Unpaid Care Work, Time Poverty, and Missed Employment Opportunities: Evidence from India's Time Use Surveys and Solutions for Global Economy

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Abstract: Unpaid care and domestic work, overwhelmingly performed by women, remains structurally invisible within national economic accounting despite its centrality to social reproduction and gender relations. Using nationally representative data from India's Time Use Surveys (2019 and 2024) published by MoSPI, this paper conducts a comparative longitudinal analysis of Indian women's time allocation across unpaid domestic services, unpaid caregiving, and paid employment in rural and urban contexts. Drawing on standard comparative descriptive analysis and state-level paired t-tests to average daily minutes by activity and gender across rural and urban contexts, the study finds statistically significant declines in time spent on unpaid domestic services and caregiving. However, these reductions have not led to increased time spent in employment among women, revealing a persistent disjuncture between declining care burdens and economic participation. Indian women continue to spend more than 450 minutes per day on unpaid care work, exceeding time devoted to paid work, highlighting enduring time poverty and the continued feminisation of care work, which has been quantified in this work using TUS data. Situating these findings within debates in feminist political economy and the care economy, the paper argues that visibility alone is insufficient to secure redistribution or recognition. It proposes that granular time-use data and data-driven policy tools can be leveraged to support the formalisation of unpaid care work through women-led micro-enterprises, community-based care services, and care cooperatives. Aligning with SDG 5.4, the study underscores the need to integrate unpaid care work into policy, statistics, and development planning to advance gender equality and inclusive growth in India, which can be replicated across economies.

INTRODUCTION

We live in a world where what we feel internally appears on our screens, making us wonder how this occurs. It is thought-provoking to realise that humanity, globally and instinctively, produces vast amounts of data on the web, thereby indirectly helping the "New Economy" kick-start and eventually drive other economic variables. On one hand, people unconsciously act as the seeds for developing "Big Data", and on the other hand, businesses or companies use these explosive datasets to inflate their pockets economically. This is the reality of the commercially interconnected world we live in today, where it is not just the exchange of tangible assets that jump-starts economic growth and development. Every click on the screen creates a "butterfly effect" on it. However, paradoxically, the very workers whose lives generate these data often remain excluded from the gains, revealing a missed opportunity to channelise data-driven growth into inclusive development.

At this point, we must understand what a new economy is, how big data drives its growth through various network effects, and why failing to connect this data revolution to unpaid work reproduces another "missed opportunity" in policy and market frameworks. In essence, the digital economy, powered by advanced technology and disruptive innovation strategies, constitutes the new economy, with big data serving as its catalyst. Big data involves using large-scale computing power and sophisticated algorithms on vast datasets to identify patterns, trends, and associations in human behaviour and other phenomena. How do those suggestion lists, based on your personal preferences, get filtered on your Amazon app or while doom-scrolling the Netflix homepage naturally? It is simply the gameplay of big data in the new economy. This infrastructure could, but has not yet been used, to recognise and reward the invisible economic drivers or caregivers whose time remains economically covered and underutilised.

Data analytics now offer higher predictive power than traditional economic modelling. How big data's significant impact drives the market at large is an altogether interesting leapfrogging phenomenon (Brynjolfsson and McAfee 2014). It is realised that, in a closely-knit, interconnected world such as today's, data is ubiquitous. When this is consciously tracked, it can reveal even the silent yet market-driving demand functions of diverse consumers. As the market emerges, it increases the volume, velocity, and variety of data produced, thereby spurring the commercial world to pursue new advances through comparative and competitive advantages. These data advantages stem from "network effects" that are distinctively present in the new economy. Here, network effects refer to the phenomenon in which, as more participants use a service, it gains greater utility or attracts more value. The internet is one classic example of such a service. In economics, it is also known as "network externality" or "demand-side economies of scale". In this context, the data produced, recorded, and analysed through data-driven tools and techniques creates a strong lock-in effect for the leading firms, making it increasingly difficult for new entrants to match the scale and insights of the incumbents, illustrating how network effects that could be harnessed to formalize and aggregate unpaid caregivers instead risk deepening the divide between those whose data generates value and those who can capture it.

Data has transformed the new economy by not only fostering business growth but also reshaping labour force dynamics, with particular emphasis on the role of unpaid labour. The collection and analysis of data from various sources have brought the often-overlooked and under-covered role of unpaid work into the spotlight, recognising its significant impact on economic development (Rubiano and Matulevich 2019). As data becomes a vital input for decision-making, its application also extends into traditionally non-economic areas such as caregiving, domestic management, and volunteer work, highlighting both the importance of recognizing and including previously invisible labour in GDP and wellbeing metrics, and the unrealized policy space where this visibility has not yet translated into income, entrepreneurship, or social protection, again signalling a missed opportunity to convert recognition into redistribution and remuneration.

More interestingly, as a ripple effect, it can also generate “social surplus” in broad strokes. Hence, it is also proposed to be utilised as a tool for income-generating activities among unpaid caregivers in the household. Applying social surplus frameworks to unpaid caregiving suggests that data-enabled redistribution mechanisms could transform caregiving into viable income sources for household members, turning what has so far been a structural missed opportunity into a deliberate strategy for care-economy entrepreneurship.

Unpaid household and care work, primarily undertaken by women in all societies, has historically been omitted from national income accounts, even though it plays a crucial role in social reproduction and human capital development. Women perform 76% of all unpaid care work, constituting the core of care economies worldwide (ILO 2018). In India, recent time-use surveys show that women spend almost three times as much time on unpaid work as men do. However, this massive contribution remains unrecognised mainly in policymaking, economic support systems, or, for that matter, in the broader entrepreneurial ecosystem, another critical missed opportunity to convert women’s time into decent work (complying with another targeted SDG), enterprise creation, and countable expanded labour-force participation.

