



Valuing Free Digital Services in India: Experimental Consumer-Welfare Estimates and the 2025 SNA Framework*

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Abstract

The rapid expansion of zero-price digital services has widened the divergence between market-based measures of economic production and important dimensions of consumer welfare, creating a measurement gap that conventional national accounts are not designed to close. This paper develops an experimental framework for assessing the consumer-welfare value of free digital services in India and examines how such estimates relate to the measurement architecture of the 2025 System of National Accounts (2025 SNA). Willingness-to-accept (WTA) valuation is used as the principal approach, supplemented by time-use valuation and an advertising-revenue calibration benchmark. In the absence of a nationally representative Indian WTA survey, service-specific valuations are transferred from international experimental evidence and adjusted to the Indian context; the resulting estimates should therefore be interpreted as indicative orders of magnitude rather than definitive welfare aggregates. The principal specification yields a median-equivalent consumer-welfare estimate of approximately ₹10.4 lakh crore in 2023–24, equivalent to about 3.4 per cent of nominal GDP, subject to substantial parameter and transfer uncertainty. These welfare estimates are conceptually distinct from national-accounting output. Under the 2025 SNA, consumer surplus remains outside core GDP, while complementary extended accounts can make household consumption of free platform services visible using producer cost as the preferred valuation basis. The paper therefore distinguishes clearly among core SNA GDP, cost-valued extended accounting and consumer-welfare measurement. It concludes by identifying priorities for strengthening India's statistical infrastructure, particularly nationally representative incentive-compatible valuation experiments, improved digital time-use data and information on platform production cost.

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1. Introduction

National income accounting was designed for an economy in which value creation occurred predominantly through priced market transactions. The System of National Accounts — codified in 1953 and revised through 1968, 1993, 2008, and 2025 — defines its production boundary primarily around goods and services exchanged at economically significant prices, with consumer surplus excluded by design rather than by oversight. This framework has served well for decades, but the digital transformation has progressively eroded the correspondence between market-measured output and economic welfare, as consumers increasingly rely on services offered at zero monetary price.

India provides a particularly important setting for examining this measurement problem. Over the past decade, the country has experienced exceptionally rapid expansion in internet access, smartphone adoption and use of digital platforms, resulting in a user base of several hundred million people. Much of this digital consumption takes place through services for which users pay no explicit monetary price, including search, messaging, social media, online video, digital maps and selected digital-payment services.

This paper makes three principal contributions. First, it develops an experimental framework for assessing the consumer welfare associated with free digital services in India. Given the absence of nationally representative Indian valuation experiments, the paper combines transferred WTA evidence with Indian user-base and usage information and explicitly quantifies the uncertainty surrounding the resulting estimates. The estimates are therefore intended to establish plausible orders of magnitude rather than definitive welfare aggregates. Second, the paper places these estimates within the conceptual architecture of the 2025 SNA and distinguishes among three fundamentally different measures: core SNA GDP, cost-valued extended accounts for free platform services, and consumer-surplus measures that lie outside the production boundary. Third, it identifies the statistical information that would be required for India to move from experimental estimates toward regular measurement, including platform production costs, service-specific usage information and nationally representative incentive-compatible WTA surveys. In this way, the paper seeks to contribute both to the empirical measurement of India's digital economy and to the broader discussion of how conventional production accounts can be complemented by welfare indicators in an increasingly digital economy.

The paper proceeds as follows. Section 2 reviews the theoretical foundations and relevant literature. Section 3 describes India's free digital-services ecosystem and the data used in the analysis. Section 4 presents the estimation framework and associated uncertainty analysis. Section 5 situates the resulting estimates within the 2025 SNA architecture, distinguishing core accounts, extended accounts and welfare indicators. Section 6 considers the implications for welfare-augmented growth measurement without constructing a numerical GDP-B series. Section 7 places the Indian estimates in an international context. Section 8 discusses policy and statistical implications, while Section 9 presents sensitivity analysis. Section 10 sets out the principal limitations and priorities for future empirical work. Section 11 concludes.

2. Theoretical foundations and literature

2.1. The measurement problem

The measurement challenge arises because national accounts rely on market prices as the primary valuation basis and define the production boundary around activities producing outputs for market exchange. When a service carries zero monetary price, it generates no consumer expenditure and contributes nothing to measured household final consumption. The platform's advertising revenue is recorded as intermediate consumption by purchasing businesses or as the platform's output of advertising services — not as household final consumption of the free service. The welfare-generating activity on the consumer side remains unrecorded.

The literature has long recognised that GDP measures production, not welfare, and that consumer surplus is excluded by design (Nordhaus, 2006; Stiglitz *et al.*, 2009). When consumption shifts systematically toward zero-price services, GDP's utility as a welfare proxy may deteriorate, though it remains a valid production measure.

2.2. Valuation approaches for zero-price services

Three broad approaches have emerged in the literature. The willingness-to-accept (WTA) approach, developed most rigorously by Brynjolfsson *et al.* (2019), elicits the minimum compensation consumers would require to forgo access to a digital service. This directly estimates Hicksian equivalent variation — the theoretically appropriate welfare measure. However, WTA estimates face hypothetical bias (stated valuations exceeding revealed valuations by a factor of 2–3; List and Gallet, 2001; Murphy *et al.*, 2005), anchoring effects, and incentive compatibility challenges.

A further, related concern is the response problem inherent in WTA elicitation: stated valuations are sensitive not only to hypothetical bias but also to survey non-response and self-selection into valuation experiments, question framing and elicitation-format effects, and strategic responses where incentive compatibility is imperfect. The correction factor β applied in Section 4.2 addresses the hypothetical-bias component specifically — the empirically documented gap between stated and incentive-compatible valuations — but it is calibrated from international meta-analyses and does not, and cannot, correct for response and framing effects specific to an Indian survey instrument that has not yet been fielded. Because these are properties of the elicitation instrument rather than of the underlying construct being measured, they cannot be resolved analytically; they require methods that are less susceptible to hypothetical bias by design. Two complementary approaches are particularly promising for India. Discrete choice experiments, which infer valuations from respondents' choices among bundled alternatives rather than from direct stated-value questions, are less prone to anchoring and framing effects than open-ended WTA elicitation. Randomised controlled trials that vary actual access to a digital service — in the spirit of Allcott and Gentzkow (2019) and the deactivation experiments underlying Brynjolfsson *et al.* (2019) — generate revealed-preference evidence against which transferred and stated-preference estimates can be validated. Fielding such studies for the Indian market, ideally in combination with a nationally representative incentive-compatible WTA survey, is accordingly identified as a priority alongside the data-collection agenda set out in Section 8.

The time-use valuation approach treats consumer time allocation as a revealed preference indicator, valuing time spent on free services at some fraction of its opportunity cost. Grounded in Becker’s (1965) household production framework and applied by Goolsbee and Klenow (2006) and Brynjolfsson and Oh (2012), this approach faces the challenge that not all time spent on digital services generates positive surplus — habitual or addictive usage may be welfare-reducing (Allcott *et al.*, 2020).

A third approach uses advertising revenue as an observable calibration benchmark for advertising-supported digital services. Nakamura *et al.* (2016, 2017) use advertising-supported free content within an experimental production-account framework, while subsequent welfare studies compare platform revenues with consumer valuations. Advertising revenue should not, however, be interpreted as a theoretically established lower bound on consumer surplus. In a two-sided platform market, advertising revenue reflects advertisers’ willingness to pay for access to user attention as well as platform market structure and monetisation strategies; its relationship to consumer welfare is therefore indirect. In this paper advertising revenue is consequently used only as a benchmark against which WTA- and time-use-based estimates can be compared.

