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THE IMPACT OF DIGITAL PROMOTION DEVELOPMENT ON TOURIST VISITATION LEVELS IN PANDANREJO VILLAGE, PURWOREJO DISTRICT, INDONESIA

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Abstract

This study analyzes the impact of digital promotion development on tourist visitation rates in Pandanrejo Tourism Village, Purworejo Regency, by linking upstream indicators (digital activities and findings) to downstream indicators (verified visits). The empirical background shows a "surge–plateau–correction" pattern in visitation data: the annual total rose drastically from 1,661 (2020) to 8,067 (2021), remained relatively stable at 8,094 (2022), and then corrected to 4,672 (2023); monthly dynamics were prominent in March 2023 (1,766) and November 2023 (716), indicating a dependence on moments/events as the main driver. Conceptually, the study positions digital promotion (social media, SEO/local search, online reviews, UGC, and OTA channels) as a stimulus that works through the mediators of destination image, trust, and visit intention before it manifests into visits. . The proposed methodology is a mixed-methods explanatory sequential: (i) quantitative quasi-experimental through Interrupted Time Series (ITS) and multi-period Difference-in-Differences (DiD) (with similar comparison villages), as well as transfer function/ARIMAX to include digital indicators as leading indicators; (ii) PLS-SEM survey to test the image–trust–intention→visit mechanism path. Descriptive results indicate that the 2021–2022 increase is in line with the possible activation of digital promotions, while the 2023 correction suggests a weakening of upstream drivers and/or the influence of external factors (access, weather, event calendar). Practical implications include orchestrating a content calendar 6–8 weeks before the "anchor moment" (e.g., March/November), strengthening Google Business Profile (photos, FAQs, booking links), activating curated UGC, and measurement by design with upstream–downstream KPIs (reach/engagement/CTR/sentiment → tickets/parking, activity participation, homestay occupancy) and cost per visit. The study's contribution lies in operationalizing a causal measurement framework in the context of tourism villages, which has been underrepresented. Key limitations, the lack of integration of digital-to-visit data and the absence of verified comparators are set as further agendas to ensure causal attribution, assess heterogeneity of impact across segments, and optimize promotional cost efficiency.

Keywords: digital promotion; eWOM; user-generated content (UGC); destination image; visit intention; tourist visits; tourist village; Pandanrejo–Purworejo

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A. INTRODUCTION

Digital transformation in tourism is not only changing the way tourism is promoted, but also how rural destinations build value and stimulate demand. Post-pandemic, reports and policy studies indicate a relatively rapid recovery in rural areas, along with opportunities to strengthen platform-based promotion in rural tourism (UN Tourism/OECD/EU, 2022–2024). Within this framework, digital promotion development is defined as the orchestration of channels (social media, SEO/local search, Google Business Profile, and online travel agents) to expand reach, strengthen image, and drive visit conversion. Meta-analytic evidence confirms that destination image is a strong predictor of tourist behavioral intentions (Afshardoost & Eshaghi, 2020), while in rural settings, the quality of digital marketing initiatives influences destination image, visit intention, and sustainability (Rodrigues et al., 2023). A recent study of destination

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accounts on Instagram also sheds light on engagement mechanisms relevant to local-level DMOs (Blanco-Moreno et al., 2024).

Mechanistically, the influence of digital promotion in tourist villages flows through electronic word-of-mouth (eWOM), reviews, and user-generated content (UGC), which provide social proof, reduce perceived risk, and strengthen visit intentions/decisions. During and after the pandemic, eWOM on social media has been shown to influence travel decision-making (Nilashi et al., 2022). Eye-tracking experiments demonstrate how visual attention to reviews (especially negative ones) alters the decision process (Chen et al., 2022). Conversely, passive access to travel UGC has been shown to increase destination intention/destination choice through the mediation of destination imagery and emotions (Nguyen & Tong, 2022). These findings underscore the importance of content governance (accuracy, source credibility) for engagement to lead to actual visits to villages like Pandanrejo.

