

AI Expansion Metrics and Gender Digital Divide (GDD) for Women at work: A Chi - Square based Analysis

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Abstract

The study explores how specific Artificial Intelligence (AI) expansion metrics contribute to the reinforcement of the Gender Digital Divide (GDD) in the workplace, particularly affecting women. Using a mixed-method approach, it first used systematic literature review which revealed four major AI metrics—*Speed of AI*, *Complexity of AI Systems*, *Frequency of AI Upgrades*, and *Volume of New AI Tools* and empirically examined their association with factors reinforcing GDD such as *pressure to adapt*, *difficulty in coping*, *emotional exhaustion*, and *feelings of left behind*. Chi-square analysis on more than 1000 responses from IT professionals not restricted to any gender in Nagpur revealed statistically significant associations for specific metric-antecedent pairs. The findings were used to construct a conceptual framework to offer both theoretical enrichment and practical implications for businesses, which significantly contributes to SDG 5.

Keywords: Artificial Intelligence, Gender Digital Divide, Digital Divide, Women Employees

1. Introduction.

Equitable employment across genders, especially concerning women employment has always been a crucial concern in all the economies. Women continue to face significant barriers like low employment rates, unequal job structures, and compromised growth opportunities in career. Over the past three decades, female participation in the workforce has declined in many countries, prompting growing concern among policymakers and researchers. Since early 2000s, the term 'Gender Digital Divide' (GDD) emerged in academic discourses under the umbrella of broader term Digital Divide. It is loosely understood as the gap between those with and without access to technology and allied tools. The proliferation and uncontrolled pace of newer forms of technological algorithms posed businesses with a challenge of skilled manpower. This highlighted how women had disproportionate representation in technical industry, especially in leadership roles and growth opportunities at work. As (Bentley et al., 2024) puts it very rightly, Digital Divide has emerged as a persistent societal concern, as the pace of its integration in almost every layer of society has given rise to socio-ethical concerns.

GDD has roots in many socio-cultural and economic background of any country, however its *gendered* dimension only became a focus of researchers and industry practitioners with the unparalleled rise of ICTs and most recently, Artificial Intelligence (AI) and analytics.

India's population and digital ecosystem are amongst the fastest-growing globally. With the incremental pace of technological upgradation, research indicates that distribution and access to modern technological tools isn't equitable. As AI witnesses a breakneck evolution, this study aims to study the perception of professionals in tech domain towards unprecedented pace of AI expansion resulting in increased Gender Digital Divide at workplace. The first section consists of introduction. The second section details methodology employed, followed by the third section, review of current literature. Next section organizes the constructs identified into a conceptual model to be empirically examined using chi-square test of independence. Sixteen associations identified, when tested empirically, resulted in confirmation of 4 crucial metrics of AI expansion, viz., *Speed of AI Expansion*, *Complexity of AI Systems*, *Frequency of AI Upgrades*, and *Volume of New AI Tools* and four antecedents of gender digital divide, *Pressure to Adapt*, *Difficulty in Keeping Up*, *Emotional Exhaustion*, and *Feeling Left Behind*, having statistically significant association. The outcomes were again organized into a refined conceptual framework, as a significant contribution of this study, which adds further dimensions to examine AI expansion influences using *Pressure to Adapt* and *Difficulty in keeping up with rapid AI* as moderating variables.

2. Methodological framework

2.1 Research context and approach

This study utilized a mixed method approach through a systematic literature review to synthesize recent research and identify key AI expansion metrics that may potentially reinforce gender digital divide in the context of women employees. The SLR approach systematically scans knowledge resources to develop a focused plan for analysing literature,

encompassing its explanatory aspects and detailed elements. The study further employed empirical examination of the collected responses to ascertain the accuracy of metrics and antecedents identified by using chi-square test of independence as it is a prominent tool to test hypothesis for nominal categorical data, and provides information on significance of group differences in data and where they are coming from (McHugh, 2013). The review was conducted in the timeline between October 2024 to December 2024.

2.2 Articles selection and qualitative assessment

To evaluate the association of AI metrics with antecedents of gender digital divide, the focus was to synthesize recent literature from 2023 and 2024, as AI is witnessing an uncontrolled pace of evolution in the current context of technological revolution. The primary source of literature was Scopus. Additionally, a few studies from snowballing and grey literature were also included. Articles not in English were excluded. The selected articles were critically examined to identify the AI metrics and key factors that lead to gender digital divide. Through this analysis, four key AI metrics and four antecedents to gender digital divide were identified, which were further examined quantitatively.

2.3 Keyword Search Algorithm

Based on context of the study, specific keywords related to AI metrics, gender digital divide, and women at work were included in the search string, as given below:

((“Artificial Intelligence” OR AI OR “ICT” OR “Digital technologies” OR AI Systems” OR “AI tools”) AND (“Digital Divide” OR “Gender Digital Divide” OR “Digital exclusion” OR))

3. Current Research and Research Gap

3.1 Expansion of Artificial Intelligence and Emergence of Novel Challenges

Innovations in artificial intelligence are advancing at a pace so rapid, they seem to evolve in the blink of an eye. Yet, few studies have effectively captured or quantified this accelerating speed of progress in the AI landscape. In the light of advancements in computing performance and big data, AI is now attaining phenomenal capabilities. After decades of stagnation, AI has demonstrated a rapid surge during the 21st century. The world is witnessing science-fiction movies converting into reality. This is happening at an unparalleled pace, which is now becoming an interest of investigation to scholars due to its widespread impact across industries. Yet, very few studies have examined the accelerated velocity of AI innovations (Tang et al., 2020). *Metrics* refer to any measurable indicators that help evaluate outcomes against a defined standard. For this study, an attempt has been made to identify AI metrics that assess how well AI systems align with factors that reinforce gender digital divide. Innovation speed, first coined by (Kessler & Chakrabarti, 1996), also termed as pace of AI has been widely examined by scholars in varying contexts, however not in the context of the purview of this study. Therefore, the first metric, as revealed from literature to measure AI expansion is *speed of AI*. Similarly, four more metrics to define AI expansion were identified from literature, viz., *Complexity of AI Systems*, *frequency of AI upgrades*, and *Volume of New AI tools*.

