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# Digital Service Trade and Cultural Consumption Shocks: An Empirical Analysis of the Korean Wave in India using Google Trends and OTT Platform Data

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Abstract:
This study quantifies the impact of the COVID-19 shock on Indian attention to the Korean Wave. Monthly Google Trends for the 'Korean drama' topic in India are modelled using an interrupted time-series (ITS) and two-way fixed-effects difference-in-differences (TWFE DiD) against close comparison topics (Japanese, Chinese, Spanish drama). The role of OTT platforms, especially Netflix, is examined as annual mediators using Statista series on Netflix India revenue and India's paid video subscriptions. A unified causal graph motivates estimands and design choices. The ITS reveals a discrete March-2020 level increase in search attention with partial mean reversion thereafter; TWFE DiD indicates that the Korean-specific increment was smaller than the lift enjoyed by comparison topics. Annual mediation suggests that OTT expansion was an enabling but not a singular pathway for Korea-specific attention. Findings are discussed in the context of India's cultural market dominated by Bollywood but increasingly open to foreign content.

Keywords: Korean wave; Covid-19; cultural consumption; digital service trade; Google trends.

JEL Classification: F14; L82; Z11; C23.

## Introduction

Since the late 1990s, the Korean Wave (Hallyu) has transformed East Asia's popular culture marketplace and, more recently, has spread globally through platformized distribution and social media coordination. The economic significance of the Korean Wave has intensified in recent years. South Korea's exports of cultural content, comprising K-pop, television dramas, film, and gaming, reached approximately USD 13.24 billion in 2022, a 6.3% increase from the previous year (MCST 2024). These exports are now considered strategic national assets, with the government targeting 50 trillion won (USD 36 billion) in cultural exports by 2030 (KOFICE 2025). Parallel to this, India's digital infrastructure advanced rapidly during the 2010s and early 2020s, transforming the content delivery landscape. Internet connections expanded from 251 million in 2014 to 969 million by mid-2024, while broadband subscriptions increased fifteenfold. The average cost of mobile data fell by over 95% during this period, leading to a 353-fold increase in per-user wireless data consumption (TRAI 2024). These changes lowered access barriers and enabled widespread streaming, positioning India as a major consumer of international digital content, including Korean media.

India presents an analytically intriguing case. On the one hand, domestic supply is deep and diversified. Bollywood and regional language industries historically dominate entertainment consumption. On the other hand, diffusion channels for foreign content have multiplied with rapid smartphone adoption, cheap mobile data, and the arrival of over-the-top (OTT) platforms. The COVID-19 pandemic created a once-in-a-generation disruption to leisure constraints and media supply chains, compressing time spent at home and redirecting attention toward streaming. The central research question of this article is therefore whether the pandemic operated as a Korea-specific shock to cultural attention in India, or as a broader genre shock that lifted multiple international cultural content categories together.

This question is operationalized with behavioural measures rather than self-reports: monthly Google Trends indices for 'Korean drama' in India, complemented by series for Japanese, Chinese, and Spanish drama as close comparison topics. Those specific countries are chosen because (i) Chinese and Japanese dramas are similar East Asian content to Korean dramas and (ii) Spanish dramas have gained popularity worldwide after titles like *Money Heist* became massive international hits. To trace dynamic responses, three complementary estimators are used. First, an interrupted time-series (ITS) isolates the discrete level change and the slope change at March 2020 when a massive scale lockdown happened in India. Second, two-way fixed-effects difference-in-differences (TWFE DiD) contrasts Korean with comparison topics and separates common shocks from Korea-specific increments; a trend-adjusted variant is preferred on diagnostic grounds. Third, a descriptive annual mediation decomposes the total COVID-era effect into indirect (via OTT) and direct components using Statista series for Netflix India revenue and India's paid video subscriptions. A unified causal graph (DAG) clarifies estimands and the conditioning strategy.

The empirical strategy extends a line of quantitative inquiry on cultural diffusion that integrates gravity-style intuition, fixed-effects identification, and attention-based proxies. Hallyu's international footprint has been shown to comove with economic scale and proximity, while digital platforms reduce distribution frictions and foster network externalities. Google Trends is a lens on contemporaneous demand, and adopting it aligns the measurement strategy with past work on cultural trade and cosmetics demand associated with the Korean Wave (Park 2015). Methodologically, difference-in-differences with fixed effects provide transparent quasi-experimental diagnostics; ITS is a natural tool for abrupt interventions; and the Pearlian mediation decomposition provides a language for attributing total to indirect pathways.

## 1. Background and Related Literature

The Korean wave (Hallyu)'s diffusion has moved through distinct phases, from early terrestrial broadcasting exports and DVD circulation to the platformed circulation of dramas, cinema, and music across OTT interfaces (Huat & Iwabuchi, 2008). The early 2000s were marked by television melodramas that travelled regionally through syndication and fan-sub communities, while the 2010s and early 2020s saw the rise of K-POP, prestige cinema, and high-production serials that were commissioned or globally distributed by streamers. Cross-category spillovers, where dramas prime viewers for K-beauty and K-food through on-screen cues and parasocial ties with performers, are widely discussed in cultural-economics and media studies, and are consistent with the observed co-movement between attention to Korean content and downstream consumer behaviour. Evidence from trade contexts already aligns with this narrative: broadcaster exports grew rapidly across Asia in the 2000s, with demand patterns shaped by importer market size, development, and cultural proximity (Jin, 2016; Yoon & Jin, 2017).

Two strands of economic literature frame these patterns. The first models cultural diffusion with gravity-style forces, where bilateral flows rise with economic mass and fall with frictions that often stand in for cultural distance. Classic results in trade and services show robust distance effects, and applications to cultural goods confirm the role of proximity and historical ties. In the Hallyu setting, importer GDP per capita and population have been found to matter for the value and quantity of Korean TV program exports, while distance diminishes in explanatory power relative to goods because transportation costs are minimal and symbolic proximity matters more than freight (Park, 2014).

The second strand emphasizes preference dynamics and network externalities, small differences in exposure can propagate through social networks and platform feeds, generating nonlinear uptake (Bala & Van Long, 2005; Katz & Shapiro, 1985). These mechanisms are salient for serial content, which benefits from episodic habits and recommendation systems that encourage completion and continuation. Within this field, prior work has used gravity models and high-frequency signals to track the diffusion and economic correlates of Hallyu.

