de activo*. CEPAL.

Coremberg, A. A. (2015). Midiendo la productividad y las fuentes del crecimiento de la economía argentina. El proyecto ARKLEMS+LAND. *Temas*, *335–403*.

Dantas, R. M., Aftab, H., Aslam, S., Majeed, M. U., Correia, A. B., Qureshi, H. A., & Lucas, J. L. (2022). Empirical investigation of work-related social media usage and social-related social media usage on employees' work performance. *Behavioral Sciences*, *12*(8), 297. https://doi.org/10.3390/bs12080297

Duke, É., & Montag, C. (2017). Smartphone addiction, daily interruptions and self-reported productivity. *Addictive Behaviors Reports*, *6*, 90–95. https://doi.org/10.1016/j.abrep.2017.07.002

Finkelsztein, S., Vera, F., Romero, F., & Caullan, F. (2025). Social network addictions and their impact on work productivity and academic performance. *DYNA*, *92*(236), 97–102. https://doi.org/10.15446/dyna.v92n236.117361

Fondo de Riesgos Laborales (n.d.). *Gestión del liderazgo y las demandas mentales en el trabajo* https://www.fondoriesgoslaborales.gov.co/wp-content/uploads/2018/09/08-Protocolo-intervencion-sector-financiero.pdf

Fox, J., & Moreland, J. J. (2015). The dark side of social networking sites: An exploration of the relational and psychological stressors associated with Facebook use and affordances. *Computers in Human Behavior*, *45*, 168–176. https://doi.org/10.1016/j.chb.2014.11.083

Gewerc, A., Fraga, F., & Rodés, V. (2017). Niños y adolescentes frente a la Competencia Digital. Entre el teléfono móvil, youtubers y videojuegos. *Revista Interuniversitaria de Formación del Profesorado*, *31*(2), 171–186. https://www.redalyc.org/articulo.oa?id=27452662013

Hoong, R. (2019). *The behavioural economics of social media: A study of self commitment devices and the facebook privacy paradox*. AEA RCT Registry. https://doi.org/10.1257/rct.4519-1.0

INDEC (2024). *Serie 2016–2024: Cuenta de generación del ingreso (CGI): Valor agregado bruto e insumo de mano de obra por sector de actividad económica. Primer trimestre de 2016 a segundo trimestre de 2024.* Instituto Nacional de Estadística y Censos.

Instituto de Ciencias Sociales y Disciplinas Proyectuales (2023). *Encuesta sobre consumos de medios y tecnología en AMBA: Resultados de investigación.* UADE.

Instituto Nacional de Seguridad y Salud en el Trabajo (INSST). (n.d.). *La carga mental de trabajo*. https://www.insst.es/documents/94886/96076/carga+mental+de+trabajo/2fd91b55-f191-4779-be4f-2c893c2ffe37

Jensen, M., & Meckling, W. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, *3*(4), 305–360. https://doi.org/10.1016/0304-405X(76)90026-X

Kumar, K. A., & Priyadarshini, R. G. (2018). Study to measure the impact of social media usage on work-life balance. *IOP Conference Series: Materials Science and Engineering*, *390* , 012045. https://doi.org/10.1088/1757-899x/390/1/012045

Kuss, D. J., & Griffiths, M. D. (2017). Social networking sites and addiction: Ten lessons learned. *International Journal of Environmental Research and Public Health*, *14*(3), 311. https://doi.org/10.3390/ijerph14030311

Leftheriotis, I., & Giannakos, M. N. (2014). Using social media for work: Losing your time or improving your work? *Computers in Human Behavior*, *31*, 134–142. https://doi.org/10.1016/j.chb.2013.10.016

Lu, B., Guo, X., Luo, N., & Chen, G. (2015). Corporate blogging and job performance: Effects of work-related and nonwork-related participation. *Journal of Management Information Systems*, *32*(4), 285–314. https://doi.org/10.1080/07421222.2015.1138573

Mark, G., Gudith, D., & Klocke, U. (2008). The cost of interrupted work: More speed and stress. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 107-110). Association for Computing Machinery. https://doi.org/10.1145/1357054.1357072

Mohamed, S., Sidek, S., Kudus, N., Abu Hassan, M., & Izharrudin, S. Z. (2017). The Instrument used in measuring employee productivity based on social media usage: A review. *Journal of Human Capital Development*, *10*(1), 81–100. https://jhcd.utem.edu.my/jhcd/article/view/2760