3.1 Artificial Intelligence and Gender-Digital Divide

Artificial intelligence is transforming and reshaping businesses, industries, and economies. Despite these pathbreaking advances, the implications on women’s representation have been broader and complex. The alarmingly low percentage of 22% of women workforce across world (Thakkar et al., 2020) further underscores the fact that this will perpetuate gender bias, as AI is visibly changing the way technology is being deployed. If there are no conscious efforts made to maintain workforce diversity, AI has potential to impact crucial business decisions. The study by (Quaid-i-Azam University, Islamabad, Pakistan & Shah, 2025) uncovers how deeply embedded gender biases in AI training datasets and algorithms amplify existing societal gender stereotypes and how they are manifesting in the under-representation of women in technical teams and career growth opportunities in the backdrop of AI driven landscape. For instance, AI applications are known not to function well in hiring decisions and female voice recognition (Franzoni, 2023). High instances of biases are identified in voice assistants, image recognition systems and job search tools, Quaid-i-Azam University, Islamabad, Pakistan & Shah. (2025) uncovers three crucial themes - (1) structural roots of gender-bias in AI; (2) the ways this bias manifest in results like in hiring healthcare, etc, leading to social inequality, and (3) how digital literacy of women may empower women to combat the flaws in AI systems. The alarming pace of world economy digitalization has presented a crucial need to alienate AI from gender-bias. If tech-savvy,

women workforce have a potential to accelerate the business outcomes with AI lead breakthroughs. Quaid-i-Azam University, Islamabad, Pakistan & Shah. (2025) further reveal that there are very less numbers of women working in technical systems and only 14% are women bosses as per (World Economic Forum, 2024). Secondly, 78% of training datasets comprise gender bias in particular to women which further comprises the accuracy of AI systems significantly. Literature in the same study further reveals that the number of men working on AI systems is consistently increasing in comparison to females, especially in manufacturing, energy, and mining. The authors stress the importance of closing the gender gap to ensure holistic use of digital revolution, especially in digital fields usually characterized by male dominance.

Additionally, the authors say that such ingrained bias against women makes it difficult for them to work in technical roles and changes their perceptions about the industry. Also, the data-driven nature of AI facilitates negative gender stereotypes, while appearing neutral (Borau, 2025). The male-dominated AI sector makes women reluctant to take up jobs in technical roles. Men are significantly dominating women in AI skill penetration, revealing a gender gap in AI skills globally (Statistica, 2025). Other than these, women also cite reasons such as being unwelcomed, AI biases making them less ambitious (Ceci et al., 2014), and flawed AI performance measurement systems likely to recommend men for senior positions (Amin Metwally Hussien et al., 2024).

The existing research on AI bias in digitally evolving landscape gave rise to digital divide, which has already been researched by scholars in recent literature mostly under demographic dimensions. The study by (Wang et al., 2024) tried to investigate the effect of AI divide and identify the vulnerable demographic groups in the backdrop of disparities in skills and competencies. This study revealed that average users of AI were 51% as compared to males, 61%, however wasn't a gender-specific study. Another work by (Kim & Lee, 2024) goes a step further and investigates the influence of socio-cultural factors on students' attitudes towards AI, highlighting gender disparities based on AI related experiences, in addition to AI-related experiences, and socio-cultural backgrounds. This study also emphasizes the importance of understanding attitudes towards AI for effective integration of technology. The study revealed that male students had more favourable attitude towards AI than their female counterparts and the difference was statistically significant. Although, measuring gendered dimension was not the main focus of the study.

Another study by (University of New South Wales et al., 2020) again focuses on examining digital inequity and divide for vulnerable groups and the barriers specific to them. The focus of study again encircled mostly around older adults, racial and ethnic minorities, newcomers, indigenous groups, and persons with disabilities. Gendered dimension was also the part of the study, indicating a crucial factor that only 41% women in India are less likely to use mobile internet due to factors like unsafe online environment, online abuse, discrimination, access to digital devices, etc. However, Mulero & Garcia-Hiernaut., (2023) in the context of identifying unemployment patterns within genders, reveal active participation of women too in online job searches, implying that women may have equal access to digital tools and actively use them, contending the traditional claims of gendered dimension of digital divide.

A significant study (Acilar & Sæbø, 2023) addressed the gendered dimension of *digital divide*, *gender digital divide* focussing on ICT adoption. It discusses how AI has transformed the social role of women, with changed dimension of women's participation in workforce. It discusses numerous dimensions specific to women like violence, discrimination, which may impact access to & attitudes towards technology. Unlike the study by (Mulero & Garcia-Hiernaut, 2023), this study says a large population of women is excluded from online communities, particularly in developing economies. Even if they do engage in ICT usage, it is mostly for communication, entertainment, travel, etc. and less career-oriented purposes in comparison to men who use it for more varied purposes like information gathering and work. Women also were found to be reporting difficulties in using ICTs, resulting in diminished usage intensity. This reflects not just access issues but also in confidence and skill levels, and digital literacy gaps of women. The study again examined impact advent of ICT and technology under the lens of various factors-social, economic, racial, geographical, cultural, literary, and psychological with special focus to women in workforce. Women reported lower self-efficacy, higher computer anxiety, higher perception of task difficulty, resulting in feeling less likely to adopt AI tools. The literature in the study also squarely indicated difficulty in navigating in existing tech ecosystem, let alone facing the newer, more challenging systems.

