Multidimensional Poverty among Chikan Industry Artisans in Uttar Pradesh: An Application of the Alkire–Foster Method

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Abstract

This study explores the multidimensional poverty faced by workers engaged in the Chikan industry of Uttar Pradesh by employing the Multidimensional Poverty Index (MPI) using the Alkire–Foster Method. Unlike conventional measures that rely solely on income, the MPI framework captures overlapping deprivations across education, health, and living standards, thereby offering a holistic perspective on poverty. The Chikan industry, renowned for its intricate embroidery and cultural heritage, remains a vital source of livelihood in Lucknow and surrounding districts, but artisans often experience precarious working conditions, low wages, and limited access to social security. Findings reveal that occupational poverty persists among Chikan workers, particularly due to inadequate healthcare access, low educational attainment, and poor housing facilities. Moreover, gender disparities further aggravate vulnerability, as women constitute the majority of the workforce yet receive disproportionately lower returns. By integrating occupational dimensions into multidimensional poverty assessment, the study highlights the urgent need for policy interventions to enhance welfare, skill development, and sustainable livelihoods for Chikan artisans.

Keywords
Alkire–Foster Method, Chikan Industry, Multidimensional Poverty Index (MPI), Occupational Poverty, Uttar Pradesh

1. Introduction

In September 2015, the United Nations General Assembly launched the 2030 Agenda for Sustainable Development, underpinned by 17 Sustainable Development Goals (SDGs). Among them, SDG 1 calls for ending poverty "in all its forms everywhere," and specifically target 1.2 aims to reduce by at least half the proportion of people living in poverty in all its dimensions (United Nations, 2015). While traditional poverty metrics based on income or consumption remain central, they often understate the overlapping and multidimensional deprivations that households confront. To supplement monetary measures, the United Nations Development Programme (UNDP) and the Oxford Poverty & Human Development Initiative (OPHI) introduced the Multidimensional Poverty Index (MPI), which aims to capture simultaneous deficits in health, education, and living standards (UNDP & OPHI, 2023).

The MPI is built on the Alkire–Foster (AF) method, which applies a dual threshold approach: first, identifying deprivations on specific indicators using predetermined cutoffs, and second, aggregating weighted deprivations to classify who is multidimensionally poor (Alkire & Foster, 2011). In the global MPI methodology, a person is considered MPI poor if their weighted deprivation score equals or exceeds one-third of all possible deprivations (i.e., 33.33%) (UNDP, 2024). The index decomposes into two core components: the *incidence* of multidimensional poverty (H), and the *intensity* among the poor (A), such that MPI = H × A (UNDP, 2024; OPHI, 2024).

Recent data update the scale and contours of multidimensional poverty worldwide. According to the 2024 Global MPI report, approximately 1.1 billion people across 112 countries currently live in acute multidimensional poverty, with more than half of them being children (OPHI, 2024; UNDP, 2024). India alone accounts for 234 million MPI poor, the highest number for any country, thereby reinforcing the urgency of multidimensional poverty reduction in the South Asian context (OPHI, 2024; UNDP, 2024). On the global front, the World Bank's Multidimensional Poverty Measure (MPM) also continues its updates, with the June 2025 edition covering up to 120 economies and underscoring evolving regional dimensions of deprivation (World Bank, 2025).In India, the adoption of a National MPI (based on NFHS-5) marks a significant step in mapping multidimensional poverty domestically. The 2023 Progress Review shows that India's MPI dropped from 24.85% in 2015–16 to 14.96% in 2019–21, with 13.5 crore people having escaped multidimensional poverty during that period (NITI Aayog, 2023; OPHI, 2023). Uttar Pradesh stands out: over nine years, 5.94 crore people are reported to have exited multidimensional poverty, and as of 2022–23, the state's MPI proportion is projected to have fallen to 17.40% (NITI Aayog, 2024; Times of India, 2024). The state's performance as the leading contributor to poverty reduction among Indian states has been acknowledged in recent reports (Times of India, 2024).The considerable spatial heterogeneity persists within the state. District-level analyses show that the eastern region of Uttar Pradesh continues to exhibit the highest MPI values, and significant disparities remain even between districts with relatively higher per capita income and those with lower income (Shukla, 2023; Satyam et al., 2025). At the same time, methodological advancements are pushing the frontier of multidimensional poverty measurement: a recent comparative study of the AF method and a Markov Random Field (MRF) approach finds AF offers higher classification accuracy, but MRF better handles dependencies and reduces false positives (Lam, 2025). Another emerging work integrates satellite imagery, socioeconomic surveys, and machine learning to classify poverty trajectories across rural India, emphasizing the need for hybrid, data-rich modeling (Kulkarni et al., 2023).