A complementary literature brings search-based measures to bear. As proprietary viewing and transaction data are often unavailable, Google Trends has been used as an attention proxy that co-moves with consumption. One application links country-level searches for "Korean drama" to Korean cosmetics exports, finding strong associations in Southeast Asia and establishing a practical pathway from media attention to product markets, an antecedent for treating K-drama search in India as a meaningful measure of exposure (Park 2015). The search-based approach is attractive because it is timely, scalable, and comparable across geographies; at the same time, its use requires attention to normalization windows, sampling variability, and the difference between attention and usage (Choi & Varian, 2012).

Digital distribution has altered both supply and discovery. Platformisation, global interfaces, localized dubbing/subtitling, and algorithmic curation, reduces search and language costs and places Korean titles alongside US and other international catalogues. Media scholarship documents how Netflix's commissioning of Korean originals and global promotions have changed reception contexts, enabling Korean series to find audiences in markets without legacy broadcast ties (Jin et al., 2023). This platform layer does not merely carry content; it curates it, which is crucial in a smartphone-first environment such as India. In such settings, home-pages and short-form clips act as gateways, while price re-positioning and mobile-only plans lower adoption barriers, potentially amplifying exposure to K-content during periods of compressed leisure time.

As for the recent studies on digital platforms, cultural trade, and post-COVID streaming, Chalaby (2024) examines how streaming platforms monetize content and structure transactions, and the analysis situates streaming in the historical transition from broadcasting to online platforms. Aguiar et al. (2024) discusses how digitization and the rise of platforms have reshaped the production and discovery of cultural goods. Broocks & Studnicka (2024) treats Netflix streaming as a form of international trade in cultural services. Using a novel dataset on Netflix catalogue availability and viewership across 20 countries, the authors apply a gravity model to explain cross-border viewing patterns.

India's specific context adds demand-side and institutional factors. The market is large and heterogeneous, with rapid uptake of mobile broadband and streaming services in the late 2010s and early 2020s, expanding the reachable audience for subtitled/dubbed East Asian content. The period around COVID-19 was characterized by sharp increases in at-home media time and a move to OTT for first-run titles in the absence of open theatres, according to industry reports and audience studies (TRAI 2021). These conditions plausibly raised the probability of first exposure to new genres, including K-drama, while local language options and influencer ecosystems lowered switching costs. From a gravity perspective, some frictions remain, language, genre familiarity, and cultural distance, but discovery via OTT and social media attenuates them.

Methodologically, the literature increasingly mixes structural intuitions with quasi-experimental and time-series approaches suited to common shocks. Interrupted time-series (ITS) is frequently used to gauge level and slope changes at policy or shock dates when a single treated series is observed (Bernal, Cummins & Gasparrini, 2017). Difference-in-differences (DiD) compares treated outcomes with "near-in" controls to purge common shocks. For cultural-attention data, near-in controls are typically adjacent genres or origin countries (e.g., Japanese, Chinese, Spanish drama), which share platform growth and pandemic-era shocks but lack the focal content's idiosyncratic momentum.

In such designs, topic-specific trends help handle mild non-parallelism, and conservative inference accounts for serial correlation and few clusters (Bertrand et al., 2004; Cameron & Miller, 2015; Callaway & Sant'Anna, 2021). The conceptual discipline of causal diagrams further clarifies what should and should not be conditioned upon, particularly the mediator role of OTT distribution when the goal is to estimate total effects of the pandemic on attention to K-drama (Pearl, 2009; Gill, 2020). Treating OTT as a mediator rather than a control avoids "bad-control" bias and motivates a separate, lower-frequency mediation exercise using annual OTT indicators.

This study's approach, therefore, fits squarely within three converging literatures: (i) gravity-style analyses of cultural diffusion and symbolic trade that emphasize importer demand, cultural proximity, and the limited role of physical distance for content; (ii) platformisation research that foregrounds how Netflix and other OTT services localize and curate Korean content for global markets; and (iii) empirical work using search-based proxies to measure attention and link it to downstream behaviours in related consumer categories. The Indian case during COVID-19 offers a setting where these strands meet: a large, smartphone-first audience experiencing a time-allocation shock, an OTT ecology that lowers discovery costs and foregrounds Korean titles, and measurable search responses that can be contrasted against adjacent Asian drama topics to separate genre-neutral from K-specific gains.

## 2. Korean Wave in India

For decades, India's cultural industries have been characterized by a rare degree of self-sufficiency. A dense, multi-lingual film-and-television system, centered on Hindi-language "Bollywood" but reinforced by powerful regional cinemas in Tamil, Telugu, Malayalam, Kannada, Bengali, and Marathi, has supplied an abundant flow of domestic content across theatrical, satellite, and terrestrial channels. This structural abundance limited the scope for sustained foreign cultural penetration relative to many Asian markets: the domestic product matched local language preferences, addressed local sensibilities, and occupied distribution bottlenecks from cinema screens to prime-time schedules. In gravity-style terms, India's large "importer mass" and strong home supply reduced the need for cultural imports even as physical trade costs fell; cultural proximity and discovery frictions remained the operative barriers rather than logistics per se.

Against this backdrop, earlier impressions of the Korean Wave (Hallyu) in India were localized and largely subcultural rather than mainstream. The earliest and most visible adoption surfaced in the country's Northeast, where cross-border interactions with East and Southeast Asia are more routine, cable distribution historically had greater latitude, and peer networks amplified imported serials and music. Anecdotal accounts over the 2000s describe a pattern in which Korean television dramas and films, circulating via DVDs, niche channels, and later fan-subtitled streams, became shared reference points among students and young professionals in states such as Manipur, Nagaland, Mizoram, and Meghalaya. This regional pathway was consistent with diffusion models in which exposure is first concentrated in socially cohesive pockets, then propagates outward through network effects rather than through national broadcast "push" (Kaisii, 2017).

The transition from localized fandom to broader national visibility came with OTT distribution. Platform interfaces compress discovery costs that previously protected incumbent content. Dubbing and subtitling in Hindi and select regional languages removed comprehension barriers; curated rows and algorithmic recommendations raised the probability that first-time viewers would sample one highly engaging title and then continue. Once OTT entry costs fell and localization improved, a series of high-salience titles acted as gateways for national audiences. Period romances and contemporary melodramas such as *Descendants of the Sun* (2016), *Goblin* (2016), and *Crash Landing on You* (2019) found loyal followings among first-time viewers attracted to polished production values, serial cliff hangers, and character-centric storytelling.