After examining the recent literature, it was revealed that academic scholarship has just begun to go beyond the traditional sources of digital divide in gender. Most of the scholars have examined AI aversion dimensions in women stemming from societal, cultural, educational, geographic, psychological contexts. However, a scarcity of enough literature on examining

specific AI factors that reinforce digital divide focussed on women was identified. Another significant study by (Peláez-Sánchez et al., 2023) revealed critical technology related factors for a wider digital inclusion for women, but it also lacked focus to evaluate the antecedents to technological proliferation, for the purpose of this study, AI metrics, which impact women's inclusion, participation, and adoption of AI, and correlating it to reinforcement of gender digital divide specifically at work. The existing literature gave us four crucial determinants of gender digital divide, viz., *pressure to adapt to upgraded AI systems, difficulty in keeping up with rapid AI innovations, emotional exhaustion due to continuous learning, and feeling left behind due to rapid AI advancements*. The synthesis of literature also presents us with significant research gaps which give us following research questions:

RQ 01: What are the numerous AI expansion metrics emerging out of increased pace of AI?

RQ 02: Is there an association between AI expansion metrics with factors leading to gender digital divide at workplace?

RQ 03: Are these AI expansion metrics reinforcing the existing gender digital divide in the context of women at workplace?

4. Research Design

4.1 Hypothesis Formulation

H0: There is no significant association between Speed of AI Expansion and Pressure to Adapt to Upgraded AI Systems Quickly.

H1: There is a significant association between Speed of AI Expansion and Pressure to Adapt to Upgraded AI Systems Quickly.

H0: There is no significant association between Speed of AI Expansion and Difficulty in Keeping Up with Rapid AI Innovations.

H2: There is a significant association between Speed of AI Expansion and Difficulty in Keeping Up with Rapid AI Innovations.

H0: There is no significant association between Speed of AI Expansion and Emotional Exhaustion Due to Continuous AI Learning

H3: There is a significant association between Speed of AI Expansion and Emotional Exhaustion Due to Continuous AI Learning

H0: There is no significant association between Speed of AI Expansion and Feeling Left Behind Due to Rapid AI Advancements.

H4: There is a significant association between Speed of AI Expansion and Feeling Left Behind Due to Rapid AI Advancements.

H0: There is no significant association between Complexity of AI Systems and Pressure to Adapt to Upgraded AI Systems Quickly.

H5: There is a significant association between Complexity of AI Systems and Pressure to Adapt to Upgraded AI Systems Quickly.

H0: There is no significant association between Complexity of AI Systems and Difficulty in Keeping Up with Rapid AI Innovations.

H6: There is a significant association between Complexity of AI Systems and Difficulty in Keeping Up with Rapid AI Innovations.

H0: There is no significant association between Complexity of AI Systems and Emotional Exhaustion Due to Continuous AI Learning.

H7: There is a significant association between Complexity of AI Systems and Emotional Exhaustion Due to Continuous AI Learning.

H0: There is no significant association between Complexity of AI Systems and Feeling Left Behind Due to Rapid AI Advancements.

H8: There is a significant association between Complexity of AI Systems and Feeling Left Behind Due to Rapid AI Advancements.

H0: There is a significant association between Frequency of AI Upgrades and Pressure to Adapt to Upgraded AI Systems Quickly.

H9: There is a significant association between Frequency of AI Upgrades and Pressure to Adapt to Upgraded AI Systems Quickly.

H0: There no significant association between Frequency of AI Upgrades and Difficulty in Keeping Up with Rapid AI Innovations.

H10: There is a significant association between Frequency of AI Upgrades and Difficulty in Keeping Up with Rapid AI Innovations.

H0: There is no significant association between Frequency of AI Upgrades and Emotional Exhaustion Due to Continuous AI Learning.

H11: There is a significant association between Frequency of AI Upgrades and Emotional Exhaustion Due to Continuous AI Learning.

H0: There is a significant association between Frequency of AI Upgrades and Feeling Left Behind Due to Rapid AI Advancements.

H12: There is a significant association between Frequency of AI Upgrades and Feeling Left Behind Due to Rapid AI Advancements.

H0: There is a significant association between Volume of New AI Tools Deployed and Pressure to Adapt to Upgraded AI Systems Quickly.

H13: There is a significant association between Volume of New AI Tools Deployed and Pressure to Adapt to Upgraded AI Systems Quickly.

H0: There is a significant association between Volume of New AI Tools Deployed and Difficulty in Keeping Up with Rapid AI Innovations.

H14: There is a significant association between Volume of New AI Tools Deployed and Difficulty in Keeping Up with Rapid AI Innovations.

H0: There is no significant association between Volume of New AI Tools Deployed and Emotional Exhaustion Due to Continuous AI Learning.

H15: There is a significant association between Volume of New AI Tools Deployed and Emotional Exhaustion Due to Continuous AI Learning.

H0: There is no significant association between Volume of New AI Tools Deployed and Feeling Left Behind Due to Rapid AI Advancements.

H16: There is a significant association between Volume of New AI Tools Deployed and Feeling Left Behind Due to Rapid AI Advancements.

5. Conceptual Model Proposed based on literature

Based on the hypotheses, we propose a conceptual model, subjected to empirical testing.