Katz and Shapiro (1985) conceptualised network effects as mechanisms where existing users amplify utility for new users. In the labour market context, this translates to: the more care workers or households submit data to a national registry or platform, the easier it becomes to quantify, support, and design models for their compensation or empowerment. Recent literature also examines policy and entrepreneurial opportunities arising from the formalisation of unpaid care and domestic work. Scholars emphasise that skill development, digital inclusion, and the promotion of micro-enterprises in care services can significantly improve both national productivity and women's economic empowerment (NITI Aayog 2022). Additionally, time-use surveys reveal that despite incremental shifts women continue to devote substantially more hours to unpaid care than men, maintaining labour-force participation gaps and economic inequalities; this persistent gap, in a context of expanding data and digital tools, underscores the central argument of this paper: a significant missed opportunity to align big data–driven growth with the formal recognition and economic inclusion of unpaid caregivers.

Problem Statement

In today's interconnected societies, data is not just abundant but also the infrastructure on which decisions are made. Every online transaction, social media post, GPS check-in, or other platform interaction contributes to the ever-growing digital footprint. This vast, daily-generated dataset can be used to conduct a thorough SWOT analysis of the workforce engaged in unpaid work, assess their needs and gaps, and design entrepreneurial avenues for them. In this process, unpaid labour, which was historically invisible due to a lack of quantification or market exchange, is gradually becoming traceable and visible. Time-use survey data, social media activity patterns, smart device usage, and digital platform engagements are beginning to capture indicators that, albeit silently, point to unpaid labour contributions to the economy and significantly contribute to its growth.

However, a paradox exists here: the problem statement itself, namely, the digitalisation of nearly all economic command posts, contrasts with the policy neglect of unpaid work, often relegated to family responsibilities borne primarily by women. Unless captured, valued, and formalised through data-driven attention, unpaid labour remains what feminist economist Marilyn Waring called the "ignored productive activity". Thus, this study explores how data can shift this legacy of invisibility from the shadows into the spotlight.

Moreover, the future of the care economy lies in fostering entrepreneurship. With accurate data on time-use burdens, localised care deficits, and demographic trends, the analysis can support the creation of women-led micro-enterprises in and around elder-care, child-care, and domestic support services, which is reflected in many of the developed states of India, contributing to the overall enhancement of family income through better use of household members' time. These digitally enabled solutions not only tackle existing time poverty but also create inclusive employment opportunities, aligning with the goals of SDG 5, especially 5.4, and India's strategy for the future of work.

This work, therefore, explores:

1. How big data-driven and time-use analytics can identify and quantify unpaid care workers whose reduced work burden has not yet translated into labour-market entry, and whether state or district-level data on time, skills, and care deficits can inform formalisation and micro-enterprise strategies.

2. Whether data-enabled platforms, digital payments, and skill-matching algorithms can formalise unpaid care into women-led enterprises, or whether they risk concentrating data-derived value among incumbent firms and deepening exclusion.

3. What policy and entrepreneurial pathways grounded in time-use evidence and data-driven analysis can convert freed time into sustainable income, gender equality, and inclusive growth through care-economy clusters, cooperatives, public procurement, and national statistical integration?

CONCEPTUAL FRAMEWORK

This exploratory study adopts a care-economy formalisation framework to document time-use patterns and identify policy pathways to transform unpaid care work into economically productive activities. The framework integrates three evidence-based pillars relevant to India's development context:

Time Poverty as a Binding Constraint

Women's unpaid care and domestic work create a structural "time poverty" that limits women's economic participation (Blackden & Wodon 2006; ILO 2018). India's TUS data for 2019 and 2024 (Ref. Figs. 1a-1d) reveal that women allocate more than 450 minutes per day to unpaid activities, exceeding their employment time (~400 minutes), indicating that this constraint persists despite observed reductions (Ref. Table II).

Care Economy as Development Opportunity

Unpaid care work constitutes 26-36% of India's GDP yet remains invisible in national accounts (NITI Aayog 2022). Formalisation occurs through: (a) statistical recognition via time-use surveys, (b) entrepreneurship development in childcare/eldercare/domestic services, and (c) infrastructure development to redistribute care burdens (Razavi 2007; Folbre 2012; SDG 5.4).

Data-Driven Localisation

Granular TUS data enables region-specific interventions by mapping care deficits to skill readiness (Ref. Fig. 2: K-means clustering results). This study examines whether freed time from reduced unpaid work (rural: 51→30 min/day; urban: 132→104 min/day; Ref. Table I) translates into employment gains or reflects unmet demand for care services.

DATA AND METHODS

This is a descriptive analysis of longitudinal TUS patterns (2019 & 2024), and not a causal hypothesis testing. Findings generate policy-relevant hypotheses for future research on care economy MSMEs.

The work synthesises academic literature, international best practices, and sectoral case studies. It prioritises examples from Asia (with a special focus on India) but also draws comparative insights from other developing economies. Evidence is gathered from policy reports, peer-reviewed articles, and authoritative databases to assess the economic impact of Data and network effects on unpaid labour and how these effects can be channelled into economically meaningful output in the form of enhanced national income and human development.

In addition to secondary sources, the analysis incorporates recent empirical data from the Time Use Survey (TUS) statistics of India – 2019 and 2024, as published by the Ministry of Statistics and Programme Implementation (MoSPI), with a focus on the comparative statistics of unpaid domestic and caregiving hours, as well as paid work hours, for rural and urban females between 2019 and 2024. The TUS follows standardised ICATUS-2016 activity classification, nationally representative sampling frames, and rigorous field protocols, which ensure high measurement reliability of daily time-use diaries. The construct validity in the paper is supported by the close alignment between the activity categories used here, that is, unpaid domestic services, unpaid caregiving, and employment, and internationally accepted definitions of unpaid care work and labour-force participation in feminist economics and ILO guidelines.

Statistical tests, including t-tests, are also incorporated to quantify and validate observed changes in time allocation and to establish the significance of trends. Aggregating at the state level and using paired t-tests on state-level averages ($n = 37$) helps reduce random measurement error in self-reported minutes while preserving meaningful variation across rural and urban locations. Internal consistency is further reinforced by cross-checks of TUS tabulations against published MoSPI summaries and by focusing on broad activity aggregates that are less sensitive to minor reporting noise.