Genre expansions into legal procedurals and workplace narratives, *Itaewon Class* (2020), *Vincenzo* (2021), *Extraordinary Attorney Woo* (2022), broadened the appeal beyond romance, while horror-thrillers like *Kingdom* (2019) and high-concept hits such as *Squid Game* (2021) made Korean drama a topic of conversation even among non-fans. On the film side, *Parasite* (2019) served as a prestige anchor, while *Train to Busan* (2016), *A Taxi Driver* (2017), *The Handmaiden* (2016), and *Oldboy* (2003) showcased a spectrum from arthouse to mainstream genre cinema. These titles circulated widely on Indian OTT services, reinforcing a pattern often identified in diffusion studies: once a few standout works reduce uncertainty about a foreign catalogue's "quality," the marginal cost of sampling the next title falls sharply. That enthusiasm manifests in the search data, which capture curiosity and intent.

The Indian recorded-music economy has long been bound to cinema; yet K-pop carved a space by exploiting the smartphone-first, social-video environment rather than terrestrial radio or film tie-ins. Idols such as BTS (Bangtan Sonyeondan) and BLACKPINK operate with multi-platform content pipelines, music videos, behind-the-scenes footage, short-form challenges, that lend themselves to fan labour (subbing, choreography tutorials) and coordinated streaming. The fandom infrastructures (ARMY, BLINK) lowered discovery thresholds for adjacent Korean content by building translation and recommendation communities.

Korean dramas and idol aesthetics normalized skincare-first routines, double cleansing, essence/serum layering, sheet masks, and popularized product types (ampoules, cushion compacts, snail mucin, cica) that were previously niche in India. The appeal hinged less on celebrity endorsement alone than on an aspirational but attainable regimen narrative: clear "glass skin" as a daily routine rather than as occasional cosmetic coverage.

K-drama's mise-en-scène is unusually food-forward. Recurrent visual cues - ramyeon, tteokbokki, jjajangmyeon, fried chicken and beer ("chimaek"), travel well on short-form video and fit the "try-at-home" pattern suited to urban Indian kitchens. As interest in authentically Korean or "K-inspired" dishes grew, cooking channels and delivery menus filled in the how-to gaps. Even where the ingredients are localized (e.g., gochujang-style sauces, kimchi variants), the adoption logic follows the literature's "attention → trial → habit" sequence. The cross-category structure is critical: entertainment provides scripts and symbols, while food offers low-commitment, repeatable experiences that keep the symbols in circulation, feeding back into new search bursts around dramas, actors, and products.

Despite high visibility online and in metros, Hallyu in India is still concentrated among young cohorts and early adopters, with uneven penetration outside major cities and the Northeast. Bollywood and regional industries continue to dominate theatrical and broadcast audiences; language diversity raises localization costs; and many households still allocate entertainment time primarily to domestic serials and sports. Yet among young, smartphone-native cohorts, Hallyu has established durable habits: playlist curation around K-POP, weekend K-drama binges, skincare regimens sourced from K-beauty playbooks, and occasional K-food experiments. In diffusion terms, India appears in the early-to-middle adoption phase: sufficient critical mass exists to sustain growth in metros and the Northeast, but large segments remain unconverted. The quantitative evidence of this paper, especially the trend-adjusted relative gain, fits that narrative: the Wave is not (yet) a mass replacement of domestic entertainment, but a rapidly deepening niche with system-wide visibility.

India provides a stress test for Hallyu's portability because domestic cultural supply is exceptionally strong. Observing meaningful K-specific gains despite that supply speaks to the power of platformised discovery and network spillovers. The mechanisms outlined in the gravity-and-diffusion literature, importer scale, cultural proximity, search costs, and network externalities, offer a coherent map for interpreting India's trajectory. The Northeast's early adoption, the youth-led national diffusion via OTT and short-form video, and the cross-category reinforcements in beauty and food together explain why a common-shock period (COVID-19) could trigger the absolute and relative changes documented in the results.

## 3. Data and Context

Monthly Google Trends indices for India were downloaded for the topics ‘Korean drama’ (treated group), and for comparison topics ‘Japanese drama’, ‘Chinese drama’, and ‘Spanish drama’, resulting in a balanced month-level panel covering both the pre-2020 and post-2020 periods. Google trends values are normalized on a 0–100 scale and are interpreted as measures of relative attention over time.

Descriptive statistics for all series, disaggregated into the pre-COVID period (2004–2019), the COVID and post-COVID period (2020–2025), and the full sample, are reported in Table 1. As shown in Table 1, interest in Korean drama exhibits a marked increase after 2020, both in terms of mean values and median attention, relative to the comparison topics.

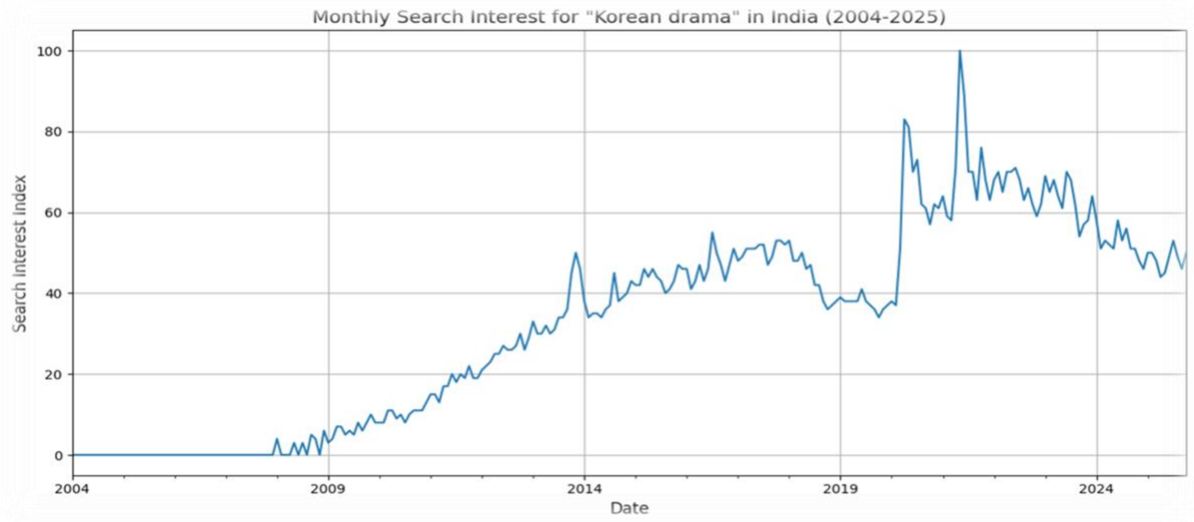
Table 1: Descriptive statistics for Google trends series (India)