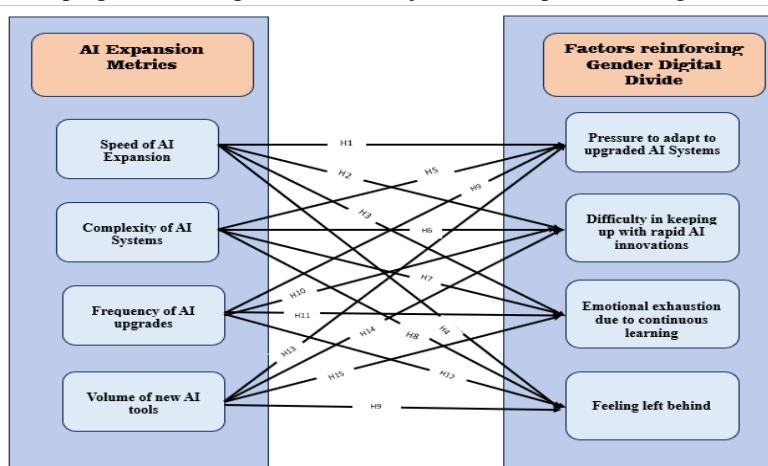


Figure 1 Theoretical Framework based on Systematic Literature Review

6. Sample Design

6.1 Target population

This study aims to analyse the association of identified AI expansion metrics with crucial factors that may reinforce gender digital divide among women employees in various sectors. The study's target population is users of technology across IT sector in different roles in Nagpur, not restricted to any particular gender, as this group is likely to have more exposure to AI technologies at work. Therefore, sample is drawn from employees having exposure to regular and rapid technological advances in tech companies. Respondents were reached out at various HR databases, industry networks, and professional technical bodies, online communities, social media platforms etc.

6.2 Sampling technique

A stratified random sampling technique was employed to ensure diverse representation across various genders, job roles, and experience levels at different stages of their careers, ensuring inclusive representation and enabling gender-disaggregated analysis. A total of 1021 responses were collected. The chosen sample size of 1000+ respondents was considered appropriate for the intended chi-square analysis, which is sensitive to sample distribution across categories.

6.3 Data Collection Methodology

Data for the study was collected using a structured, self-administered questionnaire circulated through email and online platforms such as Google Forms. The questionnaire comprised primarily of closed-ended questions, designed using nominal and ordinal scales, "Yes" "No," and "Maybe." Responses were collected anonymously to ensure authenticity and privacy.

7. Data Analysis

Hypothesis 1:

H0: There is no significant association between Speed of AI Expansion and Pressure to Adapt to Upgraded AI Systems Quickly.

Rejected

H1: There is a significant association between Speed of AI Expansion and Pressure to Adapt to Upgraded AI Systems Quickly.

Accepted

Count of Speed_AI_Expansion_Pressure	Column Labels				Expected Frequencies			(Observed - Expected) ² / Expected		
Row Labels	Maybe	No	Yes	Grand Total	Maybe (E)	No (E)	Yes (E)	Maybe	No	Yes
Female	51	67	333	451	57.43	76.89	316.68	0.72	1.27	0.83
Male	66	96	354	516	65.72	87.94	362.64	0.00	0.73	0.19
Other	13	11	30	54	6.88	9.18	37.94	5.47	0.36	1.66
Grand Total	130	174	717	1021						

At significance level 0.05, (*df*) 4, the critical value **9.488** is less than chi-square value (χ^2)**11.23**. Thus, we conclude that There is a significant association between speed of AI expansion and pressure due to speed of AI expansion at the 5% level of significance.

Hypothesis 2

H0: There is no significant association between Speed of AI Expansion and Difficulty in Keeping Up with Rapid AI Innovations.

Accepted

H2: There is a significant association between Speed of AI Expansion and Difficulty in Keeping Up with Rapid AI Innovations.

Rejected

Count of Speed_AI_Expansion_Difficulty	Column Labels				Expected Frequencies			(Observed - Expected) ² / Expected		
Row Labels	Maybe	No	Yes	Grand Total	Maybe (E)	No (E)	Yes (E)	Maybe	No	Yes
Female	83	63	305	451	77.74	72.88	300.37	0.36	1.34	0.07
Male	83	89	344	516	88.95	83.39	343.66	0.40	0.38	0.00
Other	10	13	31	54	9.31	8.73	35.96	0.05	2.09	0.69
Grand Total	176	165	680	1021						

At significance level 0.05, (*df*) 4, the chi-square value (χ^2) **5.37** is less than critical value **9.48**, we fail to reject null hypothesis. Thus, we conclude that there is no significant association between speed of AI expansion and Difficulty in Keeping Up with Rapid AI Innovations at the 5% level of significance.

Hypothesis 3

H0: There is no significant association between Speed of AI Expansion and Emotional Exhaustion Due to Continuous AI Learning

Accepted

H3: There is a significant association between Speed of AI Expansion and Emotional Exhaustion Due to Continuous AI Learning

Rejected

Count of Speed_AI_Expansion_Exhaustion	Column Labels				Expected Frequencies			(Observed - Expected) ² / Expected		
Row Labels	Maybe	No	Yes	Grand Total	Maybe (E)	No (E)	Yes (E)	Maybe	No	Yes
Female	117	124	210	451	103.42	124.2	223.4	1.790	0.000	0.810
Male	105	137	274	516	118.2	142.8	255.8	1.470	0.170	1.270
Other	12	20	22	54	12.38	14.88	26.74	0.010	1.770	0.840
Grand Total	234	281	506	1021						

At significance level 0.05, (*df*) 4, the chi-square value (χ^2) **8.13** is less than critical value **9.48**, we fail to reject null hypothesis. Thus, we conclude that there is no significant association between Speed of AI expansion and Emotional Exhaustion Due to Continuous AI Learning at the 5% level of significance.