This mixed-methods approach enables a deeper discussion of how reductions in unpaid care time can create new opportunities for entrepreneurship and policy innovation, thereby contributing to national income. As the analysis is observational and descriptive rather than causal, the study does not infer treatment effects; instead, it uses statistically significant differences over time to generate robust, policy-relevant hypotheses for future micro-level and experimental research on care-economy entrepreneurship

Ethical considerations

As a secondary-data-based study, the research does not involve direct interaction with human subjects. All data used is anonymised and publicly available. Care has been taken to ensure cultural sensitivity in interpreting gender norms and regional practices.

RESULTS AND DISCUSSION

Insights from India's Time Use Survey 2019 and 2024: A Case-Based Evidence

An analysis of India's Time Use Survey (TUS) data from 2019 and 2024 reveals critical shifts, as discussed below:

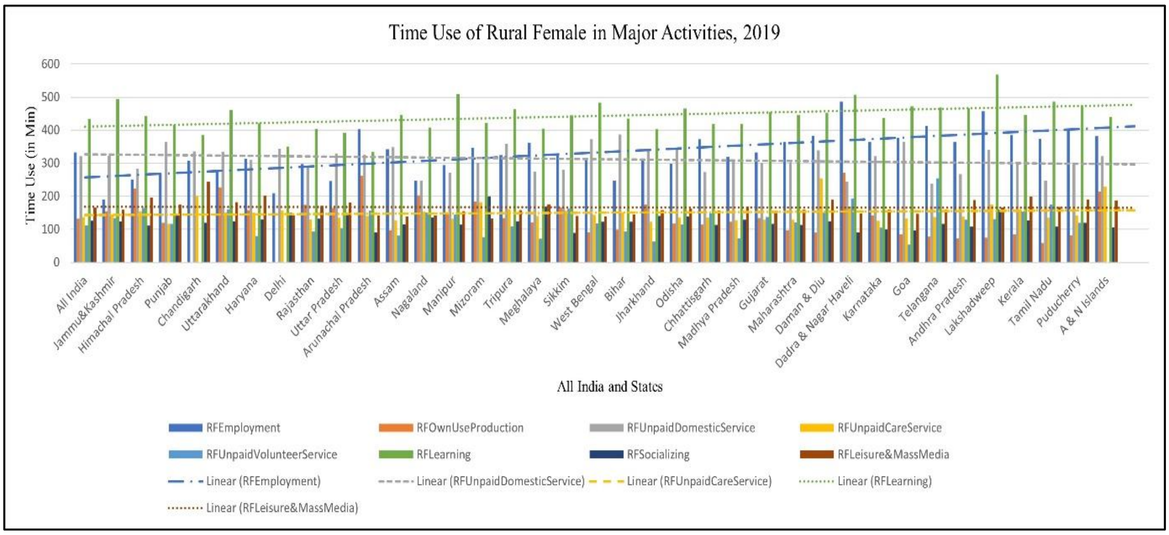

Fig.1a Time Use of India's Rural Female in Major Activities (as per ICATUS 2016), 2019
Source Based on author's calculations from TUS 2019

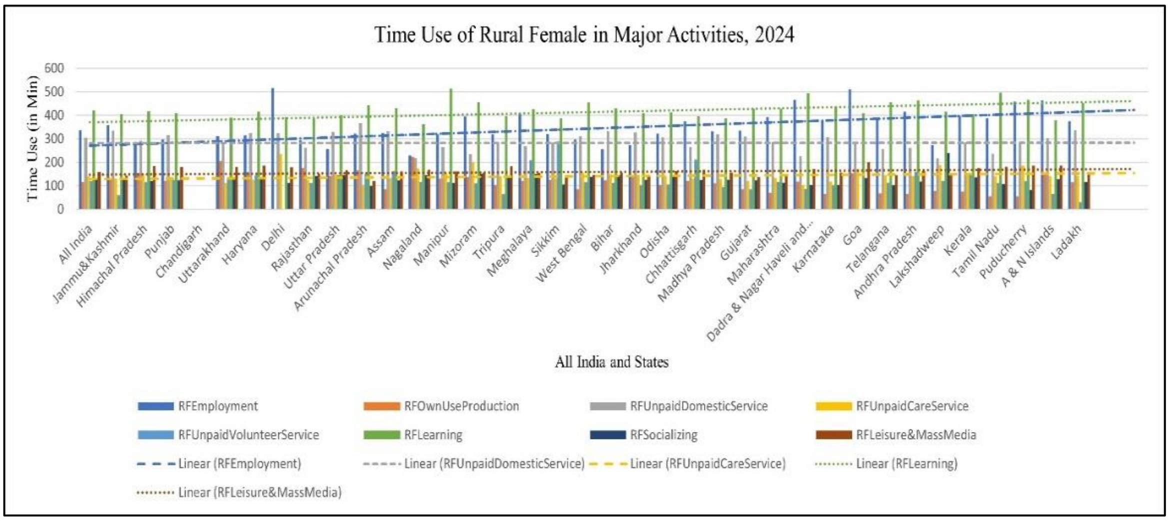

Fig.1b Time Use of India's Rural Female in Major Activities (as per ICATUS 2016), 2024
Source Based on author's calculations from TUS 2024

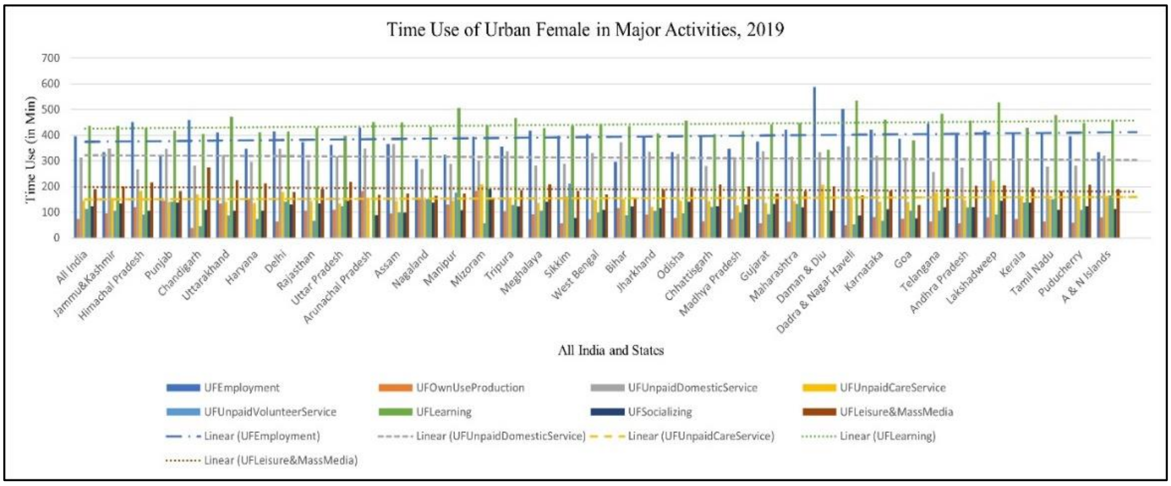

Fig.1c Time Use of India's Urban Female in Major Activities (as per ICATUS 2016), 2019
Source Based on author's calculations from TUS 2019

