THE HIDDEN CARBON COST OF SHORT-FORM VIDEO AI: EXAMINING THE SUSTAINABILITY PARADOX IN SOCIAL MEDIA MARKETING

DOI
https://doi.org/10.18690/um.epf.7.2026.38

ISBN
978-961-299-166-1

KRISZTINA FINTA,[1] DEZSŐ CSABA DÉR,[1]
KLAUDIA GABRIELLA HORVÁTH,[1]
EDWARD JAY MANSARATE QUINTO[2]

[1] Budapest Metropolitan University, Faculty of Business, Communication and Tourism, Budapest, Hungary
kfinta@metropolitan.hu; cder@metropolitan.hu, khorvath@metropolitan.hu
[2] Mapua University, School of Foundational Studies and Education, Manila City, Philippines
ejmquinto@mapua.edu.ph

This study investigates the sustainability paradox inherent in AI-driven short-form video marketing, where the rapid adoption of generative tools (e.g., Runway, Pika, Sora) increasingly conflicts with corporate Net Zero commitments. Drawing on a systematic literature review (2019-2026) at the intersection of AI ethics, environmental science, and marketing, alongside scenario-based carbon modeling, the analysis demonstrates that video generation consumes approximately 30 times more energy than image creation. Estimates indicate that a mid-sized marketing team generating 2,500 AI videos annually can emit up to 325.5 kg CO_2 - a hidden environmental cost largely obscured by decentralized "shadow AI" practices and the lack of AI-specific sustainability metrics in current KPIs. To address this reporting gap, particularly in light of expanding Scope 3 disclosure requirements under the EU CSRD, the paper introduces the Carbon Per Mille (C-CPM) indicator. By proposing algorithmic greenwashing as a conceptual lens, this research provides an initial academic assessment of the carbon footprint of AI video generation and advocates for the integration of carbon-aware operational strategies.

Keywords:
green AI,
algorithmic greenwashing,
short-form video marketing,
digital carbon footprint,
generative AI,
ESG reporting,
sustainable marketing,
shadow AI

University of Maribor Press

1 Introduction

In the contemporary digital landscape, short-form video has established itself as a dominant channel for digital interactions and consumer engagement (Luo et al., 2025). Industry reports indicate that short-form videos currently deliver the highest return on investment (ROI) for marketers, with 83% of professionals actively incorporating them into their campaigns (HubSpot, 2025). While public discourse occasionally reduces platforms like TikTok to simplistic entertainment, digital ethnographic research highlights that they actually host complex, platform-specific communicative forms and cultural artifacts that drive profound engagement (Schellewald, 2021). The specific features of short-form video content - such as usefulness, ease of use, and entertainment value - act as powerful stimuli that significantly enhance consumer trust and subsequent purchase intentions (Luo et al., 2025). From a big data perspective, these formal and content-related characteristics play a critical role in increasing consumer engagement, which explains the format's massive market share (Xiao et al., 2023).

The rapid proliferation of this format is increasingly propelled by the integration of Artificial Intelligence (AI) into content production processes. AI has moved beyond the experimental phase to become a central component of modern marketing strategies and research agendas (Mustak et al., 2021). Generative AI applications have significantly advanced targeting, personalization, content creation, and ad optimization capabilities (Gao et al., 2023; Somov et al., 2025). These tools spread rapidly because they verifiably increase management productivity and operational efficiency across multiple industries (Garg et al., 2024). However, this accelerated adoption also brings serious ethical and operational challenges. The opacity of computational advertising and highly personalized, AI-generated content raises significant concerns regarding manipulation, biases, and misleading claims (Gao et al., 2023; Huang & Rust, 2021; Najafloo et al., 2025; Szeberényi et al., 2025).

The intersection of AI-driven video marketing and corporate sustainability creates a severe, yet largely invisible, paradox. As marketing departments scale up the production of short videos relying on highly energy-intensive generative AI tools, a significant portion of the resulting carbon emissions remains completely unaccounted for in corporate Net Zero commitments.

Marketing professionals significantly exacerbate this lack of transparency by bypassing central IT infrastructure and official procurement protocols to utilize decentralized, cloud-based AI tools. This practice, identified in the literature as 'Shadow AI' (Silic et al., 2025), obscures the true scale of the carbon footprint associated with content creation. Addressing these hidden emissions is no longer merely an ethical or theoretical dilemma: the latest directive from the European Commission (2024) under the CSRD (Corporate Sustainability Reporting Directive) mandates comprehensive Scope 3 emissions reporting under ESRS E1, within which cloud-based AI usage constitutes a reportable source. No AI- or digital-specific sub-category is currently defined in the standard, yet this places immediate legal and compliance pressure on organizations.

To resolve this theoretical and practical gap, this study examines the sustainability paradox of AI-driven short-form video marketing by answering the following research questions:

- **RQ1:** To what extent does the application of generative AI tools in short-form video production contribute to unaccounted Scope 3 carbon emissions in corporate ESG reports, and how does the use of "shadow AI" amplify this reporting gap?
- **RQ2:** How do the carbon costs of AI video content creation differ across model architectures, and to what extent can a carbon cost-based indicator operationalize sustainable marketing goals?
- **RQ3:** To what extent can carbon-aware operational strategies - including renewable energy-based scheduling and model compression techniques - reduce the environmental costs of AI video generation without sacrificing marketing effectiveness?

