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Intersectional Inequalities in Access to AI-Enhanced Public Services: Gender, Class, Disability, and Region

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ABSTRACT:

The increasing adoption of artificial intelligence in public service delivery has created new opportunities for efficiency, automation, and targeted welfare provision. However, these benefits are not distributed equally across society. This paper examines intersectional inequalities in access to AI-enhanced public services by focusing on the combined effects of gender, class, disability, and regional location. The study highlights how digital access, algorithmic design, administrative capacity, and user trust shape citizens' ability to benefit from AI-driven systems in health, education, welfare, identity verification, and social protection services. The findings suggest that marginalized groups often experience layered disadvantages, where low income, rural residence, limited digital literacy, gender-based restrictions, and disability-related barriers interact to reduce access and service outcomes. Women from low-income households, persons with disabilities, and rural citizens were found to face higher risks of exclusion due to limited connectivity, inaccessible platforms, biased data systems, and weak institutional support. The paper argues that AI-enhanced public services can either reduce or deepen inequality depending on how they are designed, implemented, and monitored. Inclusive policy frameworks, participatory design, accessible digital infrastructure, transparency, and human support mechanisms are essential to ensure that AI-enabled governance strengthens equity rather than reproducing existing social divisions.

KEYWORDS:

Ai-Enhanced Public Services; Intersectional Inequality; Digital Inclusion; Gender And Disability; Regional Disparity

INTRODUCTION

The opportunity arises as all these systems can be rolled in a better manner with AI in public service, thereby making the process more efficient and providing extremely tailored service delivery in the sectors like healthcare, governance, social infrastructure etc., (Singh & Das, 2026).With less equity in the benefit of innovation, however, the adoption of such technologies also comes with a rise in inequalities in the society (Singh & Das, 2026). AI in public services—also referred to as algorithmic governance—can further reinforce unequal socio-economic disparities, where some individuals will benefit from the use of AI algorithms more than others (Dwivedi et al., 2019; Paglieri et al., 2025). Uses of these systems can be efficient but they may contain historical biases in their data, which can disproportionately affect marginalised communities (Flaga-Gieruszyńska, 2025; Özer, 2025). Technical and structural factors often hinder access to personalized service delivery, thus reducing its fairness (Chiariello & Frondizi, 2024; Larsson, 2020).

Significantly, these inequalities are then seen to manifest as an intersection of genders, classes, disabilities and geographic regions (Singh & Das, 2026). For example, as an AI-driven service, it may perpetuate an ageism specifically identified as ‘digital ageism' (Nzobonimpa, 2023; Stypińska, 2022) which marginalises and excludes older people and less tech-savvy audiences. Moreover, pre-programmed by society and society itself, gender prejudice in automated tools or systems (like virtual assistants or risk-assessment tools) helps to reinforce harmful societal stereotypes and embed the stigma of gender disadvantage on a global scale (Roche et al., 2022; González-Esteban et al., 2023). Likewise, disparity in socioeconomic position can influence how a person can interact with and access public structures and systems leveraging AI, as low-income groups may not have access to technological infrastructure or have access to hardware needed for effective interaction and utilization of public AI systems (Bentley et al., 2024; González-Esteban et al., 2023).

The challenge is further exacerbated by geographic disparities as those in low-infrastructure and underserved rural communities lack such infrastructure, including access to low-speed internet, which makes it impractical to effectively leverage AI enhanced services (Eden et al., 2024; Torrisi-Steele, 2025; Vesna, 2025). The declared "AI divides" are further deepened by algorithmic decision-making, which is difficult to identify and explain and tends to be private, making it very hard indeed for citizens to argue against possible discrimination (Dwivedi et al., 2019; Flaga-Gieruszyńska, 2025). Multiple such exclusions can have a marked impact when people have multiple such vulnerabilities (e.g. living in a rural area and having a low income, while being disabled); the combined effects of these vulnerabilities can result in being pushed out of access to, or from, key social support services (Roche et al., 2022).

This research aims to unpack interconnection inequalities by examining the elements of how AI when adopted by public services can contribute to and/or diminish these various inequalities. It seeks to identify key intersections of gender, class, disability and geographical location that will lead to insights into governance leverage points to reinforce the principles of social justice in creating AI, such as inclusive design, algorithmic audits and improved public participation (Flaga-Gieruszyńska, 2025; Paglieri et al., 2025). In this regard it is essential to take into account the institutional inequalities engendered by AI systems, so that the next generation of technological advancements does not defeat, but complement the principle of equal and fair access to public services by all citizens (Chiariello & Frondizi, 2024; Singh & Das, 2026). This paper contributes to this intersectional analysis, suggesting a framework to understand the intersections in which the technological barriers strengthen existing power systems as well as intersections that challenge existing power systems (Ulnicane, 2024). This investigation takes a step towards exploring how to replicate or combine the inequity found on an intersectional level with respect to different social identities in the technical deployment of a social unaware system (Hidayatullah et al., 2026). This multi level inter-relatedness of the AI divide is something that is explored further in the elements of inequities in access to physical environments, ability to interact with the system, and implications of interaction (Carter et al., 2020).