Hypothesis 4

H0: There is no significant association between Speed of AI Expansion and Feeling Left Behind Due to Rapid AI Advancements.

Accepted

H4: There is a significant association between Speed of AI Expansion and Feeling Left Behind Due to Rapid AI Advancements.

Rejected

Count of Speed_AI_Expansion_LeftBehind	Column Labels				Expected Frequencies			(Observed - Expected) ² / Expected		
Row Labels	Maybe	No	Yes	Grand Total	Maybe (E)	No (E)	Yes (E)	Yes	No	Yes
Female	47	111	293	451	38.87	111.7	300.4	1.70	0.00	0.18
Male	33	133	350	516	44.45	127.9	343.6	2.95	0.20	0.12
Other	8	9	37	54	4.66	13.38	36.04	2.39	1.43	0.03
Grand Total	88	253	680	1021						

At significance level 0.05, (*df*) 4, the chi-square value (χ^2) **9.00** is less than critical value **9.48**, we fail to reject null hypothesis. Thus, we conclude that there is no significant association between speed of AI expansion and Feeling Left Behind Due to Rapid AI Advancements at the 5% level of significance.

Hypothesis 5

H0: There is no significant association between Complexity of AI Systems and Pressure to Adapt to Upgraded AI Systems Quickly.

Accepted

H5: There is a significant association between Complexity of AI Systems and Pressure to Adapt to Upgraded AI Systems Quickly.

Rejected

Count of Complexity_AI_Pressure	Column Labels				Expected Frequencies			(Observed - Expected) ² / Expected		
Row Labels	Maybe	No	Yes	Grand Total	Maybe	No	Yes	Yes	No	Yes
Female	64	48	339	451	63.13	46.84	341.03	0.01	0.03	0.01
Male	73	56	387	516	73.37	53.56	389.07	0.00	0.11	0.01
Other	6	2	46	54	7.57	5.6	40.83	0.33	2.31	0.65
Grand Total	143	106	772	1021						

At significance level 0.05, (*df*) 4, the chi-square value (χ^2) **3.46** is less than critical value **9.48**, we fail to reject null hypothesis. Thus, we conclude that there is no significant association between Complexity of AI Systems and Pressure to Adapt to Upgraded AI Systems Quickly at the 5% level of significance.

Hypothesis 6

H0: There is no significant association between Complexity of AI Systems and Difficulty in Keeping Up with Rapid AI Innovations.

Rejected

H6: There is a significant association between Complexity of AI Systems and Difficulty in Keeping Up with Rapid AI Innovations.

Accepted

Count of Complexity_AI_Difficulty	Column Labels				Expected Frequencies			(Observed - Expected) ² / Expected		
Row Labels	Maybe	No	Yes	Grand Total	Maybe	No	Yes	Yes	No	Yes
Female	99	44	308	451	110	44.6	296	1.18	0.01	0.48
Male	146	51	319	516	126	51.1	339	2.89	0.00	1.11
Other	5	6	43	54	13.3	5.33	35.4	5.15	0.08	1.63
Grand Total	250	101	670	1021						

At significance level 0.05, (*df*) 4, the chi-square value (χ^2) **12.53** is more than critical value **9.48**, we reject null hypothesis. Thus, we conclude that there is a robust and significant association between Complexity of AI Systems and Difficulty in Keeping Up with Rapid AI Innovations at the 5% level of significance.

Hypothesis 7

H0: There is no significant association between Complexity of AI Systems and Emotional Exhaustion Due to Continuous AI Learning.

Accepted

H7: There is a significant association between Complexity of AI Systems and Emotional Exhaustion Due to Continuous AI Learning.

Rejected

Count of Complexity_AI_Exhaustion	Column Labels				Expected Frequencies			(Observed - Expected) ² / Expected		
Row Labels	Maybe	No	Yes	Grand Total	Maybe	No	Yes	Yes	No	Yes
Female	33	39	379	451	38.42	41.51	371.1	0.76	0.15	0.17
Male	51	53	412	516	43.97	47.51	424.5	1.12	0.63	0.37
Other	3	2	49	54	4.6	4.97	44.42	0.56	1.77	0.47
Grand Total	87	94	840	1021						

At significance level 0.05, (*df*) 4, the chi-square value (χ^2) **6.014** is less than critical value **9.48**, we fail to reject null hypothesis. Thus, we conclude that there is no significant association between Complexity of AI Systems and Emotional Exhaustion Due to Continuous AI Learning at the 5% level of significance.

Hypothesis 8

H0: There is no significant association between Complexity of AI Systems and Feeling Left Behind Due to Rapid AI Advancements.

Rejected

H8: There is a significant association between Complexity of AI Systems and Feeling Left Behind Due to Rapid AI Advancements.

Accepted

Count of Complexity_AI_Left Behind	Column Labels				Expected Frequencies			(Observed - Expected) ² / Expected		
Row Labels	Maybe	No	Yes	Grand Total	Maybe	No	Yes	Yes	No	Yes
Female	68	54	329	451	64.04	65.84	321.1	0.244	2.137	0.194
Male	76	89	351	516	73.28	75.28	367.4	0.101	2.518	0.737
Other	1	6	47	54	7.67	7.88	38.45	5.801	0.448	1.91
Grand Total	145	149	727	1021						

At significance level 0.05, (*df*) 4, the chi-square value (χ^2) **14.09** is more than critical value **9.48**, we reject the null hypothesis. Thus, we conclude that there is a robust and significant association between Complexity of AI Systems and Feeling Left Behind Due to Rapid AI Advancements at the 5% level of significance.

