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USE OF ARTIFICIAL INTELLIGENCE TO REDUCE PRODUCTION TIMES IN CORPORATE RECREATIONAL EVENT MANAGEMENT

USO DE LA INTELIGENCIA ARTIFICIAL PARA REDUCIR LOS TIEMPOS DE PRODUCCIÓN EN LA GESTIÓN DE EVENTOS RECREATIVOS CORPORATIVOS

Giancarlo Castillo Ghiotto
Universidad Internacional Iberoamericana, Peru
[giancarlo.castillo@investigacion.uneatlantico.es] [https://orcid.org/0009-0008-9052-5391]

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ABSTRACT

Introduction. Corporate recreational event agencies often rely on manual routines that extend production cycles and increase rework. This study examines whether adopting generative AI is associated with reduced event production time. Methodology. A quasi-experimental before–after single-case design was conducted in a corporate recreational events company (Bogotá, Colombia) between June and September 2025. Three comparable events were produced under a traditional approach (no AI) and then with systematic ChatGPT support for creative and administrative tasks (concept development, proposal drafting, budgeting, and supplier selection). The dependent variable was total production time (hours) from brief reception to final approval. Given the small sample, the analysis prioritized paired differences, confidence intervals, and effect sizes. Results. A consistent reduction in total production time was observed across events (51 h, 60 h, and 69 h), yielding an average saving of 60 h (19.1%). The largest savings occurred in Concept Development (23.3 h) and Proposal Preparation (20.0 h), while Final Validation slightly increased (+1.3 h), reflecting additional quality checks. Conclusions. Findings suggest generative AI can be an efficiency lever for mid-sized agencies when combined with governance, training, and human verification. Results should be interpreted as applied and exploratory due to the small sample and single organizational setting. Future research should test replicability with more events and additional outcomes (cost, quality, and client satisfaction).

Palabras clave:
ChatGPT, inteligencia artificial generativa, gestión de eventos, productividad, Colombia.

RESUMEN

Introducción. En agencias de eventos recreativos corporativos, los ciclos de producción suelen depender de rutinas manuales que elevan horas de trabajo y retrabajo. Este estudio analiza si la incorporación de IA generativa se asocia con una reducción del tiempo total de producción. Metodología. Se aplicó un diseño cuasi-experimental antes–después (caso único, fase pre y fase post) en una empresa del sector de eventos recreativos corporativos (Bogotá, Colombia), entre junio y septiembre de 2025. Se compararon tres eventos de naturaleza comparable producidos sin IA y luego con apoyo sistemático de ChatGPT en tareas creativas y administrativas (conceptualización, propuesta, presupuestación y selección de proveedores). La variable dependiente fue el tiempo total de producción (horas), medido desde la recepción del brief hasta la aprobación final. El análisis priorizó estimaciones de diferencias pareadas, intervalos de confianza y tamaños de efecto, dada la muestra reducida. Resultados. En los tres eventos se observó una reducción consistente del tiempo total (51 h, 60 h y 69 h), equivalente a un ahorro promedio de 60 h (19.1%). El mayor ahorro se concentró en Conceptualización (23.3 h) y Elaboración de propuesta (20.0 h). En Validación final se registró un leve aumento (+1.3 h), asociado a mayor revisión de calidad. Conclusión. Los hallazgos sugieren que la IA generativa puede funcionar como palanca de eficiencia en agencias medianas cuando se integra con gobernanza, capacitación y verificación humana. Las conclusiones deben interpretarse como evidencia aplicada y exploratoria por el tamaño muestral y tratarse de un único caso. Se recomienda replicar con más eventos y organizaciones y ampliar métricas (costo, calidad y satisfacción del cliente).

Introduction

This article makes a contribution on three levels. First, it provides quantitative evidence under real-world conditions regarding the temporal impact of generative AI on the production of corporate events in Colombia, a topic that has received little attention in the literature. Second, it breaks down the savings by process phase, making it possible to identify where AI adds the most value and where it could lead to additional verification costs. Third, incorporate indicators of team acceptance to discuss the sustainability of adoption. The document is organized as follows: the "Method" section describes the quasi-experimental design and the intervention; "Results" presents the observed effect and a breakdown by phase; and "Discussion and Conclusions" interprets the findings, their implications, and limitations.