In terms of impact measurement, upstream indicators—search intent and digital engagement—can predict variations in tourism demand. Time series studies show that the Google Trends index improves forecasting accuracy compared to purely autoregressive models (Önder, 2017), and a transfer function approach linking search signals to tourist arrivals enhances big data-based predictions (De Luca et al., 2024; Li et al., 2020). At the same time, the UGC literature—particularly on photos/visuals—explains how visual representations shape destination imagery that mediates visitation intentions, providing a conceptual bridge from digital promotional activities to downstream indicators such as visits, length of stay, or homestay occupancy (Li et al., 2023; Blanco-Moreno et al., 2024). This approach is relevant for linking Pandanrejo's upstream–downstream indicators: reach, engagement rate, click-through rate (CTR), review sentiment/valence → tickets/parking, activity participation, homestay occupancy.

Practical implications for Pandanrejo include linking narrative content strategies (attraction uniqueness, cultural/agro calendar), local discovery optimization (Google profiles and reviews), and UGC activation and collaboration with credible creators. Empirical evidence suggests that destination Instagram content triggers engagement patterns related to image formation and intention to act (Blanco-Moreno et al., 2024), while UGC has been shown to increase destination choice intentions through the mediating effect of image (Nguyen & Tong, 2022). Implementation can be monitored using a cost-effectiveness dashboard (CPM, CPE, CAC per visit) to assess the most productive channels at the tourism village level.

The findings reveal that tourist attractions significantly influence both revisit decisions and visiting interest, with the latter serving as an important mediating variable that strengthens this relationship. Statistically, the effect of tourist attractions on revisit decisions reached 82.1%, indicating a strong influence, while the effect on visiting interest was 47.1%, categorized as moderate. Visiting interest itself was also found to have a significant impact on tourists' decisions to return. Overall, these results emphasize that tourist attractions, either directly or indirectly, play a crucial role in shaping revisit intentions. Consequently, when attractions are well-maintained, renewed, and properly managed, destinations are more likely to encourage repeat visits, as natural tourism provides relaxation, a sense of harmony with nature, and enhances visitor satisfaction (Anggraini et al., 2025).

Although correlational evidence is increasingly strong, there are research gaps that need to be bridged to make causal conclusions at the tourism village level—including Pandanrejo—more convincing. First, there are still limited longitudinal studies linking digital channel insights with verified visitation data. Second, cross-source integration (social media, web analytics, reviews/UGC, OTAs, on-site administration) is not yet systematic. Third, control for confounders (agrarian seasonality, accessibility, government events/weather) is not yet consistent. Methodologically, interrupted time series (ITS) designs for pre-post digital interventions and difference-in-differences (DiD) with similar comparison villages, combined with search signals (Google Trends) and transfer function models, are recommended to estimate the incremental impact of digital promotion on visitation (Önder, 2017; De Luca et al., 2024). At the macro level, policy evidence confirms the opportunities for rural destinations in the recovery phase—providing an appropriate context for data-driven applied research in Pandanrejo.

B. RESEARCH METHOD

This study employed a mixed-methods explanatory sequential approach, beginning with quantitative analysis and continuing with qualitative verification. The quantitative design was conducted through a quasi-experiment using Interrupted Time Series (ITS) and Difference-in-Differences (DiD) models to assess the impact of digital promotion development on tourist visits to Pandanrejo Tourism Village. ITS was used to examine changes in visitation levels and trends before and after digital promotion interventions, while DiD was used to compare Pandanrejo with other tourism villages with similar characteristics but without digital interventions during the same period (Lopez-Bernal, Cummins, & Gasparrini, 2017; Callaway & Sant'Anna, 2021; Roth, 2023).