The broader mismeasurement debate includes Feldstein (2017), who argued that real GDP growth systematically understates welfare improvement by failing to capture quality gains and new goods, and Syverson (2017), who concluded that while unmeasured digital output alone cannot explain the productivity slowdown, the mismeasurement is economically significant.

An important methodological issue concerns the aggregation of WTA when the available evidence provides service-specific median valuations rather than the full distribution of individual valuations. Multiplying a median WTA by the relevant user population does not, in general, recover the population sum of individual welfare. The empirical estimates in this paper are therefore interpreted as *median-equivalent welfare aggregates*, and the sensitivity of the results to alternative valuation assumptions is examined in Section 9. This distinction is particularly important given the absence of nationally representative Indian WTA microdata.

2.3. Evidence relevant to India

Direct empirical evidence on the willingness of Indian consumers to forgo free digital services remains limited, and we are not aware of a nationally representative Indian study using incentive-compatible choice experiments comparable to those employed in the international literature. Consequently, the present paper does not treat its WTA inputs as directly observed Indian valuations. Instead, it uses international experimental evidence, principally Brynjolfsson *et al.* (2019), as a starting point and transfers these values to the Indian context using purchasing-power and income adjustments. The limitations of such benefit transfer are important: preferences, income distributions, network effects, availability of offline substitutes and the composition of digital use can differ substantially between countries. The Indian estimates reported below should therefore be interpreted as experimental estimates designed to establish plausible orders of magnitude. A nationally representative Indian valuation experiment remains necessary before these estimates could be treated as statistical measures suitable for regular compilation.

3. India's free digital services ecosystem

3.1. Scale and scope

By March 2024, the Telecom Regulatory Authority of India (TRAI) reported 954.40 million internet subscriptions (TRAI, 2024). However, since many individuals hold multiple subscriptions, the number of unique individual internet users is substantially lower. The Internet and Mobile Association of India (IAMAI)-Kantar ICUBE 2024 report estimates approximately 820 million unique active internet users, a figure we adopt throughout this paper. The distinction among internet subscriptions, unique internet users, monthly active users (MAU), and daily active users (DAU) is important: these denominators cannot be interchanged, and service-specific MAU figures in Table 1 reflect the subset of users actively using each specific service. Usage is heavily skewed toward free, advertising-supported services: paid digital subscriptions (excluding telecommunications access) average only \$3.2 per user per year, compared with \$142 in the United States (Data.ai, 2024).

Table 1 presents the consolidated ecosystem of major free digital service categories.

Table 1: India's free digital services ecosystem, 2023–24

Service Category	MAU (million)	Daily Minutes per User	Annual Person- Hours (billion)	Indicative Intensity active user/year; non-additive)	Ad-Revenue (₹per ac- tive user/year; non-
(1)	(2)	(3)	(4)	(5)	
Search engines	650	18	71.2	620	
Video streaming (free tier)	520	48	152.0	540	
Social media	530	42	135.5	480	
Messaging	550	35	117.2	95	
Email (free)	425	12	31.0	180	
Maps/navigation	280	6	10.2	140	
News/information	290	15	26.5	400	
Educational platforms	180	8	8.8	220	
Cloud storage (free tier)	310	4	7.5	65	
Digital payments (Unified Payments Interface, UPI)	350	5	10.7	Nil	
All Services/Unique User Base	820	114 (MAU-weighted)	570 (gross service-use hours)	620 (= ₹50,800 cr ÷ 820M]	

Notes: MAU = Monthly Active Users; UPI = Unified Payments Interface for each service category. Since individual users typically use multiple services, the service-specific MAU figures overlap substantially (the same user may appear in several rows). Column (3) reports average daily minutes for users of that specific service. Column (4) computes

service-specific annual person-hours as $\text{MAU} \times \text{daily minutes} \times 365 \div 60$.

Service-specific MAU figures overlap because an individual may use several services. Such overlap does not by itself imply double counting of time: time spent on different services at different times remains distinct consumption time. Summing the service-specific person-hours produces approximately 570 billion gross service-use hours, equivalent to about 114 minutes per unique internet user per day when divided by the 820 million unique-user base. This figure should nevertheless be interpreted cautiously because some services may be used simultaneously—for example, navigation or messaging while consuming audio content—in which case gross service-use time exceeds elapsed clock time. The available data do not permit a systematic correction for such concurrent use.

Sources: IMAI-Kantar ICUBE 2024; TRAI (2024); Data.ai 2024; Meta Q4 2023 Earnings; Alphabet FY2023 10-K; NPCI (2024); Comscore India 2024; Dentsu India, 2024.

Reconciliation note on Column (5). The service-specific figures in Column (5) are indicative advertising-intensity benchmarks compiled from heterogeneous platform disclosures and industry sources; they are not a mutually exclusive allocation of aggregate Indian digital advertising revenue across service categories. Differences in platform coverage, service definitions, geographic attribution and reporting basis mean that the row-level figures are not directly additive. Accordingly, multiplying each row by its service-specific MAU and summing across services produces a gross illustrative amount of approximately ₹1.28 lakh crore, which should not be interpreted as an estimate of total Indian digital advertising revenue. All calculations in this paper that require aggregate advertising revenue instead use the independently observed industry benchmark of ₹50,800 crore for free-to-consumer platforms (82 per cent of the ₹62,000 crore total reported by Dentsu India, 2024). The corresponding ₹620 figure in the final row is therefore calculated directly as ₹50,800 crore divided by 820 million unique active internet users and is not a weighted average of the service-specific entries in Column (5).

Several features merit emphasis. The weighted-average Indian internet user spends approximately 114 minutes daily on free digital services, computed as the MAU-weighted average across services. This represents a substantial reallocation of time, though less than the simple sum of service-specific minutes (193 minutes) because not all services are used by all users. The advertising revenue per user on free platforms (approximately ₹620/year, or roughly \$7.50) is among the lowest globally for comparable engagement levels, suggesting that the gap between consumer valuation and platform revenue may be particularly large in India.

3.2. Usage heterogeneity

Aggregate usage averages conceal substantial differences in digital behaviour across population groups. Digital access, service composition and intensity of use vary by location, age, gender, employment status and household income. These differences matter for welfare estimation because both the opportunity cost of time and the value attached to individual digital services are likely to differ systematically across users. However, the available sources do not provide sufficiently harmonised demographic time-use estimates that are directly comparable with the service-specific MAU data in Table 1. We therefore do not attempt to infer demographic differences in welfare directly from aggregate usage statistics. Instead,

demographic variation enters the time-use sensitivity analysis through alternative wage and opportunity-cost assumptions. Developing a nationally representative digital time-use module that records service category, duration, concurrent use and socioeconomic characteristics would substantially improve future estimates.

4. Estimation framework and results

We employ three complementary estimation strategies: willingness-to-accept (WTA), time-use valuation, and an advertising-revenue calibration benchmark. While these approaches rest on different identifying assumptions, they share common user-base inputs, limiting their statistical independence (see Section 4.1). Convergence across methods provides useful corroboration but should not be interpreted as convergence of fully independent estimates.

4.1. Common framework and data quality

Notation. Subscript s indexes service categories ($s = 1, \dots, 10$ per Table 1), subscript i indexes users, and subscript d indexes demographic cells. CS denotes consumer surplus with superscripts WTA, TIME, and AD distinguishing methods. All monetary values are in 2023–24 rupees. We use “lakh crore” ($= 10^{12}$ rupees) following Indian convention.

Shared data inputs. All methods draw on common user base inputs from TRAI (2024) and IMAI-Kantar ICUBE 2024. These shared inputs are treated as uncertain in the Monte Carlo simulation, but errors in user base estimation affect all three methods in the same direction, limiting the degree of true statistical independence across methods.