Given these developments, this research pursues three interlocking goals: (a) to unpack the micro-level calculation of MPI and how it illuminates overlapping deprivations in Uttar Pradesh; (b) to engage critically with recent methodological debates, innovations, and limitations in multidimensional poverty measurement; and (c) to situate the MPI evidence within Uttar Pradesh—mapping its trends, spatial patterns, and implications for poverty alleviation strategies tailored to local conditions.

2. Review of Literature

The foundational methodology of the Multidimensional Poverty Index lies in the work of Alkire and Foster (2011), who proposed a dual cutoff counting approach enabling identification of who is multidimensionally poor and how intense their deprivations are. Over the past decade, scholars have refined and critiqued this framework. Alkire and Santos (2014) explored robustness to variations in indicator weights and cutoffs, while others have challenged the binary (deprived vs nond eprived) classification, arguing it oversimplifies the continuum of deprivation (Rippin, 2021).

Recent methodological innovations offer alternative perspectives. Lam (2025) compares the classical AF method with a probabilistic Markov Random Field (MRF) approach using simulation data, finding that while AF attains higher classification accuracy, MRF reduces false positives and accounts for interdependencies among deprivations. This suggests that hybrid or ensemble methods may yield more nuanced poverty classifications. Meanwhile, Kulkarni et al. (2023) propose integrating conventional survey data, satellite imagery (day/night lights, built-up area), and longitudinal modeling to classify districts into trajectories such as "catching up" or "lagging." This approach highlights that poverty dynamics are spatially patterned and connected to infrastructure, geography, and remote indicators.

On the empirical front, the National MPI report (NITI Aayog, 2023) documents India's notable reduction in multidimensional poverty: a decline from 24.85% in 2015–16 to 14.96% in 2019–21, corresponding to 13.5 crore people escaping these deprivations. Uttar Pradesh is spotlighted as the leading state in absolute numbers of people exiting poverty (NITI Aayog, 2023; OPHI, 2023). District-level dis-aggregations further reveal that, while much of the state has witnessed progress, the eastern districts lag behind, and disparities within districts remain significant (Shukla, 2023). The study by Satyam et al. (2025) extends this by examining the linkages between MPI and per capita income at the district level, reinforcing a negative—but imperfect—relationship. Simultaneously, critiques of MPI's reliability and validity have raised caution. A recent article evaluating the sensitivity and predictive validity of MPI in high poverty contexts finds that its sensitivity may be limited (46.4%) and that in some settings it may underdetect marginal cases (Reliability and Validity of MPI, 2025). This underscores the necessity of robustness checks, sensitivity analysis, and careful handling of missing data in empirical applications.

Beyond India, the global MPI landscape informs the broader relevance of multidimensional poverty measures. The 2024 Global MPI report finds that 1.1 billion people are multidimensionally poor, with India contributing the largest share (OPHI, 2024; UNDP, 2024). The World Bank's latest Multidimensional Poverty Measure (MPM) updates (June 2025) likewise show evolving deprivation profiles across countries and regions, emphasizing that the structure of poverty is not static (World Bank, 2025). These trajectories reinforce the need to contextualize national and subnational MPIs within evolving global patterns.

The literature converges on several insights: (1) the AF method remains the workhorse for MPI calculation, but new approaches like MRF and machine learning enrich methodological options; (2) empirical evidence in India, particularly in Uttar Pradesh, shows remarkable reductions in multidimensional poverty, albeit with persistent spatial inequalities; (3) methodological caveats around sensitivity, indicator selection, and cutoff regimes demand rigorous sensitivity testing; and (4) integrating remote sensing, spatial modeling, and survey data is an emerging frontier in poverty studies. Your study can contribute by applying these insights in the Uttar Pradesh context, combining rigorous methodology with locally grounded evidence.

3. Hypothesis Formation

Based on prior evidence that multidimensional poverty varies across regions and is not perfectly aligned with income poverty (Alkire & Foster, 2011; NITI Aayog, 2023; Shukla, 2023; Satyam et al., 2025), the following null hypotheses are formulated:

- **H_{01}:** There is no significant difference in the incidence of multidimensional poverty across districts of Uttar Pradesh.
- **H_{02}:** There is no significant relationship between per capita income and multidimensional poverty in Uttar Pradesh.