2 Theoretical Background

2.1 The Energy Demand of Video-Generating AI

Beyond representing a technological shift, the rapid expansion of AI systems marks a global ecological turning point. This trajectory has been shaped by the 'Red AI' paradigm described by Schwartz et al. (2019), whereby performance improvements are pursued primarily through scaling computational resources rather than algorithmic efficiency. The scale of this tendency is illustrated by Strubell et al. (2019), who found that the complete research, development, and training process of a large language model can generate carbon emissions equivalent to the lifetime emissions of five automobiles. Pimenow et al. (2024) further highlight that the aggregate energy consumption of AI has reached such a critical level that it substantially threatens the achievement of international climate targets (Net Zero) if efficiency improvements do not keep pace with the volume of usage. Crucially, the ecological consequences of this paradigm extend beyond training: although model training emissions are expected to stagnate due to hardware optimisations, the widespread everyday use (inference) of AI systems is becoming the primary and fastest-growing operational source of carbon emissions (Patterson et al., 2022). This paradigm shift is evidenced by the measurements of Chien et al. (2023), which demonstrate that the aggregate carbon emissions derived from mass user queries of generative AI systems can exceed the ecological footprint of the model's original training by up to 25 times in a single year. Underpinning the aggregate carbon footprint of AI infrastructure are both the physical energy demands of hardware and the regional carbon intensity of supporting electricity grids (Kirkpatrick, 2023). This trend is further confirmed by Yu et al. (2024), whose comprehensive examination of 79 prominent AI systems between 2020 and 2024 underscores both the scale of aggregate emissions and the persistent lack of industry-wide transparency - notably, the authors were themselves compelled to rely on estimates, as most companies do not publicly disclose precise operational data.

Empirical energy analyses of generative systems have proven that multi-purpose and visual tasks consume orders of magnitude more power than simple text generation; image generation alone is nearly 60 times more energy-intensive than text-based tasks (Luccioni et al., 2023).

The disparity between generative modalities is dramatic: while the energy requirement for a simple text-based query is minimal, the resource intensity of visual content production increases by orders of magnitude rather than linearly. Measurements by Delavande et al. (2025) confirm that video generation processes exhibit an average energy consumption at least 30 times higher than that of generating static images (and almost 2000 times higher than simple text responses) - a conservative estimate corroborated by a large-scale benchmark study across 46 models, in which certain configurations showed energy differences exceeding 100×

between video and image generation (Chung et al., 2026). This finding is consistent with the data from Luccioni et al. (2023) and highlights how the shift toward video-centric marketing tools fundamentally overrides previous emission estimates for the digital sector.

The generation of short-form videos amplifies this effect even further, placing it among the most wasteful operations. During the inference phase of deep learning models, calculating and maintaining the temporal consistency between video frames places an extreme burden on graphics processing units (GPUs) (Desislavov et al., 2021). The spatiotemporal mechanisms of text-to-video diffusion models inherently require a substantial volume of floating-point operations (FLOPs) compared to traditional image generation (Wu et al., 2022). Furthermore, these modern systems are built on multi-billion parameter text-to-image (T2I) architectures, which are supplemented with complex spatiotemporal modules and extra decoders to achieve continuous motion and high visual quality, thereby non-linearly increasing energy consumption (Singer et al., 2022). Green AI fundamentally seeks to embed sustainability considerations directly into the lifecycle of algorithms. The theoretical framework of Alzoubi and Mishra (2024) emphasizes that, alongside software efficiency and hardware optimization, the introduction of transparent measurement metrics is essential for mitigating environmental impact.

2.2 Algorithmic Greenwashing and ESG Shortcomings

Despite the exceptionally high environmental burden of generative video models, a critical "governance gap" exists within organizations, as there is a complete lack of sustainability and accountability metrics regarding everyday AI use (Benbya et al., 2021). Exploiting this opacity, companies increasingly resort to sophisticated forms of greenwashing, which in modern corporate communication is often based on selective disclosure and the structural omission of inconvenient facts (Montgomery et al., 2023).

This is particularly relevant in the information and communication technology (ICT) sector, where companies often frame their digital developments as sustainable and 'green' CSR initiatives, while obscuring the substantial infrastructural impacts of the underlying data centers and algorithms (Famularo, 2023). This practice leads to the phenomenon of "algorithmic greenwashing". At the operational level, this is made possible by the fact that current Environmental, Social, and Governance (ESG) frameworks are often too generic and fail to specifically capture the complex environmental harms caused by AI technologies (Sætra, 2021). Furthermore, current sustainability indices often simply balance positive and negative impacts, enabling companies to appear sustainable without genuinely adopting environmental values (Horváth, 2023). Under the GHG Protocol, SaaS-based AI video generation constitutes a Scope 3, Category 1 emission source (Purchased Goods and Services) for the end-user organisation (WRI & WBCSD, 2011), meaning it falls within the mandatory reporting boundary established by CSRD's ESRS E1 standard. As a result, companies and their marketing departments can omit the massive carbon footprint originating from AI video generation from these indirect emissions reports with impunity and apparent transparency, thereby maintaining the illusion of Net Zero compliance (Sætra, 2021). Addressing this gap requires not only regulatory pressure but purpose-built measurement tools that embed environmental costs into the same decision layer as financial KPIs - a need this study addresses through the Carbon Per Mille (C-CPM) metric introduced in Section 4.3.

3 Methodology

The present study is built on a two-pillared methodological framework: a systematic literature review and scenario-based carbon modeling.

