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THE DIGITAL CREATIVE ECONOMY

Advertising and the Engineering of Consumer Demand

L'ECONOMIA CREATIVA DIGITALE

La pubblicità e la costruzione della domanda del consumatore

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SINTESI IN LINGUA ITALIANA

Questo rapporto finale studia il modo in cui l'economia creativa digitale — l'insieme formato dalla produzione di contenuti, dallo streaming, dal marketing degli influencer e dalla pubblicità gestita da algoritmi — contribuisce all'attività macroeconomica e, soprattutto, al modo in cui la domanda dei consumatori viene oggi generata.

La tesi centrale è che la pubblicità digitale ha smesso di limitarsi a soddisfare una domanda già esistente e ha cominciato a costruirla. Nell'era televisiva l'esposizione pubblicitaria era limitata dal costo: un annuncio era caro da produrre e da collocare, per cui le marche compravano poche esposizioni ad ampia copertura. Le piattaforme algoritmiche hanno rimosso questo vincolo e consegnano oggi decine di impressioni personalizzate al giorno, a un costo per mille contatti molto inferiore. Su questa base operano tre meccanismi comportamentali: l'acquisto d'impulso, la riprova sociale e la paura di restare esclusi (FOMO).

Il lavoro combina tre fonti di evidenza. La prima è costituita da dati macroeconomici e di settore: le industrie creative valgono circa 2.250 miliardi di dollari l'anno, pari a circa il 3 per cento del PIL mondiale, e circa due milioni di persone vivono a tempo pieno di produzione di contenuti. La seconda è uno studio di caso originale condotto dall'autore su Buffers, una cloud kitchen aperta a Bhopal, in India, e promossa esclusivamente tramite Instagram, senza alcun

budget pubblicitario a pagamento. La terza è un'indagine esplorativa sui comportamenti d'acquisto.

Nei dieci giorni per i quali il registro delle vendite riporta un totale giornaliero certo, il fatturato medio è stato di 4.164,50 rupie nei giorni con pubblicazione su Instagram, contro 2.891,67 rupie nei giorni senza pubblicazione, con una differenza del 44,0 per cento. Il campione è però molto piccolo: la correlazione è pari a 0,56, il test t di Welch restituisce p = 0,137 e il d di Cohen è 1,24. L'effetto è quindi ampio in termini standardizzati ma non significativo al 5 per cento, e va letto come evidenza preliminare di associazione e non come prova di un rapporto causale.

L'indagine ha raccolto diciotto risposte, di cui diciassette utilizzabili. Dieci rispondenti dichiarano di aver acquistato prodotti non previsti dopo averli visti online e Instagram è la piattaforma indicata più spesso. Gli stessi rispondenti, tuttavia, respingono in maggioranza l'idea di essere mossi dalla FOMO, di acquistare d'impulso o di fidarsi degli influencer più che delle marche. Questa distanza fra comportamento dichiarato e atteggiamento dichiarato è il risultato più interessante dell'indagine e suggerisce che l'influenza digitale agisca attraverso la familiarità, senza essere riconosciuta come persuasione.

Nel complesso il lavoro conclude che la domanda dei consumatori nell'era digitale è in misura crescente costruita più che spontanea. L'evidenza raccolta su Buffers resta preliminare, ma va nella stessa direzione dei dati macroeconomici e dei casi documentati, e ha il pregio di essere raccolta dall'interno del fenomeno anziché da un rapporto scritto su di esso.

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND AND CONTEXT

In 1971 Herbert Simon said something that now reads like a prediction. A world rich in information, he wrote, will produce a poverty of attention (Simon, 1971). Five decades later that poverty is the product. Smartphones and social media have built a machine for turning human attention into money, and advertising sits at the centre of it. The digital creative economy that grew around that machine, which covers content creation, influencer marketing and algorithmically managed advertising, now contributes an estimated USD 2.25 trillion to world GDP every year. Digital advertising spend on its own passed USD 626 billion in 2023, and roughly 50 million people worldwide call themselves content creators, of whom about 2 million earn a full-time living from it (UNESCO, 2021; eMarketer, 2023; SignalFire, 2020).

Those numbers give the scale, but scale is not the interesting part. What matters is what the money is buying. Traditional advertising gave brands a way to position a product inside a market that already ran on need. Digital advertising starts somewhere else completely. Algorithm-driven platforms deliver personalised, emotionally targeted messages continuously, and in doing that they build the infrastructure for something different: the manufacturing of desire and urgency before any need is felt. Wants without needs.

1.2 STATEMENT OF THE PROBLEM

Economics has been slow to catch up with this. Mainstream macroeconomic analysis still treats advertising and content creation as background noise rather than as independent drivers of consumer demand and GDP, and it still models demand mostly as a function of income, prices and preferences. That leaves policymakers and economists under-equipped to explain how algorithmically engineered aspiration shapes what people actually buy. The advertising industry has the opposite problem. It is running the new machine while still measuring itself with accountability frameworks built for the broadcast era.

1.3 RESEARCH OBJECTIVES

This study sets out to close part of that gap, and it does so in four steps. It first quantifies what the digital creative economy contributes to the macroeconomy. It then traces how advertising travelled from broadcast-era demand fulfilment to algorithm-driven demand creation. From there it examines the psychological and algorithmic systems that carry that shift, which are FOMO, social proof, impulse buying and personalisation. Finally it tests the whole argument against a controlled case study and a consumer survey.

1.4 RESEARCH QUESTIONS

Three questions run through those steps and stay open until Chapter 10. How big is the contribution of the digital creative economy to GDP and employment? Which psychological and algorithmic mechanisms does digital advertising

actually use to move demand? And does the evidence really support the claim that social media marketing generates measurable sales, or does it only look that way?

1.5 SIGNIFICANCE, SCOPE AND METHODOLOGY

The value of asking these three together is that it links macroeconomics to the commercial reality of the space, which is useful for economists and just as useful for the advertising professionals working inside it. The period under study is mainly 2010 to 2026.

Three kinds of evidence are combined, and they are deliberately different in kind. The first is secondary macroeconomic and industry data, which sets the size of the sector in Chapters 4 and 5. The second is an original single-business case study on Buffers, a cloud kitchen designed and operated by the author, which sets Instagram posting activity against daily sales in Chapters 7 and 8. The third is a consumer survey on purchasing habits, also reported in Chapter 8. The macro data shows what the sector is worth, the case study shows what it looks like from inside one small business, and the survey shows what consumers believe about themselves while all of it is happening.