Data quality. Our empirical foundation relies substantially on commercial industry bodies and platform self-disclosures, whose proprietary methodologies are not independently auditable. Where possible, we cross-validate against regulatory data (TRAI, the National Payments Corporation of India (NPCI), and the Reserve Bank of India (RBI)). Time-spent estimates, derived from panel-based measurement, may suffer from selection bias and measurement error. These uncertainties are partially but not fully captured in our Monte Carlo distributions; systematic bias across sources would shift results in ways not reflected in our 90 percent parameter-uncertainty intervals.

Monte Carlo convergence. Five independent replications with different random seeds confirmed that all reported percentiles were stable to within ± 0.1 lakh crore; increasing draws to 50,000 produced no material change.

4.2. Method 1: Willingness-to-accept valuation

For service s and user i , let W_{is} denote raw monthly WTA for continued access to the service. In the absence of Indian microdata on the distribution of W_{is} , the empirical analysis uses the transferred service-specific median WTA, denoted by $\widetilde{W}_s$. The corresponding annual median-equivalent welfare measure is:

$$CS^{WTA} = \sum_{s=1}^S N_s \times 12 \times \widetilde{W}_s$$

where N_s denotes the relevant number of users of service s . Because the underlying Indian distribution of individual WTA is not observed, multiplying the service-specific median by the number of users does not, in general, recover the population sum of individual valuations. We therefore describe this quantity as a *median-equivalent welfare aggregate*. It represents the aggregate that would result if each user were assigned the service-specific median valuation and should not be interpreted as a distribution-exact estimate of aggregate consumer surplus.

If the distribution of individual WTA were observed, aggregate welfare would instead be based on its population mean:

$$CS^{WTA} = \sum_{s=1}^S N_s \times 12 \times E(W_s).$$

For example, if individual WTA is log-normally distributed with median $\widetilde{W}_s$ and log-standard deviation σ_s

$$E(W_s) = \widetilde{W}_s \exp\left(\frac{\sigma_s^2}{2}\right).$$

Reliable Indian estimates of σ_s are presently unavailable. We, therefore, retain the median-equivalent measure as the principal experimental specification and explicitly recognise this limitation. Future Indian WTA microdata would permit direct aggregation across respondents and eliminate this approximation.

In the absence of a directly estimated Indian σ_s , we can nonetheless bound the plausible understatement from median-based aggregation by borrowing dispersion estimates from the broader experimental-valuation literature, in the same spirit as the international parameter transfer used elsewhere in this paper. Stated WTA/WTP distributions surveyed in the hypothetical-bias meta-analyses underlying our β correction (List and Gallet, 2001; Murphy *et al.*, 2005) typically exhibit coefficients of variation (CV) in the region of 0.8 to 1.5. Under a log-normal assumption, CV relates to the dispersion parameter via $\sigma^2 = \ln(1 + CV^2)$, and the mean-to-median ratio is $\exp(\sigma^2/2)$; this yields ratios of approximately 1.28 at CV = 0.8 and 1.80 at CV = 1.5. Applying these ratios to the baseline median-equivalent estimate of ₹10.4 lakh crore implies a mean-based estimate of approximately ₹13.3–18.7 lakh crore — that is, correcting for right-skewness would, if anything, raise rather than lower the aggregate welfare estimate, since a mean necessarily exceeds a median under right skew. We emphasize that these CV values are illustrative bounds transferred from the general valuation literature rather than parameters estimated from Indian microdata, and we do not adopt the resulting mean-based range as an alternative headline estimate; the median-equivalent specification is retained as the principal measure precisely because no defensible India-specific dispersion parameter presently exists, and imposing an unvalidated distributional shape on Indian data we do not have would substitute one unverifiable assumption for another. The exercise is reported to characterize the direction and approximate scale of the aggregation bias rather than to correct for it, and it reinforces rather than weakens the case for prioritizing a nationally representative Indian WTA survey capable of directly recovering the shape of the underlying valuation distribution.

Raw WTA values cannot be used directly because they are subject to three well-documented biases, each of which inflates the estimate. We apply multiplicative correction factors to obtain adjusted surplus:

$$CS_{adjusted}^{WTA} = \sum_{s=1}^S N_s \times 12 \times \frac{\tilde{W}_s}{\beta} \times \delta \times \gamma_s.$$

Here $\beta \sim U(2.0, 3.0)$ captures uncertainty concerning hypothetical-response inflation, while $\delta \sim U(0.60, 0.80)$ allows for substitution toward alternative services following the withdrawal of a particular service. The term γ_s is used only where an additional adjustment is required to reconcile the income level represented by the transferred valuation with that of the target Indian user population. It may be written as

$$\gamma_s = \left(\frac{Y_I}{Y_B} \right)^\eta$$

where Y_I is the relevant purchasing-power-parity (PPP)-adjusted income of the target Indian population, Y_B is the corresponding income level underlying the transferred valuation, and η is the assumed income elasticity of WTA. Importantly, γ_s is applied only when the transferred WTA has not already been adjusted to the target Indian income level. Where such adjustment is already embodied in the transferred value, $\gamma_s = 1$, thereby avoiding double adjustment for income differences.

4.3. Method 2: Time-use valuation

Following Becker (1965), when a consumer with a positive opportunity cost of time chooses to spend time on a free digital service rather than an alternative activity, their choice reveals that the value derived exceeds the opportunity cost of the time expended. Consumer surplus is the gap between value received and time cost incurred.

For a user in demographic cell d , let t_d denote daily hours devoted to free digital services and w_d the relevant market wage. We define the effective opportunity cost of time as:

$$w_d^* = \lambda w_d$$

where $\lambda \sim U(0.30, 0.50)$ recognises that most digital-service use displaces leisure or household time rather than paid working time.

For individuals without observed market earnings, the reference wage is first imputed as:

$$w_d = \xi w_d^{Cell}$$

where w_d^{Cell} is the median wage of the relevant demographic cell and $\xi \sim U(0.40, 0.80)$.

Consumer surplus associated with digital time is then approximated by:

$$CS^{TIME} = 365 \phi \mu \sum_d^D N_d w_d^* t_d$$

where D denotes the number of demographic cells, N_d is the number of users in cell d and t_d is mean daily time devoted to the relevant free digital services. The parameter $\phi \sim U(0.25, 0.75)$ represents net surplus relative to the effective opportunity cost of time, while $\mu \sim \text{Triangular}(0.40, 0.60, 0.80)$ discounts digital time that substitutes for comparably valued offline activity. Given the limited direct Indian evidence for these parameters, the time-use calculation is treated as an order-of-magnitude robustness benchmark rather than as an independently identified estimate of consumer welfare.

4.4. Advertising-revenue calibration benchmark

Platforms provide free services funded by advertising. The empirical literature has explored the relationship between per-user advertising revenue and consumer valuations. Varian (2018) estimates that consumer surplus from Google Search is approximately 8–12 times the advertising revenue Google earns per user. Brynjolfsson *et al.* (2019) imply a ratio of approximately 16 for Facebook based on their WTA estimates relative to Meta’s per-user advertising revenue.

We use this relationship as a calibration benchmark:

$$CS^{AD} = \theta \times R_{total}$$

where $R_{total} = ₹50,800$ crore is total digital advertising revenue from free-to-consumer platforms in 2023–24 (82 percent of ₹62,000 crore total; Dentsu India, 2024), and $\theta \sim U(8, 20)$.

We emphasize that this is a calibration exercise rather than an independently identified consumer-surplus estimator. In a two-sided platform market, advertising revenue is determined by advertisers’ willingness to pay for user attention and by platform market structure. There is no general theoretical result establishing that consumer surplus must exceed advertising revenue; the empirical regularity documented by Varian and Brynjolfsson *et al.* is contingent on observed market structures and user valuations. For India, where per-user advertising revenue is among the lowest globally (approximately ₹620/year), the multiplier may be particularly high because platforms provide similar-quality services despite earning far less per user, but this remains an empirical conjecture. It should be noted that advertising revenue is already part of measured GDP: as discussed in Section 2.1, it is recorded either as intermediate consumption by advertisers or as the platform’s own output of advertising services, and is therefore fully captured within the core production boundary. The point at issue here is different — namely, whether observed advertising revenue provides a reliable empirical multiplier for inferring the consumer surplus that households derive from free access, a welfare quantity that lies outside GDP by construction.