3.1 Systematic Literature Review

To theoretically ground the problem, a systematic literature review was applied, which allows for the synthesis of the latest findings in rapidly evolving, interdisciplinary fields - in this case, artificial intelligence, environmental science, and marketing strategy (Snyder, 2019). The aim of the review was to explore the conceptual relationships between "Red AI," content creation, and algorithmic greenwashing.

The literature search was conducted across Scopus, Web of Science, and Google Scholar using keyword combinations such as: ('generative AI' OR 'AI video generation') AND ('carbon footprint' OR 'energy consumption' OR 'sustainability') AND ('marketing' OR 'social media'). The search was limited to publications issued between 2019 and 2026. An initial pool of 152 sources was identified, of which 37 were retained following screening by title, abstract, and full-text relevance. Sources were excluded if they addressed AI energy consumption exclusively at the hardware infrastructure level without relevance to end-user organizational contexts.

Beyond this core SLR corpus, the study incorporates additional contextual references - including sources on consumer behavior, marketing frameworks, regulatory standards, and organizational governance - that were identified through targeted citation searches and were not part of the original systematic protocol.

3.2 Scenario-Based Carbon Modelling

Since precise architectural and energy consumption data for the most popular closed-source short-video-generating AI platforms (such as Runway or Pika) are currently not publicly available, the study employs scenario-based carbon modeling rather than direct measurements. The calculations are based on the methodology developed for quantifying the hardware energy consumption (GPU type, runtime) and carbon emissions of machine learning models (Lacoste et al., 2019).

To determine the parameters, the empirical benchmarks of Luccioni et al. (2023) regarding generative AI systems (especially multi-purpose and visual models) were utilized. The tracking and validation of the energy and carbon footprint of deep learning models is supported by the Carbontracker framework and the logic of similar open-source predictive tools (Anthony et al., 2020). The ML CO_2 Impact Calculator algorithm was applied to calculate explicit uncertainty bands and determine the final CO_2 equivalent (kg) (Schmidt et al., n.d.; Lacoste et al., 2019).

During carbon modeling, it is essential to consider the infrastructural background of software computations. For cloud providers, the use of location-based and time-specific marginal emission data is critical, as the emissions of AI models can vary significantly based on the geographical location of the serving data centers (e.g., the carbon intensity of the grid) (Dodge et al., 2022). Accordingly, three scenarios (optimistic, moderate, pessimistic) were developed for energy intensity, incorporating various model scales and respective power grid mixes (e.g., average EU and US grids). Adopting a multi-scenario approach accounts for the inherent variability in regional grid intensities, thereby ensuring methodological transparency. For regional and time-specific marginal emission data, the study draws on Chien et al. (2023), whose carbon-aware scheduling principles also constitute one of the main pillars of the mitigation strategies proposed in Section 4.3.

4 Results

Building on the theoretical framework and methodology presented earlier, this chapter answers the established research questions (RQ1-RQ3) through scenario-based modeling, quantifying the environmental burdens of short-form video generation, and formulating proposed solutions.

4.1 The "Shadow AI" Phenomenon and Establishing the SME Scenario (RQ1)

The corporate proliferation of generative AI tools has created a new, critical risk factor: the phenomenon of "Shadow AI" (Silic et al., 2025). Shadow AI practices - whereby decentralized individual subscriptions remain invisible to both corporate IT oversight and financial controlling - effectively exclude energy consumption from the scope of sustainability reporting. As a result, the associated emissions are not merely unaccounted for, but remain theoretically unmeasurable within current corporate reporting systems: Shadow AI thus constitutes one of the most critical blind spots in Scope 3 disclosure.

Although the training and maintenance of generative models are conducted by multinational technology companies, the environmental burdens of the associated cloud-based infrastructure (SaaS) directly fall upon the end-users. The SME sector forms the backbone of the global economy, and industry data confirm that small firms face the highest concentration of Shadow AI: at companies with 11-50 staff, 27% of employees actively use unsanctioned AI tools (Silic et al., 2025). Operational security data further reveal an average of 269 active shadow AI applications per 1,000 employees in this segment, indicating that individual users typically rely on multiple tools simultaneously (Reco, 2025). Given this disproportionate exposure, the micro-level modeling of this segment is essential for understanding macro-level ecological impacts.

To contextualize these impacts, we model a representative small and medium-sized enterprise (SME) scenario. In this framework, a two-person marketing team utilizes text-to-video (T2V) models daily for social media campaigns. Including tests, flawed prompts, and rejects, the team generates 10 short videos per day, which translates to 2,500 AI video generations annually, assuming an average 250-day working year.

4.2 Quantifying the Hidden Carbon Footprint

To calculate the physical environmental burden of the above 2,500 generations, we apply the validated logic of ecological footprint tracking systems (Budennyy et al., 2022), based on the following simplified formula:

$$CO_2(kg) = (E_{video} * N) * PUE * CI$$

The variables are determined based on the literature:

E_{video}: The electricity consumption of video generation. The energy demand of diffusion models is primarily determined by the resolution, the video length, and the number of denoising steps (Li et al., 2024). Relying on Delavande et al. (2025), the baseline consumption of generating a 10-second, high-resolution video was set at 0.15 kWh. This value represents a conservative estimate specifically for closed-source commercial platforms such as Runway, Pika, and Sora, for which no public energy data are available; open-source, lightweight models can operate at substantially lower consumption levels, as discussed in Section 4.3.