| Panel A. 2004–2019 (pre-COVID) | | | | | | |
|---|---|---|---|---|---|---|
| Series | N | Mean | SD | Min | Max | Median |
| Korean drama | 194 | 22.53 | 19.27 | 0.0 | 55.0 | 22.0 |
| Japanese drama | 194 | 9.91 | 9.40 | 0.0 | 33.0 | 12.0 |
| Chinese drama | 194 | 1.87 | 3.63 | 0.0 | 17.0 | 0.0 |
| Spanish drama | 194 | 3.84 | 12.27 | 0.0 | 98.0 | 0.0 |
| Panel B. 2020–2025 (COVID/post) | | | | | | |
| Series | N | Mean | SD | Min | Max | Median |
| Korean drama | 68 | 61.44 | 10.67 | 44.0 | 100.0 | 62.0 |
| Japanese drama | 68 | 58.00 | 12.55 | 38.0 | 100.0 | 57.0 |
| Chinese drama | 68 | 46.50 | 16.88 | 21.0 | 100.0 | 42.0 |
| Spanish drama | 68 | 49.59 | 13.11 | 28.0 | 100.0 | 48.5 |
| Panel C. All months | | | | | | |
| Series | N | Mean | SD | Min | Max | Median |
| Korean drama | 262 | 32.63 | 24.41 | 0.0 | 100.0 | 37.5 |
| Japanese drama | 262 | 22.39 | 23.49 | 0.0 | 100.0 | 17.0 |
| Chinese drama | 262 | 13.46 | 21.61 | 0.0 | 100.0 | 1.0 |
| Spanish drama | 262 | 15.71 | 23.65 | 0.0 | 100.0 | 0.0 |

Notes: Google Trends scales each topic independently; these statistics summarize within-topic variation.

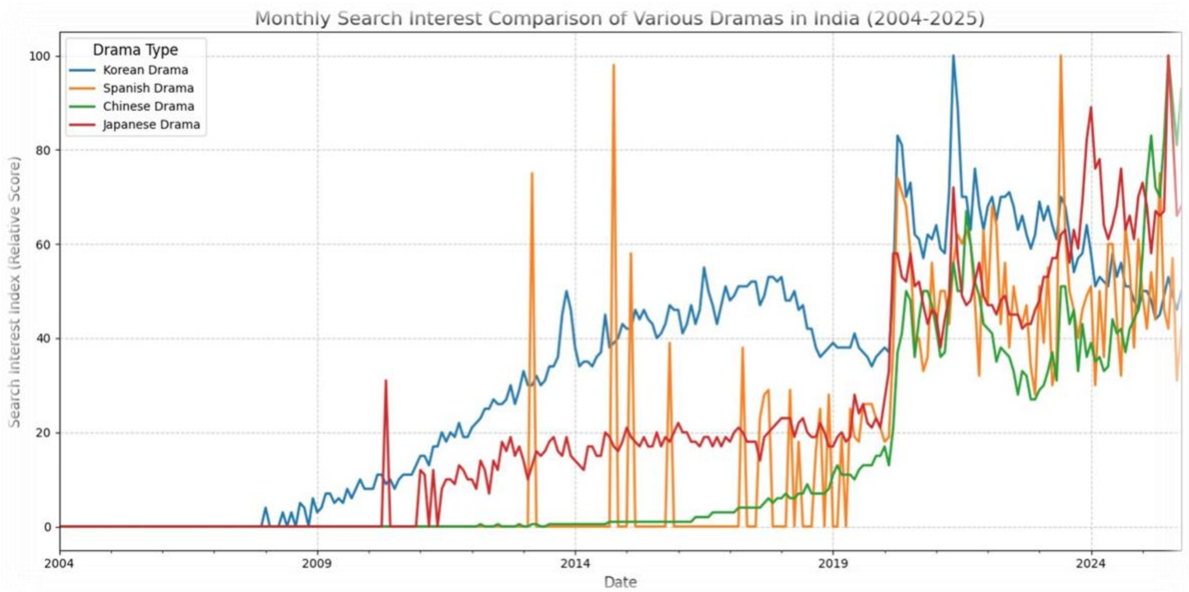
To illustrate the timing and magnitude of this shift, Figure 1 plots the monthly Google Trends index for Korean drama in India, highlighting a clear structural break around March 2020. The figure visually confirms a sustained rise in attention following the onset of the COVID-19 period.

Figure 1: Monthly ‘Korean drama’ index in India with March-2020 break




In addition, Figure 2 compares the monthly evolution of Korean drama interest with the corresponding trends for Japanese, Chinese, and Spanish dramas. This comparison shows that, while attention to international drama content increased more broadly after 2020, the rise associated with Korean drama is notably stronger and more persistent than for the control topics.

Figure 2. Korean vs. comparison topics (India), monthly

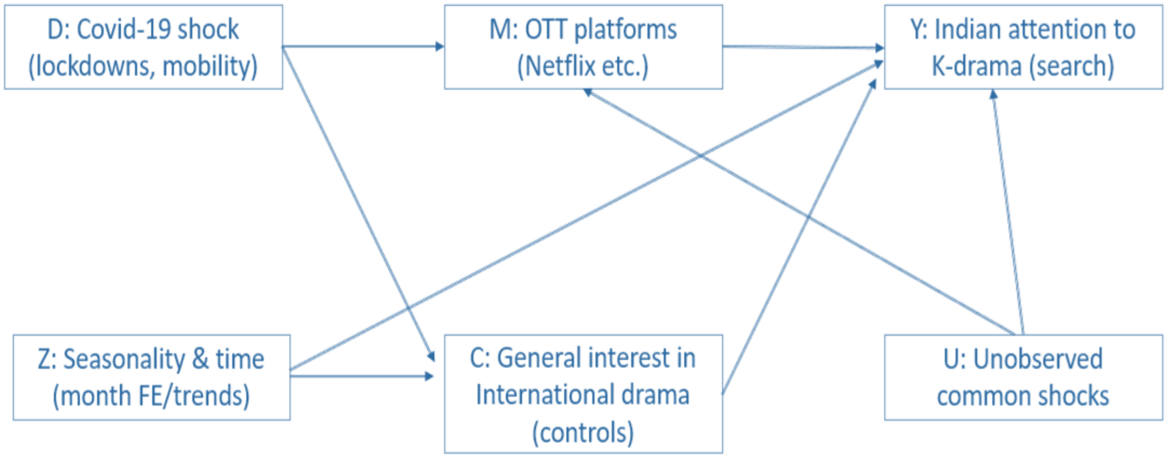



To explore potential transmission channels, OTT-related mediators were assembled at the annual frequency from Statista, including Netflix India revenue (FY 2018–2023) and the number of paid video subscriptions in India (2018–2026). To address seasonality, all monthly regressions include month-of-year fixed effects, while general interest in international drama content is controlled for by incorporating non-Korean drama topics within a Difference-in-Differences framework. For mediation analysis, monthly outcomes are aggregated to the calendar-year level and linked to the corresponding OTT indicators.