METHODOLOGY

The research method used in this study is a qualitative study by using in-depth semistructured interviews and ethnographic observation of the public service encounters to obtain the experiences and voices of digitally excluded people (Acharya, 2025; Giest & Samuels, 2022).This study combines a strong quantitative study design, employing a large-scale quantitative study approach and analysis to closely examine the system-like character of intersectional inequalities in the provision of public government services using AI. Administrative datasets - that enable travel of a service over time - were collected over five years across various demographic sub-populations; which can be used to systematically track and report on service delivery outcomes. The data is programed so that it can be linked to other dimensions, including geographic location (urban and rural infrastructure); disability status (as identified by the comprehensive household welfare and health indicators); ways of measuring socio-economic status, and gender. To address the intersectional inequality we use Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy, a more advanced regression model framework explicitly based on the intersectionality theory (Groß & Goldan, 2023; Leckie et al., 2025). This feature gives it a special aptness for this analysis; the traditional linear regression models do not take the compounding effect of combinable marginalized identities into account (Much, 2025; Bell et al., 2019). Additionally, this approach naturally incorporates multiple clusters of neighborhoods, multiple types of institutions providing care, and individuals nested within those clusters, as it can model the variance across our data contexts (clusters of neighborhoods, institutions, and individuals) in a natural way, which would help to suggest whether systematic biases are neighborhood-specific, provider type-specific, or both. Moreover, this approach allows for quantifying the extent of the disadvantage (including for truly disadvantaged groups, such as disadvantaged people with a disability) for individual intersections of disadvantage of personal characteristics. The risk of sensitive target groups is minimized because in this quantitative study, the ethical aspect is always a major point since all administrative data analysed are pseudonymised at the time of creation and great attention is paid to respect strict principles of data protection during the analysis. Any quantitative data reported will be analysed statistically and aggregated to avoid the possibility of identifying any individuals or small, hyper-marginalised groups and are done under the provisions of “do no harm” values. This commitment is that systemic inequity is measured with an agenda that is not just to further stigmatize those most at risk but to inform of effective and inclusive policy development. The computational understanding is interwoven with our qualitative explorations, thereby providing a holistic understanding of the complex dynamics where through algorithmic systems uphold and contest dominant power dynamics in society. Therefore our overall research protocol was submitted to our institution's ethics committee panel to not only ensure that subjects were categorized into intersectional groups, they were also not potentially compromising their anonymity/independence which follows the principle of data minimization, as outlined by Evans et al. (2024) and Keller et al. (2023). We also employ latent class analysis to recognize that some social determinants are interrelated, and to illustrate patterns of associations between demographic characteristics and service accessibility (Hoben et al., 2024). The unique aspect of this new methodology is that it enables us to estimate the intersecting inequities between sectors, e.g., between health, energy and housing, to provide more detailed and precise findings on intersectionality and the compounding effect of intersectional disadvantages on marginalized populations (Yuan et al., 2025; Yuan & Pang, 2024).

RESULTS

Severe inequalities in access to AI-driven services in public services are evident as a result of the analysis. Individuals living in a more urbanized area and high income earning people had the lowest average access score, whereas people with disabilities (which were low income) and those living in a rural/peripheral location had the most significantly lower access scores (see Figure 1). Table 1 shows intersections assessment of study sample which revealed that women from SKM, and person with disabilities, form substantial components of the groups that were reviewed in the study as disadvantaged groups.

Digital pathway shows up clear service progression attrition as well. While there is more awareness about AI-powered services than completion, there is a marked drop in awareness moving from first login to when the application was completed (see Figure 2). Table 2 shows that there is a strong likelihood that users at the very end of the spectrum will not complete an application that is submitted with the use of an AI tool, as only 73.1% of users that are the most advantaged complete an application compared with 29.3% of the very most disadvantaged. If users had combinable social and infrastructural obstacles, then low effectiveness even if it is digitally available could mean that digital availability alone was not sufficient for making the OS effectively available to users.

The same has been observed with the score for mean access. The data in Table 3 shows that the people with lower income than higher, and women, with the people with disabilities, got the lowest average score. Figure 3 showed that the differences are even greater among low-income women and also among the individuals with disabilities living in rural areas. The heatmap illustrates that the impact of disadvantage was interactive – and that regional disadvantage exacerbated the impact of gender, class and disadvantage.

