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# Quantifying the Digital Divide: A Mixed-Method Analysis of Socio-Economic Determinants, Educational Employment Mismatch Index (EEMI), and Female Labor Force Participation in India (2017–2024)

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## ABSTRACT

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This study analyzes how digital access and educational attainment shape female labor force participation in India from 2017 to 2024. Using nationally representative unit-level data from the Periodic Labor Force Survey (PLFS) and National Family Health Survey (NFHS-5), it examines how digital inclusion and education jointly influence women's access to formal and decent employment. The findings reveal that while digital connectivity improves women's labor market entry, entrenched socio-cultural norms and regional disparities continue to restrict participation, particularly among rural and marginalized groups. To quantify this, disconnect, the study introduces the Educational–Employment Mismatch Index (EEMI), which captures the gap between women's academic qualifications and their presence in

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the formal sector. EEMI is computed only for women with more than 12 years of education to ensure valid mismatch detection Results show that education alone does not ensure economic inclusion unless complemented by digital infrastructure, institutional support, and gender-responsive labor policies. The paper calls for integrated strategies that bridge these gaps and enable meaningful female workforce participation.

## INTRODUCTION

Gender, technology, and labor force participation now sit at the core of global development debates. In advanced economies, digital innovations have redefined work, enabling flexible and platform-based employment that expands opportunities for women (OECD, 2022; UN Women, 2021). However, this digital transformation remains unequal. In sub-Saharan Africa, women are 23% less likely than men to access mobile internet (GSMA, 2023), while in Latin America, digital literacy gaps continue to limit women's inclusion in the formal sector (ECLAC, 2021). Globally, women hold 39% of the workforce but only 22% of tech jobs, reflecting a structural exclusion that cuts across regions (ILO, 2024).

The ASEAN region also reflects this divide. Despite high female labor force participation in Vietnam and Thailand, women still face restricted access to smartphones, e-learning, and digital finance (UN Women, 2021). In the Philippines, the rise in women-led digital enterprises during COVID-19 was temporary, hindered by poor infrastructure and skills (UN ESCAP, 2022). Indonesia and Cambodia show similar trends, where rural women face multiple digital and economic barriers (World Bank, 2022). These regional experiences emphasize the urgent need to examine how education, digital access, and structural conditions jointly influence women's labor outcomes especially in developing countries.

In India, most research treats education as a standalone variable or focuses on gendered employment gaps without considering digital access as an enabling factor. No prior study has merged digital inclusion with the concept of educational–employment mismatch. This paper fills that critical gap by introducing the Educational–Employment Mismatch Index (EEMI) and applying it to nationally representative PLFS and NFHS data (2017–2024). The study quantifies how rising education among women fails to translate into formal employment due to gaps in digital infrastructure and institutional support.

This mismatch is not incidental it is structural. Women may be educated, but without access to digital platforms or enabling policies, they remain

excluded from formal work. Fragmented solutions targeting only one dimension (e.g., schooling) are insufficient. The EEMI framework exposes how marginal improvements in one area cannot compensate for systemic barriers in the others. This three-way interaction education, digital access, and formal job inclusion demands policy attention. By operationalizing this disconnect, the study shifts the policy lens from piecemeal interventions to integrated diagnostics and holistic design.

The Fourth Industrial Revolution (4IR), characterized by rapid advancements in automation, artificial intelligence, and digital platforms, presents both opportunities and challenges for achieving gender equality in the labor market. While some scholars predict job displacement due to automation, others see 4IR as a catalyst for redefining prosperity, allowing more time for intellectual and creative pursuits (Cliff, 2018; Schulte & Howard, 2019). The impact on women's employment is particularly complex. A 2016 study highlighted the vulnerability of female-dominated sectors like garment and textile manufacturing to automation-led job losses (UNIDO, n.d.).

Several studies have emphasized that gender inequality in employment persists despite rising educational enrolment among women. Verick (2014) and Chatterjee et al. (2018) argue that structural constraints and labor market segmentation continue to hinder women's absorption into decent work. These include limited access to childcare, restrictive gender norms, and an education–employment mismatch that leaves even highly qualified women underemployed.

Digital exclusion further compounds this inequality. Chaudhary and Verick (2014) illustrate how poor internet penetration and lack of digital literacy significantly inhibit women's economic participation in India. The International Telecommunication Union (2020) and World Bank Group (2022) highlight the multiplier effect of digital access, suggesting that connectivity not only increases productivity but also enhances the returns to education. However, rural women remain at a severe disadvantage, facing barriers not only in infrastructure but also in skills and autonomy (GSMA, 2023; UN Women, 2021).

From a theoretical standpoint, Amartya Sen's Capability Approach offers a meaningful framework to understand this challenge. It argues that expanding access to resources like education or technology is insufficient unless these are converted into real freedoms—choices that enable women to lead lives they value (Sen, 1999). Studies by Altasseb et al. (2024) and Bhagavatheeswaran et al. (2016) reinforce this by showing that formal education alone is not enough unless accompanied by enabling social structures and policies.

At the same time, the concept of decent work, as advanced by the International Labor Organization (1999, 2024), emphasizes the importance of

quality employment—marked by fair wages, job security, and social protection. Indian labor markets, however, remain heavily informalized, with nearly 90% of the female workforce employed in insecure and low-paying jobs (ILO, 2024).

Efforts by the Indian government, such as the Skill India Mission, aim to address these gaps by promoting vocational training and employability through public-private partnerships (Sharma, 2024). Yet studies (Munjal, 2024; Sethy & Sethi, 2024) suggest a limited alignment between skilling programs and the actual demands of the labor market, especially for women.

Corporate efforts, while promising, are also uneven. Firms such as TCS, Nestlé, and HCL have adopted gender diversity policies (Puri, 2022), but systemic barriers such as wage gaps, workplace discrimination, and lack of childcare persist.

Taken together, the reviewed literature affirms that women's economic empowerment in the 4IR era requires more than education or technology. It demands an integrated approach that recognizes intersectional challenges related to gender, class, geography, and digital access and reforms institutional, infrastructural, and cultural norms accordingly.

The economic development of Asia has been characterized by rapid structural transformation, technological integration, and demographic shifts. However, these macroeconomic gains have not uniformly translated into equitable labor market outcomes, particularly for women. Several studies highlight that Asia's female labor force participation (FLFP) presents a paradox: countries like Vietnam, Thailand, and China exhibit high participation rates, while others such as India, Pakistan, and Bangladesh lag significantly behind despite improvements in female education (Asian Development Bank, 2021).