Montag, C., Błaszkiewicz, K., Lachmann, B., Sariyska, R., Andone, I., Trendafilov, B., & Markowetz, A. (2015a). Recorded behavior as a valuable resource for diagnostics in mobile phone addiction: Evidence from psychoinformatics. *Behavioral Sciences*, *5*(4), 434–442. https://doi.org/10.3390/bs5040434

Montag, C., Błaszkiewicz, K., Sariyska, R., Lachmann, B., Andone, U., Trendafilov, B., Eibes, M., & Markowetz, A. (2015b). Smartphone usage in the 21st century: Who is active on WhatsApp? *BMC Research Notes*, *8*, 331. https://doi.org/10.1186/s13104-015-1280-z

Montag, C., Lachmann, B., Herrlich, M., & Zweig, K. (2019). Addictive features of social media/messenger platforms and freemium games against the background of psychological and economic theories. *International Journal of Environmental Research and Public Health*, *16*(14), 2612. https://doi.org/10.3390/ijerph16142612

Olmstead, K., Lampe, C., & Ellison, N. B. (2015). *Social media and the workplace*. Pew Research Center. https://www.pewresearch.org/internet/2016/06/22/social-media-and-the-workplace/

Olorunsogo, T. O., Balogun, O. D., Ayo-Farai, O., Ogundairo, O., Maduka, C. P., Okongwu, C. C., & Onwumere, C. (2024). Mental health and social media in the US: A review: Investigating the potential links between online platforms and mental well-being among different age groups. *World Journal of Advanced Research and Reviews*, *21*(1), 321–334. https://doi.org/10.30574/wjarr.2024.21.1.0015

Ortiz-Ospina, E. (2019). *The rise of social media.* Our World in Data. https://ourworldindata.org/rise-of-social-media

Reilly, M.C., Zbrozek, A.S. & Dukes, E.M. (1993). The validity and reproducibility of a work productivity and activity impairment instrument. *PharmacoEconomics*, *4*, 353–365. https://doi.org/10.2165/00019053-199304050-00006

Sarbu, M. (2017). Does social media increase labour productivity? *Jahrbücher für Nationalökonomie und Statistik*, *237*(2), 81–113. https://doi.org/10.1515/jbnst-2017-0104

Siddiqui, S., & Singh, T. (2016). Social media its impact with positive and negative aspects. *International Journal of Computer Applications Technology and Research*, *5*(2), 71–75. https://doi.org/10.7753/ijcatr0502.1006

Spira, J. B., & Feintuch, J. B. (2005). *The cost of not paying attention: How interruptions impact knowledge worker productivity* (Executive Summary). BASEX. https://www.interruptions.net/literature/Spira-Basex05.pdf

Statista (2025, November 19). *Average daily time spent on social media worldwide 2012–2025.* https://www.statista.com/statistics/433871/daily-social-media-usage-worldwide/

Sun Y, & Zhang Y. (2021). A review of theories and models applied in studies of social media addiction and implications for future research. *Addictive Behaviors*, *114*, 106699. https://doi.org/10.1016/j.addbeh.2020.106699

Tao, Y., Tang, Q., Wang, S., Zou, X., Ma, Z., Zhang, L., Liu, G., & Liu, X. (2024). The impact of long-term online learning on social anxiety and problematic smartphone use symptoms among secondary school students with different levels of fear of missing out: Evidence from a symptom network and longitudinal panel network analysis. *Journal of Behavioral Addictions*, *13*(1), 102–119. https://doi.org/10.1556/2006.2023.00081

Wang C., Lee M., & Hua Z. (2015). A theory of social media dependence: Evidence from microblog users. *Decision Support Systems*, *69*, 40–49. https://doi.org/10.1016/j.dss.2014.11.002

World Health Organization (WHO) (2024, January 22). *Traumatismos causados por el tránsito*. https://www.who.int/es/news-room/fact-sheets/detail/road-traffic-injuries

Wushe, T., & Shenje, J. (2019). The relationship between social media usage in the workplace and employee productivity in the public sector: Case study of government departments in Harare. *SA Journal of Human Resource Management*, *17,* a1116. https://doi.org/10.4102/sajhrm.v17i0.1116

Yeshambel, T., Belete, M., & Mulualem, Y. (2016). Impact of online social networking on employees productivity at work place in university of gondar - a case study. *International Journal of Computer Applications*, *135*(3), 18–24. https://doi.org/10.5120/ijca2016907844

Yemoh, M., & Amitai, F. I. (2022). The cost of workplace distractions to labor productivity; personal use of social media and hand-held devices during working hours. *International Journal of Advanced Scientific Innovation*, *4*(5).