Contributions and Structure of the Article

The main hypothesis (H1) posits that the systematic incorporation of generative AI (ChatGPT) into creative and administrative tasks is associated with a reduction in total production time (hours) compared to tasks performed without AI. The null hypothesis (H0) states that no significant differences in total time will be observed.

To clarify the operational mechanism, the following secondary hypotheses are proposed: (H1a) The greatest savings are concentrated in phases that are intensive in terms of drafting and ideation (Conceptualization and Proposal Development); (H1b) savings are lower in phases that rely on third parties (Supplier Selection); and (H1c) final validation may remain the same or increase slightly due to more rigorous verification controls. In addition, (H2) acceptance of the equipment will be high (perceived usefulness and ease of use), promoting the sustainability of adoption.

Objective, Questions, and Hypotheses

In addition, the effective adoption of AI depends on user acceptance. The Technology Acceptance Model posits that perceived usefulness and ease of use influence the intention to use a technology and actual adoption (Davis, 1989). Later models, such as UTAUT2, incorporate factors such as performance expectations, effort, social influence, and facilitating conditions (Venkatesh et al., 2012). Consequently, a comprehensive evaluation must combine operational metrics (hours saved) with indicators of team perception, since a time savings might be unsustainable if the tool is rejected or causes cognitive overload.

This study interprets generative AI as an enabling capability that can strengthen dynamic organizational capabilities: the ability to perceive opportunities, capitalize on them by reconfiguring resources, and adapt routines to sustain superior performance in changing environments (Teece, 2007). At an event agency, the ability to quickly reconfigure a concept, readjust a budget, or rethink the selection of vendors in response to client changes results in less friction, greater speed, and a higher-quality response.

Conceptual Framework: Dynamic Capabilities and Technology Adoption

In Colombia, the debate over the adoption of generative AI in organizations has intensified, and market reports point to growing interest in the region. Even so, there remains a gap between enthusiasm for the tool and its effective integration into operational processes. In the events sector, local "event tech" initiatives have emerged, but the maturity of processes and the availability of data still limit widespread adoption (Bmotik, 2024). In this context, a pragmatic approach involves introducing AI to assist with time-consuming tasks, measuring its impact using clear metrics, and refining the process through organizational learning.

State of the Art: AI Applications in the Events Industry

Research and professional practice have identified numerous applications for AI in the event value chain. In the run-up to an event, algorithms can support marketing and communication efforts through audience segmentation and message personalization; for example, industry platforms have reported improvements in engagement when AI-assisted segmentation techniques are applied to email campaigns (Bizzabo, 2023). Similarly, predictive analytics can estimate attendance and registration patterns to adjust logistics and capacity; one illustrative example is the use of machine learning models to predict participation in events in specific sectors, which makes it possible to optimize resources and reduce waste (Bayne & Innala, 2024).

During the event, applications such as chatbots for attendee support, networking recommendation tools, and real-time analytics systems for queue management and mobility are described. After the event, AI can automate reports, satisfaction analyses, and the creation of follow-up content. However, much of this literature focuses on large-scale events or conferences with robust digital infrastructure; in contrast, medium-sized agencies that manage corporate recreational events face data limitations, diverse requirements, and a high reliance on tacit knowledge. In these scenarios, generative AI is particularly appealing because, in its basic form, it does not require large volumes of structured data to add value: it can speed up writing, ideation, and document structuring tasks based on a relatively short brief.

At the regional level, the adoption of generative AI is in its early stages and varies widely. News reports based on analyses of learning platforms have indicated that Latin American countries are showing significant increases in interest in and training on generative AI, although gaps in practical implementation within organizations persist (Alburquerque, 2025). Therefore, in addition to discussing potential benefits, it is necessary to generate applied evidence that can guide investment decisions in small and medium-sized enterprises in the sector.

In summary, although there is a consensus that AI can transform the events industry, the empirical evidence on its impact on productivity—measured directly in terms of work hours—is still limited. This article addresses that gap with a quasi-experimental design focused on total production time and a breakdown by phase, generating actionable results for project managers and operations directors in the creative services industry.