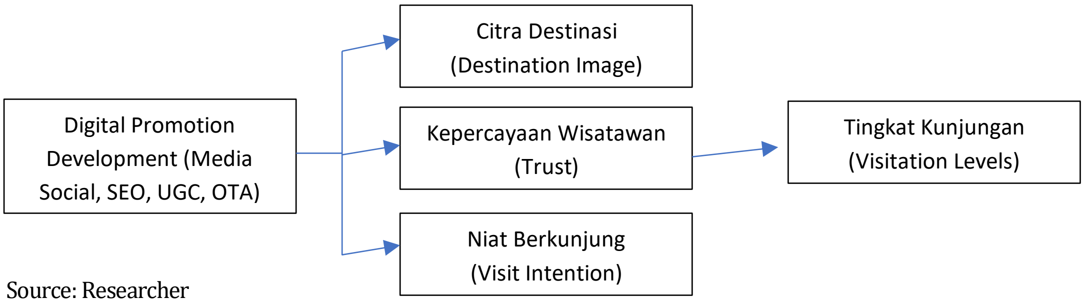
The research location was determined in Pandanrejo Tourism Village, Purworejo Regency, with a minimum observation period of 12 months, namely 6 months pre-intervention and 4 months post-intervention. The intervention was defined as the launch of a structured digital promotion strategy, including a social media content calendar (Instagram/TikTok), Google Business Profile optimization, user-generated content (UGC) activation, and collaboration with local creators. This strategy was positioned as a shock at a specific point in time (T_0) so that its impact on tourist visitation levels could be estimated (Lopez-Bernal et al., 2017).

The research data includes upstream and downstream variables. Upstream variables include digital promotion intensity (number of posts, reach, engagement rate, click-through rate), geotagged UGC, online ratings and reviews, and search index on Google Trends. Downstream variables include the number of verified visits (entrance tickets, participation in tourist activities, homestay occupancy rates). Data sources were obtained from digital channel analytics (Instagram Insights, Google Business Profile, OTA dashboards), tourist village administrative records, and Google Trends. Previous research has shown that online search data such as Google Trends can improve the accuracy of tourism demand forecasting (Önder, 2017; De Luca, Habibi, & Hernández-Maskivker, 2024; Li, Hu, & Li, 2020).

Additionally, a survey of actual and potential tourists was conducted to assess the mediating mechanisms between digital promotions and visit behavior. The survey measured tourists' perceptions of destination image, trust, and visit intention using a Likert-based instrument adapted from previous research on eWOM and UGC (Nguyen & Tong, 2022; Ahn & Lee, 2024; Chen et al., 2022). Survey data analysis used a Partial Least Squares Structural Equation Modeling (PLS-SEM) approach to examine the relationships between variables, with reliability and validity evaluations following current guidelines (Hair & Alamer, 2022; Henseler, Ringle, & Sarstedt, 2015).

To ensure internal validity, a common trends test was conducted on the DiD model and a sensitivity test on the ITS model. Robustness checks included the use of a placebo cut-off, alternative outcome variable specifications, and control for confounding variables such as season, government events, and infrastructure conditions. In the PLS-SEM model, discriminant validity was tested using HTMT, while predictive power was assessed using PLSpredict (Roemer et al., 2021). Thus, this research method design not only allows for quantitative impact estimation but also provides a mechanistic understanding of how digital promotion contributes to increased tourism visits in Pandanrejo Village.

Conceptual Framework



Source: Researcher

The conceptual framework illustrates the relationship between the independent, mediator, and dependent variables in this study. Digital promotion development, including social media strategies, search engine optimization (SEO), the use of user-generated content (UGC), and online channels such as online travel agents (OTAs), is positioned as the primary independent variable. Digital promotion influences mediator variables such as destination image, tourist trust, and visit intention. These three mediators play a role in explaining the mechanisms by which digital promotion strategies can influence tourist behavior, namely by increasing positive perceptions of the destination, fostering trust in the information and experiences offered, and encouraging travel intentions to the destination. Furthermore, the resulting visitation intention leads to the dependent variable of actual tourist visits (visit levels), which in this study is measured through the number of tickets or parking, homestay occupancy rates, and tourist participation in tourism activities in Pandanrejo Village. This model also assumes a direct pathway of influence from digital promotion on visitation intention, allowing for testing both direct and indirect effects through mediators. Thus, this conceptual framework not only tests whether digital promotion increases visitation but also explains how the mechanism of this influence works through image, trust, and tourist intentions.