N: 2,500 generations/year.

PUE (Power Usage Effectiveness): The infrastructural and cooling multiplier of data centers, which is an industry average of 1.55 (Uptime Institute, 2022, as cited in Bouza et al., 2023).

Based on the calculation (2,500 * 0.15 kWh * 1.55), the team's annual "Shadow AI" video production alone generates 581.25 kWh of extra electricity consumption.

Determining the associated actual CO_2 emissions (Carbon Intensity, CI) presents a significant challenge. While major technology providers driving state-of-the-art video generation platforms (e.g., OpenAI's Sora on Microsoft infrastructure, Veo/Lumiere on Google Cloud, Runway, and Luma) publicly commit to corporate sustainability goals (Karaarslan & Aydın, 2024; Li et al., 2024), they treat the exact geographical locations and real-time energy mixes of their inference data centers as proprietary business secrets. This structural opacity (Famularo, 2023) makes it impossible to determine the precise grid carbon intensity for specific user requests. To address this uncertainty, we applied three distinct regional grid scenarios (Dodge et al., 2022) to the estimated annual consumption of 581.25 kWh, as detailed in Table 1:

Table 1: *Annual Carbon Emission Scenarios for the SME Shadow AI Model (581.25 kWh/year)*

Scenario	Energy Mix / Region	Grid Carbon Intensity (CI)	Estimated Annual Emissions
Optimistic	Renewable energy dominant	~20 g CO_2/kWh	11.6 kg CO_2
Moderate	Average grid intensity	~230 g CO_2/kWh	133.7 kg CO_2
Pessimistic	Fossil-heavy (e.g., coal baseline)	~400 g CO_2/kWh	232.5 kg CO_2

Note: Grid carbon intensity (CI) values are based on regional scenarios by Dodge et al. (2022). The pessimistic value represents a conservative lower bound, as fully coal-dependent grids can reach 600–900 g CO_2/kWh. Estimated annual emissions are authors' calculations.

Since estimates from AI energy metering software and static models can carry a margin of error of up to 40% (Fischer, 2025), we must assign an explicit uncertainty band of ±40% to this calculation. This means that, in a pessimistic case, the "Shadow AI" activity can result in up to 325.5 kg CO_2 of invisible annual emissions for a single small marketing team, which is equivalent to driving an average gasoline-powered car for approximately 3,055 kilometers - completely missing from the company's ESG reports.

4.3 Green Marketing KPIs and Guidelines (RQ2 & RQ3)

The transition toward carbon-aware marketing requires metrics that translate environmental impact into the language of business analytics (Alzoubi & Mishra, 2024). To meet this need, we introduce the Carbon Per Mille (C-CPM) indicator. This metric intentionally mirrors the traditional Cost Per Mille (CPM) structure -

with the 'C-' prefix ensuring clear differentiation in analytics dashboards - to elevate sustainability to the same decision-making priority as financial efficiency. By linking the carbon cost of content production with actual platform engagement, C-CPM enables the optimization of marketing ROI on both ecological and financial grounds. Formally, the metric is defined as follows:

$$C - CPM = \left(\frac{CO_2\,g}{Impressions}\right) * 1000$$

where CO_2(g) denotes the total carbon emissions generated during the creation of the content asset, expressed in grams, and Impressions denote the total number of views delivered. Integrating such transparent sustainability reporting not only supports CSRD compliance but also secures a long-term competitive advantage by aligning corporate values with measurable environmental accountability (Eccles et al., 2014).

Addressing RQ3 requires a quantitative evaluation of these reduction potentials. According to the cross-model comparison by Delavande et al. (2025), model selection alone accounts for differences spanning several orders of magnitude. Between a lightweight model (e.g. AnimateDiff, 0.14 Wh/video) and a large-scale architecture (WAN2.1-14B, ~415 Wh/video), there is a nearly 3,000-fold difference in energy consumption, while both are capable of producing short-form video content for marketing purposes. Due to the quadratic scaling of resolution and frame count, halving either dimension alone yields approximately a 4-fold reduction in energy use - a measure immediately applicable during testing and draft generation phases (Delavande et al., 2025; Li et al., 2024). Model compression techniques, particularly quantization, also carry substantial potential: reducing numerical precision from FP32 to INT8 can achieve energy savings of 50-67% without meaningful loss in output quality (Vergallo et al., 2025; Khan et al., 2025). Carbon-aware scheduling - deferring non-time-critical renders to periods when the cloud provider's regional grid relies on low-carbon, renewable energy - offers savings that vary by workload duration and regional energy mix. For short tasks, reductions of 30-80% have been demonstrated in certain regions, while longer workloads yield smaller gains (Dodge et al., 2022). Through the combined application of these three strategies, the achievable emissions reduction - without any sacrifice in marketing effectiveness - can bring the pessimistic SME-scenario estimate of 232.5 kg

CO_2/year down to as little as 20-30 kg annually, representing one of the most actionable operational countermeasures against algorithmic greenwashing.

5 Discussion

The responses to the three research questions collectively expose a systemic paradox at the heart of contemporary marketing practice.