## 4. Causal Framework and Estimands

The empirical design is guided by a single, unified directed acyclic graph (DAG) that encodes the central questions of the study in the language of causes and causal paths, following Pearl’s graphical framework. Figure 3 presents this DAG and summarizes the assumed causal structure linking the COVID-19 shock, OTT exposure, and Indian attention to Korean drama.

Figure 3. Unified DAG: COVID-19 (D), OTT (M), attention (Y), comparison interest (C), seasonality/trends (Z), unobserved shocks (U)




As illustrated in Figure 3, the key nodes are COVID-19 (a common, sharply timed shock in March 2020), OTT exposure (with emphasis on Netflix as a gateway for discovery and trial), and Indian attention to K-drama (measured by Google Trends). Additional causes include genre-neutral shocks (such as seasonality, news cycles, and market-wide platform growth affecting all Asian drama topics) and latent tastes and socio-demographic factors that evolve over time.

In words, the graph asserts that COVID-19 increased OTT consumption opportunities and platform discovery (COVID-19 → OTT), that OTT exposure raises the chance of sampling and subsequently searching for Korean content (OTT → K-drama attention), and that COVID-19 could also shift attention through channels other than OTT (e.g., social media virality, peer coordination, or the reallocation of leisure time; COVID-19 → K-drama attention). The same latent factors (e.g., cohort tastes, smartphone penetration) plausibly influence both OTT adoption and content interest (latent tastes → OTT and latent tastes → K-drama attention), and genre-neutral shocks feed into all drama topics simultaneously (e.g., India-wide streaming growth, seasonal holidays).

Three identification principles follow directly from the causal structure depicted in Figure 3, applying Pearl's back-door criterion and the distinction between causes, mediators, and colliders (Pearl, 2009; Gill, 2020). First, OTT is a mediator on the causal path from COVID-19 to K-drama attention, not a pre-treatment confounder. Conditioning on OTT in monthly outcome models would absorb part of the causal effect operating through OTT and may introduce bias by opening spurious paths whenever OTT is influenced by both COVID-19 and latent tastes (i.e., acting as a collider). Accordingly, monthly estimators exclude OTT controls and are designed to recover total effects. Second, because genre-neutral shocks jointly affect K-drama and other international drama topics, a K-specific counterfactual is constructed using near-in controls (Japanese, Chinese, and Spanish drama topics). This structure, shown in Figure 3, motivates the Difference-in-Differences (DiD) strategy, which nets out shared shocks. Third, since the treatment is a single-date common shock, careful checks for pre-trends and flexible seasonality adjustments are required; event-time plots and topic-specific trends operationalize this requirement.

The OTT node aggregates multiple mechanisms, time spent on platforms, catalogue prominence, dubbing/subtitling, price re-positioning, and recommendation systems, through which pandemic-era changes could alter discovery odds. Any variable that affects both OTT and K-drama attention but is not caused by COVID-19 (e.g., long-run taste trends) represents a potential back-door confounder of the OTT → attention link; likewise, month-specific shocks that move all drama topics are confounders of the COVID-19 → attention link if unaddressed. The design blocks these back-doors paths by (i) using month fixed effects and seasonality controls in interrupted time-series models (ITS) to stand in for common shocks and (ii) contrasting with other Asian drama topics in DiD to difference out the genre-neutral component. Conversely, conditioning on OTT in monthly outcome regressions would be a "bad control": it lies on the causal pathway of interest (COVID-19 → OTT → attention) and, as a descendant of COVID-19, can turn collider paths into open ones, biasing the total effect downward (Pearl, 2009).

Finally, the graph clarifies that a true front-door identification strategy through OTT would require (i) all causal effects of COVID-19 on attention to operate exclusively through OTT, (ii) no unmeasured confounders of OTT ⟶ attention, and (iii) a high frequency measurement of the mediator. These conditions are implausible in the context: social media and peer effects provide additional pathways, latent tastes are imperfectly observed, and OTT variables are available only annually. Therefore, monthly models target total causal effects, while OTT variables are used only in is a separate, lower-frequency mediation analysis, with appropriate caution.

## 5. Empirical Strategy

Three estimators are implemented. (1) ITS with centered time and month-of-year dummies captures the level shift at March-2020 and the slope change thereafter. (2) TWFE DiD contrasts Korean with comparison topics, including topic and month fixed effects; the preferred variant adds topic-specific linear trends to relax strict pre-trend parallelism. (3) Annual mediation aggregates the outcome by year and estimates (COVID ⟶ mediator), and then (mediator ⟶ outcome | COVID), with the indirect effect as their product; standard errors for the indirect effect use nonparametric bootstrap over years.

### (1) Interrupted time-series (ITS): absolute level/slope changes at a single intervention date

The purpose of ITS is to measure the total change in India's "Korean drama" attention around March 2020, aggregating all pathways (including OTT) and separating a one-time level break from any slope change thereafter. Let $Y_t$ be the monthly Google Trends index for "Korean drama" (India), normalized to 0-100; $t$ is a month index; $D_t$ = 1[$t \geq$ 2020-03] marks the COVID break. A standard ITS with flexible seasonality is estimated:

$$Y_t = \alpha + \kappa t + \delta D_t + \phi(t \times D_t) + \sum_{k=1}^{K} [\Upsilon_k \sin\left(2\pi k \frac{t}{12}\right) + \lambda_k \cos(2\pi k \frac{t}{12})] + u_t,$$

with Fourier seasonality (e.g., K=2) to capture periodic patterns without proliferating monthly dummies. The coefficient $\delta$ is the discrete level break at March 2020, and $\phi$ captures any post-period slope change.

Ordinary least squares with Newey-West HAC errors addresses serial correlation; bandwidth follows a data-dependent rule. Autocorrelation and functional-form checks motivate either (i) keeping the HAC approach with Fourier terms, or (ii) adding a low-order ARMA filter to the error if needed.

The key assumption is continuation of pre-trend plus seasonality in the absence of COVID-19 (no other intervention precisely in 2020-03). Credibility is probed with placebo break dates (e.g., 2019-03, 2121-03), alternative seasonal controls (monthly dummies vs Fourier), and excluding the earliest months to check sensitivity to normalization windows.