In countries like the Philippines, digital entrepreneurship surged during the COVID-19 pandemic, driven largely by women-led informal businesses (UN ESCAP, 2022). However, these gains were often temporary and precarious, hindered by fragile digital infrastructure and lack of access to formal credit. In Indonesia, rural women continue to face compounded barriers low internet access, inadequate upskilling programs, and informal work traps curtailing their entry into productive sectors (World Bank Group, 2022).

Economists have increasingly emphasized the role of educational–employment mismatch in Asia's labor markets. For instance, Lee and Kim (2020) highlight in the South Korean context that a surplus of tertiary-educated workers often results in underemployment and dissatisfaction among youth, a trend mirrored in India. Similarly, Yap and Tan (2023), in their study of Malaysia, found that women with post-secondary education were more likely to be unemployed than their less-educated counterparts, suggesting misalignment between skill

supply and labor demand. Similar trends have been observed in Southeast Asia. Mendoza and Talavera (2021) highlight that educational mismatch significantly undermines women's employment outcomes in the region, despite rising levels of female schooling.

The concept of digital inequality has also entered the mainstream discourse on labor economics in Asia. According to GSMA (2023), women in low- and middle-income Asian countries are 19% less likely than men to use mobile internet. This digital gender gap limits access not only to job opportunities but also to online education and financial inclusion tools, reinforcing cyclical patterns of exclusion. Soriano (2022) found that digital literacy mediates the relationship between education and employment in several ASEAN economies, underscoring the role of ICT in shaping labor outcomes for women

In this context, the introduction of the Educational–Employment Mismatch Index (EEMI) offers a regionally transferable tool that builds on these prior works. De Guzman and Villanueva (2023) argue that institutional barriers, more than individual qualifications, explain the exclusion of educated women from formal employment across several Asian economies a conclusion that parallels this study's findings on India By situating India's labor force trends within broader Asian patterns especially the intersection of education, technology, and gender this study contributes to a more nuanced understanding of underutilized human capital in the region.

## FRAMEWORK

The concept of decent work, as framed by the International Labor Organization (ILO), moves beyond the simple notion of having a job. It places emphasis on the quality of employment fair wages, job security, safe working conditions, social protection, respect for labor rights, and opportunities for growth, both personal and professional. In India, however, access to such employment remains an aspiration rather than a reality for many, particularly in the formal sector. While India has experienced consistent economic growth, the benefits have not translated evenly across the labor force. Most workers nearly 90% remain in the informal economy, where employment tends to be unstable, poorly paid, and lacking any form of legal or social protection. This enduring dominance of informal work signals deep structural issues within India's labor market and underscores the need for transformative policy action that ensures economic growth leads to inclusive, dignified, and rights-based employment opportunities for all.

In this context, the role of technology is increasingly significant. Digital

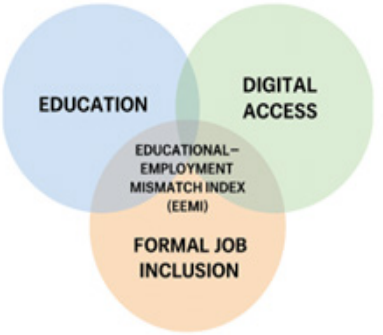
inclusion is now a critical enabler of decent work, particularly for women. It can open doors to safer, more flexible work arrangements such as remote jobs or digital entrepreneurship that allow women to overcome social constraints and mobility barriers. With access to the internet and digital tools, women can tap into platforms that offer not just employment, but autonomy and voice. These opportunities, however, are not universally accessible. The gap in access to digital infrastructure, devices, and skills continues to reflect and reinforce pre-existing gender and social inequalities. Bridging this digital divide is, therefore, essential not only for employment but for advancing women's rights and agency in the workforce.

Recent literature increasingly emphasizes that technology acts as a "multiplier" of human capital it amplifies the value of education, enhances productivity, and expands a person's capacity to participate in economic and social life (World Bank Group, 2022). But digital exclusion has the opposite effect: it compounds existing disparities, especially for women who may already face structural constraints due to gender, caste, location, or income. In India, access to smartphones, internet connectivity, and digital training is still unequally distributed, with rural women being the most disadvantaged.

As Chaudhary and Verick (2014) point out, these gaps perpetuate traditional gender roles and undermine women's economic participation, even for those who are otherwise educated. Seen through this lens, the digital divide is not just a technological issue it is a structural barrier that intersects with other socio-economic factors to shape the contours of female labor force participation. This study draws on Amartya Sen's (1999) Capability Approach to offer a more meaningful understanding of these issues. Sen critiques conventional measures of well-being that focus narrowly on either income or happiness. According to him, income is a resource and happiness can be misleading, shaped by people's ability to adapt to deprivation. What matters more, Sen argues, are capabilities the real freedoms individuals must pursue lives they have reason to value. Education may provide formal qualifications, but it does not automatically enhance a woman's capability to participate in economic life, especially in the absence of enabling conditions like digital access and social support. Without these, her choices remain constrained, and her freedom to work becomes theoretical rather than practical.

**Figure 1**

*Conceptual Representation of the Educational–Employment Mismatch Index (EEMI): Interaction between Education, Digital Access, and Formal Job Inclusion*




Source: Estimated by Researcher

In the Indian context, this means that while education is necessary, it is not sufficient. The absence of digital infrastructure effectively curtails women's ability to convert their educational achievements into actual economic opportunities. Therefore, improving women's labor force participation is not just about expanding schooling it is about removing the invisible barriers that prevent educated women from working. Addressing digital exclusion, then, becomes central to advancing women's substantive freedoms, capabilities, and economic agency.