Based on the conceptual framework, this study formulates several hypotheses as follows:

H1: The development of digital promotions has a positive effect on the destination image of Pandanrejo Tourism Village.
H2: The development of digital promotions has a positive effect on tourist trust in Pandanrejo Tourism Village.
H3: The development of digital promotions has a positive effect on tourist visitation intentions to Pandanrejo Tourism Village.
H4: Destination image has a positive effect on tourist visitation intentions.
H5: Tourist trust has a positive effect on tourist visitation intentions.
H6: Tourist visitation intentions have a positive effect on tourist visitation levels in Pandanrejo Tourism Village.
H7: The development of digital promotions has a direct positive effect on tourist visitation levels in Pandanrejo Tourism Village.
H8: The development of digital promotions has an indirect effect on tourist visitation levels through destination image, trust, and visitation intentions as mediating variables.

This hypothesis is based on previous findings that emphasize the role of digital promotion in shaping destination image (Afshardoost & Eshaghi, 2020), strengthening trust through eWOM (Nilashi et al., 2022), and increasing visitation intentions through UGC and visual content on social media (Nguyen & Tong, 2022; Blanco-Moreno et al., 2024). Furthermore, Google Trends-based tourism demand forecasting studies indicate that online search activity can serve as an early indicator of actual demand (Önder, 2017; De Luca et al., 2024), thus supporting the hypothesis of a relationship between digital promotion and actual visitation rates.

C. RESULTS AND ANALYSIS

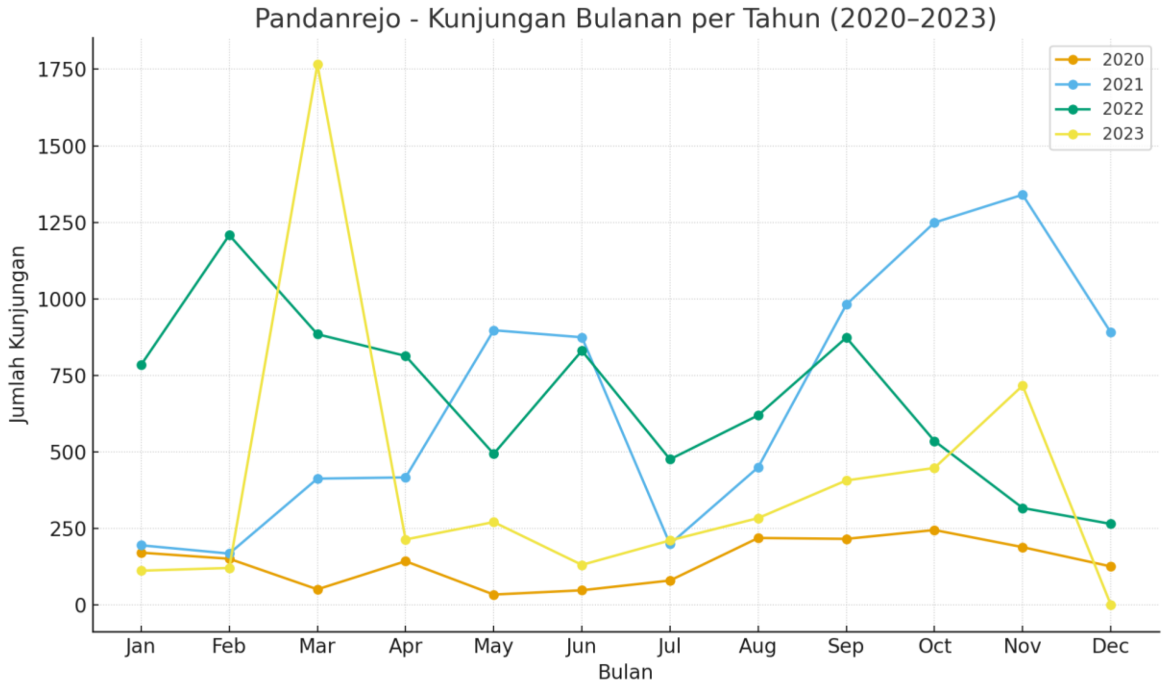
The data below shows tourist visits to Pandanrejo Tourism Village, Purworejo Regency, from 2020 to 2023.