The investigation of RQ1 confirmed that decentralized Shadow AI use represents one of the most critical blind spots in Scope 3 emissions reporting. The SME scenario modeling indicates that a single two-person marketing team may generate up to 325.5 kg CO_2 annually under the pessimistic scenario - emissions that remain entirely invisible to current ESG frameworks and corporate IT governance structures. This opacity is further compounded by the proprietary nature of closed-source generative AI models such as OpenAI's Sora, whose server locations and computational requirements are treated as trade secrets (Liu et al., 2024), as well as by the structural tendency of existing sustainability indices to aggregate positive and negative impacts, thereby enabling organizations to maintain the appearance of compliance without genuinely internalizing environmental values (Montgomery et al., 2023; Horváth, 2023). The exclusion of unmonitored activities from ESG reports is one of the most characteristic manifestations of algorithmic greenwashing - a phenomenon further amplified in the digital advertising market by the rapid proliferation of interactive and immersive content formats (Szeberényi et al., 2025).

The answer to RQ2 was developed through a cross-model comparison of carbon costs and the introduction of the Carbon Per Mille (C-CPM) indicator, which translates those differences into a metric directly comparable to existing financial KPIs, thereby elevating sustainability considerations to the same decision-making priority. This instrument directly addresses the measurement gaps of existing ESG frameworks (Sætra, 2021) and provides an operationalizable structure for Scope 3 compliance under CSRD ESRS E1 - within which cloud-based AI inference is now a mandatory reportable source under European Commission (2024) directives. As van Wynsberghe (2021) observes, the narrative must pivot from "AI for sustainability" toward ensuring the "sustainability of AI" itself - and the C-CPM introduced in this study is precisely what makes that shift measurable.

The findings of RQ3 demonstrated that through the combined application of carbon-aware operational strategies - model size optimization, quantization, and carbon-aware scheduling - the pessimistic scenario estimate of 232.5 kg CO_2/year can be reduced to as little as 20-30 kg annually, without any meaningful sacrifice in marketing effectiveness. This potential cannot be realized automatically, however: genuine mitigation requires institutional commitment and a robust sustainability governance culture (Sharma et al., 2026). On the technological side, parameter-efficient fine-tuning procedures such as SimDA (Xing et al., 2023), combined with the organizational integration of Green AI principles, together constitute the infrastructural foundation upon which carbon-aware marketing strategies can be built (Verdecchia et al., 2023).

Taken together, this research documents a systemic paradox in which the pace of technological adoption far outstrips the development of existing ecological frameworks (Lin, 2025; Cowls et al., 2021), while AI tools simultaneously offer practical pathways to increase energy efficiency and support conscious consumption patterns (Bozsik et al., 2025). Regulatory pressure - most notably the climate neutrality targets of the European Green Deal and the challenges of the renewable energy transition (Horváth, 2020; Szeberényi et al., 2024) - signals that what was once an ethical oversight is fast becoming a tangible compliance risk, rendering the adoption of carbon-aware marketing practice not only an ecological imperative but a business necessity as well.

6 Conclusions and Future Research

6.1 Summary and Theoretical Contribution

By quantifying the hidden ecological costs of digital marketing, this research identifies that a single micro-level team can generate between 133.7 kg CO_2 (moderate scenario) and 325.5 kg CO_2 (pessimistic upper estimation) annually through decentralized 'Shadow AI' usage. The upper estimate is equivalent to the electricity consumption of an average European household over a 6-7 week period. These findings illustrate how unmonitored digital activities can undermine broader corporate Net Zero commitments.

Central to the study's contribution is the introduction of the Carbon Per Mille (C-CPM) metric. By drawing an intentional terminological parallel with traditional cost-per-thousand metrics, this indicator facilitates an integrated relationship between marketing performance and environmental accountability. Integrating this parameter into analytics enables marketing ROI to be optimized on both ecological and financial grounds, providing a functional tool for organizations navigating the complexities of CSRD compliance.

6.2 Managerial and Practical Implications

This study offers highly actionable insights for marketing professionals, agency leaders, and corporate compliance teams. First, the identification of the 'Shadow AI' blind spot necessitates an immediate revision of internal IT governance. Marketing departments must audit decentralized, unsanctioned generative AI subscriptions to bring these hidden emissions into Scope 3 ESG reporting boundaries.

Second, the proposed Carbon Per Mille (C-CPM) metric provides a pragmatic tool for digital marketers. By integrating C-CPM into standard analytics dashboards alongside traditional financial KPIs, campaign managers can evaluate content ROI through a dual lens of cost-efficiency and ecological impact. Finally, the findings demonstrate that adopting carbon-aware operational workflows - such as rendering non-time-critical video assets during periods of high renewable grid capacity, or defaulting to computationally lighter models and lower resolutions for draft iterations - can drastically reduce a team's carbon footprint without compromising campaign performance or creative quality.

6.3 Limitations and Future Research

While scenario-based modeling addresses the current lack of primary data, the proprietary nature of commercial AI models remains a constraint on absolute precision. To address these estimation errors, the study employed explicit uncertainty bands (Fischer, 2025); however, future inquiries must prioritize direct collaboration with platform providers to replace estimation models with primary energy consumption data.

Beyond technical data refinement, the robustness of the C-CPM metric should be tested within large-scale corporate campaign environments to ensure its scalability within complex ROI analyses. Furthermore, a critical but less explored direction involves investigating the shifting environmental trade-offs between AI-generated workflows and traditional, human-led productions. As global energy grids transition toward renewables, the carbon-intensity ratio between these two modalities will likely evolve in ways that current static models cannot yet fully encapsulate.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Claude AI and Gemini for language editing, structural refinement, and proofreading. After using these tools, the authors reviewed and edited the content as needed and took full responsibility for the publication's final content.