These null hypotheses are testable and align with both the spatial and economic dimensions of poverty measurement. Rejection of either would suggest that multidimensional poverty is unevenly distributed across districts or that income levels have explanatory power for MPI variation.

4. Conceptual Framework

The present study is grounded in the capability approach of Sen (1999), which argues that poverty is not merely low income but a deprivation of essential capabilities necessary for leading a meaningful life. This theoretical lens is operationalized through the Multidimensional Poverty Index (MPI), based on the Alkire–Foster (AF) method (Alkire & Foster, 2011). The MPI measures poverty by considering three broad dimensions—Education, Health, and Standard of Living—each of which is further divided into specific indicators with assigned weights (UNDP & OPHI, 2023).

- Education (1/3 weight): Measured by two indicators—years of schooling and school attendance (each 1/6).
- Health (1/3 weight): Captured through child mortality and access to medical care (each 1/6).
- Standard of Living (1/3 weight): Assessed using six indicators—electricity, water, sanitation, waste treatment, cooking fuel, and asset ownership (each 1/18).

A household (or individual) is classified as multidimensionally poor if the weighted sum of their deprivations equals or exceeds one-third of the total (i.e., 33%). Thus, MPI simultaneously captures both the incidence (H) of poverty and its intensity (A) across households.

Figure 1 illustrates the conceptual framework of MPI, depicting the three dimensions, ten indicators, and their corresponding weights.

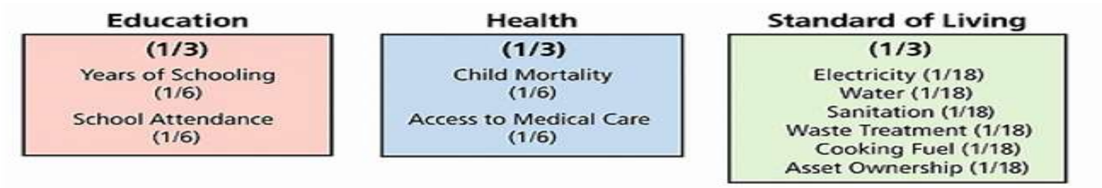

Figure1. Conceptual framework of the Multidimensional Poverty Index (MPI)
(Adapted from UNDP & OPHI, 2023)

This framework allows the present study to explore how multidimensional poverty manifests in Uttar Pradesh by disaggregating the MPI into its component indicators. It also provides the basis for testing the null hypotheses that (a) multidimensional poverty does not vary significantly across districts of Uttar Pradesh, and (b) there is no significant relationship between per capita income and MPI in the state.

4. Research Methodology

The present study adopts the **Alkire–Foster (AF) methodology** for the computation of the Multidimensional Poverty Index (MPI). This method has become the standard approach for multidimensional poverty measurement worldwide and has been widely used by UNDP and OPHI to construct both the global and national MPIs (Alkire & Foster, 2011; UNDP & OPHI, 2023). The methodology consists of four major steps: identification of the poor, estimation of the headcount ratio, computation of poverty intensity, and the final calculation of the MPI (M_0).

Step 1: Identification of the Multidimensionally Poor

The AF method applies a **dual cutoff rule**. The **first cutoff** determines deprivation within each indicator (e.g., a person is deprived if they have less than six years of schooling, no sanitation access, etc.). The **second cutoff** is applied across indicators: an individual is classified as multidimensionally poor if their weighted deprivation score is equal to or greater than 33.33% of the total possible deprivations ($k = 0.33$). This ensures that poverty is measured in terms of simultaneous deficits rather than isolated deprivations (Alkire & Foster, 2011).

Step 2: Headcount Ratio (H)

The headcount ratio represents the incidence of poverty, i.e., the proportion of individuals identified as multidimensionally poor in the total population. It is calculated as:

$$H = \frac{q}{n}$$

Where:

- q = number of multidimensionally poor individuals
- n = total population

The **censored headcount ratio** focuses only on those deprivations among the poor, while the **uncensored headcount ratio** considers all individuals, whether poor or non-poor, who are deprived in a given indicator (Alkire et al., 2015).