Data Kunjungan Wisatawan di Desa Pandanrejo, Kabupaten Purworejo							
	2020	2021	2022	2023	YoY 21/20 %	YoY 22/21 %	YoY 23/22 %
Jan	170	194	784	111	14.1	304.1	-85.8
Feb	150	167	1208	120	11.3	623.4	-90.1
Mar	50	412	884	1766	724	114.6	99.8
Apr	142	416	813	213	193	95.4	-73.8
May	33	897	493	270	2618.2	-45	-45.2
Jun	47	874	830	130	1759.6	-5	-84.3
Jul	79	198	475	210	150.6	139.9	-55.8
Aug	218	449	619	283	106	37.9	-54.3
Sep	215	981	873	406	356.3	-11	-53.5
Oct	244	1249	535	447	411.9	-57.2	-16.4
Nov	188	1340	316	716	612.8	-76.4	126.6
Dec	125	890	264	0	612	-70.3	-100

Source: Pokdarwis Pandarejo

Key Results: The visit series shows four contrasting phases. First, 2020—at the start of the pandemic—set a low baseline (1,661 visits) with a fragmented monthly pattern (range ±33–244; peak October=244 and August–September=218–215). Second, 2021 recorded a significant surge to 8,067 visits, or +385.7% yoy, compared to 2020, indicating a recovery in demand and/or more systematic digital promotion activation. This surge was also evenly distributed across the months, particularly May–June=897–874 and September–December=981–1249–1340–890. Third, 2022 was relatively stable at 8,094 visits (+0.33% yoy), indicating a plateau after the drastic increase. However, on a monthly basis, strong dynamics are visible—January–March=784–1208–884 high, weakening in May–July=493–475, then rising again in September=873 before falling in Q4=535–316–264. Fourth, 2023 experienced a sharp contraction to 4,672 (−42.28% yoy), so that the 2023 level is equivalent to 57.9% of 2021 and 57.7% of 2022. The 2023 monthly pattern shows an anomaly of March=1,766 (≈38% of the annual total) and a partial recovery in Q4 (September–October–November=406–447–716), while December=0 (nil/nil reporting). Roughly calculated, the CAGR 2020–2023 ≈ +41.2%/year; However, this metric is misleading because the extreme increase in 2021–2022 was followed by a sharp decline in 2023—so the CAGR does not represent a fundamental trend. Visually and conceptually, the pattern resembles a "surge–plateau–correction" pattern: a major boost increases the visit base, then plateaus, and then corrects. At this point, causal attribution to digital promotion development cannot be confirmed without digital promotion data (reach, engagement, reviews/UGC, SEO) and without comparable villages; however, the sudden increase (2021) and structural decline (2023) are strong signals that there have been changes in upstream drivers (digital promotion, access, events, pricing policies) and/or confounding factors (seasonality, weather, external policies) that need to be quantitatively tested.