However, the adoption of AI in services that require a high degree of creativity and coordination presents challenges. On the one hand, there is a risk of producing generic content that fails to capture the client's context; on the other hand, privacy and data usage concerns arise when external systems are used to process participant information or internal company details. The literature identifies concerns regarding trust, transparency, and data protection in AI- “augmented” events (Adams, 2021). Furthermore, field experience in knowledge work suggests that the impact of AI is not uniform: it depends on the type of task, the degree of structure, the user’s ability to formulate effective instructions, and the need for subsequent verification (Dell'Acqua et al., 2023).

The management of a corporate recreational event can be viewed as a short-cycle project: it begins with a client brief, continues with conceptualization and design, moves on to proposal and budget development, vendor selection, validation, and closure. Each stage includes specific deliverables (concepts, visual elements, timelines, financial proposals, contracts, assembly plans) and decisions that feed into one another. In these types of projects, response time and rapid iteration are key to gaining a competitive edge, especially when the client is comparing several agencies. Generative AI can serve as an "assistant" in tasks such as brainstorming, drafting proposals, structuring budgets, and evaluating alternatives. In economic terms, these tools function as predictive and cognitive support technologies that reduce the cost of producing and reviewing information, thereby shifting the productivity frontier of knowledge work (Agrawal et al., 2022).

Event-specific empirical evidence is growing, but it remains limited in terms of operational metrics. Recent studies report improvements in efficiency in content planning and production with the support of generative AI, provided that human verification is maintained to ensure accuracy and relevance (Keiper, 2023). Systematic reviews in event management also indicate that most applications focus on personalization, analytics, and automation, and recommend further quantitative studies using direct productivity indicators in real-world settings (Kumar & Ratten, 2025). In this context, tracking production hours by phase provides actionable insights for medium-sized agencies.

Generative AI and Managing Events as Projects

The central issue addressed in this article is the lack of empirical evidence—under real-world operating conditions—regarding the extent to which the production time for corporate recreational events can be reduced by incorporating generative AI as a support tool for key tasks in the process. The question is not solely a technological one: for AI to generate value, it must be integrated into a workflow with clear roles, quality criteria, version control, and verification mechanisms. In this regard, the research is designed as an applied study that quantifies the temporal impact of a specific intervention (the use of ChatGPT) in a real-world company, employing an appropriate quasi-experimental design when it is not possible to randomly assign treatments in a production environment (Shadish et al., 2002).

At the same time, the emergence of large-scale language models and generative artificial intelligence (AI) tools has opened up opportunities to automate and accelerate cognitive tasks across multiple industries. Recent studies show that these systems can improve productivity in tasks such as writing, summarization, customer service, and analytical support, with results varying depending on the type of work and the user's experience (Brynjolfsson et al., 2025; Eloundou et al., 2024). In the field of events, the literature shows a growing interest in AI applied to personalization, predictive analytics, communication optimization, and creative support, although descriptive approaches predominate and there is a lack of causal evidence in Latin American contexts (Abdul Halim et al., 2023).

The corporate events industry in Colombia has regained momentum in recent years, but its day-to-day operations continue to rely on labor-intensive practices: coordination via email and courier services, preparing proposals in non-standardized documents, creating budgets from scratch, and sourcing vendors based on prior experience. These routines, while functional, tend to lengthen the production cycle and increase indirect costs per man-hour, especially in medium-sized agencies where a single person takes on multiple roles (design, logistics, purchasing, and customer service). Various sources have highlighted the sector's economic importance and its need for modernization through digital solutions, in an environment where customers demand faster responses, personalized offers, and cost transparency (Forbes Staff, 2024).

Method

The study used the company's internal operational information and did not collect personal data from event participants. Interactions with AI were limited to information necessary for conceptualizing and developing proposals, avoiding the sharing of sensitive data. Policies were adopted to ensure that all AI-generated content undergoes human verification, recognizing that the tool can produce plausible but incorrect responses, which requires quality controls and professional accountability (Dell'Acqua et al., 2023).

Ethical and Governance Considerations

The analysis was conducted on two levels. First, the absolute and relative savings were estimated for each event and as an average for the period. Second, the average difference was assessed using a paired t-test with $n = 3$ pairs ($df = 2$). The 95% confidence interval was reported using the t-distribution, and the effect size was reported using Cohen's dz. Given the low statistical power when n is small, this was supplemented with a percentile bootstrap interval for the differences. A nonparametric test (Wilcoxon) was also calculated as a conservative verification, acknowledging its limited power when $n=3$. Finally, the savings were broken down by phase, and the contribution of each phase to the total average savings was calculated. The perception data were summarized using means and the percentage of agreement (4–5).