Nakamura *et al.* (2017), often cited in this context, are primarily concerned with production-account treatment of advertising-supported free content rather than establishing a general advertising-revenue multiplier for consumer surplus.

This method also cannot capture surplus from non-advertising-funded services such as UPI, which we estimate contributes approximately 9 percent of total consumer surplus through the WTA and time-use methods.

4.5. Monte-Carlo combination

We treat the bias-adjusted WTA specification as the principal experimental welfare measure because it is most directly related to consumers’ valuations of access. The time-use and advertising-revenue calculations are reported as calibration and robustness exercises. For completeness, we also report an equal-weight average of the three measures, but this combined statistic has no optimal-weighting interpretation and is not used as the paper’s headline estimate. In particular, convergence among the three approaches should not be interpreted as statistical validation because the methods share several data inputs and are

affected by common sources of model uncertainty

Each of the three methods depends on parameters that are uncertain — in some cases substantially so. Rather than presenting a single point estimate with an ad hoc sensitivity range, we propagate uncertainty from all input parameters simultaneously using Monte Carlo simulation. This produces a full probability distribution over consumer surplus estimates, from which we can extract 90 percent parameter-uncertainty intervals that honestly characterise what we know and do not know.

Procedure. We draw 10,000 independent realisations of the full parameter vector. For each draw ($k = 1, \dots, 10,000$):

- (a) Sample all uncertain parameters from their specified distributions (see Table 2 below).
- (b) Compute the resulting surplus estimate under each of the three methods independently: CS_k^{WTA} , CS_k^{Time} , and CS_k^{AD} .
- (c) Record all three estimates.

For each of 10,000 independent draws of the full parameter vector (Table 2), we compute all three method-specific estimates. We designate the bias-corrected WTA estimate as our principal welfare estimator, given its direct theoretical grounding in Hicksian equivalent variation, and present the time-use and advertising-revenue estimates as robustness benchmarks.

For comparison purposes, we also report a combined estimate using equal-weighted averaging:

$$CS_k^{COMBINED} = \frac{1}{3} (CS_k^{WTA} + CS_k^{TIME} + CS_k^{AD}).$$

Equal weighting is a convenience rather than a statistically justified aggregation: the three methods are not repeated measurements of exactly the same quantity with known sampling properties, and their identifying assumptions differ substantially. The combined estimate should be interpreted as a summary indicator rather than a precision-weighted optimal estimate. As robustness checks, alternative weights of (0.50, 0.30, 0.20) — privileging the WTA method — and (0.25, 0.50, 0.25) yield median combined estimates of ₹10.0 and ₹10.5 lakh crore respectively.

We refer to the 5th–95th percentile range of the Monte Carlo output distribution as a “90 percent simulation-based uncertainty interval.” This terminology reflects the fact that the interval propagates *assumed* parametric uncertainty through the model; it is not a Bayesian credible interval derived from a formally estimated posterior distribution. The interval honestly characterizes the sensitivity of results to parameter assumptions but does not capture systematic biases (such as demand-curve shape assumptions) that affect all draws equally.

Table 2 documents the distributional assumptions for each stochastic parameter, the empirical basis for each distribution choice, and the method(s) in which each parameter enters.

Table 2: Monte Carlo parameter distributions

Parameter (1)	Distribution (2)	Basis (3)	Method(s) (4)
WTA per user, by service	Transferred service-specific median; no individual-level parametric distribution imposed.	International experimental evidence transferred and adjusted to the Indian context; alternative valuation levels examined in sensitivity analysis	WTA
Hypothetical bias correction (β)	Uniform(2.0, 3.0)	List and Gallet (2001); Murphy <i>et al.</i> (2005)	WTA
Substitution discount (δ)	Uniform(0.60, 0.80)	Brynjolfsson <i>et al.</i> (2019) cross-service experiments	WTA
Active user count	Triangular(DAU at 67% of MAU; MAU; MAU + 5%)	Platform disclosures; TRAI	WTA; Time-use
Income elasticity of WTA (η)	Triangular(0.3, 0.5, 0.7)	Cross-country income variation implicit in Brynjolfsson <i>et al.</i> (2019); consistent with digital-goods income-elasticity estimates in the literature (Coyle and Nguyen, 2020)	WTA
Surplus ratio (ϕ)	Uniform(0.25, 0.75)	Allcott <i>et al.</i> (2020) deactivation experiment bounds	Time-use
Wage rate	Periodic Labour Force Survey (PLFS) 2023–24 distribution by demographic cell	National Statistical Office (NSO) earnings data;	Time-use
Digital attribution factor (μ)	Triangular(0.40, 0.60, 0.80)	Substitution rates for offline leisure displacement	Time-use
Ad revenue multiplier (θ)	Uniform(8, 20)	Brynjolfsson <i>et al.</i> (2019); Varian (2018)	Advertising
Non-worker discount (ξ)	Uniform(0.40, 0.80)	Abraham and Mackie (2005); Bridgman (2016)	Time-use
Leisure-time discount (λ)	Uniform(0.30, 0.50)	Opportunity cost of non-work time; sensitivity assumption	Time-use

Note:

The three methods share common user base inputs (TRAI, IAMAI), limiting true independence. Cross-method convergence provides less corroboration than fully disjoint methods would.

Table 3: Experimental welfare estimates and calibration benchmarks, 2023–24 (₹ lakh crore)

Method	5th %tile	25th %tile	Median	75th %tile	95th %tile	IQR
(1)	(2)	(3)	(4)	(5)	(6)	(7)
WTA-based median-equivalent welfare measure (principal estimate)	5.8	8.2	10.4	13.8	19.6	5.6
Time-use valuation	7.2	10.8	14.1	18.3	24.8	7.5
Advertising-revenue calibration benchmark	4.4	5.6	7.1	8.6	9.9	3.80
Equal-weight combined diagnostic	5.8	7.8	9.6	12.2	16.4	4.4
Combined as % of GDP (₹302 lakh crore)	1.9%	2.6%	3.2%	4.0%	5.4%	1.4 pp

Notes: All monetary values in 2023–24 current prices. The 90 percent simulation-based uncertainty interval for the combined estimate is ₹5.8–16.4 lakh crore. The WTA-based estimate is our preferred principal estimate; the combined figure is reported for comparison.

4.6. Results

Table 3 presents the Monte Carlo results for each method individually and for the combined estimate.

As an internal consistency check, the advertising-revenue calibration has a particularly transparent analytical range. With aggregate advertising revenue fixed at ₹50,800 crore and $\theta \sim U(8, 20)$, the implied welfare benchmark is bounded between ₹4.064 lakh crore and ₹10.16 lakh crore. The corresponding 5th, 25th, 50th, 75th and 95th percentiles are approximately ₹4.4, ₹5.6, ₹7.1, ₹8.6 and ₹9.9 lakh crore, respectively. These analytically implied values provide a direct check on the Monte Carlo implementation.

The WTA-based measure is treated as the principal experimental welfare estimate because it most directly addresses the value consumers attach to continued access to the services considered. The time-use estimate and advertising-revenue calculation serve different analytical purposes and are reported primarily as robustness and calibration benchmarks. Their numerical proximity to, or divergence from, the WTA estimate should not be interpreted as statistical validation because the approaches rely on different identifying assumptions and share some common inputs. The width of the WTA simulation interval reflects uncertainty in the assumed parameters and transferred valuations; it should therefore be interpreted as a model- and parameter-uncertainty range rather than as a conventional sampling-based confidence interval.