1.6 CENTRAL THESIS

Together they support a single claim. Consumer demand in the digital era is largely generated by algorithms, social proof and FOMO rather than by need. Before Industry 4.0 a brand used advertising to show you its product. Today it shows you the product and the problem that buying it will solve, and the problem is that you do not own it yet. Advertising has moved from passively serving

demand to actively creating it, and that shift shows up not only in global figures but in the daily sales of one small kitchen, as Chapters 7 and 8 will show.

CHAPTER 2

CONCEPTUAL FRAMEWORK

2.1 DIGITAL CREATIVE ECONOMY AND CONSUMER BEHAVIOUR

Before any of that can be tested it needs a vocabulary. Content creation, platform distribution, streaming and algorithmic advertising are the working tools of the digital creative economy, and brands use them to shape behaviour rather than simply to announce a product. The consumer sees the product again and again until he buys it. This was never possible before. We used to know when we wanted something, because the want came out of the gap left by not having it. Today the digital creative economy opens that gap first and then sells the thing that fills it. The models below are the ones that have shaped how the industry thinks about doing this.

2.2 ADVERTISING INFLUENCE MODELS

The oldest of them is AIDA, which walks a buyer through attention, interest, desire and action in a straight line (Lewis, 1898; see Barry, 1987). The Elaboration Likelihood Model complicates that line by splitting it in two: a central route where people buy after reasoning, and a peripheral route where they buy on emotion and mental shortcuts (Petty and Cacioppo, 1986). Almost everything about digital advertising is optimised for the second route. The digital influence funnel is the modern version of both, and what distinguishes it is speed. Algorithmic exposure, social proof and frictionless checkout compress the

distance from first sight to purchase into seconds, which is exactly what a Meta-ads-to-Shopify funnel does in practice.

2.3 DEMAND CREATION VERSUS DEMAND FULFILMENT

Behind those models sits the distinction this whole study turns on. Demand fulfilment satisfies a need that is already there. Demand creation manufactures a want that was not there, using repeated exposure and algorithmic personalisation to do it. The claim made here is that digital advertising has shifted the balance decisively towards the second.

2.4 ATTENTION ECONOMY AND BEHAVIOURAL ECONOMICS

That shift is only possible because of what the platforms are competing for. Attention is the scarce resource, and engagement-optimised algorithms such as the one behind Instagram Reels reward whatever holds it longest. In practice that tends to be aspirational or emotionally activating content, which is also the content advertisers want to sit beside.

Attention on its own is not a purchase, though, and three behavioural mechanisms do the work of turning one into the other. Impulse buying is the decision taken with almost no deliberation, made easier every year by frictionless payment systems like Apple Pay and Google Pay. Social proof is the tendency to copy behaviour we can see in other people, and platforms amplify it by making likes, comments, shares and influencer endorsements visible by default (Cialdini, 1984). FOMO, the fear of missing out, is the anxiety of being left out of something

valued, and scarcity cues, countdown timers and the visible purchases of peers are all built to set it off (Przybylski et al., 2013).

2.5 CHAPTER SUMMARY

So the models explain how a consumer travels from interest to purchase, the creation and fulfilment distinction defines what this study is actually measuring, and the three mechanisms supply the psychological vocabulary used from Chapter 6 onwards to read both the secondary cases and the Buffers data. What is left is to show how advertising got here, which is where the next chapter starts.

CHAPTER 3

EVOLUTION OF ADVERTISING

3.1 THE TRADITIONAL ERA

The traditional era ran on one-way broadcast messages carried by television, print and cinema, and those messages took up only a modest share of anyone's day. The reason is economic rather than cultural. A single advertisement was expensive to produce and expensive to place, so brands bought a small number of high-production, wide-reach messages instead of a continuous presence. Exposure frequency was capped by cost, and advertising mostly sped up demand that already existed rather than inventing it.

3.2 THE DIGITAL ERA

Digital advertising removed that cap. Algorithm-driven platforms deliver personalised, micro-targeted content without pause, and repeated exposure on its own raises preference, which is the mere exposure effect (Zajonc, 1968). A television campaign might reach someone a handful of times in a week. A social media feed will deliver dozens of brand-relevant impressions in a day, and at a fraction of the production cost of a broadcast spot (Media Dynamics, 2025; Triple Whale, 2026). That is not a difference of degree. It is the economic structure that later made it possible for a single small business with no advertising budget to run the experiment described in Chapter 7.

Table 3.1 — Advertising in the traditional and the digital era

Dimension	Traditional era	Digital era
Direction	One-way broadcast	Personalised, two-way, algorithmic
Frequency	A few exposures per week	Dozens of exposures per day
Cost of entry	High (production and media buy)	Low (a smartphone and a platform account)
Primary function	Demand fulfilment	Demand creation

Source: author's elaboration on Media Dynamics (2025) and Triple Whale (2026).

3.3 KEY ARGUMENT: FROM DEMAND RESPONSE TO DEMAND CREATION

Everything else in this study follows from that change. Moving from infrequent one-way broadcast to continuous hyper-personalised exposure is the structural mechanism behind the central thesis, and it is what makes demand creation, rather than demand fulfilment, the dominant economic function of advertising today. The question that follows is how much that function is worth.

CHAPTER 4

IMPACT ON GDP

4.1 CONTRIBUTION TO GDP AND GROWTH OF DIGITAL CONTENT MARKETS

A fair amount, as it turns out. Creative industries are worth somewhere around USD 2.25 trillion a year, roughly 3 per cent of global GDP (UNESCO, 2021), and three markets inside that total show how far the ground has moved. Streaming has rewritten how audiovisual content earns its money and is now valued at around USD 160 billion (Precedence Research, 2026). Influencer marketing was worth about USD 1.4 billion in 2014 and reached an estimated USD 32.55 billion in 2025. Paying an individual creator to talk about a product used to be an experiment run with spare budget, and it is now a standard line in a media plan, with brands reporting an average return of USD 5.78 for every dollar they put in (Influencer Marketing Hub, 2025).

4.2 ADVERTISING AS AN ECONOMIC MULTIPLIER

Those figures would matter less if advertising only shuffled spending between brands. It does not. Advertising spend also generates activity further down the chain, in production, retail, logistics and marketing employment, and that is a large part of why creative-sector output is counted as a driver of growth rather than as a transfer (UNCTAD, 2024). It is also the first piece of macro evidence for the argument running through this study, which is that advertising is an active

force in creating demand and not a passive one serving it. The same logic applies to the jobs it creates.