Anggraini, M., Putri, V. O., Simangunsong, K. T., & Agus, W. (2025). *The Effect of Tourist Attraction on Revisit Decisions with Visiting Interest as an Intervening Variable (Case Study : Punti Kayu Nature Park in Palembang)*. *4*(1), 39–50. https://doi.org/10.34013/ijscot.v4i1.1624



Interpretation of the ITS/Did framework (based on annual data): With four annual time points, a formal ITS cannot be adequately conducted (too few observations to estimate level, slope, seasonality, and autocorrelation). However, descriptive insights can guide the design of subsequent causal tests. Suppose T_0 (structured digital promotion intervention) is assumed to fall in early 2021, then the 2020→2021 pattern reflects a major step change likely related to the intervention; 2022 shows a plateau, while 2023 shows a decline. For DiD, we need 1–2 comparison villages that are comparable in attraction typology and did not implement digital interventions during the same period; a 2018–2020 pre-trend analysis (if available) will determine the adequacy of the parallel trend assumption (Lopez-Bernal, Cummins, & Gasparrini, 2017; Callaway & Sant'Anna, 2021; Roth, 2023). The methodological recommendation is to reconstruct monthly series (≥24–36 months) of ticket/parking and homestay occupancy, then run multi-period ITS and DiD with the latest estimators for stronger causal inference. In this stage, available annual data serve as a baseline to validate the direction of the effect (positive post-2020, then corrected in 2023) and to set recovery targets (e.g., returning to the 7,500–8,000 range within 12–18 months).

Linking digital mechanisms (image-trust-intention-->visit), Literature from the last decade confirms that destination image is a strong predictor of visit intention (Afshardoost & Eshaghi, 2020), while eWOM/UGC and review quality reduce perceived risk and increase intention/decision. Within that framework, the 2021 surge can be read as the activation of mediators (image & trust) that drive intention—which then converts on-site. The 2022 plateau implies the exhaustion of momentum gains without new impetus (e.g., content creativity, source/influencer credibility, curated UGC programs). The 2023 contraction suggests an external shock (extreme weather, access changes, event scheduling, pricing dynamics) or a weakening of the digital upstream (decreased content frequency/quality, decreased review valence, decreased search results) situations that can only be distinguished when reach/engagement/review/SEO data is available and linked to visits. Practically, this reinforces the need for an orchestrated content calendar (local narratives + peak moments), review management (quick response, encourage visitors to write informative reviews), and authentic UGC to keep the trust-intent image loop active throughout the year, not just around major events.

Managerial Diagnosis, For decision-making, three concise indicators are useful. (1) Peak-to-current ratio: 2023 level ≈58% of 2021–2022 peak; this can be targeted for gradual recovery (70% in 6 months; 85–90% in 12–18 months) with always-on strategies and seasonal boosts. (2) Compound decline 2021→2023 ≈ −23.9%/year; the ideal digital promotion target is to reverse this rate to +15–20%/year over two years through campaign bursts leading up to peak season, local SEO (complete Google profiles, Q&A, geo-tagging), and credible micro-creator collaborations. (3) Base stabilization: 2021–2022 average = 8,080; 2023 is −42.2% below this figure. A recovery program could target a "gap closure" of 20–25 p.p. in the first year (mid-funnel focus: reviews, access/cost FAQs, booking calls-to-action), then 15–20 p.p. in the second year (upper-funnel focus: creator & community reach). The monthly choreography seen in the Q1 2022 peak, the very high March 2023, and the improving Q4 2023 data supports the practice of "anchor moments" (major events as acquisition drivers) combined with UGC activation & retargeting to maintain traffic flow beyond events.

Strengthening the evidence, To verify causal attribution to digital promotion development, feasible next steps are: (i) building a monthly series of homestay visits and occupancy (2019–present); (ii) integrating upstream digital data from Instagram Insights (reach, ER, CTR), Google Business Profile (rating, number of reviews, clicks), geotagged UGC (volume/caption intent), and search interest (Google Trends) as leading indicators; running ITS (pre/post segmentation, step & slope change), multi-period DiD with similar comparison villages, and transfer/ARIMAX functions that link upstream signals to downstream visits. On the mechanism side, a PLS-SEM survey with image, trust, and intention constructs will test the indirect pathway that, according to the literature, is usually dominant in digital tourism. The combination of (i)–(iii) will produce a strong evidence ladder: descriptive → association → causal (quasi-experimental) → mechanism (PLS-SEM).