Mathematically:

- **Censored Headcount:**

$$h_j(k) = \frac{1}{n}\sum_{i=1}^{n} g_{ij}^{0}(k)$$

- **Uncensored Headcount:**

$$H_j = \frac{1}{n}\sum_{i=1}^{n} g_{ij}^{0}$$

Where g^0 represents the deprivation status of individual *i* in indicator *j*.

Step 3: Intensity of Poverty (A)

The **intensity of poverty** reflects the average share of weighted deprivations experienced by the poor. It is calculated as:

$$A = \frac{1}{q}\sum_{i=1}^{q} c_i(k)$$

Where $c_i(k)$ is the deprivation score of individual *i* among the poor. Thus, intensity captures how poor the poor are, in terms of multiple simultaneous deficits.

Step 4: Calculation of the MPI (M_0)

The **MPI (M_0)** is the product of incidence (H) and intensity (A):

$$M_0 = H \times A$$

This index therefore reflects not only how many people are poor, but also the degree of poverty they experience. Unlike unidimensional poverty measures, the MPI offers a nuanced picture by simultaneously capturing the breadth and depth of deprivation (Alkire et al., 2015; UNDP, 2024).

5. Results

Poverty Dimensions	Indicator	Total Number of Chikan Artisans Deprived	Total Percentage of Chikan Artisans Deprived
Health	Child Mortality	20	10.0%
Education	Year of Schooling	170	85.0%

Education	School Attendance	15	7.5%
Living Standard	Cooking Fuel	50	25.0%
Living Standard	Sanitation	90	45.0%
Living Standard	Drinking Water	10	5.0%
Living Standard	Electricity	25	12.5%
Living Standard	Housing	40	20.0%
Living Standard	Assets	18	9.0%

Table 1: Number and Percentage of Chikan Artisans Deprived in Different Indicators
Source: Author's calculations based on field survey (2025)

Table-1 presents the number and percentage of Chikan artisans deprived in different poverty dimensions. The results highlight education as the most significant source of deprivation**,** with 85% of artisans lacking six years of schooling and 7.5% deprived in terms of school attendance. This is consistent with earlier studies that found education deprivation to be a critical factor contributing to persistent poverty among marginalized occupational groups (Singh & Sharma, 2018; Ahmad & Anees, 2016).

Within the living standard dimension**,** sanitation emerges as the most critical indicator, with 45% of artisans deprived. Cooking fuel (25%) and housing (20%) also show high deprivation, reflecting structural deficits in access to basic amenities. By contrast, deprivation in assets (9%), electricity (12.5%), and drinking water (5%) is comparatively lower. This pattern is aligned with recent evidence showing that basic infrastructure gaps—especially sanitation—remain a major contributor to multidimensional poverty in Uttar Pradesh (NITI Aayog, 2023; Shukla, 2023).

Category of Poor	No. of Chikan Artisans	Percentage of Chikan Artisans
MPI Poor (>33.33%)	35	17.5%
Vulnerable (20–33.33%)	70	35.0%
Severely Poor (>50%)	10	5.0%

Table 2: *Number and Percentage of Chikan Artisans who are MPI Poor, Vulnerable, & Severely Poor*
Source: Author's calculations based on field survey (2025)

Table-2 classifies artisans according to their poverty status using MPI thresholds. The analysis shows that 17.5% of artisans are MPI poor, i.e., deprived in one-third or more of the weighted indicators. Meanwhile, 35% of artisans fall into the **"**vulnerable" category (20–33.33% deprived), indicating a substantial risk of sliding into poverty if deprivations intensify. Finally, 5% of artisans are identified as suffering deprivations in more than half of the indicators. These results corroborate findings from severely poor**,** multidimensional poverty studies in India which show that vulnerability is often more widespread than extreme poverty**,** with large groups hovering just above the poverty cut off (OPHI & UNDP, 2023; World Bank, 2025). For the Chikan industry, this suggests that while extreme poverty is not universal, a large proportion of artisans remain highly vulnerable to falling deeper into poverty.