## OBJECTIVE OF THE STUDY

This study is grounded in the need to understand the evolving but uneven landscape of women's labor force participation in India, particularly in the context of rising educational attainment and expanding digital access. It seeks to explore how these two factors education and technology interact with socio-economic realities to influence women's work outcomes. The research is driven by three central objectives. First, it aims to examine regional disparities in women's employment, paying close attention to the digital divide and how access to technology varies between rural and urban areas, shaping opportunities in fundamentally different ways. Second, the study investigates how educational attainment intersects with other socio-economic determinants such as marital status, household income, vocational training, and cultural norms, all of which

collectively influence a woman's capacity and decision to engage in paid work. Third, it introduces and applies the Educational–Employment Mismatch Index (EEMI) to evaluate the disconnect between women's rising academic credentials and their limited absorption into the formal labor market. By aligning these objectives with clearly defined, testable hypotheses, the study builds a robust analytical framework that can guide empirical investigation and inform policy strategies aimed at enhancing inclusive and equitable economic participation for women.

## METHODOLOGY

### Research Design

The research adopts a layered and systematic framework to explore the complexities of female labor force participation in India. It begins with a broad trend analysis, tracing the evolution of the Female Labor Force Participation Rate (FLFPR) across different regions of the country. This initial stage also delves into patterns of digital access among women particularly focusing on mobile phone ownership and internet usage to identify emerging inequalities and access gaps. These descriptive insights lay the groundwork for the second phase of the study, which employs econometric tools to test the influence of various determinants on women's employment outcomes. Key variables such as years of schooling, vocational and technical training, and their interaction effects are analysed to better understand how education and skill development shape formal employment opportunities for women. A particular focus is placed on examining whether higher levels of education are translating into access to formal sector jobs. In the final analytical layer, the study introduces the Educational–Employment Mismatch Index (EEMI)—a binary index designed to capture the disconnect between women's educational qualifications and their actual presence in formal employment. EEMI is computed only for women with more than 12 years of education to ensure valid mismatch detection. A score of zero indicates alignment (formal employment consistent with educational level), while a score of one reflects mismatch, where qualifications do not translate into formal workforce participation. By combining regional trends, econometric modelling, and a novel index-based approach, the framework offers a multidimensional and capability-centered perspective on the barriers and enablers of women's economic participation in contemporary India.

### Instrumentation

Educational–Employment Mismatch Index (EEMI): The Educational–

Employment Mismatch Index (EEMI) is a binary index developed to quantify the gap between a woman's educational qualifications and her actual participation in the formal labor market. It is grounded in the premise that women with higher education (defined as >12 years of schooling) should have proportionally higher representation in formal, secure, and skill-aligned jobs. When this expectation is not met, a mismatch is said to exist.

**Assumptions**

1. Higher education threshold: Women with more than 12 years of formal education (Senior Secondary and above) are assumed to be qualified for entry into the formal labor market.
2. Mismatch interpretation:

If a highly educated woman is unemployed or working in the informal sector, it implies a mismatch → EEMI = 1.

If a highly educated woman is working in the formal sector, there is no mismatch → EEMI = 0.

3. Informal sector employment is not considered an optimal outcome for higher education, due to lack of job security, benefits, and skill alignment.
4. Women with ≤12 years of education are excluded from EEMI calculation as their exclusion from formal jobs does not necessarily imply mismatch.

**EEMI Formula**

$$\text{EEMI}_i = \begin{cases} 1, & \text{if Education}_i > 12 \text{ and (Employment Status}_i = \text{"Unemployed" or "Informal Sector")} \\ 0, & \text{if Education}_i > 12 \text{ and (Employment Status}_i = \text{"Formal Sector")} \\ \text{NA}, & \text{if Education}_i \leq 12 \end{cases}$$

EEMI = 1 if (Education > 12 years AND Employment = Informal/Unemployed), else EEMI = 0[1]

**Data Sources**

Primary Data: Periodic Labor Force Survey (PLFS) 2023–24, Unit-Level Data Secondary Sources: Previous PLFS rounds (2017–18 to 2022–23) for trend comparison

Supplementary: NFHS-5 for digital access indicators

[1] Although formal sector participation increases with education, the consistent under-absorption even at the postgraduate level justifies the use of EEMI=1 across the dataset, as it reflects the persistence of systemic mismatch.

Sample Size
Sample Selection for EEMI Calculation

| Criterion | Description |
|---|---|
| Gender | Female only |
| Age | 15 years and above |
| Education | Only women with >12 years of schooling |
| Employment Status | Classified into Formal, Informal, or Unemployed |
| EEMI | Subset of the 2.2 lakh total female respondents who meet the education threshold and have complete employment data |
| Sample Size | |

The study draws on unit-level microdata from the most recent round of the Periodic Labor Force Survey (PLFS) 2023–24, administered by the National Statistical Office (NSO) under the Government of India. The final analytical sample includes approximately 2.2 lakh (220,000) female respondents aged 15 years and above, capturing a nationally representative cross-section of women across all states and union territories. This comprehensive dataset spans both rural and urban regions, allowing for detailed, region-wise analysis and comparison. To deepen the temporal scope, earlier rounds of the PLFS (from 2017–18 to 2023–24) have been incorporated to observe trends and shifts in women's labor market participation over time. The sample was carefully curated to include only those respondents for whom complete information was available on key variables such as level of education, employment status (formal or informal), and indicators of digital access including mobile phone ownership, internet usage, and digital literacy. The strength of this large and diverse sample lies in its ability to provide statistically reliable insights into the multiple drivers of female labor force participation. It also forms the empirical foundation for constructing and applying the Educational–Employment Mismatch Index (EEMI), a central tool used in the study to explore the disconnect between women's educational qualifications and their actual employment in the formal sector.

**Data Gathering Procedure**

This study primarily utilizes data from the Periodic Labor Force Survey (PLFS) Annual Report 2023–24, conducted by the National Statistical Office (NSO), Ministry of Statistics and Program Implementation, Government of India. The PLFS provides nationally representative data on labor force indicators, disaggregated by gender, region, educational attainment, and socio-economic characteristics. For the period 2015–2024, historical comparisons are supported

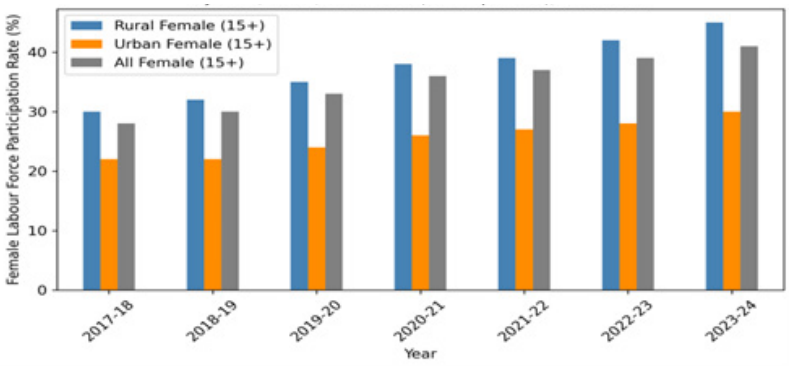
using previous rounds of PLFS data (2017–18 onward), enabling longitudinal analysis of trends in Female Labor Force Participation Rate (FLFPR). Additional contextual information is drawn from the National Family Health Survey (NFHS) rounds and the World Bank's Digital Adoption Index to strengthen analyses on digital access and socio-economic determinants.