### (2) Two-way fixed-effects DiD: K-specific increment relative to other countries' dramas

The purpose is to purge genre-neutral shocks (lockdowns, OTT growth) by contrasting "Korean drama" with near-in control topics - Japanese, Chinese, and Spanish drama - thereby recovering the K-specific increment. A topic × month panel is built as follows; $i \in$ {Korean, Japanese, Chinese, Spanish}, $t$ is monthly 2004–2025, and outcome $Y_{it}$ is the corresponding Trends index. Baseline TWFE DiD is:

$$Y_{it} = \mu_i + \lambda_t + \beta(T_i \times D_t) + \varepsilon_{it},$$

*where* $T_i$ = 1[i = Korean], $D_t$ marks 2020-03+, $\mu$ are topic fixed effects (absorbing time-invariant differences in average popularity and Google normalization), $\lambda$ are month fixed effects (absorbing shocks common to all topics - e.g., national OTT expansion, festivals, macro conditions). The coefficient $\beta$ is the average K-specific post increment.

The trend adjusted DiD ($\beta$*) estimator is as follows:

$$Y_{it} = \mu_i + \lambda_t + \theta_i t + \beta^*(T_i \times D_t) + \varepsilon_{it}.$$

With one treated group and a single common adoption date, standard TWFE does not suffer the negative-weight problems that arise with staggered timing. The design thus provides a clean K-specific contrast after removing common shocks. The DiD captures the incremental attention that is specific to Korean content, over and above the across-the boead OTT-era lift that also benefited other countries' dramas.

Recent methodological literature has raised concerns about the two-way fixed effects (TWFE) estimator when treatment timing varies across units. Goodman-Bacon (2021) demonstrates that in staggered settings with heterogeneous effects, TWFE estimators may yield biased estimates due to negative weighing in comparison groups. However, this concern is less pronounced when treatment occurs simultaneously across all units. The empirical design of this study centres on a single, sharply timed treatment – the COVID 19 lockdown in March 2020 – which affected all comparison groups concurrently. This simultaneity eliminates the core issue of staggered adoption and negative weighting. Furthermore, visual inspection of pre-treatment trends shows no major divergence between the treated (Korean drama) and control (other international drama) series prior to March 2020. The trend-adjusted TWFE specification implemented here accommodates potential deviations from strict parallelism, providing additional robustness. These features support the credibility of the identification strategy despite recent critiques of the TWFE framework.

### (3) Annual causal mediation through OTT (Netflix; paid video subscriptions)

The purpose is to decompose the total COVID effect into (i) an indirect path operating through OTT growth (with emphasis on Netflix India revenue and paid video subscriptions) and (ii) a residual direct component (social-media virality, peer coordination, etc.). Because mediators are annual, monthly outcomes are averaged to calendar years. $\overline{Y}_y$ is defined as the annual mean of India's K-drama index in year *y*; $M_y$ denotes either mediator; $D_y$ = 1[y ≥ 2020]. The models are as follows:

$$(a) M_y = \alpha_0 + \alpha_1 D_y + w_y' \alpha_2 + u_y, \qquad (b) \bar{Y}_y = \beta_0 + \beta_1 D_y + \beta_2 M_y + w_y' \beta_3 + u_y,$$

*where*: $w'_y$ may include a linear time trend and year fixed effects in sensitivity checks. The indirect effect is $\widehat{IE}$ = $\hat{\alpha}_1 \widehat{\beta_2}$; the direct is $\widehat{DE}$ = $\widehat{\beta_1}$; the total equals $\widehat{IE}$ + $\widehat{DE}$. Small-sample OLS is used with heteroskedasticity-robust standard errors. Uncertainty for $\widehat{IE}$ is obtained by non-parametric bootstrap of years. Because units differ (INR bn; millions of subs), versions in logs are also reported to read $\hat{\beta}_2$ as elasticities.

The exercise follows Pearl's definitions of natural direct/indirect effects and the Imai–Keele–Tingley product-of-coefficients approach, while emphasizing that sequential ignorability is a strong assumption with short, aggregate series; results are therefore interpreted as descriptive decomposition rather than a front-door identification. (Pearl, 2009; Imai et al., 2010; Gill, 2020.)

## 6. Results and Discussions

Three complementary designs were estimated: (i) an Interrupted Time-Series (ITS) on monthly Google Trends for "Korean drama" in India; (ii) a two-way fixed-effects (TWFE) Difference-in-Differences (DiD) contrasting Korean with closely related topics (Japanese/Chinese/Spanish drama) to purge common shocks; (iii) annual mediation/decomposition with OTT indicators, Netflix India revenue and India's paid video-subscription base, as mediators. Monthly models report HAC (Newey–West) or month-clustered standard errors; mediation uses non-parametric bootstrap for the indirect effect.

### (1) Interrupted Time-Series (ITS): Absolute impact on Korean drama search attention

Specification includes centered time, a dummy for March 2020 onward, their interaction, and month-of-year dummies. HAC (Newey–West) standard errors were applied. The level shift of the main coefficients (Table R1) at March 2020 is +20.228 index points and post-period slope change is -0.689 index points per month. The 24-month cumulated effect (level +24 × slope) is +3.70 index points, implying a sharp discrete jump at the onset of the pandemic that partially decayed thereafter.

Table R1: ITS with month-of-year dummies (selected terms)

| Term | Estimate (SE) |
|---|---|
| Constant | 54.070*** (4.362) |
| Time (per month) | 0.319*** (0.033) |
| Post (2020-03 and after) | 20.228*** (4.965) |
| Post × Time | −0.689*** (0.085) |
| Cumulated 24-month effect (level + 24×slope) | 3.7 |
| Month dummies | Yes |

Re-estimating the break in March 2019 and March 2021 as part of Placebo checks (Table R2) yields small, statistically weaker shifts relative to the actual March 2020 break, supporting the interpretation that the salient discontinuity coincides with the pandemic shock rather than generic time drift. The ITS indicates that attention to Korean drama in India rose abruptly with COVID-19–era home entertainment constraints, then gradually trended back, netting a modest positive cumulative increase over two years.

Table R2: ITS placebos against actual break

| Break date | Level shift (Post) | Slope change |
|---|---|---|
| 2019-03 | 67.60 | −0.348* |
| 2020-03 (actual) | 154.42*** | −0.688*** |
| 2021-03 | 197.60*** | −0.878*** |

### (2) Two-Way Fixed-Effects DiD: Korean-specific increment relative to close controls

A *month* × *topic* panel was constructed for Korean (treated) and Japanese/Chinese/Spanish drama (controls). Estimands are the average post-2020 Korean-specific increment over common shocks (OTT adoption, general "Asian drama" appeal, etc.). Two variants were estimated: Baseline TWFE with topic and month fixed effects and Trend-adjusted TWFE adding topic-specific linear trends to address mild pre-trends.