Data Analysis

The analysis was conducted in three steps. First, we estimated the absolute and relative savings per event and the average for the period, as well as a breakdown by phase to identify where the change is concentrated. Second, supplementary estimates (confidence interval and effect size) were reported for the paired differences. Given the sample size ($n=3$ pairs), any statistical inference is interpreted as exploratory; therefore, the emphasis is placed on the directional consistency of the change, the magnitude of the effect, and consistency with the logic of the process. Third, the acceptance data were summarized using means and percentages of agreement (4–5) on a Likert scale.

Comparability and Measurement Quality Control

Comparability across events is a recurring challenge in applied project management studies, as each client introduces variations in scope, urgency, and the number of iterations. To mitigate this threat, the three cases were selected based on similarities in the type of service (corporate recreational events), the structure of deliverables, and the general approval process (brief → concept → proposal and budget → validation). In addition, the same core production team was retained, and the same time-tracking system was used both before and after the intervention.

Time tracking was conducted using internal logs for each event, in which each team member recorded the actual hours spent on project tasks. To ensure data consistency, the records were cross-checked against operational evidence: document versions (proposal and budget), file timestamps, and the timeline of communications with clients and suppliers. The goal was not to estimate individual productivity, but rather to capture the team’s aggregate effort by phase, thereby avoiding incentives for underreporting or overreporting.

With regard to the intervention, minimum guidelines for using ChatGPT were established to ensure that the results would not depend on sporadic or improvised use. These practices included: (a) use of structured prompts (context, role, constraints, output format), (b) brief iteration to improve accuracy (maximum of three rounds per deliverable), (c) mandatory human validation before sending to the client, and (d) tracking of hours spent interacting with AI as an auxiliary variable. These practices aim to strike a balance between speed and quality control, given that AI can produce persuasive texts that contain errors if they are not verified.

Finally, it is recognized that a before-and-after design may be subject to learning (maturation) effects: the team naturally improves with practice. However, the observation period was limited and the operational change was explicit (the incorporation of generative AI); therefore, the magnitude of the savings and their concentration in specific phases are indicators consistent with an intervention effect rather than a gradual improvement. Even so, future simulations with a larger number of observations could model pre-existing trends more accurately.

Procedure

To assess acceptance and barriers, an internal survey was administered to the team (n=10) using a 1-to-5 Likert scale, based on the dimensions of perceived usefulness and ease of use proposed by the TAM and expanded upon by UTAUT2 (Davis, 1989; Venkatesh et al., 2012). The survey included questions about ease of use, efficiency, perceived quality, and willingness to continue using AI.

The dependent variable was total production time (in hours), defined as the number of hours spent by the team from the time the brief was received until the final proposal was approved. Time was tracked using internal logs and deliverable tracking. In addition, the timeline was broken down into five phases of the actual workflow: (1) Conceptualization, (2) Proposal development, (3) Budgeting, (4) Supplier selection, and (5) Final validation. The independent variable was operationalized as "use of generative AI" (without AI vs. with AI), and, in addition, the actual hours of interaction with ChatGPT per event were recorded.

Variables and Instruments

The initiative involved incorporating ChatGPT as a support tool for specific tasks: (a) conceptualization and development of thematic ideas and experience scripts; (b) drafting and structuring the business proposal; (c) support for budgeting by organizing line items, making assumptions, and verifying consistency; and (d) support in the selection of suppliers through comparative matrices, criteria, and drafting of communications. The use of these was guided by standardized prompts and internal quality criteria (relevance to the client, consistency with the brand, logistical feasibility).

Presentation: Use of Generative AI (ChatGPT)

The study was conducted at a company in the corporate recreational events sector—an events agency located in Bogotá, Colombia—that specializes in corporate recreational events. The unit of analysis was the entire event production process, from receiving the brief to the client's approval of the final proposal. Three comparable events were selected—first produced using a traditional approach (without AI) and then produced with the support of generative AI—during the period from June to September 2025. The events analyzed were: Father's Day, Five-Year Anniversaries, and the Wind Festival.