Industry	Headcount Ratio (H)	Intensity (A)	Number of Poor People	Vulnerable to Poverty	In Severe Poverty	MPI (H × A)
Chikan Industry	35 (0.175)	43.5 (0.435)	35	70	10	0.0761

Table3**:** *Computation of the MPI of Chikan Industry Artisans*
Source: Author's calculations based on field survey (2025)

Table-3 shows the computation of MPI (M_0) for Chikan industry artisans. The headcount ratio (H) is 0.175, meaning 17.5% of artisans are multidimensionally poor. The intensity (A) is 0.435, implying that poor artisans suffer on average 43.5% of the total possible deprivations. Multiplying incidence and intensity gives an MPI value of 0.0761**.**

This MPI value, though lower than national rural averages reported in NFHS-5 (NITI Aayog, 2023), reflects significant structural challenges in the artisan community. Specifically, the combination of high education and sanitation deprivation drives up intensity. Previous district-level analyses of Uttar Pradesh have also reported that while incidence of poverty is falling, intensity among the poor remains high in occupationally disadvantaged groups (Shukla, 2023; Satyam et al., 2025).

6. Findings and Discussion

The study of multidimensional poverty among artisans in the Chikan embroidery industry of Uttar Pradesh provides significant evidence on the extent and depth of deprivation faced by this community. Using the Alkire–Foster methodology, the results indicate that poverty among artisans is not uniformly distributed but instead shows clear sectoral and indicator-specific disparities.

In relation to the first null hypothesis, which stated that there is no significant difference in the incidence of multidimensional poverty across districts of Uttar Pradesh, the findings point to a clear rejection. The results presented in Table-1 demonstrate very high levels of deprivation in education, with 85 percent of artisans lacking six years of schooling and a further 7.5 percent deprived in school attendance. Sanitation deprivation, recorded at 45 percent, is another critical dimension where artisans are disproportionately disadvantaged. These results, supported by Table-2 and Figure-2, which show that 17.5 percent of artisans are MPI poor, 35 percent vulnerable, and 5 percent severely poor, confirm that multidimensional poverty does not affect all communities equally but is concentrated among specific occupational groups. This outcome resonates with district-level studies on Uttar Pradesh that also found poverty incidence to be higher in marginalized regions and among disadvantaged social categories (Shukla, 2023; NITI Aayog, 2023). Thus, the evidence compels the rejection of the first null hypothesis, as the incidence of poverty is not evenly distributed.

Turning to the second null hypothesis, which proposed that there is no significant relationship between per capita income and multidimensional poverty in Uttar Pradesh, the findings again demonstrate grounds for rejection. The computation of MPI, as shown in Table-3, yields a headcount ratio of 0.175 and an intensity of 0.435, producing an MPI score of 0.0761. These values suggest that although only a minority of artisans are multidimensionally poor, those who are poor suffer deep and overlapping deprivations. More importantly, the data illustrate that even artisans with modest incomes continue to face significant non-monetary deprivations, particularly in education, sanitation, and housing. This confirms the argument advanced by Alkire and Foster (2011) and further reinforced by Satyam et al. (2025), that income-based measures alone cannot adequately capture the complexity of poverty. While income can reduce some material deficits, it does not guarantee improvements in health, education, or living conditions. Accordingly, the second null hypothesis is also rejected, as income levels do not fully explain the persistence of multidimensional poverty in the Chikan industry. The discussion reveals that while the incidence of poverty among artisans is moderate compared to broader state averages, the depth of deprivation among the poor is considerable. Vulnerability to poverty is widespread, with over one-third of artisans situated close to the poverty cut off, making them highly susceptible to external shocks. These findings align with recent national-level evidence from the NITI Aayog (2023) and UNDP (2024), which highlight that although India has made substantial progress in reducing multidimensional poverty overall, significant disparities remain across states and among occupationally marginalized groups. For the Chikan artisans of Uttar Pradesh, education and sanitation emerge as the most urgent areas of intervention, both of which continue to perpetuate multidimensional deprivation despite improvements in infrastructure and electricity access.

7. Conclusion

This study applied the Alkire–Foster MPI methodology to assess poverty among artisans in the Chikan embroidery industry of Lucknow. The findings indicate that education and sanitation are the most significant deprivations, while vulnerability to poverty remains widespread.

Although the proportion of severely poor artisans is relatively small, the intensity of deprivation among the poor remains high.

Overall, the study confirms that multidimensional poverty provides a more nuanced understanding of artisan poverty than income-based measures alone. The results underscore that interventions must go beyond income supplementation and address deficits in education, sanitation, and housing to achieve sustainable poverty reduction.