The key estimates are found in Table R3 where the baseline TWFE *Treated* × *Post* is -7.24 and Trend-adjusted *Treated* × *Post* is -32.36. Relative to peer drama (Chinese, Japanese, and Spanish) topics, Korean drama's incremental gain is negative, meaning all four topics rose during the pandemic, but non-Korean comparators rose even more on Google search intensity. This is consistent with a broad genre-wide pull of international drama during lockdowns, where Japanese/Chinese/Spanish content captured disproportionate incremental search growth. It should be noted that Google Trends indexes are topic-normalized; cross-topic levels are not absolute counts. Hence DiD should be viewed as relative share shifts, not absolute viewership changes. The ITS and DiD together imply (i) absolute interest in Korean drama increased, yet (ii) Korean-specific incremental rise was smaller than that for some close comparators.

Table R3: TWFE estimates (dependent variable: monthly search index)

| Term | Baseline TWFE Estimate (SE) | Trend-ajusted TWFE Estimate (SE) |
|---|---|---|
| Treated × Post (Korean × 2020+) | -7.240** (2.541) | -32.362*** (3.331) |
| Topic FE | Yes | Yes |
| Month FE | Yes | Yes |
| Topic trends | No | Yes |
| Number | 1,048 | 1,048 |

## (3) Annual Mediation: OTT as a channel (Netflix revenue and paid subscriptions)

Annualized outcome (calendar-year average of the Korean drama index) was linked to a COVID indicator (2020+) and each mediator. The indirect effect (IE) equals (COVID ⟶ mediator) × (mediator ⟶ outcome | COVID); direct effect (DE) is COVID's residual effect controlling for the mediator; total effect (TE) is IE + DE. Bootstrap (5,000 resamples) was used for IE SEs.

Table R4 shows the Netflix India revenue during 2018-2023. The COVID to Revenue Indirect effect is -0.034, Direct effect is +24.846, and Total effect is +24.812. Table R5 shows the Paid video subscriptions in India during 2018-2025/26. The COVID to Subscriptions Indirect effect is -25.27, Direct effect is +45.059, and Total effect is +19.789.

OTT expanded markedly post-2020, but the mediated channel is statistically weak/ambiguous at annual frequency: the indirect path is small and imprecise, while the direct COVID-era effect on Korean-drama interest remains positive and significant even when conditioning on OTT measures. This pattern supports a reading that OTT was a necessary infrastructure, but not a sufficient single mediator of Korea-specific attention; genre-wide demand, catalogue breadth, dubbing/subtitling availability, and social media virality likely contributed in parallel.

Table R4: Annual mediation via Netflix India revenue

| Quantity | Estimate (SE) |
|---|---|
| $a_1$: COVID (2020+) ⟶ Mediator | 13.615** (4.282) |
| $b_2$: Mediator ⟶ Outcome | −0.002 (0.493) |
| $b_1$: Direct effect of COVID | 24.846* (7.933) |
| Indirect effect ($a_1 \times b_2$) | −0.034 |
| Total effect | 24.812 |
| Number of Years | 6 |

Table R5. Annual mediation via paid video subscriptions (India)

| Quantity | Estimate (SE) |
|---|---|
| $a_1$: COVID (2020+) ⟶ Mediator | 36.000*** (5.869) |
| $b_2$: Mediator ⟶ Outcome | −0.702 (0.385) |
| $b_1$: Direct effect of COVID | 45.059** (14.906) |
| Indirect effect ($a_1 \times b_2$) | −25.270 |
| Total effect | 19.789 |
| Number of Years | 8 |

### (4) Substitution vs Expansion Discussion

The sharp rise in Korean content consumption during the COVID-19 pandemic in India raises the question of whether such attention substituted for domestic entertainment or expanded the overall cultural consumption market. Microeconomic theory suggests that when consumers face a fixed time budget, new content may displace pre-existing options (a substitution effect). Alternatively, an increase in leisure time – as occurred during lockdowns, can shift the consumption frontier outward, enabling expansion across multiple categories.

Industry indicators and search behaviour suggest that the latter dynamic was prevalent. Video content consumption rose globally by over 50% in early 2020, with similar surges observed in India (Nielsen 2020). Korean drama consumption on Indian OTT platforms increased significantly, yet this growth occurred alongside continued domestic content viewership, including direct-to-digital Bollywood releases during cinema closures (Hindustan Times 2021). These patterns are consistent with an expansionary response in attention, rather than a zero-sum substitution. Korean content appears to have supplemented rather than supplanted Bollywood during the COVID period.

### (5) OTT Expansion – Supply and Demand Drivers

The growth of OTT media consumption in India during COVID-19 was driven by both demand-side shocks and platform-led supply responses. On the demand side, strict lockdowns and mobility restrictions in 2020 significantly reallocated leisure time to home-based entertainment. According to FICCI–EY (2021), India added nearly 18 million new paying OTT subscribers in 2020 alone, with paid video subscriptions reaching 53 million and digital subscription revenue rising by 49% (FICCI–EY 2021). RedSeer (2021) reported a 35% increase in paid OTT users between April 2020 and February 2021, while monthly OTT subscription revenues rose 42% year-on-year. These surges indicate that consumers substituted cinema and live entertainment expenditures with digital streaming during the pandemic.

Simultaneously, supply-side adaptations played a crucial role. OTT platforms rapidly acquired new content and premiered feature films directly on streaming services. Between March and July 2020, India Brand Equity Foundation (IBEF 2020) estimates paid OTT subscriptions grew from 22.2 million to 29 million, partly due to bundling services and the launch of mobile-only, low-cost plans. Netflix, Amazon Prime Video, and ZEE5 led this trend by releasing high-profile films directly to digital platforms. Regional and Hindi-dubbed catalogues also expanded rapidly. According to CII–BCG (2020), total OTT subscriptions rose by over 55% in 2020, and the pandemic created a behavioural shift that industry analysts expect to persist in the long term. Ormax Media (2022) confirms that India's OTT audience base reached over 420 million by 2022—a 20% increase from the previous year, underscoring the scale and durability of this transformation. These developments illustrate that the COVID-19 period produced both a temporary demand shock and structural supply innovations that reshaped India's digital content ecosystem.

## Conclusion

This article examined whether the COVID-19 shock altered Indian attention to the Korean Wave, focusing on K-drama as the primary search-based outcome and treating OTT platforms, especially Netflix, as a key channel of diffusion. A unified causal graph guided the empirical choices: monthly designs were kept "total-effect" by not conditioning on post-treatment OTT measures, while annual decompositions were used to describe the share of the total effect plausibly mediated by OTT. Three complementary estimators, an interrupted time-series (ITS), a two-way fixed-effects difference-in-differences (TWFE DiD), and annual causal mediation, were implemented on Google Trends series for India (treated) and closely related drama topics (controls), alongside Statista series for Netflix India revenue and paid video subscriptions.