Before presenting the results, a conceptual caveat is warranted. The WTA method as applied here measures total access value — the compensation required for complete loss of access — which includes quasi-rents from network effects rather than conventional Marshallian surplus measured along a demand curve. For network-dependent services such as WhatsApp, losing access would impose coordination costs far exceeding the hedonic value

of messaging functionality alone. The hypothetical bias correction partially compensates for this but is calibrated for hypothetical inflation, not for the conceptual gap between access value and Marshallian surplus.

4.7. Service composition of the WTA-based welfare estimate

To maintain consistency with the designation of WTA as the principal welfare estimator, the service-level decomposition is based on the median-equivalent WTA specification. For service s , its share of the aggregate is proportional to $N_s W_s \gamma_s$, since the common hypothetical-bias correction (β), substitution discount (δ), and annualization factor cancel when contributions are expressed as shares. Table 4 makes the arithmetic underlying the reported decomposition explicit and, in addition to the service shares, reports the implied per-user valuations required to reproduce the aggregate estimate.

For transparency, the service shares are obtained by normalizing the service-specific contributions entering the WTA calculation. Specifically, for service s , the relevant contribution is proportional to $N_s W_s \gamma_s$, because the common hypothetical-bias correction β , substitution factor δ , and annualisation factor cancel when service contributions are expressed as shares of the total. Thus,

$$Share_s = \frac{N_s \tilde{W}_s \gamma_s}{\sum_{j=1}^S N_j \tilde{W}_j \gamma_j} .$$

Replication of the decomposition therefore requires disclosure not only of the service-specific user counts but also of the transferred WTA values, their original sources and the income/PPP adjustments applied to them. Table 4 reports these inputs explicitly so that the service composition can be independently reproduced.

The implied adjusted annual welfare per user is the service-specific welfare contribution divided by the corresponding MAU, and the monthly figure is its annual value divided by 12. The final column reports the combined transferred-valuation and income-adjustment term $\tilde{W}_s \gamma_s$ implied at the baseline common correction factors $\beta = 2.5$ and $\delta = 0.70$. Because the underlying foreign valuation and the India adjustment cannot be separately identified from the information presently available, the table reports their product rather than assigning an arbitrary decomposition between W_s and γ_s . Figures may not sum exactly because of rounding.

Table 4 shows that the reported decomposition implies substantial variation in adjusted welfare per user across service categories. The implied annual values range from approximately ₹335 per cloud-storage user to around ₹3,600 per video-streaming user, with search, messaging and video generating the highest per-user values. These figures should be interpreted as values implied by the transferred-WTA specification rather than as directly observed Indian WTA estimates. Their principal purpose is to make the service decomposition transparent and reproducible and to indicate the service-level valuations that future Indian incentive-compatible experiments would need to test.

Under the transferred WTA specification, search engines account for the largest estimated share (approximately 22 per cent), followed by messaging (19 per cent), video streaming (18 per cent), social media (16 per cent) and UPI digital payments (9 per cent). Maps account for approximately 6 per cent, email 4 per cent, education 3 per cent, news 2 per cent

Table 4: Service-level replication of the WTA-based welfare decomposition, 2023–24

Service	MAU (mil- lion)	Reported welfare share (%)	Welfare contribu- tion (₹lakh crore)	Implied adjusted wel- fare per user/year (₹)	Implied adjusted WTA per user/month (₹)	Implied $W_s\gamma_s$ before common cor- rections (₹/month)
Search en- gines	650	22	2.288	3,520	293	1,048
Messaging	550	19	1.976	3,593	299	1,069
Video stream- ing	520	18	1.872	3,600	300	1,071
Social media	530	16	1.664	3,140	262	934
UPI/digital payments	350	9	0.936	2,674	223	796
Maps/ navi- gation	280	6	0.624	2,229	186	663
Email	425	4	0.416	979	82	291
Educational platforms	180	3	0.312	1,733	144	516
News/ infor- mation	290	2	0.208	717	60	213
Cloud storage	310	1	0.104	335	28	100
Total	—	100	10.400	—	—	—

Notes: MAU figures are from Table 1. Service-specific welfare contributions are obtained by applying the reported WTA shares to the principal median-equivalent welfare estimate of ₹10.4 lakh crore.

and cloud storage 1 per cent. These shares reflect the combined effect of service-specific user populations and adjusted transferred WTA values and should not be interpreted as precisely estimated structural welfare weights. Particularly noteworthy is UPI: despite generating no advertising revenue in the calibration used here, it receives a positive WTA-based welfare contribution. This illustrates why advertising revenue cannot provide a comprehensive allocation of consumer welfare across zero-price digital services.

5. Situating estimates within the 2025 SNA framework

The 2025 SNA represents the most significant revision to international statistical standards since the 2008 SNA. Its treatment of digitalization, set out principally in Chapter 22, is largely enabling rather than prescriptive — establishing frameworks within which national statistical offices may develop approaches rather than mandating specific imputations. Three features are directly relevant to this paper, and it is essential to distinguish clearly among the concepts they address.

5.1. Three distinct concepts

Throughout this paper we maintain a strict distinction among three concepts that are easily conflated:

- (a) ***Core SNA GDP*** — the production-boundary aggregate, in which free platform services do not generate recorded household consumption expenditure. Consumer surplus is excluded by design, not by oversight.
- (b) ***2025 SNA extended account for free platform services*** — Chapter 22 of the 2025 SNA encourages the construction of extended or thematic accounts in which household consumption of free platform services is made visible. Crucially, for this extended account, the SNA regards the *platform’s cost of producing the free services* as the most suitable valuation method, not consumer willingness-to-pay or advertising revenue per user. Furthermore, the SNA explicitly notes that recording these services as household consumption while simultaneously retaining their existing use as inputs to advertising and data production would create double counting within GDP. Extended accounts therefore, require careful supply-use rebalancing.
- (c) ***Consumer surplus / welfare measures outside GDP*** — the 2025 SNA endorses a “Beyond GDP” measurement agenda as a legitimate complement to production-based accounting. Consumer surplus from free digital services is a welfare indicator that belongs in this category. Our estimate of ₹10.4 lakh crore is not “missing GDP” but a welfare measure that GDP is not designed to capture.

5.2. Data as a produced asset

The 2025 SNA extends the asset boundary to recognize data as a produced asset (addressed in the asset classification chapters of the 2025 SNA). However, the SNA draws an important distinction between the platform’s production of a data asset through collection, curation, and processing, and the household’s passive permission for its characteristics or behaviour to be observed. Passive permission to collect household data is not treated as household production under the SNA framework. The SNA allows that the free platform service may be regarded, in an extended account, as payment in kind for a licence to collect data, with the household-side receipt classified as rent rather than as compensation for production. Only where households actively perform actions specifically assisting data collection — beyond normal service usage — might household production arise. Chapter 22 of the 2025 SNA provides this distinction explicitly.

The platform produces the data asset; the household provides access to observable behaviour, for which the free service may constitute implicit compensation (a licence fee or rental payment in the extended account).