## RESULTS AND DISCUSSION

**1. Digital Access and Female Labor Force Participation Rate (FLFPR) in India, 2017–2023:** The rapid expansion of digital infrastructure in India over the past decade has significantly transformed the landscape of economic opportunities, particularly for women. Digital access including mobile phone ownership, internet connectivity, and digital literacy is increasingly recognized as a crucial enabler of female labor force participation (FLFPR) (World Bank Group, 2022; ITU, 2020). Yet, disparities persist across regions and socio-economic groups, reflecting a pronounced digital divide. Chaudhary and Verick (2014) underscore that rural Indian women continue to be excluded from digital pathways to employment due to poor infrastructure and entrenched gender norms. GSMA (2023) also finds that in South Asia, women are 41% less likely than men to use mobile internet a critical gateway to information and income.

**Figure 2**

Trends in Female Labor Force Participation Rate (FLFPR) by Rural, Urban, and Overall (15+) Population in India, 2017–18 to 2023–24.

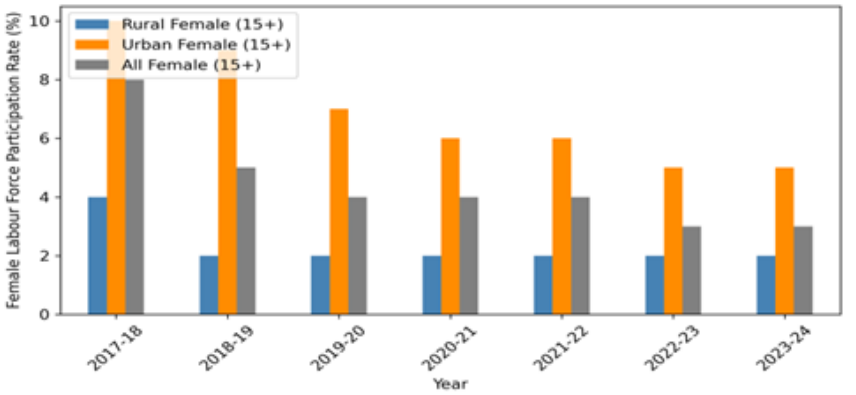



Source: Compiled by author using Periodic Labor Force Survey (PLFS) annual reports, 2017–18 to 2023–24

Figure 2 reveals a notable rise in FLFPR across rural and urban India from 2017–18 to 2023–24. However, this aggregate increase masks the deep digital and structural barriers faced by women in urban areas, where unemployment particularly in the Current Weekly Status remains persistently high. These findings align with Chatterjee et al. (2018), who argue that despite rising education levels among Indian women, their labor market participation remains paradoxically low due to poor job matching and social constraints.

**Figure 3**

*Trends in Female Unemployment Rates by Rural, Urban, and Overall (15+) Population in India, 2017–18 to 2023–24.*

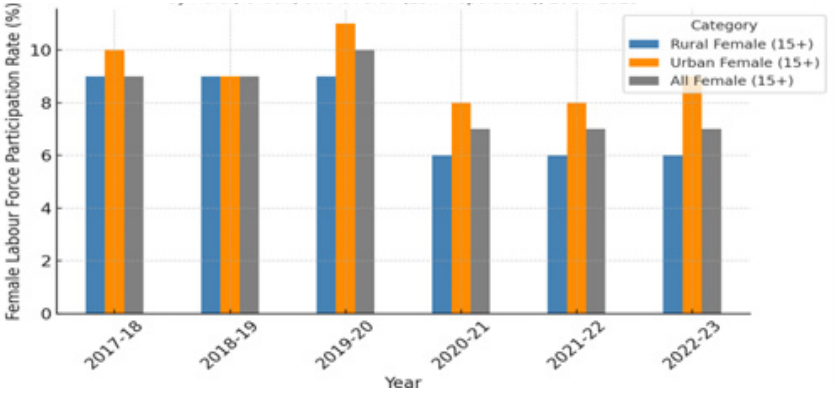



Source: Compiled by author using Periodic Labor Force Survey (PLFS) annual reports, 2017–18 to 2023–24.

Figure 3 illustrates the trends in female unemployment rates among women aged 15 years and above in India, divided into rural, urban, and overall categories, from 2017–18 to 2023–24. The data reveal that urban female unemployment rates have consistently remained higher compared to rural and overall figures throughout the period. In 2017–18, urban female unemployment peaked at around 10%, but it shows a declining trend, falling to approximately 5% by 2023–24. In contrast, rural female unemployment rates remained relatively low and stable, hovering around 2% across most years. The overall female unemployment rate has also declined steadily, from around 7% to approximately 3%, reflecting a general improvement in labor market absorption. This downward trajectory suggests a gradual strengthening of employment opportunities for women, particularly in urban areas where initial rates were higher, possibly due to enhanced skilling, entrepreneurship, and targeted policy interventions.