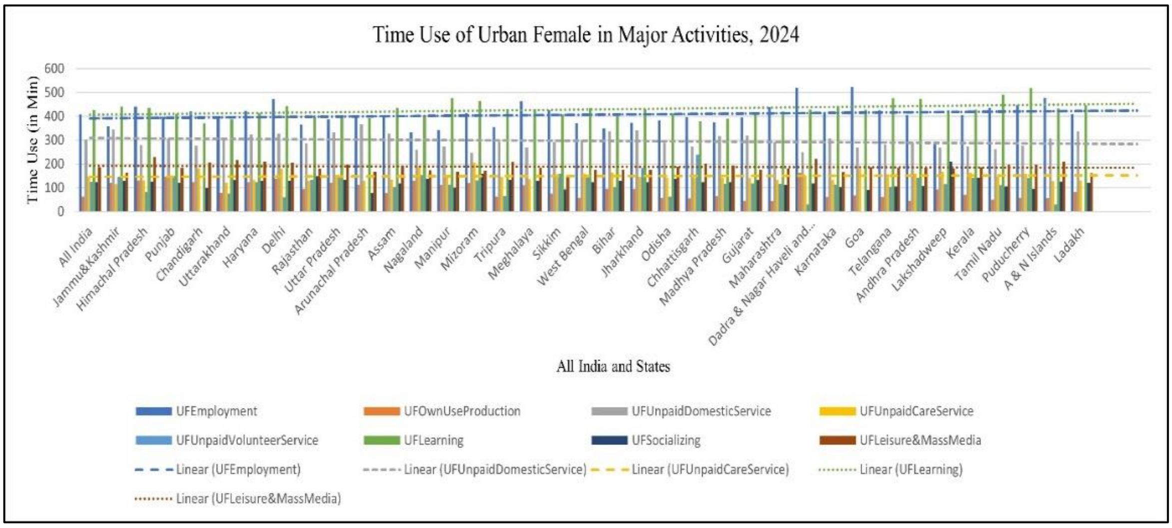

Fig.1d Time Use of India's Urban Female in Major Activities (as per ICATUS 2016), 2024
Source Based on author's calculations from TUS 2024

Following the graphical representation above (Ref. Fig.1a - 1d), the combined time spent by a female in India, be it in rural or urban setup, in unpaid domestic services care giving, happens to be more than 450 min/day which is more than the average time spent by a female in employment (~ 400 min/day), even in 2024. The comparative analysis of Time Use Survey data from 2019 and 2024 reveals that both rural and urban women in India reported spending less time on unpaid domestic services and caregiving in 2024 than in 2019. This shift suggests a potential redistribution of household responsibilities, possibly due to increased access to paid services or changes in household composition.

Furthermore, the data show that time spent on learning activities has also declined during the same period. This reduction may reflect time trade-offs or diminishing opportunities for meaningful capacity-building among women, thereby reducing income-generating activities.

Notably, the time spent on employment-related activities has remained essentially unchanged over the two years for rural and urban women. This further suggests that the time gained from decreased domestic and caregiving responsibilities has not been reallocated to income-generating activities. Such a trend highlights the critical need to explore how this "freed time" can be converted into economically productive engagement. In this context, mobilising caregiving and domestic services as recognised vocational or professional sectors presents a strategic opportunity. Doing so would not only improve labour force participation among women but also help bridge longstanding gender gaps in employment and income.

The regional patterns further substantiate this need. For instance, urban women in states such as Delhi and Mizoram continue to devote significantly more time to caregiving than the national average. This underscores the continued unmet demand for caregiving services, particularly in urban contexts, and suggests that these regions may be well-suited to the development of caregiving service entrepreneurship.

International experiences offer valuable insight in this regard. In countries such as Japan and across Europe, the demand for caregiving, particularly for older adults, is substantial. In India, skilling women in caregiving and domestic services and supporting them in setting up small-scale enterprises in these sectors could yield considerable economic returns. Such initiatives may also help formalise segments of the care economy that otherwise remain undervalued and invisible in national accounts.

Moreover, the TUS data further indicate that Indian women continue to devote a significant amount of time to learning activities, reinforcing the feasibility of skilling interventions. In this regard, Big Data and Artificial Intelligence (AI) tools can be instrumental in identifying location-specific, viable income-generating activities, tailored to prevailing ecosystem conditions, skill gaps, available resources, and individual preferences/aptitude. Once identified, targeted vocational training programmes can be developed to enable women currently engaged in unpaid work to transition into sustainable micro-enterprises. Facilitating forward and backward market linkages would further ensure the viability and longevity of these enterprises.

To translate these gains into tangible outcomes, henceforth, policy interventions and support must focus on removing structural barriers that hinder women's access to vocational training cum entrepreneurship and/or formal employment. Only then can the reduction in unpaid work observed between 2019 and 2024 lead to genuine economic advancement and empowerment for women in India.