5.3. Thematic or extended accounts

The 2025 SNA’s framework for satellite and thematic accounts is set out in Chapter 38. Digital-economy thematic accounts may be constructed at multiple levels of extension. The least expansive level captures ICT-sector output within the existing production boundary; a more extended level may include an imputation for household consumption of free

Table 5: Treatment of free digital services under the 2025 SNA

Component (1)	Correct treatment (2)	2025 SNA (3)	Current recording (4)	Indian as	Measurement gap (cross-border attribution)
Platform output (advertising services)	Core production boundary: market output (Chapters 6–7)	Recorded IT/advertising output	as	Minor	(cross-border attribution)
Data produced by platforms from user observation	Asset boundary: data as produced asset (asset classification chapters)	Not separately identified	Platform-side data asset not capitalised		
Household permission for data collection	Extended account: implicit rental income to household (Ch. 22)	Not recorded		Licence-fee / rental flow unmeasured	
Free services consumed by households	Extended account (Ch. 22, Ch. 38): valued at producer cost	Not recorded as household consumption	Full consumption value unmeasured; cost-based valuation preferred by SNA		
Consumer surplus from free services	Beyond GDP welfare indicator	Not measured; excluded by design	₹10.4 lakh crore (this paper)		

Sources: 2025 SNA, Chapters 6, 7, 22, and 38; BPM7 (IMF, 2025); OECD (2020); authors’ assessment of Indian national accounts recording practices based on NSO (2024) methodology documentation.

services, valued at producer cost. Chapter 22 provides guidance on these extensions.

5.4. Mapping our estimates to the 2025 SNA

Table 5 maps the components of our analysis onto these three concepts.

The most immediately actionable gap for India’s NSO is the construction of a digital-economy satellite account along the lines encouraged by Chapter 22. Within this account, household consumption of free platform services would be made visible, valued at the platform’s cost of producing those services. A rough order of magnitude can be obtained from platform cost data, though obtaining service-level cost allocations from multinational platforms operating in India will present practical challenges.

It is important to note that valuing free services at advertising revenue per user (as sometimes proposed in the literature) is not the preferred 2025 SNA valuation for the extended account. Furthermore, simply adding imputed free-service consumption to GDP without rebalancing the supply-use framework would create double counting, since the resources used to produce free services are already recorded as costs of producing advertising output.

Our consumer-surplus estimates (Section 4) are explicitly welfare measures belonging

Table 6: Alternative measurement perspectives on free digital services

Measurement perspective (1)	Valuation (2)	Status under 2025 SNA (3)	Interpretation (4)
Core SNA accounts	Market / accounting prices	Core accounts	Records platform market output but excludes consumer surplus
Extended account for free platform services	Producer cost	Encouraged supplementary/extended treatment	Makes household use of free services visible without treating WTA as GDP
Consumer-welfare measure	WTA/consumer valuation	Outside core GDP	Measures welfare associated with access to free services
Advertising-revenue calibration	Advertising revenue/multiplier	Analytical benchmark only	Robustness comparison; not SNA-preferred valuation

to the “Beyond GDP” framework. They complement, but do not substitute for, the cost-valued extended account.

The preceding discussion suggests that free digital services can be viewed from several distinct measurement perspectives, each addressing a different analytical question and requiring a different valuation basis. To make these distinctions explicit, Table 5 summarises the relationship among the treatment of free digital services in the core SNA accounts, their representation in an extended account, and their valuation for consumer-welfare analysis. The table also identifies the more limited role of advertising revenue as an analytical calibration benchmark. These approaches should not be interpreted as alternative estimates of the same aggregate; rather, they correspond to different measurement objectives and accounting boundaries.

The central implication of Table 5 is that these measures answer different questions and should not be added mechanically to one another. The cost-valued extended account concerns the organization and visibility of production and consumption within an expanded accounting framework, whereas WTA-based consumer surplus concerns welfare. The latter is therefore complementary to, rather than a correction of, GDP.

As Table 6 makes clear, the distinction between production measurement and welfare measurement is central to the interpretation of the estimates presented in this paper. Core GDP records economic production according to SNA accounting principles and excludes consumer surplus by design. The extended-account approach recommended in the 2025 SNA can make household consumption of free platform services more visible, but values such services on a producer-cost basis rather than by consumers' willingness to pay or accept. The WTA-based estimates developed in this paper address a different question: the welfare consumers associate with continued access to these services. Advertising revenue provides a useful observable benchmark but is neither the SNA-preferred valuation for the extended account nor a direct measure of consumer surplus. Accordingly, the four perspectives in Table 5 should be reported alongside one another rather than combined into a single augmented

GDP measure.

6. Implications for welfare-augmented growth measurement

The final distinction in Table 5—between production-based accounting and consumer-welfare measurement—also provides the appropriate starting point for considering welfare-augmented growth measures such as GDP-B. Whereas the WTA estimates reported in Section 4 describe the level of consumer valuation in a particular period, a welfare-growth measure requires information on how that valuation changes over time.

Brynjolfsson *et al.* (2025) develop GDP-B as a framework for incorporating the welfare contributions of new and free goods into measures that complement conventional production-based statistics. The framework is particularly relevant to rapidly expanding digital economies because changes in the consumer valuation of zero-price services need not be reflected proportionately in market expenditure.

Applying GDP-B rigorously to India requires repeated observations on consumer valuations over time. In particular, the welfare contribution of free digital services to growth depends on changes in consumer surplus rather than its level:

$$\Delta CS_t = CS_t - CS_{t-1} .$$

A valid implementation would therefore require comparable annual or periodic estimates of WTA, appropriately adjusted for changes in the number and composition of users, the introduction and disappearance of services, quality change and inflation. The cross-sectional 2023–24 estimates developed in this paper do not provide this longitudinal information.

We, therefore, refrain from constructing a numerical GDP-B growth series from interpolated consumer-surplus levels. Instead, our results establish a benchmark welfare level for 2023–24 that could serve as a starting point for future longitudinal measurement. Repeated incentive-compatible WTA experiments—preferably conducted at regular intervals using a consistent survey design—would permit India to construct a genuine welfare-growth series and assess the contribution of free digital innovation using the GDP-B methodology.

This distinction is important. A large level of consumer surplus does not necessarily imply a correspondingly large annual welfare-growth contribution: GDP-B growth depends on the change in welfare between periods. As internet penetration approaches saturation, extensive-margin gains may diminish even while quality improvements, new services and artificial intelligence generate continuing intensive-margin welfare gains.

7. International context

Evidence from other economies consistently indicates that zero-price digital services can generate consumer valuations substantially exceeding the market expenditures directly associated with their use. Experimental studies for the United States and other advanced economies have demonstrated large valuations for services including search, social media, digital maps and online communication. However, the magnitudes reported across studies are not directly comparable because survey designs, service definitions, elicitation methods,

user populations and price concepts differ.

These comparability problems are particularly important when transferring results to India. Lower per-capita income might reduce willingness to pay or accept in monetary terms, while extensive reliance on free rather than subscription-based services, strong network effects and limited availability of some offline substitutes may work in the opposite direction. Consequently, cross-country ratios of estimated digital consumer surplus to GDP should not be interpreted as comparable national-accounting statistics.

The international literature therefore supports a qualitative rather than a precise quantitative conclusion: substantial consumer welfare from zero-price digital services is a general feature of digital economies and not unique to India, but its magnitude cannot be read off from other countries' experience and must ultimately be estimated using country-specific evidence. This observation motivated the measurement framework developed in Section 4 of this paper, and it is revisited in the Conclusion when we set out priorities for building India's own valuation evidence base.

8. Policy implications and implementation road map

Our results suggest a phased measurement agenda for India's National Statistical Office. In the near term, priority should be given to improving the visibility of digital production and transactions within supply-use and thematic-account frameworks and to developing information on the costs incurred by platforms in supplying zero-price services to Indian users. Such information would support the cost-of-production valuation preferred by the 2025 SNA for an extended account of free platform services. In parallel, experimental welfare measurement should be developed separately, beginning with nationally representative, incentive-compatible WTA surveys and improved digital time-use information. Over the longer term, repeated valuation exercises could support a broader welfare dashboard and permit the construction of longitudinal measures such as GDP-B. Maintaining the distinction between cost-valued extended accounts and consumer-valued welfare indicators is essential to preserving the conceptual integrity of both exercises.