Hypothesis 9

H0: There is a significant association between Frequency of AI Upgrades and Pressure to Adapt to Upgraded AI Systems Quickly.

Rejected

H9: There is a significant association between Frequency of AI Upgrades and Pressure to Adapt to Upgraded AI Systems Quickly.

Accepted

Count of Frequency_Upgrade_Pressure	Column Labels				Expected Frequencies			(Observed - Expected) ² / Expected		
Row Labels	Maybe	No	Yes	Grand Total	Maybe	No	Yes	Yes	No	Yes
Female	122	152	177	451	113.1	148.4	189.5	0.698	0.086	0.818
Male	122	158	236	516	129.5	169.8	216.8	0.433	0.815	1.696
Other	12	26	16	54	13.55	17.82	22.63	0.178	3.756	1.942
Grand Total	256	336	429	1021						

At significance level 0.05, (*df*) 4, the chi-square value (χ^2) **10.42** is more than critical value **9.48**, we reject the null hypothesis. Thus, we conclude that there is a significant association between Frequency of AI Upgrades and Pressure to Adapt to Upgraded AI Systems Quickly at the 5% level of significance.

Hypothesis 10

H0: There no significant association between Frequency of AI Upgrades and Difficulty in Keeping Up with Rapid AI Innovations.

Accepted

H10: There is a significant association between Frequency of AI Upgrades and Difficulty in Keeping Up with Rapid AI Innovations.

Rejected

Count of Frequency_Upgrade_Difficulty	Column Labels				Expected Frequencies			(Observed - Expected) ² / Expected		
Row Labels	Maybe	No	Yes	Grand Total	May be	No	Yes	Yes	No	Yes
Female	35	96	320	451	34.01	92.7 6	324. 23	0.028 7	0.113	0.05 51
Male	35	103	378	516	38.91	106. 13	370. 95	0.393 8	0.0924	0.13 38
Other	7	11	36	54	4.07	11.1 1	38.8 2	2.104 5	0.001	0.20 5
Grand Total	77	210	734	1021						

At significance level 0.05, (*df*) 4, the chi-square value (χ^2) 3.12 is less than critical value 9.48, we fail to reject the null hypothesis. Thus, we conclude that there is no significant association between Frequency of AI Upgrades and Difficulty in Keeping Up with Rapid AI Innovations.
at the 5% level of significance.

Hypothesis 11

H0: There is no significant association between Frequency of AI Upgrades and Emotional Exhaustion Due to Continuous AI Learning.

Accepted

H11: There is a significant association between Frequency of AI Upgrades and Emotional Exhaustion Due to Continuous AI Learning.

Rejected

Count of Frequency_Upgrade_Exhaustion	Column Labels				Expected Frequencies			(Observed - Expected) ² / Expected		
Row Labels	Maybe	No	Yes	Grand Total	Maybe	No	Yes	Yes	No	Yes
Female	64	91	296	451	64.47	86.59	299.9	0.003	0.224	0.052
Male	78	99	339	516	73.76	99.09	343.2	0.243	0	0.05
Other	4	6	44	54	7.74	10.32	35.94	1.81	1.811	1.802
Grand Total	146	196	679	1021						

At significance level 0.05, (*df*) 4, the chi-square value (χ^2) **5.99** is less than critical value **9.48**, we fail to reject the null hypothesis. Thus, we conclude that there is a no significant association between Frequency of AI Upgrades and Emotional Exhaustion Due to Continuous AI Learning at the 5% level of significance

Hypothesis 12

H0: There is a significant association between Frequency of AI Upgrades and Feeling Left Behind Due to Rapid AI Advancements.

Accepted

H12: There is a significant association between Frequency of AI Upgrades and Feeling Left Behind Due to Rapid AI Advancements.

Rejected

Count of Frequency_Upgr ade_Difficulty	Column Labels				Expected Frequencies			(Observed - Expected) ² / Expected		
Row Labels	Maybe	No	Yes	Grand Total	Maybe	No	Yes	Yes	No	Yes
Female	35	96	320	451	34.01	92.76	324.23	0.0287	0.113	0.0551
Male	35	103	378	516	38.91	106.13	370.95	0.3938	0.0924	0.1338
Other	7	11	36	54	4.07	11.11	38.82	2.1045	0.001	0.205
Grand Total	77	210	734	1021						

At significance level 0.05, (*df*) 4, the chi-square value (χ^2) **3.13** is less than critical value **9.48**, we fail to reject the null hypothesis. Thus, we conclude that there is a no significant association between Frequency of AI Upgrades and Feeling Left Behind Due to Rapid AI Advancements at the 5% level of significance

Hypothesis 13

H0: There is a significant association between Volume of New AI Tools Deployed and Pressure to Adapt to Upgraded AI Systems Quickly.

Accepted

H13: There is a significant association between Volume of New AI Tools Deployed and Pressure to Adapt to Upgraded AI Systems Quickly.

Rejected

Count of Volume_NewTools_Pressure	Column Labels				Expected Frequencies			(Observed - Expected) ² / Expected		
Row Labels	Maybe	No	Yes	Grand Total	Maybe	No	Yes	Yes	No	Yes
Female	64	55	332	451	61.38	65.39	324.23	0.112	1.649	0.186
Male	66	88	362	516	70.25	74.76	370.99	0.257	2.332	0.218
Other	9	5	40	54	7.36	7.85	38.79	0.369	1.035	0.036
Grand Total	139	148	734	1021						

At significance level 0.05, (*df*) 4, the chi-square value (χ^2) **6.194** is less than critical value **9.48**, we fail to reject the null hypothesis. Thus, we conclude that there is a no significant association between Volume of New AI Tools Deployed and Pressure to Adapt to Upgraded AI Systems Quickly at the 5% level of significance.