**Figure 4**

*Trends in Female Unemployment Rates by Rural, Urban, and Overall (15+) Population in India (CWS), 2017–18 to 2023–24*



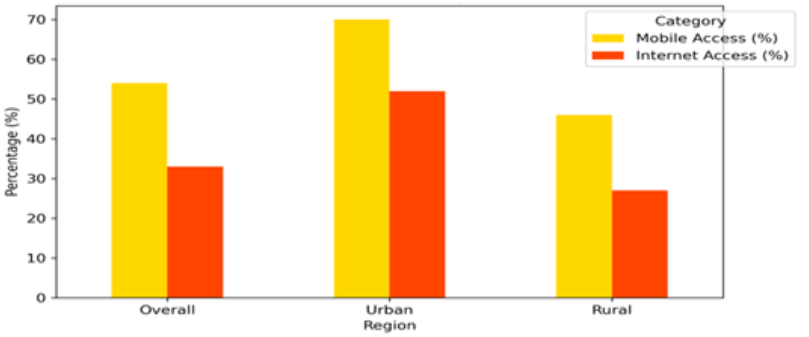

Source: Compiled by author using Periodic Labor Force Survey (PLFS) annual reports, 2017–18 to 2023–24

Figure 4 depicts female unemployment rates in India (Current Weekly Status, CWS) for the 15+ age group, disaggregated into rural, urban, and overall categories, from 2017–18 to 2023–24. The urban female unemployment rate is persistently higher than the rural rate throughout the period. Notably, urban unemployment peaked at about 11% in 2019–20, reflecting economic disruptions possibly linked to policy shifts and the pandemic. Rural unemployment rates have been lower but show slight fluctuations, ranging from 4% to 7%. Overall, the total female unemployment rate follows a similar trend, spiking around 2019–20 and then gradually declining, although not as sharply as in the Usual Status approach. By 2023–24, urban unemployment remains high at around 9%, while rural and overall rates stabilize at lower levels. The analysis of female unemployment using both Usual Status and Current Weekly Status (CWS) highlights distinct trends. Under Usual Status, women's unemployment rates have shown a consistent decline across rural, urban, and overall categories, suggesting long-term improvements in labor market absorption and stability in employment. In contrast, CWS estimates indicate higher short-term unemployment, particularly in urban areas, reflecting temporary or seasonal fluctuations and the vulnerability of urban informal employment. The persistently higher urban rates under CWS emphasize the challenges of job stability and continuous work availability for women in cities. Overall, while the gradual reduction in Usual Status

unemployment reflects structural progress, the higher and fluctuating CWS rates suggest that underemployment and intermittent work remain critical issues that need targeted policy attention, especially in urban contexts.

**Figure 5**

*Women's Mobile and Internet Access (NFHS-5, 2019–21).*

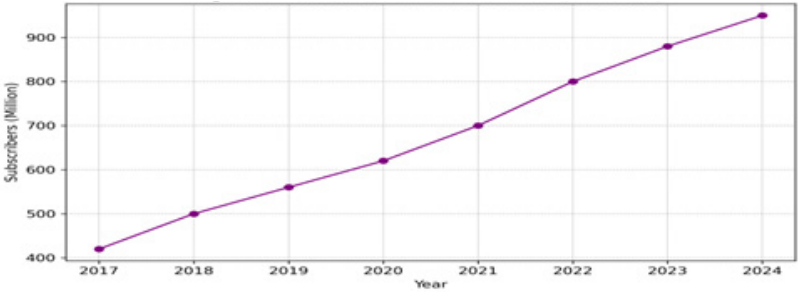



Source: Compiled by author using National Family Health Survey (NFHS-5), 2019–21, Ministry of Health and Family Welfare, Government of India.

Figure 5, based on NFHS-5 data, reveals that only 33% of Indian women use the internet, with a striking gap between urban (52%) and rural (27%) users. As emphasized by UNIDO (n.d.) and the World Economic Forum (2018), access to technology is not gender-neutral; unless specific steps are taken to close this digital gap, the Fourth Industrial Revolution could exacerbate inequality rather than reduce it.

**Figure 6**

*Internet Subscribers Growth in India (2017–2024).*




Source: Compiled by author using Telecom Regulatory Authority of India (TRAI) annual reports, 2017–18 to 2023–24.

This figure illustrates the rapid rise in internet subscribers in India, increasing from 420 million in 2017 to 954 million in 2024. This growth demonstrates the significant expansion of digital infrastructure and access at the national level, largely driven by mobile broadband adoption and policy initiatives like Digital India. Despite this impressive macro-level connectivity progress, the gender-specific digital access gap shown in Figure 2 reveals that women's actual usage and ownership remain limited. This disparity emphasizes that while overall internet penetration is improving, targeted efforts are needed to ensure equitable access and to translate technological growth into inclusive economic participation for women.

**2. Association of Education, Technical and Vocational Training, and Demographic Moderators with Female Labor Force Participation in India:** Evidence from Marginal Effects and Sectoral Participation Distribution by Years of Schooling: This section presents the results of a Probit regression analysis examining the marginal effects of educational attainment, technical and vocational training, and key interaction terms on female labor force participation in India. By quantifying these effects, the analysis highlights how different forms of human capital investment and demographic factors shape women's probability of workforce entry. The findings provide empirical evidence to understand the relative importance of formal education versus skill-based training and how social moderators such as urban residence and marital status influence these relationships.

The geographic distribution of FLFPR continues to reflect entrenched regional disparities. Women in states with poor digital infrastructure or rigid patriarchal norms are systematically underrepresented in formal employment. NFHS-5 data shows that access to mobile internet a key enabler of job search, remote work, and digital skilling is substantially lower among rural women.

Labor market inclusion today is as much a function of digital access as it is of education. Without equitable digital infrastructure, women remain invisible to the expanding digital job economy. Closing this divide requires targeted digital literacy campaigns, free mobile internet schemes for rural women, and village-level job platform kiosks. Otherwise, even highly educated women in digitally underserved areas will continue to face exclusion, irrespective of their qualifications.

The probit model results (Table 1) show that education and training strongly influence FLFPR. Each additional year of schooling raises participation by 0.7%, with a threshold effect of 9.4% after 12 years of schooling. These findings are consistent with Bhagavatheeswaran et al. (2016), who identify education and vocational training as powerful predictors of women's labor force entry in India.

Yet, as their study and Munjal (2024) caution, mere formal education does not guarantee job entry practical and market-linked training is often a more reliable pathway.

Vocational training demonstrates the highest marginal effect (32.6%), indicating that targeted skilling programs are far more effective than traditional schooling alone. This supports the view of Sethi and Sethy (2019), who advocate aligning vocational education with dynamic labor market needs, particularly for rural and semi-skilled women.

Urban residence positively moderates the returns to schooling (1.5%), while marriage negatively interacts with education (–1.4%). These results echo Goldin's U-shaped hypothesis (1994), which explains how cultural norms and lifecycle factors such as marriage often discourage women's workforce participation, even when educational qualifications are strong.