Three broader implications merit mention. First, the potentially substantial consumer welfare indicated by our experimental estimates should be considered in regulatory cost-benefit analysis for competition policy and digital regulation affecting free service access. Second, the substantial consumer welfare generated by free digital services — much of it provided by platforms headquartered outside India — is relevant context for understanding the digital economy's contribution to Indian wellbeing. However, consumer surplus generated by foreign platforms is not directly evidence regarding the appropriate allocation of taxable profits; the taxation question requires separate analysis of value creation, profit allocation, and international tax frameworks. Third, the high surplus-to-cost ratio for publicly funded digital infrastructure — particularly UPI — provides a welfare-based framework for evaluating digital public goods investment.

9. Sensitivity analysis

The Monte Carlo analysis in Section 4 propagates uncertainty across the parameters entering the experimental estimates. Because the WTA-based median-equivalent measure is

Table 7: Sensitivity of experimental welfare estimates to key assumptions across valuation methods

Parameter	Baseline	Low (10th %tile)	CS at Low	High (90th %tile)	CS at High	Range
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Wage rate	PLFS median	PLFS 25th %ile	7.4	PLFS 75th %ile	12.1	4.7
Surplus ratio (ϕ)	0.50	0.30	7.8	0.70	11.4	3.6
Ad revenue multiplier (θ)	14	9.2	7.9	18.8	11.2	3.3
Hypothetical bias (β)	$2.5\times$	$2.1\times$	11.4	$2.9\times$	8.2	3.2
Digital attribution (μ)	0.60	0.44	8.5	0.76	10.8	2.3
Active user count	820 mn	680 mn	8.0	860 mn	10.1	2.1
Substitution discount (δ)	0.70	0.62	8.7	0.78	10.6	1.9
Income elasticity (η)	0.50	0.35	8.9	0.65	10.4	1.5

Note: Each row varies one parameter while holding all other parameters at their baseline values. The parameters enter different component methods: β , δ , and η primarily affect the WTA specification; wage rate, ϕ , and μ affect the time-use specification; and θ affects the advertising-revenue calibration. Active-user assumptions affect the relevant user-based calculations. Accordingly, the table reports sensitivity of the combined diagnostic rather than of the WTA-based principal estimate.

designated as the paper’s principal welfare estimator, the present section focuses primarily on the sensitivity of that measure to its key assumptions. Sensitivity of the time-use and advertising-revenue calculations is secondary, since these measures are used as robustness or calibration benchmarks rather than as alternative headline estimates.

Table 7 presents a structured one-at-a-time sensitivity analysis of the equal-weight combined diagnostic, varying selected parameters from the WTA, time-use and advertising-revenue approaches while holding all other parameters at their baseline values. For each parameter, Columns (3) and (5) report the low and high values examined, and Columns (4) and (6) report the resulting combined welfare estimate (₹ lakh crore) when that parameter alone is moved to the low or high value while every other parameter is held at its Table 2 baseline; Column (7) reports the resulting range (High minus Low). Reading down Column (7) therefore, ranks parameters by how much the combined estimate moves in response to each one, from the wage rate at the top (the most influential assumption) to income elasticity at the bottom (the least influential). The exercise is intended to identify the assumptions to which the cross-method summary measure is most sensitive and should not be interpreted as a sensitivity analysis of the principal WTA estimate alone.

Extended sensitivity to the substitution discount reveals that ($\delta = 0.40$) (high substitutability) and ($\delta = 0.95$) (near-zero substitutability) yield combined medians of ₹7.2 and ₹11.8 lakh crore respectively — within the overall 90 percent parameter-uncertainty interval and not altering the qualitative finding.

9.1. Sensitivity to the aggregation of WTA

A further source of uncertainty concerns the aggregation of service-specific WTA values. Our principal calculation uses transferred median WTA values and therefore represents a median-equivalent welfare aggregate rather than the population sum of individual valuations. Without Indian microdata, the shape and dispersion of the WTA distribution cannot be identified reliably. Consequently, we do not attempt to impose a specific linear or other functional form on the underlying demand curve.

As an illustrative sensitivity exercise, we uniformly vary the transferred service-specific median WTA vector by ± 30 per cent around the baseline specification. Holding the remaining WTA-model assumptions unchanged, a 30 per cent downward adjustment would reduce the baseline median-equivalent estimate of ₹10.4 lakh crore to approximately ₹7.3 lakh crore, while a 30 per cent upward adjustment would increase it to approximately ₹13.5 lakh crore. These values are mechanical sensitivity scenarios rather than statistical confidence limits or formal welfare bounds.

The exercise demonstrates that the magnitude of the estimated welfare value remains materially dependent on the transferred WTA inputs. It therefore reinforces the paper's central statistical recommendation: nationally representative, incentive-compatible Indian WTA experiments are the highest-priority data investment for producing more defensible consumer-welfare estimates of free digital services.

10. Limitations

Several limitations warrant acknowledgement, ordered by consequence for our central estimates.

First, and most importantly, the WTA inputs are not directly observed for India. They are transferred from international experimental evidence and adjusted to the Indian context. Neither PPP nor income adjustment can fully capture cross-country differences in preferences, network effects, available substitutes, digital literacy or service quality. Moreover, because Indian WTA microdata are unavailable, the paper uses median-equivalent rather than distribution-exact aggregation. These limitations imply that the reported monetary estimates should be interpreted as experimental orders of magnitude. A nationally representative Indian survey using incentive-compatible elicitation is therefore, the single most important requirement for improving the estimates.

Second, the time-use benchmark relies on strong assumptions concerning the opportunity cost and marginal welfare value of digital time. Time spent on digital services cannot automatically be equated with consumer surplus: some use may substitute for similarly valued offline leisure,

Third, substitution patterns are simplified. Our synergy discount ($= 0.60 - 0.80$) captures cross-service substitutability only approximately; a structural demand model with estimated cross-elasticities would improve precision but requires unavailable micro-data.

Fourth, the three methods are not fully independent: they share user base data and certain calibration parameters draw on overlapping empirical literature. Cross-method convergence is therefore, partially mechanical.

Fifth, and importantly, this paper's framework measures only the gross positive value that consumers derive from access to free digital services; it does not net out the welfare costs that accompany that access, nor does it address producer surplus or the distribution of net benefits across the population. Three distinct extensions would be required for a genuinely comprehensive welfare accounting:

- The first concerns digital “bads”. Free digital services also generate documented negative externalities, including financial losses from cyber fraud and phishing, the erosion of privacy through data collection and secondary use, the mental health costs associated with problematic or compulsive use (particularly among adolescents), and the social costs of misinformation and manipulated content spread through social media and messaging platforms. Each of these has a growing dedicated empirical literature — for example, on the welfare costs of social media use (Allcott, Braghieri, Eichmeyer, and Gentzkow, 2020, cited above as Allcott *et al.*) and on privacy valuation more generally — but the magnitudes are not currently estimated on a basis comparable to the WTA framework used here, and Indian evidence is particularly sparse. Our ₹10.4 lakh crore estimate should therefore, be understood as a measure of gross access value, not of net welfare; the true net welfare contribution of free digital services is smaller, potentially substantially so, once these costs are netted out. Constructing a comparable “digital bads” valuation exercise — ideally using elicitation methods consistent with the WTA approach used here, so that gross and negative components can be legitimately netted against one another — is accordingly among the priorities we identify for future work in Section 8.
- The second concerns producer surplus. Platforms capture value through advertising revenue, data monetization and market power; a complete welfare accounting would set consumer surplus alongside producer surplus (and, where relevant, government revenue from digital taxation) to assess how the total surplus generated by the digital economy is divided among households, firms and the state. Our framework, being calibrated from the household side, is silent on this division.
- The third concerns distributional effects. The MAU-weighted averages underlying Table 1 and the aggregate estimates in Table 3 conceal potentially large differences in consumer surplus across income groups, urban and rural populations, age cohorts and gender, both because usage intensity varies systematically across these groups (Section 3.2) and because the opportunity cost of time and marginal utility of money used to value that usage are also likely to differ across them. A population-average welfare estimate of the kind reported here is therefore compatible with very different distributional profiles — for example, a pattern in which affluent, urban, digitally literate users capture a disproportionate share of estimated welfare would have materially different policy implications from a more evenly distributed pattern, even at an identical aggregate. Disaggregating the valuation exercise by demographic and socioeconomic strata, which would require the nationally representative time-use and WTA microdata called for throughout this paper, is necessary before firm distributional conclusions can be drawn.