Hypothesis 14

H0: There is a significant association between Volume of New AI Tools Deployed and Difficulty in Keeping Up with Rapid AI Innovations.

Accepted

H14: There is a significant association between Volume of New AI Tools Deployed and Difficulty in Keeping Up with Rapid AI Innovations.

Rejected

Count of Volume_NewTools_Difficulty	Column Labels				Expected Frequencies			(Observed - Expected) ² / Expected		
Row Labels	Maybe	No	Yes	Grand Total	Maybe	No	Yes	Yes	No	Yes
Female	52	6	393	451	58.32	10.16	382.52	0.685	1.705	0.287
Male	75	15	426	516	66.74	11.63	437.63	1.021	0.971	0.309
Other	5	2	47	54	6.98	1.22	45.8	0.561	0.474	0.034
Grand Total	132	23	866	1021						

At significance level 0.05, (*df*) 4, the chi-square value (χ^2) **6.047** is less than critical value **9.48**, we fail to reject the null hypothesis. Thus, we conclude that there is a no significant association between Volume of New AI Tools Deployed and Difficulty in Keeping Up with Rapid AI Innovations at the 5% level of significance.

Hypothesis 15

H0: There is no significant association between Volume of New AI Tools Deployed and Emotional Exhaustion Due to Continuous AI Learning.

Rejected

H15: There is a significant association between Volume of New AI Tools Deployed and Emotional Exhaustion Due to Continuous AI Learning.

Accepted

Count of Volume_NewTools _Exhaustion	Column Labels					Expected Frequencies			(Observed - Expected) ² / Expected		
Row Labels	Maybe	No	Yes	(blank)	Grand Total	Maybe	No	Yes	Yes	No	Yes
Female	131	30	290		451	144	35.33	271.67	1.173	0.804	1.208
Male	185	48	283		516	165.02	40.43	310.55	2.415	1.408	2.379
Other	10	2	42		54	17.25	4.24	32.51	3.047	1.182	2.765
(blank)											
Grand Total	326	80	615		1021						

At significance level 0.05, (*df*) 4, the chi-square value (χ^2) **16.38** is more than critical value **9.48**, we reject the null hypothesis. Thus, we conclude that there is a significant and robust association between Volume of New AI Tools Deployed and Emotional Exhaustion Due to Continuous AI Learning at the 5% level of significance.

Hypothesis 16

H0: There is no significant association between Volume of New AI Tools Deployed and Feeling Left Behind Due to Rapid AI Advancements.

Accepted

H16: There is a significant association between Volume of New AI Tools Deployed and Feeling Left Behind Due to Rapid AI Advancements.

Rejected

Count of Volume_NewTools_LeftBehind	Column Labels					Expected Frequencies			(Observed - Expected) ² / Expected		
Row Labels	Maybe	No	Yes	(blank)	Grand Total	Maybe	No	Yes	Yes	No	Yes
Female	59	94	298		451	63.59	94.08	293.33	0.331	0.001	0.075
Male	74	104	338		516	72.84	107.65	335.51	0.019	0.124	0.018
Other	11	15	28		54	7.62	11.27	35.11	1.501	1.24	1.442
(blank)											
Grand Total	144	213	664		1021						

At significance level 0.05, (*df*) 4, the chi-square value (χ^2) **4.751** is less than critical value **9.48**, we fail to reject the null hypothesis. Thus, we conclude that there is no significant association between Volume of New AI Tools Deployed and Feeling Left Behind Due to Rapid AI Advancements at the 5% level of significance.

8. Discussion

This study makes a significant contribution by identifying crucial AI expansion metrics by synthesizing recent literature and further empirically establishing how they are reinforcing gender digital divide (GDD) for women at work. Not all associations between AI metrics and GDD antecedents were statistically significant, revealing a nuanced pattern in which only some AI metrics proved critical in exacerbating gender inequities. The methodology of Systematic Literature Review was first used to identify 4 significant AI metrics, based on which, a comprehensive conceptual model was developed to explore their relationship with factors reinforcing the gender digital divide. The literature review pointed toward 16 possible associations between four independent variables—*Speed of AI Expansion*, *Complexity of AI Systems*, *Frequency of AI Upgrades*, and *Volume of New AI Tools*—and four dependent variables: *Pressure to Adapt*, *Difficulty in Keeping Up*, *Emotional Exhaustion*, and *Feeling Left Behind*. This model was tested empirically using chi-square analysis. The Chi-square test of independence was chosen to statistically analyse the responses as it is one of the most reliable tool to examine the associations between categorical variables. With a large sample size of 1021, it ensured reliable results, making it effective for analyzing group differences in nominal responses like "Yes," "No," and "Maybe." The outcomes resulted in a refined model, retaining only statistically significant associations. This empirically validated model narrowed the scope of associations but enhanced their precision and reliability, offering a clearer picture of which factors truly contribute to the gender digital divide in the context of AI, as given below:

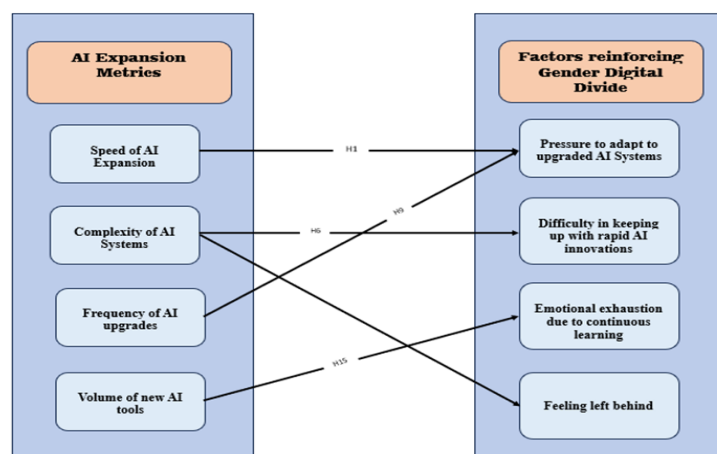


Figure 2 Proposed Empirically validated Conceptual Model

Speed of AI expansion was found to significantly correlate with *pressure to adapt* but not with *emotional exhaustion* or *difficulty in keeping up*. This suggests an initial strain, especially on women, to keep pace with AI transitions, though not necessarily leading to burnout. *Complexity of AI systems* demonstrated robust associations with both *difficulty in coping* and *feeling left behind*, underlining how increasing sophistication in AI marginalizes women who may lack access to training or confidence in their digital skills. *Frequency of AI upgrades* only significantly affected *pressure to adapt*, suggesting a need for continuous learning infrastructures that are more inclusive. *Volume of new AI tools* was notably linked to *emotional exhaustion*, hinting at cognitive overload among female professionals due to constant changes in tech ecosystems.

9. Implications, Limitations, and Future Research Directions

9.1 Theoretical Implications

This study synthesized current literature in an attempt to identify AI specific expansion metrics as novel constructs which contribute to factors leading to gender digital divide. The outcomes contribute to the existing literature significantly. Firstly, the systematic literature review identifies four crucial AI expansion metrics, viz., *Speed of AI expansion*, *complexity of AI systems*, *frequency of AI upgrades*, and *volume of new AI tools*. Secondly, the study identified four antecedents that facilitate gender digital divide the most, viz., *pressure to adapt*, *difficulty in keeping up with rapid AI systems*, *emotional exhaustion due to continuous learning*, and *feeling left behind*. Thirdly, based on the synthesized literature, the study tested a conceptual model, consisting of sixteen associations between the constructs. Fourthly, in addition to qualitative synthesis, this research also provides quantitative support by empirical testing of those associations using chi-square testing for the theorized but untested relationship. Lastly, the study proposes a refined conceptual framework that pinpoints the most valid constructs reinforcing gender-based exclusion in AI-intensive environments for women.

9.2 Practical Implications

The unparalleled pace of AI and the newer forms like Gemini, GPT-4 Turbo, Copilot, and many more, their ever-increasing integration with social systems has now become a norm. This is posing newer forms of threats to businesses especially in the job disruption, and the way work is being carried. This also represents many dilemmas and pressures in the form of skills and tasks that have become obsolete. The most vulnerable are women, due to their existing perceived socio-cultural and traditional role, the implications of which extend to workplaces. As world economies are devising new strategies to address SDG 5, which aims at bringing gendered inclusion to forefront of businesses, with ever rising complexities at workplace, women's participation in technical domain is being challenged, especially if they respond negatively to automation. Thus, the outcomes of this study present significant practical implications. In addition to significantly aligning with SDG 5, this study firstly could facilitate organizations to enhance the learning programs, tailored to specific needs of women, facilitating them to adapt to fast paced changes. Secondly, the complexity of AI systems could be further simplified to make them easier to learn to facilitate quick learning and alignment. Thirdly, companies could also address the frequency of AI versions, by implementing structured and phased rollouts. Fifthly, recruitment strategies could be strategized to include more women, to eliminate gendered bias from AI training datasets. This could as well eliminate the feeling of being left behind as women will be placed equally at the forefront of onset of implementation of new technology. Lastly, the HR and DEI teams could use the proposed framework to strategize equitable AI integration into organizational policy framework.

9.3 Limitations

The outcomes of this study are significant, albeit limited to a few inadequacies. Firstly, the study was restricted to Nagpur-based professionals, limiting generalizability to other regions. Secondly, reliance on autonomous responses may introduce response bias or social desirability effects. Thirdly, a few other relevant AI metrics were not included in the study, as they are being extensively testified in current academic scholarship. Lastly, although inclusive, the analysis has excluded the nuances of non-binary and intersectional gender identities.

9.4 Future Research Directions

Firstly, this study is limited to IT sector, and could be extended to other sectors such as healthcare, education, manufacturing) to compare how AI-induced GDD manifests differently across industries. Secondly, the refined conceptual framework could be further tested empirically using advance statistical tools for deeper insights. Thirdly, expanding the geographical scope beyond Nagpur will enhance the generalizability of results and capture regional differences in AI

adoption and gender dynamics. Fourth, future studies must adopt an intersectional lens that considers non-binary gender identities and overlapping factors like socioeconomic status, disability, or ethnicity. Finally, longitudinal studies are essential to understand the evolving impact of AI on workplace gender equity over time, particularly as AI systems and corporate policies continue to mature.

10. Conclusion

This study reveals a troubling yet important reality: the rapid expansion of AI technologies is not gender-neutral. Certain dimensions of AI development—particularly its speed, complexity, and volume—have demonstrable impact on reinforcing the gender digital divide, especially in workplaces with rapid digital transitions. By offering a data-driven view of how technological progress can unintentionally marginalize women, the study underscores the urgent need for AI systems, workplace cultures, and policies that are not only innovative but also inclusive.

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