Results from Available Averaged TUS Data for 2019 and 2024:

Paired t-tests quantify the statistical significance of gender disparities, comparing Female Unpaid Work (domestic services + caregiving) against Male Employment Time across India's 37 states/union territories (df=36).

a) **Table I: Paired t-Test Results Summary**

Location	Year	t-statistic	p-value	Mean Difference (min/day)	95% CI Lower	95% CI Upper
Rural	2019	-4.847	<0.001	-50.95	-72.26	-29.63
Rural	2024	-2.357	0.024	-29.59	-55.06	-4.13
Urban	2019	-12.619	$<10^{-14}$	-131.59	-152.74	-110.44
Urban	2024	-10.035	$<10^{-12}$	-104.38	-125.47	-83.28

Source Author's calculations from Time Use Surveys 2019/2024 (n=37 states).
Notes Negative differences indicate that female unpaid work exceeds male employment time—all tests paired by state (n=37).

b) **Table II: Graphical and Statistical Results Summary**

Year	Group	Unpaid Domestic + Caregiving (min/day)	Employment (min/day)	Gender Gap Vs Male Employment	Statistical Significance
2019	Rural Females	Higher	Unchanged	51 min (t= - 4.85, $p<0.001$)	↓ Significant
2024	Rural Females	Lower	Marginally ↑ (5-10%)	30 min (t= - 2.36, $p=0.024$)	↓ Significant
2019	Urban Females	Higher	Unchanged	132 min (t= - 12.62, $p<10^{-14}$)	↓ Highly Significant
2024	Urban Females	Lower	Improved (10-15%)	104 min (t= - 10.04, $p<10^{-12}$)	↓ Highly Significant

Source Author's calculations from Time Use Surveys 2019/2024 (n=37 states).
Notes ↓ = Statistically significant reduction in gender gap.

Statistical Interpretation

1. While the Table-I above summaries the results obtained, a detailed analysis of the results shared above yields statistically significant results reflecting a significant reduction in time spent by both rural and urban females on unpaid domestic services and caregiving, both together accounting for more than 450 minutes/day, which is more than the average time spent in employment (~ 400 minutes/day), between 2019 and 2024.

2. As tabulated in Table I, a paired t-test for rural female vs rural male yielded a mean difference of -50.95 minutes, with a 95% confidence interval of -72.26 to -29.63 minutes and a p-value < 0.001, indicating strong statistical significance.

3. Similarly, a paired t-test for urban female vs urban male found a mean difference of -131.59 minutes, with a 95% confidence interval of -152.74 to -110.44 minutes, again with a p-value < 0.001.

4. The negative t-value indicates a decrease in the average time. Both rural and urban women spent less time on unpaid care work in 2024 than in 2019, and this decline is unlikely to be due to random variation.

5. The highly significant p-value (p < 0.001) confirms that the observed reduction in unpaid care and domestic work time among females is real and meaningful, not a product of random fluctuations. This trend underscores an important policy and development window to formalise the care economy and support female entrepreneurship in these sectors.

6. Further, despite fluctuations in unpaid work, the time females spend on employment has remained almost unchanged for both rural and urban groups over the same period.

7. The persistence of employment hours alongside decreasing unpaid care and domestic responsibilities may indicate a gradual rebalancing between productive and reproductive work for females.

The above points, which are statistically significant and vital, indicate a major missed opportunity to advance women's economic empowerment in the country, as the reduction in unpaid work has not been translated into increased paid-work participation in practice. This gap presents both a challenge and an opportunity: the challenge of unutilized productive time and the opportunity to transform unpaid labour into formal economic activity.

Inferences Drawn

The likely range of the actual difference in the population is estimated to be between 30 and 72 additional minutes (mean = 51 minutes) of unpaid work per day for rural women, and between 110 and 153 additional minutes (mean = 132 minutes) for urban women. These estimates, derived from averaged data at the state and/or national level, are expected to vary when disaggregated district-level data are analysed. Such micro-level data will enable the identification of existing correlations and statistically significant variables, thereby enabling the use of Data Science (DS) and Machine Learning (ML) modelling to design efficient strategies for channelling unpaid work into customised, small-scale yet high-impact enterprises.

For instance, in Delhi, where policy proposals are being considered to provide hand-holding support for income-generating activities among the unpaid female workforce, it is evident that significant customisation is required. The economic and social ecosystem, as well as the prevailing skill gaps, vary widely between women in Nangloi (North Delhi) and those in Seemapuri (East Delhi), necessitating differentiated intervention strategies. A similar distinction applies to women from Aizawl and Zoram in Mizoram, who may require tailored approaches to enterprise development.

Accordingly, there is a pressing need for access to Big Data generated at the micro level, derived from primary respondent-level data collection. Such data are essential for training AI models to accurately assess the diverse and nuanced requirements of target beneficiaries, thereby minimising errors in needs assessment. This, in turn, will facilitate the effective implementation of policy interventions to transform unpaid work into viable, income-generating enterprises.

This massive economic contribution, overwhelmingly provided by women, presents both a challenge and an opportunity. A significant policy shift is required: accounting for unpaid work in national statistics and developing entrepreneurial ecosystems capable of transforming unpaid labour into income-generating, productive activities. Data-driven technologies can play a key facilitative role in this transition.

Entrepreneurial and Policy Opportunities in Developing Countries like India

It is worth noting that India's care economy is still in its early stages. The ORF 2023 report proposes a national care policy that combines entrepreneurship, skills development, and gender-sensitive data systems. NITI Aayog and state missions on start-ups can catalyse by investing in women-led start-ups to scale and formalise domestic service industries. Public-private projects can build care entrepreneurship clusters with digital networks, incubation support, and market linkage.

The working future needs to incorporate the invisible support structure of unpaid work into its economic plan. By harnessing the latent strength of meaningful information extraction from the data available and converting it to knowledge through appropriate tools of Data-driven Analytics in formalizing care provisioning, India or any developing country, can avoid time poverty and gender-based injustice, while also exploring a significant opportunity for GDP growth of an estimated 27% if women's engagement in the economy increases substantially (IMF, 2018). Here is an example of such a possibility in the case of India:

A K-Means clustering simulation done with the help of the data available, using conventional Machine Learning (ML) techniques and trained on five key indicators-- (i) percentage of skilled workforce, (ii) employability index, (iii) vocational training participation, (iv) digital literacy rate, and (v) education level (secondary and above)-- has enabled the classification of Indian states into three distinct clusters of skill readiness: High, Moderate, and Low. The “Skill Map” (Ref. Fig.2) below provides a snapshot of India’s preparedness for targeted entrepreneurship investment, indicating the robustness of the techniques used for replication in the global context.