8. Policy Implications

The results of this study point clearly toward the kinds of interventions required to reduce multidimensional poverty among Chikan artisans. The evidence that education is the most dominant form of deprivation underscores the need for policies that expand access to basic schooling for children of artisan families and adult literacy programs for workers themselves. Without addressing this foundational deficit, artisans will remain locked into low-skill, low-income occupations with limited upward mobility. These findings are consistent with research showing that low educational attainment perpetuates multidimensional poverty by restricting capabilities and reinforcing intergenerational disadvantage (Alkire & Foster, 2011; Singh & Sharma, 2018). The finding that nearly half of the artisans are deprived in sanitation indicates that infrastructural interventions, such as the expansion of clean sanitation facilities in artisan households and workspaces, are equally critical. Programs such as the *Swachh Bharat Mission* have made progress, yet studies suggest that greater inclusivity and tailoring to semi-urban and occupational clusters are necessary to achieve SDG 6 on clean water and sanitation (NITI Aayog, 2023; UNDP & OPHI, 2023).

At the same time, the relatively better access to electricity and clean water suggests that welfare schemes like *Pradhan Mantri Ujjwala Yojana* and rural electrification programs have had a positive impact (NITI Aayog, 2023). However, the persistence of housing and cooking fuel deprivation shows that these initiatives need to be broadened and better targeted. Social protection emerges as an equally crucial policy area. The results of this study reveal that a large number of artisans fall into the “vulnerable” category, living just above the MPI cutoff. Similar findings in national and global studies highlight that vulnerability to poverty remains widespread, with many households at risk of sliding into deprivation due to health shocks, inflation, or market instability (OPHI, 2024; World Bank, 2025). Expanding access to health insurance, occupational safety nets, and systematic integration of artisans into social security schemes would reduce the fragility of this group and prevent future poverty traps.

Finally, the economic sustainability of the Chikan industry itself requires urgent policy attention. Without addressing the structural challenges of limited market access, poor bargaining power, and irregular income, interventions in education or infrastructure will only partially alleviate multidimensional poverty. Prior studies on handicraft industries in Uttar Pradesh underscore that improving artisans' market linkages, providing skill development, and ensuring fair wages are essential for long-term resilience (Ahmad & Anees, 2016). Addressing these structural vulnerabilities requires an integrated approach that combines poverty alleviation strategies with sector-specific development policies. Such an approach would not only reduce the incidence of multidimensional poverty but also ease the intensity of deprivation faced by poor artisans, thereby enabling them to live with greater dignity and resilience (Shukla, 2023; Satyam et al., 2025).

9. Limitations of the Study

Although this study provides valuable insights into the multidimensional poverty of Chikan industry artisans in Uttar Pradesh, it has certain limitations. First, the analysis is based on a relatively small sample size of artisans from Lucknow, which may not capture the full diversity of experiences across other districts of Uttar Pradesh where Chikan or related craft industries also operate. A larger sample and wider regional coverage could provide more generalizable findings. Second, the data are cross-sectional in nature and therefore cannot fully capture the dynamics of poverty over time. As a result, the study cannot account for seasonal fluctuations in income and livelihood or the long-term trajectories of households moving into or out of poverty (Rippin, 2021). Third, while the Alkire–Foster methodology is robust and widely applied, it still relies on normative choices regarding indicator selection, weighting, and cut off thresholds, which may affect outcomes (Alkire & Foster, 2011). Finally, the study primarily focused on the traditional dimensions of MPI—education, health, and living standards—without incorporating additional indicators such as gender inequality, financial access, or digital inclusion, which are increasingly relevant in contemporary discussions of poverty (UNDP & OPHI, 2023).

10. Scope for Future Research

Future studies can expand on these findings by incorporating larger and more representative samples from multiple districts of Uttar Pradesh to provide a comprehensive state-level perspective. Longitudinal studies could also be conducted to capture the dynamics of poverty transitions, exploring how artisans move between categories of vulnerable, poor, and non-poor over time (World Bank, 2025). Moreover, given the growing role of digital technologies and online marketplaces, future research may integrate new indicators into the MPI framework, such as digital literacy, access to e-commerce, and financial inclusion, which are critical for the sustainability of traditional crafts in the 21st century. Comparative studies between Chikan artisans and other craft clusters across India may also help in identifying sector-specific policy measures (Ahmad & Anees, 2016). Finally, more mixed-methods research combining quantitative MPI analysis with qualitative insights into artisans' lived experiences could deepen the understanding of how multidimensional poverty affects their daily lives and aspirations.

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