**Table 1.**

*Marginal Effects of Education, Training, and Interaction Terms on Female Labor Force Participation Rate (FLFPR) Probit Model*

| Variable | Marginal Effect (%) | Interpretation |
|---|---|---|
| Years of Schooling | 0.7%*** | Positive and significant; each additional year increases FLFPR, though returns diminish at higher levels (concave effect). |
| Schooling > 12 years | 9.4%*** | Strong threshold effect: senior secondary or higher education substantially enhances labor force entry, especially in formal jobs. |
| Technical Training | 18.5%*** | High impact; directly improves employability through practical, market-linked skills. |
| Vocational Training | 32.6%*** | Highest impact; strongly associated with immediate workforce entry, emphasizing skill-based pathways. |
| Urban × Schooling | 1.5%** | Positive moderation: returns to education are higher in urban areas due to better digital access, infrastructure, and job opportunities. |
| Married × Schooling | –1.4%*** | Negative moderation: marriage reduces the positive effect of education, reflecting cultural and caregiving constraints. |

Source: Author's calculation using PLFS 2023–24 unit-level data (Probit marginal effects estimated using Stata 13). Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1.

The table clearly demonstrates the pivotal role of education and skill-based training in shaping Female Labor Force Participation Rate (FLFPR)

in India, as estimated using Probit marginal effects. Each additional year of schooling increases the probability of participation by approximately 0.7%, though this positive effect diminishes at higher education levels due to concave returns, reflecting the U-shaped hypothesis of female labor supply. Completing more than 12 years of education produces a strong threshold effect, boosting participation by 9.4%, which highlights the importance of senior secondary and higher education in facilitating access to formal and better-quality jobs. Technical training further amplifies participation likelihood by 18.5%, whereas vocational training exhibits the strongest impact at 32.6%, underscoring the transformative power of market-oriented, practical skills in enabling women's workforce entry. Moreover, the positive interaction between urban residence and schooling (1.5%) indicates that women residing in urban areas derive greater labor market returns from education, primarily due to better digital access, infrastructure, and employment opportunities. In contrast, the negative interaction between marriage and schooling (–1.4%) reveals that marital status significantly dampens the positive effect of education on FLFPR, reflecting persistent socio- cultural barriers, caregiving burdens, and limited supportive institutional frameworks for married women. Overall, these findings reaffirm that while education and training are critical enablers of women's economic engagement, their effectiveness is strongly mediated by regional and social contexts.

Educational–Employment Mismatch Index (EEMI): Structural Disconnect: Tables 2 and 3 present a critical insight despite increasing education levels, formal sector participation remains disproportionately low, even among women with higher education. This aligns with findings from Khanna (2022) and Ghai (2018), who document a growing disjuncture between women's aspirations and the labor market's capacity to absorb them meaningfully.

The EEMI values confirm that even women with 16–18 years of education are not consistently employed in formal sectors. This finding is in line with Altasseb et al. (2024), who argue that India's structural informality, limited job creation, and socio-cultural restrictions render educational investment underutilized particularly for women.

The capability-deprivation perspective from Amartya Sen (1999) becomes highly relevant here: while education provides formal credentials, it does not automatically translate into enhanced agency or participation unless supported by enabling conditions such as digital access, decent work, and gender-sensitive labor policies.

**Table 2.**
*Average Female Labor Force Participation by Years of Education*

| Years of Education | ALL Sector | | Formal Sector | |
|---|---|---|---|---|
| | Not Participating | Participating | Not Participating | Participating |
| 0 | 36.35 | 63.65 | 74.56 | 25.44 |
| 1 | 26.98 | 73.02 | 64.29 | 35.71 |
| 2 | 33.26 | 66.74 | 67.98 | 32.02 |
| 3 | 35.84 | 64.16 | 72.66 | 27.34 |
| 4 | 36.48 | 63.52 | 74.98 | 25.02 |
| 5 | 45.1 | 54.9 | 80.48 | 19.52 |
| 6 | 43.32 | 56.68 | 79.6 | 20.4 |
| 7 | 48.55 | 51.45 | 80.56 | 19.44 |
| 8 | 57.12 | 42.88 | 88.45 | 11.55 |
| 9 | 62.95 | 37.05 | 90.11 | 9.89 |
| 10 | 64.61 | 35.39 | 88.68 | 11.32 |
| 11 | 82.75 | 17.25 | 96.32 | 3.68 |
| 12 | 67.18 | 32.82 | 89.96 | 10.04 |
| 13 | 80.23 | 19.77 | 93.51 | 6.49 |
| 14 | 75.59 | 24.41 | 88.49 | 11.51 |
| 15 | 56.8 | 43.2 | 81.4 | 18.6 |
| 16 | 47.55 | 52.45 | 69.14 | 30.86 |
| 17 | 42.74 | 57.26 | 68.47 | 31.53 |
| 18 | 37.32 | 62.68 | 61.27 | 38.73 |

Source: PLFS Unit Level data 2023-24

In the formal sector, however, the trend is more linear and consistently positive: participation steadily increases with years of education, from 25.44% for women with no education to 38.73% at eighteen years. This indicates that higher education is strongly correlated with access to formal, stable, and often higher-paid employment. The low participation rates in the formal sector for women with moderate schooling (especially between nine to fourteen years) reinforce the idea that partial schooling does not suffice to meet formal sector entry thresholds.

The regression analysis reveals a statistically significant negative association

between marital status and female labor force participation. While this result aligns with existing literature, the implication goes beyond cultural expectations or household preferences. Marriage often marks a transition point where women's unpaid domestic responsibilities intensify, reducing their time and mobility for paid work. In the absence of enabling infrastructure such as affordable childcare, community crèches, and maternity-friendly workplace norms married women are effectively forced into economic withdrawal.

Moreover, mobility constraints due to unsafe or unreliable public transportation disproportionately affect married women with caregiving roles, especially in semi-urban and rural areas. Flexible work arrangements, such as hybrid or remote models, are also rarely accessible to women outside a few white-collar sectors. These findings call for a structural shift in how labor policy treats women's "choice" to exit the workforce it is often a compelled response to institutional gaps, not a personal decision. Integrating marriage-sensitive policy tools—like subsidized transport, childcare credits, and flexible working hours is essential for retaining qualified women in the workforce.