D. CONCLUSION

Based on the synthesis of Pandanrejo visitation data (2020–2023), monthly–annual descriptive analysis, and scientific findings from the past decade, it can be concluded that the development of digital promotion has the potential to increase visitation rates, especially through indirect channels—namely by improving the destination image and tourist trust so that visiting intentions are encouraged and manifested into actual visits. The local empirical pattern shows a "surge–plateau–correction" curve: a large jump in 2021 (total 8,067; +385.7% YoY) indicates strong activation/recovery, 2022 remains relatively high (8,094; +0.33% YoY), while 2023 is corrected (4,672; −42.28% YoY) with a dependence on anchor moments (March 1,766; November 716). This configuration aligns with marketing funnel theory and the SOR (stimulus–organism–response) framework: digital stimuli (content, reviews, search results) influence cognitive–affective representations (image/trust), then intentions, and finally behavior. Furthermore, the increasingly heavy concentration of visits during peak months indicates that digital promotions haven't fully maintained the flow of interest outside of events, making the effect more pronounced during seasonal pushes or major events.

Within a causal framework, this conclusion is supported but not definitive: the available annual and monthly data are robust for mapping patterns and generating hypotheses, but insufficient to separate the impact of digital promotions from other factors (access, weather, pricing policies, event calendars). Therefore, a more convincing causal attribution requires the reconstruction of monthly series of ≥24–36 months linked to upstream metrics (Instagram Insights: reach/ER/CTR; Google Business Profile:

rating/number of reviews/clicks; geotagged UGC; Google Trends) and comparable village benchmarks. With these tools, multi-period Interrupted Time Series (ITS) and Difference-in-Differences (DiD) designs can be used to estimate the step change and slope change due to digital interventions, while controlling for pre-trends and seasonality. At the mechanism level, PLS-SEM on potential/actual tourists would test that digital promotion works primarily through image–trust → intention → visits, as the literature suggests.

Managerially, the findings suggest that the quality of channel orchestration, rather than simply content volume, is crucial. Consistent strategies include: (i) strengthening "anchor moments" (e.g., March/November) with a 6–8-week content calendar, UGC seeding, and a comprehensive Google profile (photos, FAQs, booking links); (ii) smoothing seasonal valleys (May–July) through a series of micro-events, micro-influencer/community collaborations, and review management to lower perceived risk; (iii) measurement-by-design with an upstream–downstream dashboard linking reach/engagement/CTR/sentiment → tickets/parking, activity participation, and homestay occupancy; (iv) outcome-based budgeting using CPM, CPE, and CAC per visit to objectively evaluate promotional budget allocation across channels. Realistic recovery targets, based on the 2021–2022 peak average (~8,080), are 70% in 6 months (~5,650), 85% in 12 months (~6,870), and 90% in 18 months (~7,270), driven by always-on content and planned seasonal boosts.

This study's scientific contribution is to place the context of tourism villages within the digital promotion discourse, which has been dominated by large cities/destinations. By integrating digital indicators as leading indicators into a quasi-experimental framework and mechanism modeling, the research provides an operational measurement roadmap: from upstream signals to auditable downstream visits. Its practical contribution is a package of implementation recommendations that village managers can immediately use—from local narrative curation and review management to event calendar design and CAC measurement—to raise the bottom of the curve while reducing reliance on single events.

Finally, the main limitations of the unavailability of an integrated upstream-to-downstream data set and the absence of verified comparators provide a clear agenda for further research: (1) building an integrated data pipeline (social media, UGC, Google profiles, OTAs, visit administration); (2) implementing ITS/DiD with pre-registration specifications and robustness tests (placebo cut-off, alternative aggregation, weather/access/event control); (3) testing for heterogeneity of effects by market segment and content type; and (4) evaluating cost per visit across channels to optimize the promotional mix. With these steps, the impact of digital promotion development on Pandanrejo's visitation rate can be proven causally, its efficiency can be increased, and translated into sustainable growth for the tourism village and its local economic ecosystem.

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