Finally, the rapid emergence of generative AI services at zero price means these estimates reflect the 2023–24 landscape and may require significant revision as AI reshapes the free digital ecosystem.

11. Conclusion

Free digital services have become an important component of household consumption and everyday economic life in India, yet the welfare they generate is only imperfectly reflected in market-based economic statistics. As the international evidence reviewed in Section 7 makes clear, this is not a uniquely Indian phenomenon, but its magnitude for India could not be inferred from other countries' experience alone. This paper develops an experimental framework for assessing the order of magnitude of that welfare and, equally importantly, clarifies how such estimates should be related to the 2025 SNA.

Using transferred WTA evidence adjusted to the Indian context, the principal specification produces a median-equivalent welfare estimate of approximately ₹10.4 lakh crore in 2023–24, or about 3.4 per cent of nominal GDP. This figure should not be interpreted as missing GDP or as a statistical estimate of output omitted from India's national accounts. It is an experimental welfare measure whose precise magnitude remains sensitive to the transferred WTA values, assumptions concerning substitution and hypothetical response bias, and the absence of Indian micro-level valuation data. Time-use and advertising-revenue calculations provide useful benchmarks but do not eliminate these sources of uncertainty.

The 2025 SNA provides an important conceptual framework for separating these issues. As summarised in Table 5, core GDP remains a measure of production and deliberately excludes consumer surplus, while an extended account can make household consumption of free platform services more visible using producer cost as the preferred valuation basis. Consumer-surplus estimates answer a different question and are therefore appropriately treated as complementary welfare indicators rather than additions to GDP.

The most important next step is empirical rather than conceptual. India would benefit from nationally representative incentive-compatible WTA experiments, improved service-specific digital time-use statistics and information on the costs incurred by platforms in supplying free services to Indian users. Repeating such exercises over time would also permit application of welfare-growth frameworks such as GDP-B without relying on interpolated consumer-surplus series.

The central contribution of the paper is therefore not to propose a revised measure of Indian GDP, but to demonstrate how the economically important welfare generated by zero-price digital services can be measured experimentally while maintaining a clear boundary between production accounting and welfare analysis. That distinction is essential for extending economic measurement in the digital era without compromising the conceptual coherence of the national accounts. As generative AI services increasingly enter the zero-price digital ecosystem, the measurement challenges documented in this paper are likely to intensify, reinforcing the urgency of building the statistical infrastructure — nationally representative valuation experiments, platform cost data, and digital time-use surveys — that would allow India to track welfare changes in real time rather than relying on retrospective, transferred estimates.

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Conflict of interest

The authors do not have any financial or non-financial conflict of interest to declare for the research work included in this article.

References

- Abraham, K. G. and Mackie, C. (eds.) (2005). *Beyond the Market: Designing Nonmarket Accounts for the United States*. National Academies Press, Washington, D.C.
- Allcott, H., Braghieri, L., Eichmeyer, S., and Gentzkow, M. (2020). The welfare effects of social media. *American Economic Review*, **110**, 629–676.
- Becker, G. S. (1965). A theory of the allocation of time. *The Economic Journal*, **75**, 493–517.
- Bridgman, B. (2016). Home productivity. *Journal of Economic Dynamics and Control*, **71**, 60–76.
- Brynjolfsson, E., Collis, A., and Eggers, F. (2019). Using massive online choice experiments to measure changes in well-being. *Proceedings of the National Academy of Sciences*, **116**, 7250–7255.
- Brynjolfsson, E. and Oh, J. (2012). The attention economy: Measuring the value of free digital services on the internet. *Proceedings of the International Conference on Information Systems*.
- Brynjolfsson, E., Collis, A., Diewert, W. E., Eggers, F., and Fox, K. J. (2025). GDP-B: Accounting for the Value of New and Free Goods. *American Economic Journal: Macroeconomics*, **17**, 312–344. <https://doi.org/10.1257/mac.20210319>.
- Coyle, D. and Nguyen, D. (2020). *Free Goods and Economic Welfare*. ESCoE Discussion Paper 2020-18, Economic Statistics Centre of Excellence, London.
- Data.ai (2024). *State of Mobile India 2024*. San Francisco. Dentsu India (2024). *Digital Advertising in India 2024*. Mumbai.
- Feldstein, M. (2017). Underestimating the real growth of GDP, personal income, and productivity. *Journal of Economic Perspectives*, **31**, 145–164.
- Goolsbee, A. and Klenow, P. (2006). Valuing consumer products by the time spent using them: An application to the internet. *American Economic Review Papers and Proceedings*, **96**, 108–113.
- IAMAI and Kantar (2024). *ICUBE 2024: India's Internet and Digital Report*. New Delhi.
- IMF (2018). *Measuring the Digital Economy*. Washington, D.C.
- IMF (2025). *Balance of Payments and International Investment Position Manual, Seventh Edition (BPM7)*. Washington, D.C.
- List, J. and Gallet, C. (2001). What experimental protocol influence disparities between actual and hypothetical stated values? *Environmental and Resource Economics*, **20**, 241–254.

- Murphy, J., Allen, P.G., Stevens, T., and Weatherhead, D. (2005). A meta-analysis of hypothetical bias in stated preference valuation. *Environmental and Resource Economics*, **30**, 313–325.
- Nakamura, L. I., Samuels, J., and Soloveichik, R. (2016). Valuing “Free” Media in GDP: An Experimental Approach. *BEA Working Paper WP2016-3*, U.S. Bureau of Economic Analysis.
- Nakamura, L. I., Samuels, J., and Soloveichik, R. (2017). Measuring the “Free” Digital Economy within the GDP and Productivity Accounts. *BEA Working Paper WP2017-9*, U.S. Bureau of Economic Analysis.
- Nordhaus, W. (2006). Principles of national accounting for nonmarket accounts. In D. Jorgenson, J.S. Landefeld, and W. Nordhaus (eds.), *A New Architecture for the U.S. National Accounts*, University of Chicago Press, 143–160.
- NPCI (2024). *UPI Product Statistics 2023–24*. Mumbai.
- NSO (2024). *Sources and Methods: National Accounts Statistics*. New Delhi.
- NSO/PLFS (2024). *Periodic Labour Force Survey Annual Report, July 2023–June 2024*. New Delhi.
- OECD (2020). *A Roadmap Toward a Common Framework for Measuring the Digital Economy*. Paris.
- Statistics Canada (2023). Experimental Estimates of Household Digital Intermediation Services. Catalogue No. 13-605-X.
- Stiglitz, J., Sen, A., and Fitoussi, J. P. (2009). *Report by the Commission on the Measurement of Economic Performance and Social Progress*. Paris.
- Syverson, C. (2017). Challenges to mismeasurement explanations for the US productivity slowdown. *Journal of Economic Perspectives*, **31**, 165–186.
- TRAI (2024). *Indian Telecom Services Performance Indicators Report, January–March 2024*. New Delhi.
- United Nations, European Commission, IMF, OECD, and World Bank (2025). *System of National Accounts 2025*. United Nations, New York.
- Varian, H. (2018). The value of the internet now and in the future. *The Economists’ Voice*, **15**, 1–10.