Case Study and Unit of Analysis

A quasi-experimental before-and-after design (single case, pre-phase and post-phase) with an interruption logic was used: the interruption corresponds to the systematic adoption of ChatGPT as a support tool for specific tasks in the production workflow. The unit of analysis was the entire production process for an event (from the brief to final approval). In total, six aggregated time-series measurements were identified (three events in the pre-phase without AI and three events in the post-phase with AI), selected based on the comparability of deliverables, approval workflow, and core team.

Given the limited number of observations, the design is considered applied and exploratory: it allows us to estimate the magnitude of the change and identify the phases in which the savings are concentrated, but it does not aim to establish a strong causal attribution equivalent to designs with long time series or control groups.

Results

However, organizational barriers (PI-4) were identified, including initial resistance, the need for training to develop effective prompts, and concerns about errors or generic content. Likewise, the need arose for clear policies regarding what information can be shared with external systems and how to document the verification process, in line with privacy concerns reported in qualitative studies of the sector (Adams, 2021).

The internal survey (n=10) shows a high level of acceptance of the tool. Ease of use received an average score of 4.2 (SD=0.9), and the perceived improvement in efficiency received an average score of 4.4 (SD=0.8). The statement “I would continue to use AI tools in future projects” received a score of 4.8 (SD=0.6) and a 90% agreement rate (4–5). These results are consistent with the TAM: perceived usefulness and ease of use are high, which promotes intention to use (Davis, 1989).

In addition to perceived efficiency, the team reported improvements in the quality of their work/proposals (mean 4.0; SD=0.7) and a high level of comfort in using the tool (mean 4.3; SD=0.8). The agreement rates (responses 4–5) were 80% for efficiency, quality, and comfort. These results suggest that, although further verification is needed, AI was viewed as a tool that improves speed without compromising the perceived quality of the deliverable.

As for barriers, the main ones fall into three categories: (1) competition barriers (prompting learning and criteria for evaluating outputs), (2) process barriers (defining at which points AI is used and where human approval is required), and (3) governance barriers (privacy, handling of confidential information, and decision logging). These barriers are consistent with industry experience, which indicates that technology must be accompanied by organizational changes in order to realize benefits (Abdul Halim et al., 2023).

Team Perception and Emerging Barriers

In addition, the actual interaction time with ChatGPT per event was recorded (Table 1). On average, 14.7 hours of AI were used per event. This approach allows us to view AI as a productive resource: hours are invested in interaction (prompts, iterations, and refinement) to save hours in the overall process. Although a robust functional relationship is not established when n=3, the metric suggests that the tool's time-based return may vary depending on the complexity of the event and the degree to which the brief is structured. At the operational level, this underscores the need to develop prompting skills and reusable templates to increase the marginal efficiency of AI use.

By correlating the time saved with the number of hours of AI use, we obtain a productivity metric called AI-Leverage (hours saved per hour of interaction with AI). On

Father's Day, the IA-Leverage was 5.10; during the Quinquenios, 5.00; and at the Festival del Viento, 3.14. The average was 4.41. The variation suggests that, although AI generates savings in all cases, more complex events may require more interaction time to achieve appropriate outcomes, thereby reducing the hourly return on AI. In practice, this underscores the fact that AI is not "automatic": its performance depends on the clarity of the brief, the quality of the prompts, and the availability of internal data to provide context for responses (lists of vendors, rates, venue restrictions).

Derived Indicators: Intensity of Use and Productivity

One notable finding is that, in the final validation phase, the duration increases slightly (+1.3 h; -6.7% relative). This increase suggests a shift in focus toward the final review and refinement of AI-generated content (for example, verifying cost assumptions, adapting the language to the client's culture, and ensuring narrative consistency). From a management perspective, this is consistent with field evidence regarding the "irregular technology front," where AI can accelerate certain tasks but requires human verification and editing to ensure quality (Dell'Acqua et al., 2023).

To directly answer questions PI-1 through PI-3, the total time was broken down into five operational phases. Table 1 summarizes the averages by phase for the three events, as well as the absolute savings, relative savings, and contribution to the average total savings (60 h). The greatest savings are concentrated in Conceptualization (23.3 hours; 29.2% relative) and Proposal Development (20.0 hours; 22.2%), which together account for approximately 72% of the total savings. In Budgeting, there is an average time savings (13.0 hours; 15.6%), while in Supplier Selection, the time savings are smaller (5.0 hours; 12.5%).