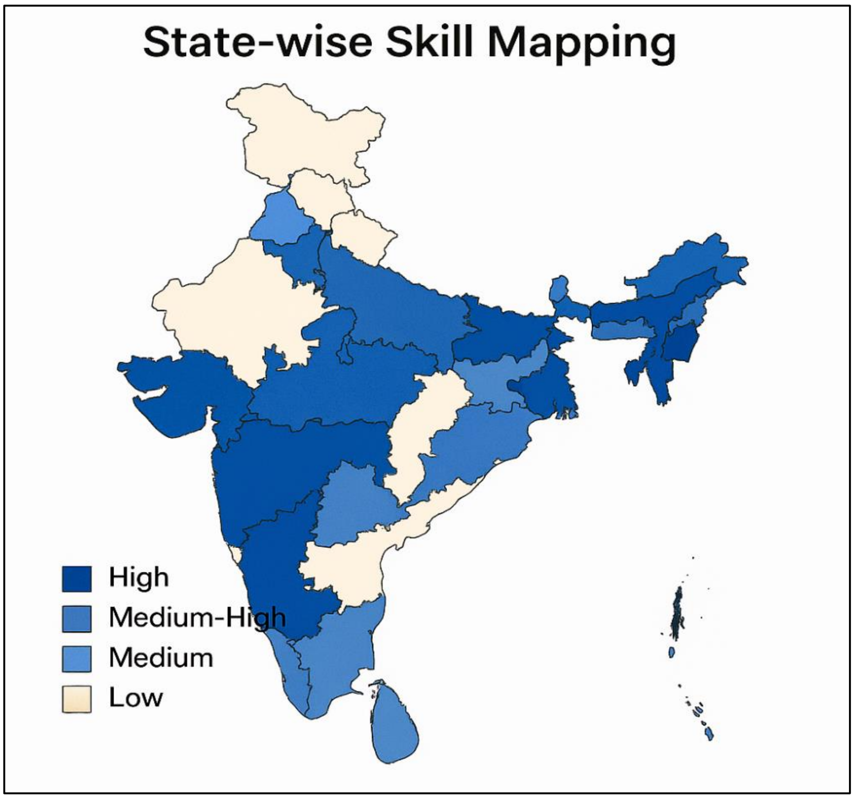

Fig.2 State-wise Women-centric Skill Mapping in India post-intervention of a globally suitable technique: ML-based simulation results based on the data available on skill from MSME, MoS, Govt. of India.

In addition, and very interestingly, even with one of the most robust models applied to state-averaged data, the results reveal certain inconsistencies. For example, Andhra Pradesh, one of the southernmost states in India, is identified as "not skill-ready". At the same time, the entire North-Eastern Region (NER) of India appears to fall into the "skill-read" category. Such findings highlight the limitations of state-level aggregation, which may mask regional disparities and local potential.

To address this, it is imperative to shift the focus toward district-level analysis without averaging, especially when formulating strategies to leverage the vast pool of unpaid female workers engaged in domestic and caregiving roles. A more granular dataset linking unpaid work to women's existing skill sets in the working-age population would enable policymakers to develop highly customised, location-specific prescriptions for enterprise promotion.

For instance, had such a dataset been available, the Skill Map could have accurately identified whether weaving or readymade garment manufacturing should be prioritised in Jaipur, Rajasthan, a state in India’s western border or at Sualkuchi, located in Assam, a bordering state in the eastern border, based on local expertise, time availability, and market alignment. To further substantiate this argument, this is especially relevant in the context of the recently signed India–UK Free Trade Agreement, which aims to promote local products in global markets with assured quality, compliance, and adherence to international standards.

Analysing Data and the Landscape of Unpaid Labour: Uncovering the Invisible

Through time-use survey data, India's 2019 Ministry of Statistics report revealed a 300% gender time gap in routine caregiving and domestic chores, reaffirming the long-standing gender inequalities in the country. Globally, unpaid care work accounts for 10–39% of GDP, depending on the country and valuation metric (OECD 2019). In India, women's unpaid care work accounts for an estimated 15–17% of the country's GDP—more than the manufacturing sector's share (NITI Aayog 2022). With the advent of Big Data, there is an unprecedented opportunity to quantify and acknowledge these contributions, thereby highlighting their significant impact on the economy. While older surveys relied on paper-based diaries or enumerator estimates, newer digital tools—such as smartphones, home assistants, and app data—offer continuous data flows that can provide high-frequency updates on unpaid activities in the region.

This Data-driven analytics enables the collection and analysis of vast amounts of information from various sources, including time-use surveys, social media platforms, and other digital footprints. These data can be used to estimate the time individuals spend on unpaid labour, providing a clearer picture of its economic value. For instance, time-use surveys can reveal how many hours people devote to activities such as cooking, cleaning, childcare, and elder care. By aggregating and analysing this data, economists and policymakers can gain insights into the true scope of unpaid labour and thereby uncover its hidden contribution to the economy. Intelligent kitchen assistants track the time spent on food preparation. Health-monitoring devices record elder-care routines. Motion-sensor data in smart homes can establish patterns of caregiving. As this data aggregate, AI models can be trained on gender-disaggregated time-use data, which can help recognise, compare, and even estimate the opportunity costs of unpaid work across geographies.

Recognising the value of unpaid labour has several important implications. Firstly, it can lead to more informed and equitable policy-making. Governments can use data on unpaid labour to design policies that better support those who perform these essential tasks. For example, recognising the economic value of caregiving can inform the development of social safety nets, tax credits, or subsidies for caregivers, thereby providing financial support to unpaid caregivers. It can also help create an entrepreneurial support network by formalising and recognising the informal and unrecognised sector, known as the Care Economy, which, in turn, fuels economic growth in any country.

Secondly, it can raise public awareness about the importance of unpaid labour. By quantifying and showcasing the economic impact of these activities, it becomes easier to advocate for greater recognition and appreciation of unpaid work and, thereby, to inform policy formulation toward a gender-inclusive society. This can lead to cultural shifts that value and respect the contributions of unpaid labourers, ultimately fostering a more gender-inclusive and fair society.