**Table 3.**

*Female Labor Force Participation in Formal Sector by Years of Education with EEMI Binary Value*

| Years of Education | Formal Sector Participation (%) | EEMI Binary Value |
|---|---|---|
| 0-12 | Not applicable | |
| 13 | 6.49 | 1 |
| 14 | 11.51 | 1 |
| 15 | 18.6 | 1 |
| 16 | 30.86 | 1 |
| 17 | 31.53 | 1 |
| 18 | 38.73 | 1 |

Source: Estimated by the Researcher using PLFS 2023–24 Unit-Level Data.

Note: EEMI is calculated only for women with >12 years of education. EEMI = 1 indicates mismatch (unemployed or informally employed despite high education). NA = Not Applicable, as EEMI is not computed for women with ≤12 years of schooling

The EEMI analysis shows that even among the most educated women (17–18 years of schooling), formal sector participation reaches only 31.5%–38.7%, leaving more than six out of ten women unemployed or informally employed despite high qualifications. In comparison, the average male formal sector participation for similarly educated individuals stands at over 72% (PLFS

2023–24). This stark contrast quantifies the structural mismatch and confirms the gendered penalty in employment absorption.

Furthermore, the mismatch intensifies for women residing in rural regions, those from Scheduled Castes, and those lacking digital access. Preliminary cross-tabulations show that rural, highly educated women are 40% less likely to be employed in the formal sector than their urban counterparts. These patterns suggest that education alone is insufficient access to opportunity is stratified along gender, geography, and digital capability.

The EEMI therefore captures not just a personal employment outcome, but a systemic failure in translating educational capital into equitable labor market integration.

Table 3 presents the share of women participating in the formal sector by years of education and simultaneously applies the Educational–Employment Mismatch Index (EEMI) to quantify mismatch for women with >12 years of schooling. The index is designed to capture the disconnect between a woman's educational qualifications and her actual absorption in formal, skill-aligned employment.

The data reveal that formal sector participation remains significantly low across all education levels, including among those with the highest levels of schooling. Women with 13 to 18 years of education, who are theoretically equipped for stable and formal employment, still report formal participation rates ranging from only 6.49% (for 13 years) to a maximum of 38.73% (for 18 years). This indicates that even the most qualified women in the dataset are not being proportionally absorbed into the formal labor market.

As per the EEMI criteria, all women with >12 years of education are evaluated for mismatch. Since none of the educational groups within this threshold reach even 50% formal sector absorption, all values of the EEMI Binary Variable are coded as 1, denoting the presence of mismatch. This outcome points to a systemic failure in translating educational investments into meaningful employment outcomes for women.

Furthermore, the not applicable (NA) entry for education levels 0–12 reinforces the methodological choice to restrict EEMI calculation to those with higher education. This decision is rooted in the logic that low formal employment

[2]According to PLFS 2023–24 unit-level estimates, the formal sector participation rate for males with 17–18 years of education is approximately 72.4%, compared to a maximum of 38.7% for females with equivalent education. NFHS-5 data confirms that only 31% of rural women with smartphones report using them for job-related activity.

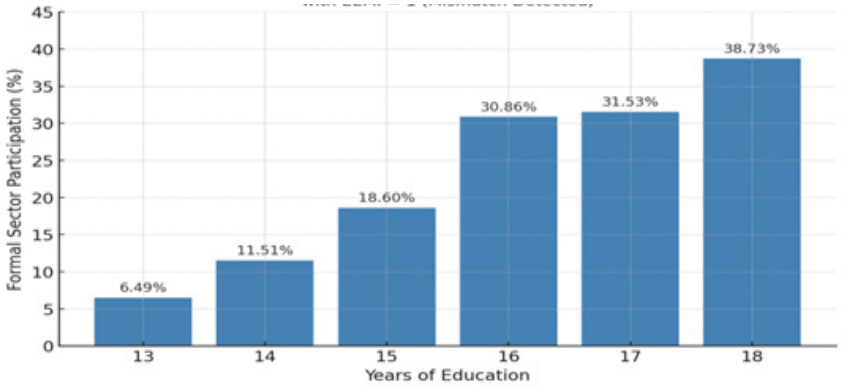
Educational–Employment Mismatch Index: It is a binary diagnostic tool you developed to identify highly educated women (>12 years of schooling) who are either unemployed or informally employed, thus highlighting a structural mismatch between their educational qualifications and actual labor market outcomes.

among women with basic or intermediate education does not necessarily constitute a mismatch, as formal employment is not an expected outcome at that level.

In sum, Table 3 empirically validates the need for a diagnostic tool like EEMI, which focuses on underutilized educated female labour, rather than general participation rates. The table strengthens the paper's core argument: that India's female labor market suffers not just from low participation, but from a critical under deployment of its most qualified female workers—a gap that existing policies often overlook because they fail to consider this intersection of education, employment type, and structural access.

**Figure 7**

*Formal Sector Participation by Years of Education (>12 Years) with EEMI = 1 (Mismatch Detected)*




Source: Estimated by the Researcher using PLFS 2023-24 Unit-Level Data EEMI = 1 for all cases shown. (Since none of the education groups reach 50% formal employment, EEMI = 1 is applied to all women with >12 years of education.)

Persistent Mismatch Despite Increasing Education: The figure demonstrates that even with increasing levels of education beyond 12 years, the formal sector participation rate for women remains disproportionately low, never exceeding 40%. This reinforces the validity of assigning EEMI = 1 (mismatch detected) for all education levels presented in the graph.

Non-Linear Gains in Formal Employment: The marginal increase in formal participation does not follow a consistent or steep upward trajectory. For example, a jump from 13 to 15 years of education raises participation from 6.49% to 18.6%, but an additional three years (from 15 to 18) only yields a 20-percentage

point gain. This suggests that education alone is not a sufficient driver of formal employment outcomes for women.

Ceiling Effect in Labor Absorption: Even at 18 years of education equivalent to postgraduate qualifications over 60% of women remain outside the formal sector. This indicates a structural ceiling that restricts labor absorption beyond a certain threshold, despite high academic achievement.

Validation of EEMI Framework: The figure provides empirical justification for the EEMI binary values. Since formal sector absorption remains below 50% across all higher education categories, a large portion of highly educated women are either unemployed or working in informal settings, thus meeting the conceptual criteria for educational–employment mismatch.