CHAPTER 5

EMPLOYMENT GENERATION

5.1 DIRECT AND INDIRECT EMPLOYMENT

Employment in the digital creative economy comes in two layers. The direct layer looks like ordinary work: filmmakers, editors, designers and marketing professionals. The indirect layer is the one the platforms made possible, and it covers content creators, influencers and social media managers. Around 2 million people worldwide now earn a full-time living from content creation, out of a self-identified creator population of more than 50 million (SignalFire, 2020). That ratio is worth noticing, because it says that getting in is easy and that staying in is not.

Table 5.1 — Employment generated by the digital creative economy

Category	Representative roles
Direct employment	Filmmakers and directors, editors, designers, marketing professionals
Indirect / platform-enabled	Content creators and influencers, social media managers, freelance production crews

Source: author's elaboration on SignalFire (2020) and UNCTAD (2024).

5.2 DEMOCRATISATION AND SCALABLE INCOME

Getting in is easy because the gatekeepers are gone. Studio backing, record deals and publishing contracts used to stand between a creator and an audience, and platforms have dismantled all three. What is left as a barrier is a smartphone and an internet connection. What sits on the other side of that door is also unlike ordinary employment, because creator income scales non-linearly. A single piece

of content keeps earning long after it is made, as YouTube advertising revenue does, which makes the creator economy structurally different from a conventional labour market (SignalFire, 2020). The same low barrier is what let the Buffers case study in Chapter 7 run as a one-person operation with no marketing budget and no team.

But knowing what the sector is worth and who works in it still does not explain why any of it changes what people buy. That is the subject of the next chapter.

CHAPTER 6

INFLUENCE ON CONSUMER DEMAND

This chapter is the analytical core of the study. Chapters 4 and 5 established how big the digital creative economy is, and what follows is the mechanism. Demand gets shaped on two levels at once, one psychological and one algorithmic, and the shift in consumption patterns that comes out of it is the product of both working together.

6.1 PSYCHOLOGICAL INFLUENCE

The psychological level uses the three mechanisms set out in Chapter 2, and each of them has a practical job. Trend manufacturing comes first: hyper-personalisation and influencer seeding can take a niche interest and put it in front of a mass audience inside twenty-four to forty-eight hours. Building FOMO comes second, and it is engineered rather than accidental. Countdown timers, artificial scarcity in the form of limited drops, and the plain visibility of what other people have already bought add up to an urgency that a purchase relieves (Przybylski et al., 2013). The third is the social validation architecture of the platforms themselves, where likes and positive comments work as a kind of social currency and aspirational content is rewarded with organic reach far beyond what its quality alone would earn (Cialdini, 1984).

6.2 ALGORITHMIC INFLUENCE

None of that would scale without the machinery underneath it, which is built for one purpose, and that purpose is maximum exposure. Personalised advertising uses machine-learning targeting to match messages to individual behavioural profiles, so a brand selling an energy drink mostly shows its ads to people who are into fitness and already buy that kind of thing. Repetition and frequency management then deliver dozens of brand impressions a day, far past anything the broadcast era could afford, and the only reason that is possible is that distribution on social media is cheap (Media Dynamics, 2025; Lebesgue, 2026). Short-form mechanics such as infinite scroll and autoplay close the loop by keeping people on the platform longer, which simply means more exposure.

6.3 SHIFT IN CONSUMPTION PATTERNS

Put the two levels together and what changes is what consumption is for. Spending moves from necessity towards aspiration, and from reasoning towards emotion. That is a large claim to make from theory alone, so Chapters 7 and 8 test it against documented cases and an original controlled case study run by the author.

CHAPTER 7

CASE STUDIES AND EMPIRICAL EVIDENCE

The test begins with money, because cost is what made the shift possible in the first place. This chapter looks at the cost structure of digital advertising, then at how one large advertiser reallocated its budget in response, and finally at the study's own case study: Buffers, an independently operated cloud kitchen marketed entirely through Instagram, which supplies the first-hand evidence for the central thesis.

7.1 COST AND TARGETING EFFICIENCY OF DIGITAL ADVERTISING

Digital platforms deliver a much lower effective cost per thousand impressions than television or print once targeting precision is taken into account, and they add behavioural retargeting and lookalike modelling on top, neither of which has any broadcast-era equivalent (Media Dynamics, 2025; Triple Whale, 2026).

Table 7.1 — Typical cost per thousand impressions by channel

Channel	Typical CPM (USD)	Source
Broadcast television (prime time)	40–50	Media Dynamics (2025)
Cable television	19–21	Media Dynamics (2025)
Streaming / CTV	25–30	Media Dynamics (2025)
Meta Ads (United States)	6–15	Triple Whale (2026)
TikTok Ads (United States)	5–13	DigitalApplied (2026)
YouTube pre-roll	4–10	Onramp Funds (2025)

Channel	Typical CPM (USD)	Source
Meta Ads (India)	≈ 1.4	Lebesgue (2026)

Source: as indicated in the final column; vendor-published benchmark data.

The Indian figures are what make the case study possible. Meta CPM in India averages around USD 1.36 against a United States range of roughly USD 6 to 15 (Lebesgue, 2026; Triple Whale, 2026). Bhopal, where Buffers operated, therefore sits in a market several times cheaper than the American benchmarks most published data is built on, and at about one thirtieth the cost of broadcast television (Media Dynamics, 2025).

Organic posting costs less still, because it needs no media budget at all, and that is what made a zero-paid-media strategy a real test rather than a compromise forced by a small wallet. In a market where even paid reach costs about a dollar per thousand impressions, the marginal cost of an organic post is basically the founder's time.

7.2 CORPORATE BUDGET SHIFT: THE BMW CASE

Large advertisers reached the same conclusion earlier, and with far more data behind them. BMW is a useful case because its spending is tracked publicly, and what the tracking shows is a steady reallocation towards digital channels rather than a single dramatic switch.

Table 7.2 — Reported evidence on the BMW and automotive advertising mix

Period	Reported evidence	Source
2019	Analysis of paid and organic social campaigns found BMW distributing its major-platform social budget across Facebook, YouTube, Instagram and Twitter, with YouTube taking between a third and more than half of that budget across luxury brands	BrandTotal, in Forbes (2019)
2019–20	Across the automotive sector, television was forecast to fall to 52.1 per cent of ad spend while digital rose to 24.4 per cent	Zenith, in MarketingCharts (2019)
2023	BMW of North America invested close to USD 180 million through November. Digital media rose 92 per cent year on year and print 29 per cent, while television fell 23 per cent; total spend grew 18 per cent. Digital growth was driven by paid social on Meta platforms and TikTok	MediaRadar (2023)
2025	US automotive digital ad spend forecast at USD 22.25 billion, growing only 2.2 per cent after tariff pressure, against 11.1 per cent previously expected	eMarketer (2025)

Source: as indicated in the final column.