Three main findings emerge. First, the ITS detects a sharp level increase in Indian searches for "Korean drama" at the onset of the pandemic (March 2020), followed by a negative post-period slope, so that the two-year cumulative gain remains positive but modest. This pattern is consistent with a strong contemporaneous push into home entertainment and a subsequent partial normalization in search intensity once mobility and offline options returned.

Second, the panel contrast to near-in controls indicates that the K-specific increment, the rise unique to Korean drama relative to Japanese, Chinese, and Spanish drama, was smaller than the across-the-board lift enjoyed by the broader drama category during lockdowns. Once topic-specific pre-trends are accounted for, the *treated* × *post* coefficient is negative and statistically precise. The monthly evidence implies that Indian interest in Korean drama did increase in absolute terms, but not disproportionately compared with closely related foreign drama categories during the pandemic spike in streaming demand.

Third, OTT expanded rapidly in the period (Netflix India revenue; paid video subscriptions), yet the annual mediation shows an imprecise indirect channel and a sizable positive direct component of COVID-era effects on Korean-drama attention after conditioning on the mediators. At annual frequency and given short post-period spans, OTT should thus be viewed as enabling infrastructure rather than a single sufficient pathway for Korea-specific attention; other factors, catalogue breadth, localization (dubbing/subtitling), social-media coordination, and cross-genre spillovers from K-pop and K-beauty, likely contributed in parallel.

The conclusion that COVID-19 was a broad genre shock rather than a uniquely Korea-specific one in India dovetails with the literature's view that cultural diffusion is competitive and networked: multiple cultures can rise together when distribution frictions fall, with relative shares shaped by catalogue timing, localization, and platform strategies.

Several limitations should be emphasized. (i) Google Trends scaling is relative and can vary with the download window and competing topics; cross-topic DiD should therefore be read as a share-of-attention estimand, not an absolute viewership effect. (ii) Short series and annual mediators restrict statistical power for decomposition; fiscal-year/calendar-year alignment for revenue adds measurement noise. (iii) The treated set is a single topic contrasted to a small set of controls, limiting the effective number of clusters. (iv) Search interest is a proxy of demand, not consumption; linking attention to realized streams, purchases, or time-use would strengthen external validity. These caveats mirror common constraints in the quantitative Hallyu literature.

Future work can deepen identification and expand external validity along several complementary margins. A first priority is to link attention to consumption by combining Google Trends with platform-level viewership micro data (episode play counts, completion rates, hours watched) and with downstream behaviours in related markets (e-commerce sales for K-beauty; restaurant and grocery delivery for K-food). Establishing how search attention translates into realized consumption would connect attention shocks to market outcomes, extending prior evidence of Hallyu-driven demand spillovers in cosmetics.

Second, the content-level margin offers quasi-experimental variation that was not exploited here. Title-specific events, India release dates, sudden catalogue additions/removals, recommender placements, and especially localization milestones such as first Hindi/Tamil dubbing—can serve as event anchors in high-frequency designs. Show-by-show panels enable difference-in-differences within platforms, sharpen causal attribution to supply-side shocks, and allow heterogeneity by genre or rating.

Third, the counterfactual for relative attention can be strengthened. A broader pool of comparator topics (e.g., additional non-Korean Asian dramas, Western drama subgenres) would support synthetic control or augmented synthetic control constructions with longer pre-periods. Ratio outcomes, such as the share of "K-drama" in total "international drama" queries, could stabilize scaling across Google Trends windows and mitigate amplitude artifacts.

Fourth, Indian heterogeneity deserves dedicated analysis. State and city-level panels (where Google Trends provides sufficient volume) could be matched to OTT availability, language dubbing coverage, mobile-data rollout, and demographics, with special attention to early-adopting Northeast states. Spatial variation in catalogue localization and broadband quality would help distinguish access frictions from taste shocks.

Fifth, the OTT mediation pathway can be identified more credibly using front-door instrumental-variables strategies built on exogenous platform-side supply. Natural candidates include staggered studio deals, contractual exclusivity windows, catalogue purges tied to global licensing cycles, or recommender experiments that alter exposure without targeting Korea-specific demand. Measuring multiple mediators, Netflix, competitors, and aggregate subscription video on demand (SVOD) time use, would help separate platform expansion from genre-specific programming choices.

Sixth, a multi-outcome, cross-vertical design should be developed to trace spillovers across K-culture. Joint models could connect shocks to K-drama attention with K-pop (playlist follows, music video views, concert searches), K-beauty (brand queries and sales), K-food (restaurant and recipe searches), and education (Korean-language learning).

Seventh, robustness to alternative attention sources should be routine. Wikipedia pageviews, YouTube search and view panels, app-store rankings, and advertising-auction query volumes can be triangulated against Google Trends to verify sign and timing. When combined with ratio-based outcomes, such triangulation can benchmark sensitivity to scaling and platform composition.

Finally, comparative studies across large emerging markets with strong domestic industries (e.g., Indonesia, Turkey) would test external validity. Parallel designs using matched data structures could show whether the Indian pattern, absolute gains for K-content but modest relative advantage during COVID-induced streaming booms—generalizes or reflects India-specific institutional features.

Overall, the evidence points to COVID-19 as a catalyst that lifted Indian attention to international drama broadly, with Korean content benefiting in absolute terms but not disproportionately relative to close foreign comparators. OTT platforms and Netflix in particular, appear to have facilitated access but do not, in aggregate annual data, fully account for the Korea-specific movements in search behaviour. The Korean Wave in India thus remains early-stage and youth-skewed, building from pockets of strong fandom to wider adoption. Continued catalogue localization, cross-media synergy (K-pop, K-beauty, K-food), and the deepening of OTT infrastructure are likely to shape the trajectory. The methodological template used here, grounded in a clear causal graph, multiple quasi-experimental estimators, and attention-based measurement, offers a portable approach for analysing cultural diffusion in other large emerging markets.

## Credit Authorship Contribution Statement

The author contributed the writing, the visualization, the validation, the supervision, the software, resources, the project administration, the methodology, the investigation, the funding acquisition, the formal analysis, the data curation, and the conceptualization.

## Conflict of Interest Statement

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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N/A

## Data Availability Statement

Data available on request: The data that support the findings of this study are available from the corresponding author upon reasonable request.

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