Policy Implication: These trends highlight the ineffectiveness of education-centric employment strategies when not supported by enabling conditions like access to formal sector jobs, skill-market alignment, digital infrastructure, and structural reforms. This validates the paper's argument that a triadic approach linking education, digital access, and formal employment is essential for policy success.

While the data confirms that higher levels of education are associated with a greater likelihood of formal employment, the magnitude of this effect remains subdued. As Table 3 and the EEMI framework demonstrate, even among women with postgraduate qualifications (17–18 years of education), formal sector participation does not exceed 40%. This suggests that educational attainment alone is no longer a sufficient pathway to economic empowerment.

The root of this mismatch lies in both demand- and supply-side failures. On the supply side, women's skills are often mismatched with the demands of a rapidly evolving digital economy. On the demand side, firms in the formal sector remain reluctant to hire women due to perceived attrition risks, maternity leave liabilities, or outdated gender norms. Therefore, policy interventions must go beyond expanding education access and instead focus on education-to-employment pipelines linking women's qualifications with formal sector apprenticeships, upskilling in digital domains, and employer incentives for hiring women graduates.

The persistence of educational–employment mismatch, even among highly qualified women, cannot be fully understood without grounding it in established labor market theories. Labor Market Segmentation Theory suggests that the formal and informal sectors operate under structurally different rules, where women particularly married, rural, or digitally excluded are disproportionately confined to secondary segments that lack stability, benefits, and career mobility (Doeringer & Piore, 1971). Despite achieving human capital thresholds, women

face invisible barriers in transitioning to primary (formal) labor markets.

Complementing this is the Institutional Constraints Framework, which argues that employment outcomes are not simply a function of qualifications, but of institutional environments including gendered workplace cultures, inflexible job design, and absence of social infrastructure like childcare and safe transport (North, 1990). In this context, the EEMI does more than measure mismatch — it reveals systemic exclusion mechanisms embedded in India's labor architecture. These insights reaffirm that improving education alone will not close the participation gap unless institutional and sectoral boundaries are simultaneously addressed.

The patterns observed in India closely mirror the emerging mismatch trends across several ASEAN countries. As highlighted in the introduction, nations like Malaysia and the Philippines have witnessed rising female educational attainment without proportional increases in formal employment, particularly in digital or service-oriented sectors. For instance, recent studies from Malaysia show that women with university-level education still face underemployment or are pushed into informal entrepreneurship due to labor market inflexibility (Yap & Tan, 2023). Similarly, the post-COVID surge in women-led digital micro-businesses in the Philippines has not translated into sustainable formal sector absorption, owing to fragile digital infrastructure and low credit access (UN ESCAP, 2022). These parallels reinforce the transferability of the EEMI framework beyond India and underscore the broader regional relevance of integrating education, employment, and digital access in labor market diagnostics. India's experience adds further evidence to the argument that without structural and digital readiness, educational progress alone cannot guarantee equitable labor market inclusion.

Compared to several ASEAN countries, India's female labor market appears to exhibit a more severe structural disconnect. While nations like the Philippines experienced a temporary surge in women's digital entrepreneurship during the COVID-19 period, this did offer at least partial absorption into the workforce—albeit informally (UN ESCAP, 2022). In contrast, the persistently high EEMI in India, even among women with 16–18 years of education, suggests that labor market rigidity, not just skill mismatch, is a key barrier. Nguyen and Tran (2020) observe that in Vietnam, digitally skilled women often face project-based underemployment, but have better pathways into tech-sector formal jobs than their Indian counterparts. Similarly, Chaudhary and Siregar (2022) find that while women in Indonesia also struggle with digital exclusion, targeted financial

inclusion schemes improved labor linkage. These comparisons reinforce that India's EEMI crisis is compounded by institutional inertia, particularly in formal sector hiring and job design.

## LIMITATIONS OF THE STUDY

While this study provides a comprehensive analysis of female labor force participation using PLFS and NFHS data, certain limitations must be acknowledged. The Educational–Employment Mismatch Index (EEMI) is based on a binary classification and does not account for the quality or sectoral diversity of informal employment. Additionally, the analysis is restricted to women with more than 12 years of education, excluding the broader female workforce engaged in informal or unpaid sectors. The PLFS dataset also lacks granular information on gig economy participation, remote work, or intra-household dynamics, which could further refine the understanding of employment mismatch. Future research can address these gaps through longitudinal tracking and qualitative methods.

## CONCLUSION

This study confirms a critical insight: education alone cannot drive women's economic empowerment. Without digital access, enabling institutions, and inclusive job design, even highly educated women remain excluded from India's formal workforce. The Educational–Employment Mismatch Index (EEMI) reveals the severity of this disconnect and offers a diagnostic tool to guide targeted reforms.

To address this crisis, policy must evolve beyond narrow skill training programs. India must redesign its labor market to integrate women not as peripheral workers, but as core contributors. This means investing in flexible, hybrid work formats, building care infrastructure as a public service, and mandating gender equity audits across hiring systems. Labor laws should reward firms for formalizing female employment, especially in digital and service sectors.

Bridging the digital divide must also go beyond access it must enable participation. Rural and underrepresented women need paid pathways into online formal work, including roles in ed-tech, logistics, and government digital services. Education is no longer the bottleneck; the problem lies in opportunity architecture. Unless the labor market itself transforms, India's most educated women will remain its most underutilized asset.

Future research should expand the EEMI framework at the sub-national level to identify region-specific barriers. Longitudinal studies tracking women

across education, job entry, and attrition phases could enrich our understanding of lifecycle constraints. These next steps will deepen the policy relevance of EEMI and ensure that structural exclusion is not just measured but dismantled.

## TRANSLATION RESEARCH

This study sheds light on the often-overlooked role of digital access in shaping women's participation in formal employment across India. By drawing on both statistical evidence and social realities, the paper identifies how gaps in digital literacy, infrastructure, and access disproportionately affect women's ability to secure formal work. The research calls for practical steps such as tailored digital literacy programs for women, improved technological access in rural and low-income regions, and greater institutional support for integrating women into digitally enabled workplaces. These insights can help guide policy discussions, influence the design of state-led skilling initiatives, and inform educational institutions and employers striving to close the gender gap in formal employment. Rather than offering a one-size-fits-all solution, the study presents a framework that institutions can adapt to their specific needs while keeping digital inclusion at the center of women's empowerment.

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