Additionally, businesses can leverage Big Data to understand the interplay between paid and unpaid labour. For instance, companies can analyse data to identify how unpaid labour influences consumer behaviour and purchasing decisions. Understanding these dynamics can help businesses develop products and services that better cater to the needs of individuals who perform unpaid labour. For example, recognising caregivers' time constraints can inspire the development of time-saving household products or services, thereby improving their quality of life.

Moreover, gender disparities in unpaid labour can also be uncovered using these Data-driven tactics. Historically, unpaid labour has been disproportionately shouldered by women, contributing to gender inequality. By analysing data on the distribution of unpaid labour, policymakers and advocates can identify and address these disparities, promoting gender equality. This can lead to initiatives that encourage more equitable sharing of unpaid labour between genders, as well as policies that support women’s role in balancing paid and unpaid work, thereby putting a check on time poverty.

The integration of Big Data into the analysis of unpaid labour offers a powerful tool for recognising and valuing these essential contributions to the economy. By providing a clearer understanding of the scope and impact of unpaid labour, Data can help structure more equitable policies, raise public awareness, and promote gender equality. As we continue to harness the power of Big Data, it is crucial to ensure that the value of unpaid labour is acknowledged and incorporated into our economic systems and societal norms, thereby enabling us to meet the Sustainable Development Goals.

Moreover, the household member involved in caregiving activities may be trained in various data-handling tools, ranging from labelling and annotation to data processing and AI/ML operations, so that their allied service can, in more ways, add further value to the economy.

Uncovering the Dual Impact of Data-driven AI Technologies: From Marginalisation to Empowerment in Unpaid Labour

The shift to Data-driven automation through Artificial Intelligence (AI) has significantly impacted the value of unpaid labour. Many repetitive, mundane, and rule-based tasks, such as pumping water to overhead tanks, switching lights on and off, cooking standard dishes, and washing dishes or clothes, are increasingly being automated. This trend raises concerns about the further deprivation of compensation for unpaid labour. As machines take over these routine tasks, the already unrecognised and uncompensated contributions of unpaid labour may be further marginalised, potentially leading to greater economic and social disparities for those traditionally performing these tasks (Siebert & Wilson 2013). Hence, the question arises whether this shift will result in greater deprivation of compensation for unpaid labour.

This economic dilemma, however, leads us to a few other possibilities. AI and Big Data have enabled the development of smart home technologies and robotics that can perform routine household tasks. This automation of unpaid labour through Data-driven AI technologies has led to significant time savings for individuals, thereby allowing them to allocate their time to other productive activities or leisure. This shift in the agent of work has the potential to increase women's overall economic productivity and well-being. Besides, by reducing the burden of unpaid labour, these technologies have the potential to contribute towards greater gender equality, as women have traditionally performed a larger share of household chores. For example, in India, platforms like UrbanClap (now Urban Company) began onboarding domestic workers formally through apps in major cities. Although not fully representative, they reveal initial steps: providing visibility, payment systems, and labour rating mechanisms for a class of work that was previously informal and non-transactable.

Strikingly, by automating previously unpaid tasks through the production of newer technologies, the economic value of these tasks has become more visible and measurable, potentially leading to a greater appreciation of traditionally undervalued labour.

Additionally, the automation of unpaid labour through Big Data-driven AI technologies not only reduces the burden of routine tasks but also leads to the creation of new paid labour opportunities and innovation in R&D. As technology advances, new industries and job roles emerge in areas such as AI development, data analysis, and the maintenance and operation of smart home devices. This shift creates employment opportunities in high-tech fields, thereby diversifying jobs.

Further, by automating repetitive, time-consuming tasks, Big Data-driven AI technologies allow individuals to focus on more complex, productive activities in both their personal and professional lives. This increase in productivity can lead to higher economic output, as individuals can contribute more effectively to the workforce. The time saved from household chores can be redirected towards professional development, entrepreneurship, or other productive endeavours, further boosting economic growth.

The economic benefits of automating unpaid labour are not confined to individual households or local economies. As AI and Data-driven technologies become more widespread, they have the potential to boost global economic growth. Increased productivity, job creation, and consumer spending contributed to a more robust and dynamic global economy, with positive impacts on international trade and economic development.

The intersection of Big Data, AI, and unpaid labour presents both opportunities and challenges. While automation can significantly reduce the burden of unpaid labour and create new economic opportunities, it also necessitates a rethinking of how we value and compensate for such work. By addressing these challenges thoughtfully, we can harness the power of AI and Big Data to create a more equitable and productive society.

Using Data in the Development of Entrepreneurship in the Unpaid Care Economy

The unpaid care economy, including caregiving, domestic work, and housekeeping, is an intangible yet indispensable force behind the global economy. Despite its central role, unpaid work is largely absent from national accounting systems. Unpaid care and domestic work worldwide account for nearly 9% of global GDP, valued at approximately USD 11 trillion (APEC 2022). In India, the value of unpaid domestic work accounts for 26%-36% of the country's GDP, depending on the valuation method used (replacement cost versus opportunity cost).

By applying AI and Data-driven technologies to identify patterns in household time-use and area-based care deficits, time-poverty hotspots can be mapped, and specific interventions informed. For example, India's time-use surveys (TUS) reveal that women spend more than 4.6 hours per day on unpaid domestic work, more than twice as much as men. Such data can inform the establishment of community-based care cooperatives, daycare centres, elder-care services, and domestic support platforms, thereby create local employment and reduce the burden of unpaid work.

One significant approach in this direction is to advance entrepreneurship in the care economy, particularly within the framework of women's economic empowerment. Online marketplaces based on AI, as well as on Data-driven technologies, can:

- Match caregivers with service users in need (childcare, elder-care, domestic help).
- Offer real-time scheduling and optimisation solutions for gig-based care work.
- Enable mobile-based micro-entrepreneurship among rural women, with training and digital payment integration.
- Develop forecast models for future demand for care services, with implications for vocational education and skills development.

Not only do these innovations value informal work, but they also align with Sustainable Development Goal 5.4, which recognises the need for the redistribution of unpaid domestic and care work.