The 2023 figures are the clearest single snapshot. Digital rose by 92 per cent in a year while television fell by 23 per cent, and the digital growth came specifically from paid social on Meta and TikTok rather than from display (MediaRadar, 2023). That is money moving to exactly the mechanisms described in Chapter 6. Working with automotive YouTubers and lifestyle influencers buys earned reach at a fraction of broadcast CPM and arrives with more credibility than an interruption does (Influencer Marketing Hub, 2025), while programmatic display catches people already in the consideration phase and so complements the demand-creating work rather than repeating it.

The sector-level numbers put that in context. Automotive was slower to move than most industries, with digital still at around a quarter of spend at the end of the last decade while television held roughly half (Zenith, in MarketingCharts, 2019), and the direction has not reversed since, even where growth has slowed for reasons outside advertising, such as the tariff pressure that cut forecast US automotive digital growth from 11.1 to 2.2 per cent in 2025 (eMarketer, 2025). As attention moved from broadcast to digital, the money followed it, which says that budget allocation now tracks measurable attention and behavioural influence rather than reach on its own.

BMW, though, has a media agency and a budget with nine figures in it. The question this study is more interested in is whether the same mechanism does anything at all for a business with neither.

7.3 THE BUFFERS CASE STUDY: AN INSTAGRAM-ONLY MARKETING EXPERIMENT

To answer that without leaning on somebody else's reporting, the author set up and ran Buffers, a digital-first cloud kitchen in Bhopal, India, marketed exclusively through Instagram, with no paid advertising and no offline channel such as print or radio. The design isolates one variable, Instagram posting activity, and sets it against daily recorded sales. It is small, but it is controlled, and it is a real-world test of the claim that social media exposure drives measurable demand.

Two records were kept across the operating period of June and July 2026: a handwritten daily sales ledger, and a log of Instagram posting dates with post counts (Buffers, 2026). Ten of those dates carry a daily sales total clear enough to

use, and they form the basis of the comparison in the next chapter. Sixteen posts were recorded in total, spread across ten posting dates.

Table 7.3 — Instagram posting log, Buffers, June–July 2026

Date	Number of posts
23 June	1
24 June	1
27 June	1
28 June	1
29 June	1
30 June	4
5 July	2
9 July	3
10 July	1
19 July	1

Source: Buffers (2026), Instagram posting record, www.instagram.com/buffers.co.

The comparison in Chapter 8 uses only the ten dates with an unambiguous daily total, and the posting dates come from the Buffers Instagram page (Buffers, 2026).

CHAPTER 8

DATA ANALYSIS

This chapter reports what the ledger actually showed, and then what eighteen consumers said about their own behaviour. The two sources answer different halves of the same question: whether posting moves sales, and whether anyone notices when it does.

8.1 PRIMARY CASE STUDY: THE BUFFERS EXPERIMENT

Of the ten dates with a clearly documented daily total, four were Instagram posting days and six were not. Average documented revenue was ₹4,164.50 on posting days against ₹2,891.67 on non-posting days, a gap of 44.0 per cent. The medians tell the same story, ₹4,344.50 against ₹3,162, and that matters because it rules out the possibility that one unusually good day is doing all the work (Buffers, 2026).

That said, ten observations are ten observations. The exploratory tests in Appendix C put numbers on the caution. The correlation between the posting-day flag and sales is r = 0.56, Welch's t-test returns p = 0.137, and Cohen's d is 1.24. So the difference is large in standardised terms and still not significant at the 5 per cent level, which is more or less what a sample this size should be expected to produce (Buffers, 2026).

Table 8.1 — Daily Instagram posts and documented sales, Buffers, June–July 2026

Date	Instagram posts	Documented sales
30 June	4	₹4,355

Date	Instagram posts	Documented sales
1 July	0	₹2,926
2 July	0	₹3,398
4 July	0	₹3,855
5 July	2	₹2,477
7 July	0	₹1,574
8 July	0	₹2,154
9 July	3	₹4,334
10 July	1	₹5,492
11 July	0	₹3,443

Source: Buffers (2026), handwritten daily sales ledger and Instagram posting record.

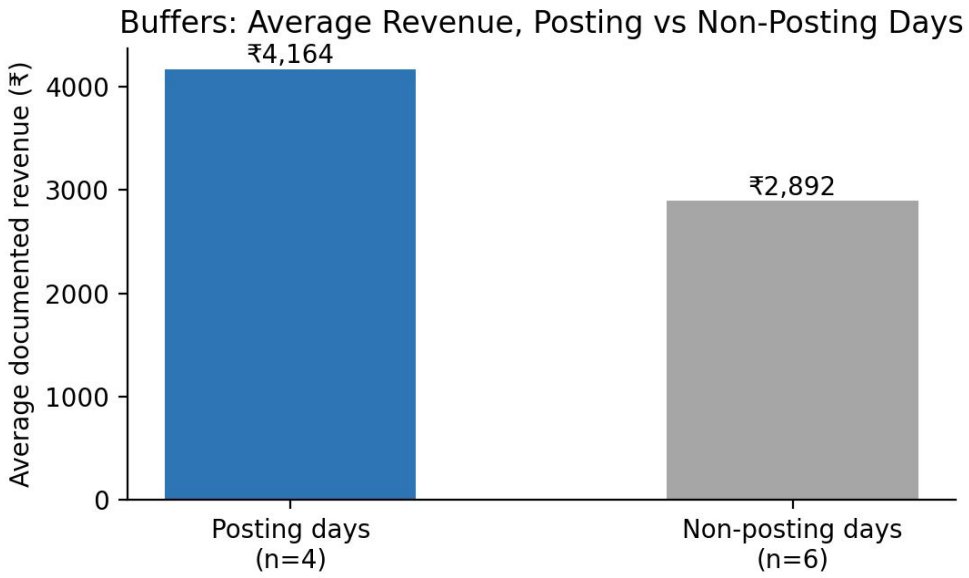


Figure 8.1 — Average documented revenue on posting and non-posting days

Source: author's elaboration on Buffers (2026).

Three days in the middle of July show the pattern at its clearest. Three posts on 9 July preceded sales of ₹4,334. One post on 10 July preceded ₹5,492, the highest

daily total anywhere in the dataset. No post on 11 July, and sales dropped back to ₹3,443 (Buffers, 2026).