Table 1

Averages by phase: hours without AI vs. with AI, relative savings, and contribution to total savings

Phase	Average without AI (h)	Average with AI (h)	Savings (h)	Relative savings (%)	Contribution to total savings (%)
Conceptualization	80.0	56.7	23.3	29.2%	38.9%
Proposal Development	90.0	70.0	20.0	22.2%	33.3%
Budgeting	83.3	70.3	13.0	15.6%	21.7%
Supplier Selection	40.0	35.0	5.0	12.5%	8.3%

Final Validation	20.0	21.3	-1.3	-6.7%	-2.2%

Note. Contribution calculated as (Phase savings / 60 h). Negative values indicate an increase in the time spent with AI during that phase. Created by the author.

Breakdown of Savings by Process Phase

Table 2 presents additional estimates of the average difference (Without AI – With AI). Paired t-tests and effect sizes are reported as exploratory estimates given the sample size (n = 3 pairs). At the same time, the exact nonparametric test (Wilcoxon) did not reach statistical significance (p=0.25), a result that is to be expected given the low statistical power due to the small sample size. Consequently, the interpretation is based primarily on (i) the consistency of the savings across the three events, (ii) the practical magnitude of the change (average of 60 hours; 19.1%), (iii) the confidence interval for the average difference, and (iv) the concentration of the savings in specific phases of the process.

Table 2

Statistical inference regarding the reduction in total time (n=3 events)

Statistician	Result
Average Difference (Without AI - With AI)	60.0 h
95% CI (t, df=2)	[37.6 h, 82.4 h]
Student's t-test (paired)	t(2) = 11.54; p = 0.0074
Effect size (Cohen's dz)	dz=6.67 (very large)
95% Bootstrap IC (percentile; n=3)	[51 h, 69 h]
Paired Wilcoxon (exact; n=3)	W=0; p=0.25 (low power with a small n)

Note. The 95% CI was estimated using a t-distribution (df=2). The bootstrap reports the percentile range for the differences (n=3).

Table 3 shows the total production times in hours for the three events analyzed, comparing the traditional approach (without AI) and the approach supported by generative AI. In all three cases, there is a substantial reduction in total time: Father's Day went from 300 hours to 249 hours (51 hours less), Quinquenios from 360 hours to 300 hours (60 hours less), and the Wind Festival from 280 hours to 211 hours (69 hours less). The average time saved was 60 hours, equivalent to a 19.1% reduction compared to the time taken without AI.

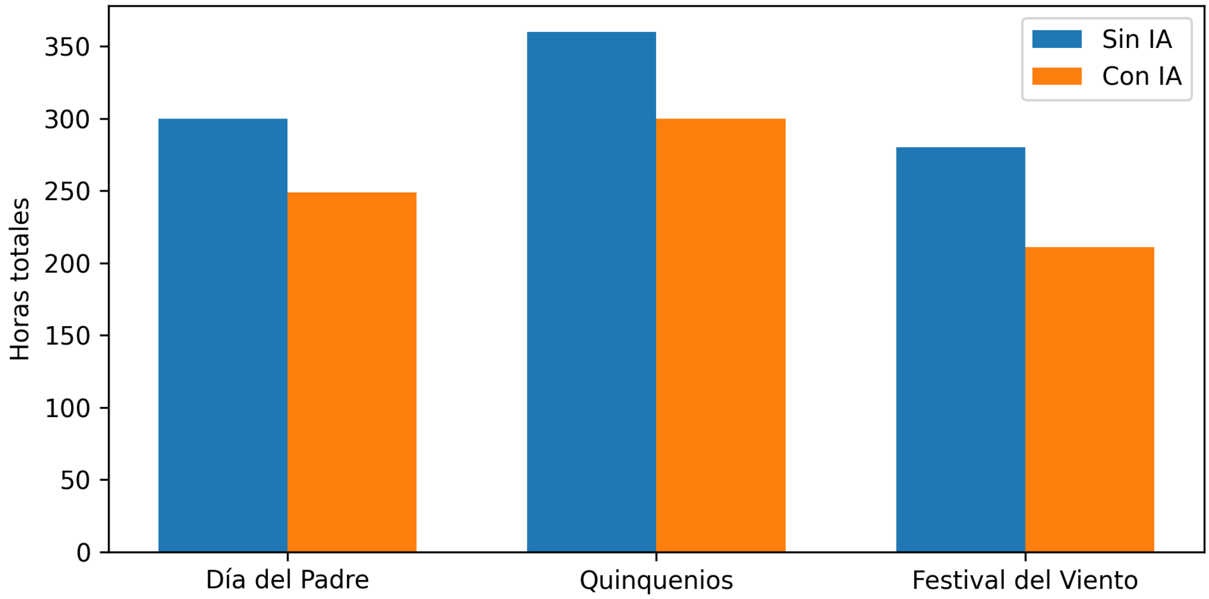
Table 3

Total production time per event (hours)