Acknowledgment
This study was supported by the S.M.A.R.T. International Research Group.

References

Alzoubi, Y., & Mishra, A. (2024). Green artificial intelligence initiatives: Potentials and challenges. *Journal of Cleaner Production*. https://doi.org/10.1016/j.jclepro.2024.143090

Anthony, L. F. W., Kanding, B., & Selvan, R. (2020). Carbontracker: Tracking and predicting the carbon footprint of training deep learning models. *arXiv*. https://arxiv.org/abs/2007.03051

Benbya, H., Pachidi, S., & Jarvenpaa, S. (2021). Artificial intelligence in organizations: Implications for information systems research. *Journal of the Association for Information Systems*. https://doi.org/10.17705/1jais.00662

Bouza, L., Bugeau, A., & Lannelongue, L. (2023). How to estimate carbon footprint when training deep learning models? A guide and review. *Environmental Research Communications*, *5*. https://doi.org/10.1088/2515-7620/acf81b

Bozsik, N., Fűrész, Á., & Szeberényi, A. (2025). Smart Energy, Conscious Future: The Role of Artificial Intelligence in Energy Efficiency. *9th FEB International Scientific Conference: Sustainable Management in the Age of ESG and AI: Navigating Challenges and Opportunities*, 511-520. https://doi.org/10.18690/um.epf.5.2025.47

Budennyy, S., Lazarev, V., Zakharenko, N., Korovin, A., Plosskaya, O., Dimitrov, D., Arkhipkin, V., Oseledets, I., Barsola, I., Egorov, I., Kosterina, A., & Zhukov, L. (2022). eco2AI: Carbon emissions tracking of machine learning models as the first step towards sustainable AI. *Doklady Mathematics*, *106*, S118-S128. https://doi.org/10.1134/s1064562422060230

Chien, A. A., Lin, L., Nguyen, H. B., Rao, V., Sharma, T., & Wijayawardana, R. (2023). Reducing the carbon impact of generative AI inference (today and in 2035). In *Proceedings of the 2nd Workshop on Sustainable Computer Systems (HotCarbon '23)* (Article 11, pp. 1-7). Association for Computing Machinery. https://doi.org/10.1145/3604930.3605705

Chung, J.-W., Wu, R., Ma, J. J., & Chowdhury, M. (2026). Where Do the Joules Go? Diagnosing Inference Energy Consumption. *arXiv*. https://arxiv.org/abs/2601.22076

Cowls, J., Tsamados, A., Taddeo, M., & Floridi, L. (2021). The AI gambit: Leveraging artificial intelligence to combat climate change - opportunities, challenges, and recommendations. *AI & Society*, *38*(1), 283-307. https://doi.org/10.1007/s00146-021-01294-x

Delavande, J., Pierrard, R., & Luccioni, S. (2025, September 23). Video Killed the Energy Budget: Characterizing the latency and power regimes of open Text-to-Video models. *arXiv*. https://arxiv.org/abs/2509.19222

Desislavov, R., Martínez-Plumed, F., & Hernández-Orallo, J. (2021). Compute and energy consumption trends in deep learning inference. *arXiv*. https://arxiv.org/abs/2109.05472

Dodge, J., Prewitt, T., Combes, R. T. D., Odmark, E., Schwartz, R., Strubell, E., Luccioni, A. S., Smith, N. A., DeCario, N., & Buchanan, W. (2022). Measuring the carbon intensity of AI in cloud instances. *arXiv*. https://doi.org/10.48550/arXiv.2206.05229

Eccles, R. G., Ioannou, I., & Serafeim, G. (2014). The impact of corporate sustainability on organizational processes and performance. *Management Science*, *60*(11), 2835-2857. https://doi.org/10.1287/mnsc.2014.1984

European Commission. (2024). *CSRD technical standards: Digital emissions reporting (Delegated Regulation 2023/2772)*. https://eur-lex.europa.eu/eli/reg_del/2023/2772/oj

Famularo, J. (2023). Corporate social responsibility communication in the ICT sector: Digital issues, greenwashing, and materiality. *International Journal of Corporate Social Responsibility*, *8*, 1-25. https://doi.org/10.1186/s40991-023-00082-8

Fischer, R. (2025). Ground-truthing AI energy consumption: Validating CodeCarbon against external measurements. *arXiv*. https://doi.org/10.48550/arxiv.2509.22092

Gao, B., Wang, Y., Xie, H., Hu, Y., & Hu, Y. (2023). Artificial intelligence in advertising: Advancements, challenges, and ethical considerations in targeting, personalization, content creation, and ad optimization. *SAGE Open*, *13*. https://doi.org/10.1177/21582440231210759

Garg, S., Haralayya, B., Qudah, A. A. M., Maguluri, P. L., Szeberényi, A., & Sameen, Z. A. (2024). The impact of artificial intelligence on management productivity and efficiency. *Business Management and Economics Engineering*, *22*(1), 424-434. https://doi.org/10.2139/ssrn.5000221

Horváth, K. G. (2020). Az Európai Zöld Megállapodás és a 2021-2027-es többéves pénzügyi keret kapcsolata. *Európai Tükör*, *23*(1), 91-110. https://doi.org/10.32559/et.2020.1.5