The tempting conclusion is that more posting means more sales, and the data refuse it. Four posts on 30 June preceded ₹4,355, a single post on 10 July preceded ₹5,492, and two posts on 5 July preceded ₹2,477. Volume is not the variable. That is exactly why Buffers belongs in this thesis as one modest data point inside a larger argument, and not as evidence of a simple proportional mechanism running from Instagram to the till (Buffers, 2026).

8.1.1 Data limitations

Two limitations need saying plainly. The ledger is small, and the observation window is short enough that a reader is entitled to ask whether it proves anything at all. The observations are also not randomised, which leaves open the possibility that posting was timed around demand that was expected anyway, without the person recording it being aware of doing so.

None of that makes the data worthless. Read next to the case evidence in Chapter 7, Buffers adds a first-hand, controlled observation to the argument that social media activity contributes to measurable increases in real demand. It is a case study of digital demand engineering rather than proof of a causal link, and its job is to reinforce the macro-level and secondary evidence rather than to stand in for it (Buffers, 2026).

8.2 SURVEY EVIDENCE AND THE ATTITUDE–BEHAVIOUR GAP

The case study shows what happened. It does not show whether anybody noticed it happening, which is why a consumer survey was run alongside it. Eighteen responses were collected and seventeen are analysed here, one having been set aside because the respondent did not confirm the consent item (Appendix B).

Ten of the seventeen reported buying something they had not planned to buy after seeing it online, five said they might have, and two said no. Instagram led on every measure: sixteen of seventeen named it as the platform they use most, and thirteen named it as the platform that led to the purchase, ahead of YouTube and Snapchat (Appendix B).

The interesting part is what the same people said next. Eleven disagreed that FOMO drives their purchases, twelve rejected the idea that they buy within minutes of seeing something online, and ten rejected the idea that they trust influencers more than brands (Appendix B). So most of them reported the behaviour and denied the mechanism inside the same questionnaire. That is an attitude–behaviour gap, and it is the most useful thing the survey produced.

One further result cuts against a claim this study might otherwise have been tempted to make. Asked what influenced the purchase more, seven pointed to a brand's own advertisement and only four to an influencer or a creator, with six saying all of them equally (Appendix B). Influencer marketing is therefore one channel inside the system rather than the engine of it, which is consistent with the argument built in Chapter 6 that exposure and frequency, not any single messenger, are what manufacture demand. The sample is self-reported,

uncontrolled and small, so none of this establishes causality, but it does support digital demand engineering as something real rather than something theoretical.

Table 8.2 — Selected survey indicators

Indicator	Survey result
Responses collected / analysed	18 / 17
Unplanned purchase after digital exposure: yes	10 (58.8%)
Unplanned purchase after digital exposure: maybe	5 (29.4%)
Unplanned purchase after digital exposure: no	2 (11.8%)
Instagram named as the platform that led to the purchase	13 (76.5%)
Disagree that FOMO drives their purchases	11 of 17
Disagree that they purchase within minutes of seeing something online	12 of 17
Disagree that they trust influencers more than brands	10 of 17
Attributed the purchase mainly to a brand's own advertisement	7 of 17
Attributed the purchase mainly to an influencer or creator	4 of 17

Source: author's consumer survey, August 2026 (full results in Appendix B).

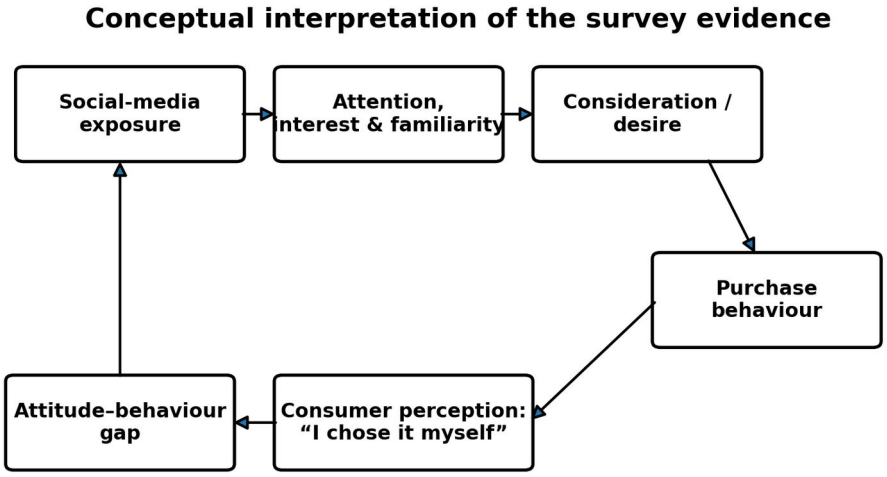


Figure 8.2 — Conceptual model of the attitude–behaviour gap

Source: author's elaboration on the survey results reported in Appendix B.

CHAPTER 9

DISCUSSION

9.1 IS THIS GROWTH SUSTAINABLE?

Two questions hang over everything above, and neither has a comfortable answer. The first is whether this growth can continue. The digital creative economy only expands while the user base expands and advertisers keep paying, and there are at least three reasons to expect friction. Attention is finite, and engagement is already saturating under the weight of overproduced content. Effectiveness may fall as people develop banner blindness and habits of avoidance, which will force another round of new formats. And regulation is tightening, with data-protection rules and limits on targeting likely to push up the operating cost of precision advertising over time.

9.2 ARE CONSUMERS BECOMING LESS RATIONAL?

The second question is whether consumers are becoming less rational. High-frequency emotional stimulation combined with frictionless checkout clearly moves decisions from deliberate towards fast and emotional, particularly for cheap items. But it would be wrong to treat that as total. People still think carefully about expensive purchases even when they think barely at all about small ones, and digital advertising has done far better in the second category than in the first. A growing minority of consumers now talk openly about being manipulated, and deinfluencer content has appeared as a counter-reaction to manufactured demand, which keeps some pressure on the market. Disclosure

requirements for influencers and the new rules on labelling AI-generated advertising add friction of a different kind, and friction is what deliberate purchasing needs.

9.3 IMPLICATIONS FOR THIS THESIS

Both questions bear directly on how the Buffers result should be read. A 44 per cent difference between posting and non-posting days is exactly what the framework built in Chapters 2 and 6 predicts. But the same framework predicts that effects like this will be noisy and dependent on context, and that is precisely what the data delivered: large, and statistically inconclusive. The case study earns its place as one data point among several, and it claims nothing more than that (Buffers, 2026).

CHAPTER 10

CONCLUSION

10.1 A MAJOR MACROECONOMIC EFFECT

Three conclusions follow. The first is about scale. The digital creative economy, taken as streaming, the creator economy, digital advertising and brand collaboration together, is a major and fast-growing driver of macroeconomic activity, contributing an estimated USD 2.25 trillion to global GDP and employing tens of millions of people directly and indirectly (UNESCO, 2021; SignalFire, 2020).