Event	Time without AI (hours)	Time with AI (hours)	Difference (hours)	Hours of AI Use
Father's Day	300 h	249 h	51 h ↓	10 a.m.
Five-Year Periods	360 h	300 h	60 h ↓	12 h
Wind Festival	280 h	211 h	69 h ↓	10 p.m.
Average	313.3 h	253.3 h	60 h ↓	2:07 p.m.

Note. Difference expressed as (Without AI - With AI). Prepared by the author based on internal records from a company in the corporate recreational events sector (Bogotá, Colombia).

Figure 1
Comparison of Total Production Hours Without AI vs. With AI



Note. Shorter bars indicate a reduction in total time with the help of generative AI.

Discussion and Conclusions

In conclusion, the incorporation of generative AI (ChatGPT) into the production workflow for corporate recreational events in Bogotá, Colombia, was associated with an average reduction of 19.1% in total production time, primarily in the conceptualization and proposal development phases. The evidence suggests that AI can be a driver of efficiency for medium-sized agencies, provided it is accompanied by training, standardized prompts, governance, and quality assurance. For future research, the following is recommended: (a) expand the number of events and organizations to assess replicability; (b) incorporate cost and quality metrics (not just time); (c) compare different tools and modes of use (assisted, automated, using templates); and (d) assess the impact on customer satisfaction and business performance in the medium term. In an environment where generative AI is transforming knowledge work, generating applied evidence in Latin American contexts is key to guiding responsible and effective adoption (Brynjolfsson et al., 2025; Eloundou et al., 2024).

Conclusions and Future Directions

The study has significant limitations. The main limitation is the small sample size (three events), which limits statistical power and generalizability. However, the consistency of direction across all three cases, the very large effect size, and the confidence interval provide useful pragmatic evidence for internal decision-making. Second, this is a single organizational case; agencies with more mature processes or different types of events may experience different impacts. Third, although comparability was sought, each event has unique characteristics that may influence timing; therefore, the interpretation focuses on the combined effect with reasonable controls, not on perfect causality.

Limitations

A critical aspect is data governance. Although this study avoided the use of attendees' personal data, in practice many agencies manage databases of participants and sensitive client information. Therefore, privacy policies and responsible information management must accompany the adoption of this technology, given the concerns raised in the sector (Adams, 2021). In addition, the organization must define criteria for use: which tasks are delegated to AI, which tasks require mandatory validation, and how to document decisions and sources.

Implementation Recommendations for Medium-Sized Agencies

Based on the results and operational experience from this case study, five recommendations are proposed for implementing generative AI in medium-sized corporate event agencies. First, define use cases prioritized by time spent and frequency. In this study, the greatest gains came from conceptualization and proposal; therefore, those areas should be the starting point. The recommendation is to map the "as-is" process, estimate the number of hours per phase, and identify repetitive or partially structurable tasks (for example, drafting standard sections, option matrices, and draft timelines).

Second, build a library of prompts and templates organized by event type and client industry. The evidence suggests that the quality of the results depends on the accuracy of the context provided to the AI. Standardizing prompts reduces variability among users, accelerates the learning curve, and enables the replication of best practices. In the events industry, standardization may include storytelling templates, experience scripts, lists of deliverables, and proposal formats, aligned with practical recommendations on how generative AI can support event planning (Estanyol, 2024).

Third, strengthen the internal "knowledge base." Although AI can generate useful structures without data, its accuracy improves when it is fed with specific information: rate schedules, cost histories, supplier catalogs, venue restrictions, and client policies. This recommendation ties into the economics of AI as a predictive technology: value arises when the cost of making informed decisions is reduced, but it requires calibrated inputs and assumptions (Agrawal et al., 2022). In practice, this means having well-organized and accessible repositories, as well as protocols for updating critical information.