Horváth, K. G. (2023). Vállalati fenntarthatóság és fenntartható vállalkozások. *Acta Humana: Emberi Jogi Közlemények*, *11*(3), 165-184. https://doi.org/10.32566/ah.2023.3.8

HubSpot. (2025). *Not another state of marketing report: 2025 marketing trends*. https://www.hubspot.com/state-of-marketing

Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, *49*(1), 30-50. https://doi.org/10.1007/s11747-020-00749-9

Karaarslan, E., & Aydın, Ö. (2024). Generate impressive videos with text instructions: A review of OpenAI Sora, Stable Diffusion, Lumiere and comparable models. *TechRxiv*. https://doi.org/10.36227/techrxiv.170862194.43871446/v1

Khan, S., Naz, N. S., Mazhar, T., Tariq, M. U., Shahzad, T., Guizani, S., & Hamam, H. (2025). Green AI techniques for reducing energy consumption in AI systems. *Array*, *29*, 100652. https://doi.org/10.1016/j.array.2025.100652

Kirkpatrick, K. (2023). The carbon footprint of artificial intelligence. *Communications of the ACM*, *66*, 17-19. https://doi.org/10.1145/3603746

Lacoste, A., Luccioni, A., Schmidt, V., & Dandres, T. (2019). Quantifying the carbon emissions of machine learning. *arXiv*. https://arxiv.org/abs/1910.09700

Li, B., Jiang, Y., & Tiwari, D. (2024). Carbon in motion: Characterizing Open-Sora on the sustainability of generative AI for video generation. *ACM SIGENERGY Energy Informatics Review*, *4*, 160-165. https://doi.org/10.1145/3727200.3727224

Lin, B. (2025). Research on the impact, risks and ethical boundaries of AI-generated content in advertising creativity and delivery. *Frontiers in Humanities and Social Sciences*. https://doi.org/10.54691/c5z3a890

Liu, Y., Zhang, K., Li, Y., Yan, Z., Gao, C., Chen, R., Yuan, Z., Huang, Y., Sun, H., Gao, J., He, L., & Sun, L. (2024). Sora: A review on background, technology, limitations, and opportunities of large vision models. *arXiv*. https://doi.org/10.48550/arxiv.2402.17177

Luccioni, A. S., Jernite, Y., & Strubell, E. (2023). Power hungry processing: Watts driving the cost of AI deployment? *arXiv*. https://doi.org/10.48550/arxiv.2311.16863

Luo, C., Hasan, N. A. M., Zamri bin Ahmad, A. M., & Lei, G. (2025). Influence of short video content on consumers' purchase intentions on social media platforms with trust as a mediator. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-94994-z

Montgomery, A. W., Lyon, T. P., & Barg, J. (2023). No end in sight? A greenwash review and research agenda. *Organization & Environment*, *37*(2). https://doi.org/10.1177/10860266231168905

Mustak, M., Salminen, J., Plé, L., & Wirtz, J. (2021). Artificial intelligence in marketing: Topic modeling, scientometric analysis, and research agenda. *Journal of Business Research*, *124*, 389-404. https://doi.org/10.1016/j.jbusres.2020.11.001

Najafloo, A., Soltani, A., & Szeberényi, A. (2025). Enhanced Marketing Strategies in the Metaverse: Opportunities and Challenges. *Acta Carolus Robertus*, *15*(1), 246-263. https://doi.org/10.33032/acr.6235

Patterson, D., Gonzalez, J., Hölzle, U., Le, Q. V., Liang, C., Munguía, L.-M., Rothchild, D., So, D. R., Texier, M., & Dean, J. (2022). The carbon footprint of machine learning training will plateau, then shrink. *arXiv*. https://doi.org/10.48550/arxiv.2204.05149

Pimenow, S., Pimenowa, O., & Prus, P. (2024). Challenges of artificial intelligence development in the context of energy consumption and impact on climate change. *Energies*. https://doi.org/10.3390/en17235965

Reco. (2025). *2025 State of Shadow AI Report*. https://www.reco.ai/state-of-shadow-ai-report

Sætra, H. (2021). A framework for evaluating and disclosing the ESG related impacts of AI with the SDGs. *Sustainability*. https://doi.org/10.3390/su13158503

Schellewald, A. (2021). Communicative forms on TikTok: Perspectives from digital ethnography. *International Journal of Communication*, *15*, 21. https://ijoc.org/index.php/ijoc/article/view/16414

Schmidt, V., Luccioni, A., Lacoste, A., & Dandres, T. (n.d.). *Machine learning CO2 impact calculator*. https://mlco2.github.io/impact/

Schwartz, R., Dodge, J., Smith, N. A., & Etzioni, O. (2019). Green AI. *arXiv*. https://arxiv.org/abs/1907.10597

Sharma, V., Kour, M., Vass, V., & Szeberényi, A. (2026). How Does Sustainability Governance Shape the Green Finance and Climate Nexus? *Sustainability*, *18*(2), 1022. https://doi.org/10.3390/su18021022

Silic, M., Silic, D., & Kind-Trüller, K. (2025). From shadow IT to shadow AI - threats, risks and opportunities for organizations. *Strategic Change*. https://doi.org/10.1002/jsc.2682

Singer, U., Polyak, A., Hayes, T., Yin, X., An, J., Zhang, S., Hu, Q., Yang, H., Ashual, O., Gafni, O., Parikh, D., Gupta, S., & Taigman, Y. (2022). Make-A-Video: Text-to-video generation without text-video data. *arXiv*. https://arxiv.org/abs/2209.14792