10.2 ADVERTISING AS A MARKET-SHAPING FORCE

The second is about what advertising now does. It has outgrown the job of serving demand that already exists and has started shaping it instead, and the mechanism behind that change is structural rather than creative: the move from one-way broadcast exposure to personalised, algorithm-driven exposure at a frequency the broadcast era could never have paid for (Zajonc, 1968; Media Dynamics, 2025).

10.3 CONSUMER DEMAND AS INCREASINGLY ENGINEERED

The third is the claim this thesis set out to defend. Behavioural economics supplies the theory, Chapter 7 supplies the documented cases, and Chapter 8 supplies a small experiment that recorded a 44 per cent revenue difference between posting and non-posting days in a business with no advertising budget at all (Buffers, 2026). Taken together they support the argument that consumer

demand in the digital era is increasingly engineered rather than arising on its own out of functional need. The Buffers evidence is preliminary and it is not conclusive by itself, and it was never expected to be. Its value is that it points the same way as everything else in this study, and that it does so from inside the phenomenon rather than from a report written about it.

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The sources behind this study fall into two groups. The first is the macroeconomic and industry data used to size the sector, meaning published estimates of creative-industry GDP contribution, digital advertising spend and creator-economy employment, each cited in Chapters 1, 4 and 5 at the point where it is used. The second is original primary research carried out by the author: the Buffers Independent Sales and Instagram Evidence Report, compiled in Bhopal over June and July 2026, on which Chapters 7 and 8 rest, and the exploratory consumer survey reported in Section 8.2, whose instrument and supporting material appear in Appendices B and C.

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APPENDICES

SUPPORTING MATERIAL

APPENDIX A — BUFFERS CASE STUDY: SOURCE BASIS

Chapters 7 and 8 take their findings from the Buffers Independent Sales and Instagram Evidence Report, which was built out of the handwritten daily sales ledger kept over the operating period, the Instagram posting-date record for the same window, and the Buffers brand and identity materials. The report is reproduced in full in Appendix C. The underlying ledger is handwritten and is held by the author, available on request (Buffers, 2026).

APPENDIX B — CONSUMER SURVEY: INSTRUMENT AND RESULTS

This appendix contains the full material behind the survey reported in Section 8.2: the instrument as it was fielded, the sample and how it was handled, the complete response distributions, and the verbatim answers to the open question.

B.1 The instrument

The survey was distributed online in August 2026 and was answered anonymously. It opened with a consent item restricting participation to respondents aged eighteen or over, and then moved through demographics and platform use, purchasing behaviour, three attitude statements and one open question.

Table B.1 — Survey instrument: items and response options

Question	Type	Response options	Req.
By continuing, you confirm you are 18+ and agree to take part in this anonymous survey.	Choice	Yes / No	Yes
Age group	Choice	18–24 / 25–34 / 35+	Yes
Gender	Choice	Male / Female / Prefer not to say / Other	Yes
Which platform do you use most?	Choice	Instagram / TikTok / YouTube / Facebook / Snapchat / Other	Yes
On an average day, how much time do you spend on social media?	Choice	Under 30 min / +30 min / More than 3 hours	Yes
Have you ever purchased a product or service you weren't planning to buy before seeing it on social media or a digital platform?	Choice	Yes / Maybe / No	Yes
If yes, which platform led to that purchase?	Choice	Instagram / YouTube / Snapchat / Facebook / TikTok / Other	No
What kind of product was it?	Choice	Fashion / Beauty / Electronics / Food & Beverage / Other	No
How often does this happen to you?	Choice	Multiple times a month / About once a month / A few times a year / Rarely or never	Yes
What influenced the purchase more?	Choice	An influencer / A creator's content / A brand's own ad / All of them	No
I sometimes buy something because I'm worried I'll miss out if I don't.	Attitude	Strongly agree / Strongly disagree	Yes
I've made a purchase within minutes of seeing it online, without thinking it over.	Attitude	Strongly agree / Strongly disagree	Yes

Question	Type	Response options	Req.
I trust an influencer's recommendation more than a brand's own advertisement.	Attitude	Strongly agree / Strongly disagree	Yes
In your own words, what usually makes you buy something you saw on social media?	Open text	Free text	No

Source: author's survey instrument, August 2026.

B.2 Sample and data handling

Eighteen responses were received. One respondent selected "No" on the consent item but completed the remaining questions; that response has been excluded, leaving seventeen analysed responses. Two respondents entered an email address in the optional account field, so the raw file is not fully anonymous; no identifying field is reproduced anywhere in this report, and counts alone are reported throughout. One respondent's age group was recorded as a form placeholder rather than a valid band and is shown below as unclassified.

B.3 Respondent profile and platform use

Table B.2 — Respondent profile and social media use (n = 17)

Item	Response	Count
Age group	18–24	10
	35+	5
	25–34	1
	Unclassified (form error)	1
Gender	Male	10
	Female	7
Platform used most	Instagram	16

Item	Response	Count
	Snapchat	1
Daily time on social media	More than 3 hours	8
	Over 30 minutes	7
	Under 30 minutes	2

Source: author's consumer survey, August 2026.

B.4 Purchasing behaviour

Table B.3 — Reported purchasing behaviour (n = 17)

Item	Response	Count
Unplanned purchase after digital exposure	Yes	10
	Maybe	5
	No	2
Platform that led to the purchase	Instagram	13
	YouTube	3
	Snapchat	1
Product category	Fashion	8
	Beauty	3
	Electronics	3
	Food and beverage	3
Frequency of unplanned purchase	About once a month	8
	Rarely or never	6
	Multiple times a month	2
	A few times a year	1
Main influence on the purchase	A brand's own advertisement	7

Item	Response	Count
	All of them equally	6
	An influencer	2
	A creator’s content	2

Source: author’s consumer survey, August 2026.

B.5 Attitude items

Table B.4 — Attitude statements (n = 17)

Statement	Strongly agree	Strongly disagree
I sometimes buy something because I’m worried I’ll miss out if I don’t.	6	11
I’ve made a purchase within minutes of seeing it online, without thinking it over.	5	12
I trust an influencer’s recommendation more than a brand’s own advertisement.	7	10

Source: author’s consumer survey, August 2026.

Age offers one further cut of the data, although the cells are far too small to carry weight. Both of the middle-aged and older bands report unplanned purchasing at least as often as the youngest group, which runs against the assumption that this behaviour belongs mainly to younger consumers. With one respondent in the 25–34 band, the comparison is illustrative only.