CONCLUSION AND POLICY RECOMMENDATIONS

The careful integration of recognition of care work into the digital economy development strategies has significant implications for achieving the Sustainable Development Goals, particularly those related to gender equality (SDG 5), decent work (SDG 8), and reducing inequalities (SDG 10). Yet, as this paper demonstrates, through India's Time Use Survey data (2019 and 2024), a critical missed opportunity significantly persists where women's freed time from reduced unpaid care work has not translated into labour-market participation, leaving substantial scope for time poverty and economic potential unrealised.

Policy Pathways to Bridge the Missed Opportunity

- **Incorporate Unpaid Labour in Economic Surveys:** Expand the scope and frequency of Time Use Surveys using mobile-friendly, participatory data collection methods. District-level, unaggregated data are essential for identifying care deficits and skill readiness, moving beyond state averages that mask regional disparities and local potential.

- **Facilitate Data-Driven Entrepreneurship:** Use granular time-use and skill data to target support and transition informal, unpaid care work into formalised micro-enterprises, women-led cooperatives, and care-economy clusters. This addresses the core missed opportunity: converting freed time into viable income and labour-force participation.

- **Recognise and Value Care Work in Social Protection:** Provide pension credits, caregiver stipends, or service vouchers linked to formalised care platforms, ensuring that recognition translates into tangible economic support and social security coverage.

- **Offer Digital Skills Training for Informal Workers:** Prioritise women entering care platforms with combined skill development, safety measures, and insurance coverage, reducing the risk that automation and AI further marginalise unpaid caregivers.

- **Incentivise Ethical Care Platforms:** Develop standards for care economy platforms, including minimum wages, grievance redressal, and data security compliance, ensuring that data-enabled formalisation does not reproduce exploitation.

- **Democratize Data:** Create anonymised, disaggregated public datasets on unpaid work to aid researchers, NGOs, and technologists in building inclusive ecosystems and identifying location-specific entrepreneurial opportunities.

Recent developments in international trade policy underscore the growing recognition of gender-inclusive economic frameworks. The India–UK Free Trade Agreement (FTA) has introduced gender-sensitive trade provisions, enabling duty-free access to the UK's $23 billion market specifically for women artisans and entrepreneurs. The agreement also includes targeted support for women-led SHGs, cooperatives, and MSMEs through training, finance, and skill development, while providing protection of intellectual property rights and zero tariffs to enhance global market access for women weavers, stitchers, and crafters.

This policy shift creates a compelling opportunity to leverage micro-level data analysis to identify women engaged in unpaid domestic and caregiving work, particularly those whose time burdens have declined without commensurate labour-market entry, and to guide them toward work-from-home enterprises that are viable in their local contexts. Such data-informed planning can ensure that women are not only economically empowered but also gain social recognition within households. When women's earnings become visible and significant, it paves the way for greater household cooperation in unpaid work, fostering equity in responsibilities and parity in decision-making, thereby addressing both the economic and social dimensions of gender empowerment and reducing time poverty at the household level.

The revolutionary potential of AI, Big Data and Data-driven analytics lies not only in optimising market-driven profit mechanisms but also in transforming how we measure human labour, including the invisible, unpaid work that sustains households and societies. As this work demonstrates, unpaid care work accounts for an estimated 26–36% of India's GDP, yet it remains excluded from formal economic measures globally. By incorporating data-driven analyses into time-use research, we open pathways for recognition, visibility, and transformative change in the workforce and economy. Yet realising this potential requires deliberate policy action to ensure that visibility translates into opportunity capture and that freed time becomes genuinely available for income generation.

Entrepreneurial growth is the future for the care economy. With precise, district-level data on time-use burdens, care deficits, and demographics, unmasked by state-level averaging, it is possible to develop women-centred, tailored micro-enterprises in childcare, eldercare, and home-based support services. Data-driven analytics tools can incorporate individual choices, preferences, and constraints of the workforce engaged in unpaid work and match them to client needs. Digitally enabled solutions tackle time poverty and create inclusive jobs, aligning with targets for SDG 5.4 and India's future work policies, while directly addressing the missed opportunity of converting reduced unpaid care hours into sustained economic participation.

Big data is a key driver of the new economy, reshaping how businesses operate and engage with consumers through automation that detects and predicts evolving anomalies across economic sectors. By analysing large datasets, companies can improve efficiency, customise offerings, and promote innovation, leading to substantial economic growth. However, this also raises concerns about data privacy, security, and monopolistic concentration of value.

A critical issue which is directly evident in this paper's findings concerns the potential regressive impact of data-driven AI-based automation on unpaid labour. India's 2019 and 2024 TUS data reveal that, although women's time in domestic services, caregiving, and self-learning has declined, their employment time remains unchanged, and time poverty persists. This paradox suggests that automation and algorithmic efficiency may hollow out unpaid work without creating commensurate formal opportunities, thereby missing an opportunity to harness automation for inclusive growth.

We can turn this challenge into an opportunity by consciously adopting big data and AI transformations with deliberate equity safeguards. As the new economy evolves, it is crucial to strike a balance between the benefits of big data and its inherent risks, ensuring that data-driven technologies serve inclusion rather than concentration. By recognising and valuing unpaid labour in developing economies, policymakers can foster a more comprehensive understanding of the economy and support fairer policies. AI-driven technology and data analytics can enable both individual empowerment and long-term sustainability. This is the transformative agenda this paper advances: converting the missed opportunity of invisible care work into a data-enabled, gender-inclusive care economy that alleviates time poverty, generates decent income, and rebalances power within households and labour markets.

Only through integrated policy reform, investment in care infrastructure, the establishment of gender-disaggregated micro-level data systems and extension of the present analysis to extract the otherwise invisible attributes influencing women’s time poverty, and the creation of ecosystems that enable informal workers to become entrepreneurs can we connect digital transformation with gender justice and realise the next economic revolution: a data-rich, care-inclusive, time-equitable, sustainable economy in the global perspective.

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Statement and Declarations

Ethical Considerations:

As a secondary-data-based study, the research does not involve direct interaction with human subjects. All data used is anonymised and publicly available. Care has been taken to ensure cultural sensitivity in the interpretation of gender norms and regional practices.

Declaration of Conflicting Interest:

- The author has no relevant financial or non-financial interests to disclose.
- The author has no competing interests to declare that are relevant to the content of this article.
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