Fourth, implement quality gates and traceability. The slight increase in time for final validation reflects the need to review outputs. Instead of viewing it as a loss, it can be interpreted as an investment in risk management (budgeting errors, inconsistencies with the brief, unrealistic promises). It is recommended to create checklists for each deliverable (proposal, budget, supplier selection) and document which parts were assisted by AI and how they were verified. This approach helps prevent uncritical dependence and improves organizational learning.

Fifth, managing change and training. The survey revealed a high level of acceptance, but also highlighted barriers related to competition and governance. To maintain profitability, it is necessary to train the team in crafting prompts, critically evaluating responses, and adapting to the client's tone. From the perspective of technology acceptance, enhancing perceived usefulness and reducing perceived effort increases intention to use and actual adoption (Davis, 1989; Venkatesh et al., 2012). In addition, leadership must promote responsible use: AI as a complement to human talent, not as a substitute for professional judgment, in line with the discussion on how digital technologies amplify capabilities when processes are redesigned and new skills are developed (Brynjolfsson & McAfee, 2014).

Taken together, these recommendations make it possible to turn generative AI into a sustainable operational lever: not only to speed up tasks, but also to institutionalize a faster, more consistent, and verifiable way of working. For organizations competing on response speed, this capability can translate into a competitive advantage (more proposals addressed, higher conversion rate) and free up time to design experiences with greater impact.

The breakdown by phases provides a clear roadmap for prioritization. First, integrating AI into the conceptualization and proposal phases offers the greatest return in terms of time. Here, practices such as prompt templates by client type, storytelling generators by industry, and consistency checklists can standardize quality and speed up iteration. Second, in budgeting, AI helps structure budget items and verify consistency, but it requires access to internal data (rates, historical data) to maximize accuracy. Third, when it comes to supplier selection, the benefit is smaller, likely because there are external constraints (supplier response times, human negotiation) that AI cannot eliminate.

Operational Implications: Where to Integrate AI and How to Govern It

Furthermore, the finding of high intent to continue suggests that adoption is feasible when users perceive utility and low effort. In line with TAM and UTAUT2, the adoption strategy should reinforce enabling conditions: training, prompt standards, example libraries, and leadership support to reduce anxiety and resistance (Davis, 1989; Venkatesh et al., 2012). In organizations with high turnover or a steep learning curve, these conditions can be critical to sustaining the observed benefits.

From the perspective of dynamic capabilities, generative AI can be viewed as a complementary resource that enables faster reconfiguration of routines: it speeds up the creation of proposals, facilitates the exploration of alternatives, and supports decision-making under time pressure. By shortening the production cycle, the company can capitalize on more business opportunities or devote more time to high-value activities (customer relations, experiential design, strategic negotiation). This is consistent with the idea that sustainable performance stems from organizational microfoundations that enable organizations to sense and capitalize on opportunities in changing environments (Teece, 2007).

Implications for Dynamic Capabilities and Competitive Advantage

The slight increase in final validation offers an important lesson: AI does not eliminate professional responsibility or quality control. The agency must invest time in verifying and adapting the tool's output to the specific context, which aligns with field findings regarding the need to "calibrate" AI and manage its limitations (Dell'Acqua et al., 2023). In practical terms, a mature implementation should incorporate checklists, peer review, and version control to capture the net benefit without compromising quality.

These results are consistent with the literature on generative AI and productivity in knowledge work. Research in corporate settings finds that AI can speed up writing and analysis tasks, and that the benefits tend to be greatest when the work is partially structureable and when human capabilities are combined with AI support (Brynjolfsson et al., 2025). Furthermore, evidence regarding potential impacts on the labor market suggests that language models are widely used in administrative and support tasks, which are precisely key components in event production (Eloundou et al., 2024).

The study's main empirical contribution is evidence of an average reduction of 19.1% (60 hours) in the total production time for corporate recreational events in Bogotá, Colombia, following the introduction of generative AI as a systematic support tool. The phased savings model suggests that AI adds the most value in activities that are cognitively demanding and involve rapid iteration: conceptualization and proposal development. At these stages, the tool serves as a catalyst for generating alternatives, structuring texts, and synthesizing ideas, which reduces the time it takes to produce a first draft and facilitates iterations with the client.

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