Table B.5 — Unplanned purchasing by age group (n = 17)

Age group	n	Yes	Maybe	No
18–24	10	5	4	1
25–34	1	0	0	1
35+	5	4	1	0

Age group	n	Yes	Maybe	No
Unclassified	1	1	0	0

Source: author's consumer survey, August 2026.

B.6 Open responses

Nine of the seventeen respondents answered the optional open question. Two themes recur across them: the attributes of the product as presented, meaning video, description, quality, price and reviews, and the pull of wanting the thing itself. They are reproduced exactly as written, including the original spelling and punctuation.

Table B.6 — Verbatim responses to the open question

"In your own words, what usually makes you buy something you saw on social media?"
It's just the urge of having something that makes a person who's earning will buy anything he or she see's on Social Media
Video and detailed description of the object.
Attractive ads, brand, quality with affordable cost
Branded fabrics
Reviews from creators and others and it's low price or discounts from offline market
I buy stuff only when I needed it
Quality, reviews and presentation
My intrigued self, & the need for those recommended products, by several influencers, makes me buy those things off social media.
Good

Source: author's consumer survey, August 2026; responses reproduced as written.

B.7 Limitations of the survey

Three limitations should be kept in view when reading these results. The sample is small and self-selected, drawn from the author's own network, so it is not representative of any wider population. The attitude statements were fielded with two options rather than a full five-point scale, which pushes respondents to the extremes and removes any middle ground. And every measure here is self-reported, which is precisely what makes the attitude–behaviour gap interesting but also means the survey can describe an association and never a cause.

APPENDIX C — BUFFERS INDEPENDENT SALES & INSTAGRAM EVIDENCE REPORT

What follows reproduces the Buffers Independent Sales and Instagram Evidence Report, the primary document behind Chapters 7 and 8.

C.1 Buffers Independent Sales & Instagram Evidence Report (Bhopal, June–July 2026)



Figure C.1 — Buffers brand logo, as used on the digital storefront and in the evidence report

Source: Buffers brand identity materials (Buffers, 2026).

The report was compiled to test whether documented Instagram posting dates coincided with higher recorded sales at Buffers, a digital-first cloud kitchen operating in Bhopal between June and July 2026. Its findings are summarised in Section 8.1 of this thesis and are reproduced here in full.

Across the ten dates for which the ledger contains a clearly documented daily sales total, four were identified as Instagram posting days from the supplied posting-date record. Average documented revenue was ₹4,164.50 on posting days against ₹2,891.67 on non-posting days, an observed difference of 44.0 per cent. The relationship is directionally positive but not statistically conclusive in so small a sample: the binary posting-day correlation is r = 0.56 and Welch's t-test gives p = 0.137. The effect size is large, with a Cohen's d of approximately 1.24, but the sample consists of only ten daily observations. The result is therefore presented as preliminary evidence of association rather than as proof that Instagram posting caused the increase in sales.

Table C.1 — Headline figures of the Buffers evidence report

Documented sales	Observations	Posting days	Posts on those days	Posting-day difference
₹34,008	10 days	4	10	+44.0%

Source: Buffers (2026).

Two primary records were used: the handwritten sales ledger supplied in the case materials, and the handwritten list of Instagram posting dates supplied separately. Only dates on which the sales ledger contains a clear daily total are used in the statistical comparison. The posting-date list contains sixteen posts in total,

recorded on 23, 24, 27, 28, 29 and 30 June and on 5, 9, 10 and 19 July; several of those dates have no reliable corresponding daily sales total in the surviving ledger and are therefore excluded from the quantitative comparison.

Table C.2 — Source data: documented sales and posts by date

Date	Instagram posts	Documented sales
30 June	4	₹4,355
1 July	0	₹2,926
2 July	0	₹3,398
4 July	0	₹3,855
5 July	2	₹2,477
7 July	0	₹1,574
8 July	0	₹2,154
9 July	3	₹4,334
10 July	1	₹5,492
11 July	0	₹3,443

Source: Buffers (2026), handwritten daily sales ledger and Instagram posting-date record.

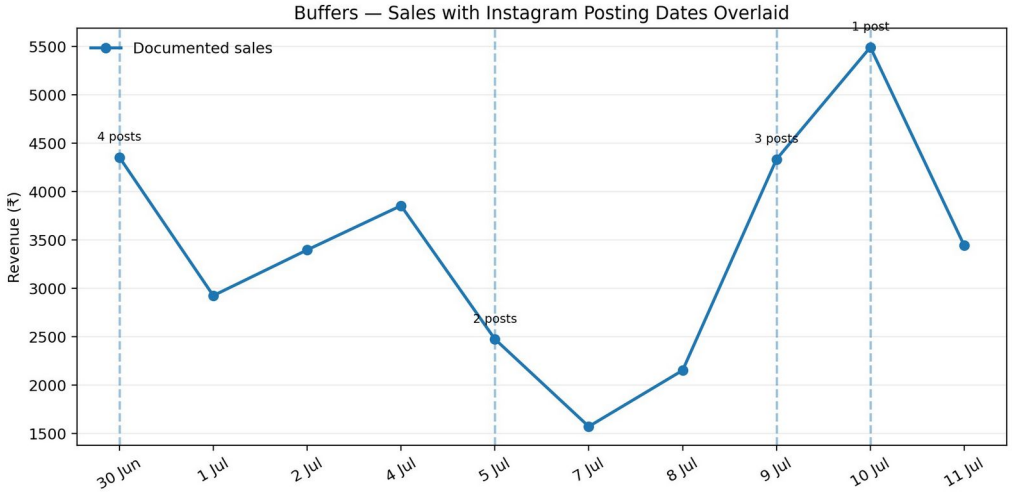


Figure C.2 — Documented daily sales with Instagram posting dates overlaid

Source: Buffers (2026).

The first test treats posting as a binary variable, in which a value of one indicates at least one Instagram post on the date and a value of zero indicates no recorded post. The test is intentionally simple, because the available evidence contains no post-level data on reach, impressions, saves, shares or clicks. The average revenue comparison that follows from it is reproduced in the body of this thesis as Figure 8.1.

Table C.3 — Exploratory statistical test

Measure	Result	Interpretation
Mean revenue, posting days	₹4,164.50	Higher than non-posting days
Mean revenue, non-posting days	₹2,891.67	Comparison baseline
Observed difference	+44.0%	Posting days had higher average revenue
Correlation, posting-day flag against sales	r = 0.56	Moderate positive association

Measure	Result	Interpretation
Welch's t-test	p = 0.137	Not statistically significant at 5%
Cohen's d	1.24	Large standardised difference, but unstable with n = 10

Source: Buffers (2026).