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, *104*(1), 333-339. https://doi.org/10.1016/j.jbusres.2019.07.039

Somov, A. G., Ergunova, O. T., & Szeberényi, A. (2025). The influence of artificial intelligence on decision-making in the field of personnel management of large corporations. In V. Krastev, C. Rani, O. Ergunova, P. Kansra, & T. Kajla (Eds.), *Empowering human resources through human-computer interaction* (pp. 181-206). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3373-1676-5.ch007

Strubell, E., Ganesh, A., & McCallum, A. (2019). Energy and policy considerations for deep learning in NLP. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics* (pp. 3645-3650). https://doi.org/10.18653/v1/p19-1355

Szeberényi, A., Fűrész, Á., & Rokicki, T. (2024). Renewable energy in Hungary: Awareness, challenges, and opportunities. In J. Belak & Z. Nedelko (Eds.), *8th FEB International Scientific Conference: Challenges in the Turbulent Economic Environment and Organizations' Sustainable Development* (pp. 509-518). University of Maribor Press. https://doi.org/10.18690/um.epf.5.2024

Szeberényi, A., Akbar, S., Araz, N., & Balku, R. (2025). Interactive and Immersive Advertising in the Metaverse: User Perceptions and Engagement Compared to Traditional Online Environments. *Acta Carolus Robertus*, *15*(Special Issue), 3-19. https://doi.org/10.33032/acr.7019

van Wynsberghe, A. (2021). Sustainable AI: AI for sustainability and the sustainability of AI. *AI and Ethics*, *1*(1), 213-218. https://doi.org/10.1007/s43681-021-00043-6

Verdecchia, R., Sallou, J., & Cruz, L. (2023). A systematic review of Green AI. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *13*. https://doi.org/10.1002/widm.1507

Vergallo, R., Aprile, M., Cruz, L., Vadacca, R., & Mainetti, L. (2025). Large-scale evaluation of quantization for reducing the energy footprint of deep learning models. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.5719661

World Resources Institute (WRI) & World Business Council for Sustainable Development (WBCSD). (2011). *Corporate value chain (Scope 3) accounting and reporting standard*. GHG Protocol. https://ghgprotocol.org/scope-3-standard

Wu, J. Z., Ge, Y., Wang, X., Lei, W., Gu, Y., Shi, Y., Hsu, W., Shan, Y., Qie, X., & Shou, M. Z. (2022). Tune-A-Video: One-shot tuning of image diffusion models for text-to-video generation. *arXiv*. https://arxiv.org/abs/2212.11565

Xiao, L., Li, X., & Zhang, Y. (2023). Exploring the factors influencing consumer engagement behavior regarding short-form video advertising: A big data perspective. *Journal of Retailing and Consumer Services*, *70*, 103170. https://doi.org/10.1016/j.jretconser.2022.103170

Xing, Z., Dai, Q., Hu, H., Wu, Z., & Jiang, Y.-G. (2023). SimDA: Simple diffusion adapter for efficient video generation. *arXiv*. https://arxiv.org/abs/2308.09710

Yu, Y., Wang, J., Liu, Y., Yu, P., Wang, D., Zheng, P., & Zhang, M. (2024). Revisit the environmental impact of artificial intelligence: The overlooked carbon emission source? *Frontiers of Environmental Science & Engineering*, *18*. https://doi.org/10.1007/s11783-024-1918-y

About the authors

Krisztina Finta has been working in digital marketing for more than 10 years, with a strong focus on campaign planning, data analysis, and the application of AI-based tools. As Marketing Manager of Oszkár Telekocsi, she played an active role in both strategic and operational functions. She currently works as an independent consultant and teaches Social Media and SME Marketing at Budapest Metropolitan University, where the integration of AI solutions is a key focus of her courses.

Dr. **Csaba Dezső Dér** is an associate professor and the Head of the Institute of Marketing and Communication at Budapest Metropolitan University. With extensive experience in higher education, he has been contributing to the development of METU's marketing programmes through his work in teaching, academic leadership, and curriculum design. His primary professional focus lies in the rebranding of traditional brands, with particular interest in how established brand identities can be revitalized in contemporary markets.

Dr. **Klaudia Gabriella Horváth** has been working in the field of innovation management since 2019, focusing on collaborations between universities and Hungarian SMEs, product development processes, and the interconnections between corporate sustainability and product positioning. She earned her PhD in Public Management at the University of Public Service in Hungary. Alongside her teaching and research activities, she has gained experience in public administration as well as in multinational

corporations such as P&G and Tungsram, providing her with strong practical insight into the corporate implementation of sustainability.

Prof. **Dr. Edward Jay M. Quinto** is a Full Professor and Dean of the School of Foundational Studies and Education, Mapúa University, Manila, Philippines. He obtained his Ph.D. in Applied Linguistics from De La Salle University in 2018. His research on psycho- and sociolinguistics appeared in top linguistics journals, including English World-Wide (EWW), International Journal of Multilingualism (IJM), and Asian Englishes (AE). A member of the Mapúa AI Strategy Group, he represented Mapúa University at the 2022 and 2024 editions of the Wharton-Quacquarelli Symonds Reimagine Education Awards, dubbed as the Oscars of Education, held respectively at the Wharton School, University of Pennsylvania, Philadelphia, Pennsylvania, USA, and the Queen Elizabeth II Center, City of Westminster, London, UK.