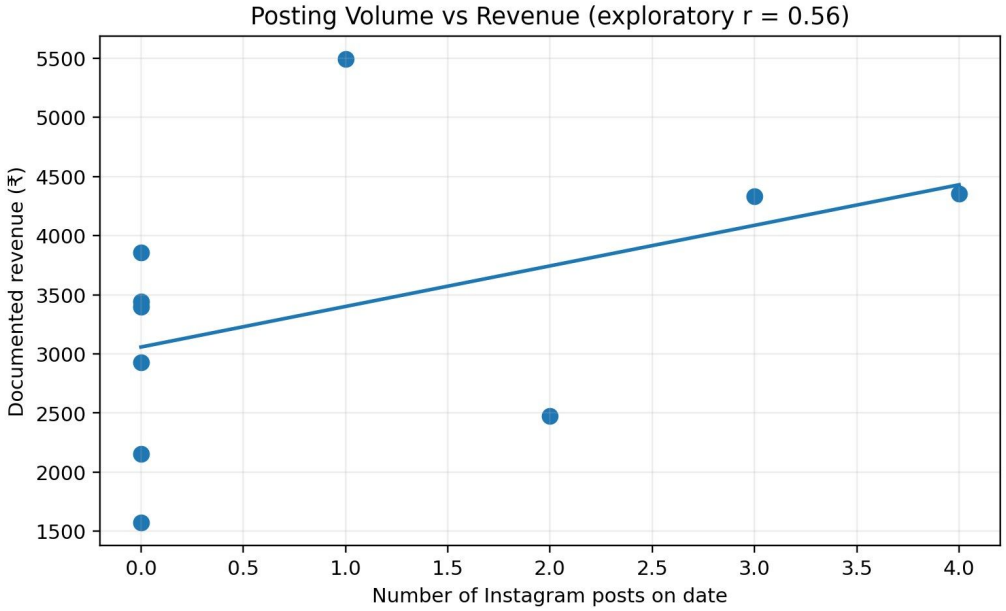


Figure C.3 — Exploratory relationship between number of posts and documented revenue

Source: Buffers (2026).

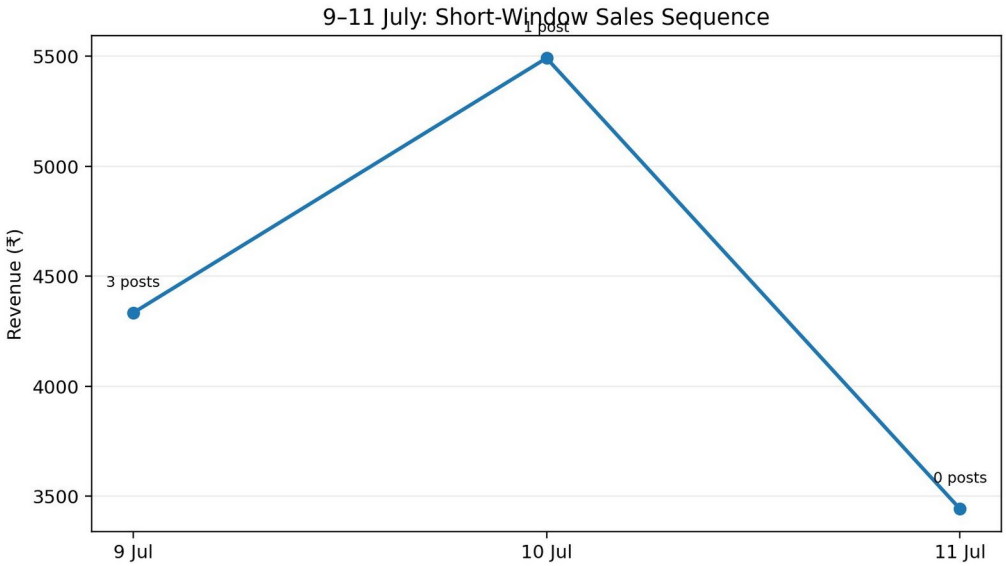


Figure C.4 — Sales and posting activity around the 9–11 July sequence

Source: Buffers (2026).

On 9 July three posts were recorded and sales were ₹4,334. Sales then reached the highest documented daily total in the dataset, ₹5,492, on 10 July, when one further post was recorded. On 11 July, with no recorded post, sales fell to ₹3,443. The sequence is suggestive of a possible short lag between content exposure and demand, but three days are nowhere near enough to establish causality.

The report sets out plainly what the test does and does not support. It supports the observations that posting days in the sample had substantially higher average documented revenue than non-posting days, that the association is positive across the available ten-day sample, that the 9–11 July sequence offers a plausible example of a short-term relationship between posting and sales, and that the data justify further investigation of Instagram as a demand-generation mechanism.

It does not prove that Instagram posts caused the additional revenue, nor that posting more frequently always increases sales, since 5 July carried two posts but only ₹2,477 in documented revenue. It does not isolate Instagram from other factors such as day-of-week effects, menu changes, repeat customers, word of mouth, delivery availability or operational capacity. It does not establish the effect of the blue verification badge or of AI-assisted branding, and it does not measure the quality or reach of individual posts.

The stated data limitations are equally explicit. The sales ledger is handwritten and contains corrections, overwritten figures and some ambiguous entries. Only ten dates are used, because those are the dates for which a clear daily sales total is available in the supplied evidence. The Instagram record supplies dates and post counts, but not reach, impressions, engagement, profile visits, link clicks or orders attributed to individual posts. The observations are not randomised, and posting may itself have been triggered by expected demand or by product launches, which would create reverse causality. The sample is, finally, too small for a strong causal claim.

The report therefore recommends that Buffers be used as a case study of digital demand engineering rather than as proof of a simple causal relationship between Instagram and sales. The evidence shows that the business generated meaningful revenue while operating primarily through a digital storefront, and that documented posting days coincided with higher average sales in the observed sample, with the statistical result best framed as preliminary evidence of association. A stronger future test would combine the publication time of each

post with its reach, views and engagement, together with profile visits, ordering-channel clicks and transaction timestamps.

Table C.4 — Posting-date record, Buffers, June–July 2026

Date	Posts recorded
23 June	1
24 June	1
27 June	1
28 June	1
29 June	1
30 June	4
5 July	2
9 July	3
10 July	1
19 July	1
Total	16

Source basis: Buffers handwritten sales ledger, supplied Instagram posting-date record and supplied Buffers brand materials (Buffers, 2026).