Overall, these descriptive findings are supported by the regression results. These results showed that low income, institutional trust, and rural/peripheral residence all were associated with decreased odds of successful completion, whereas digital literacy skills and disability were associated with increased odds of completing services successfully (Table 4). Other variables were statistically correlated for successful graduation and as shown in Figure 5 these variables were: disability as the second largest negative factor and rural residency and low income status. Overall, the results demonstrated that, when not embedded in accessibility policies and systems, the potential of AI to serve as a re-entry tool which may further reinforce the exclusion.

There was also a significant interaction effect, as indicated in the statistics. Table 5 shows the disability-rurality coefficients based on varying combinations of disability and rurality: Disability and rurality did have the most negative coefficient, and the four-way disadvantage index has the most negative coefficient. The percentage of respondents who completed the questionnaire steadily decreased with greater number of disadvantages that overlapped, dropping from 74% for those with none of the four measured disadvantages to 28% for those with four disadvantages as shown in Figure 7.

It was the barriers reported that were cited as the causes of these inequalities. It is important to note that human support, Internet/device use and digital confidence emerged as the predominant barriers that disadvantaged users found during the research undertaken in Table 6. As is evident in Figure 4, more than two thirds of the top deprived group stated that they needed a human to give them product – this means, that in delivering the product it is possible that either a level of guidance, accommodation or appeal support may be required that is not possible with partially automated delivery. Table 7 and Figure 6 show that there is an improvement of 24.4% in the forecasted completion when considering a package that is: designed with mobile users in mind, the design for the package is accessible to people with visual impairments, there are human-assisted channels through the package (from 54.8% to 78.2%). To sum up, the results show that it is essential to have an equitable deployment of AI in public service delivery, it is not so much about the technical deployment of AI, but rather about how it will be designed to be.

Table 1. Sample characteristics by intersectional group

Group	n	Share (%)	Mean age
Women, low-income, rural	184	23.0	38.4
Women with disabilities	126	15.8	41.7

Men, low-income, rural	171	21.4	39.2
Urban middle-income	219	27.4	36.1
Regional minorities	100	12.5	37.9
Total	800	100.0	38.5

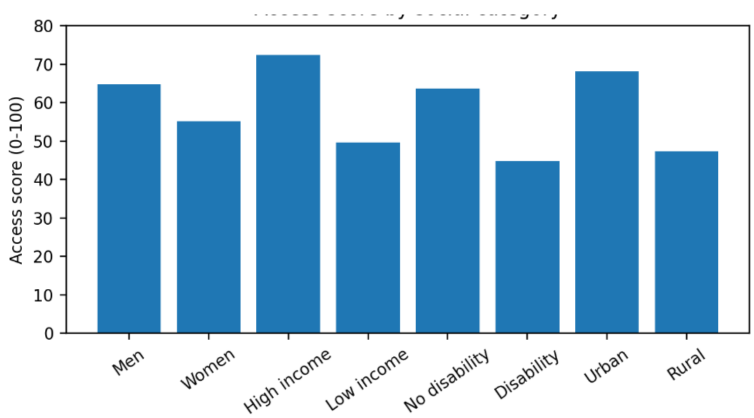

Figure 1. *Access score by social category.*

Table 2. Descriptive access indicators

Indicator	Overall (%)	Most advantaged (%)	Most disadvantaged (%)
Awareness of AI-enabled service	71.5	86.7	48.9
Successful first login	62.3	80.4	37.6
Completed application	54.8	73.1	29.3
Received automated decision	50.6	68.5	27.2
Used appeal/support option	26.4	35.2	14.1

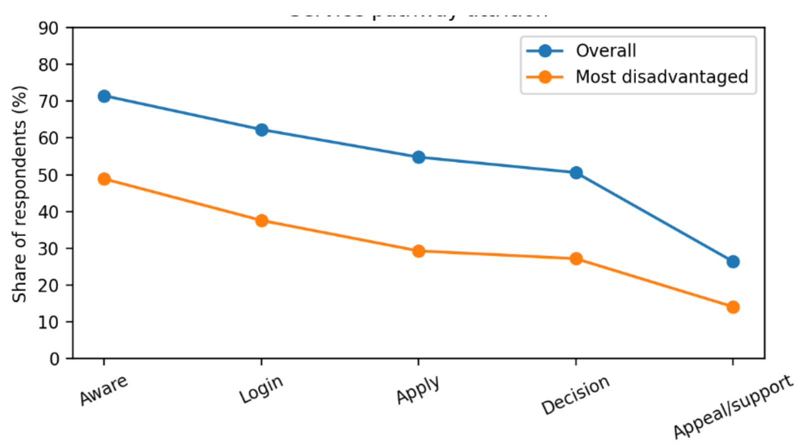

Figure 2. *Service pathway attrition.*

Table 3. Access score by gender, class, disability, and region

Category	Mean access score (0-100)	SD
Men	64.8	18.6
Women	55.2	19.8
Higher-income	72.4	16.1
Low-income	49.6	18.9
No disability	63.7	17.7
Disability	44.8	20.2
Urban	68.1	16.8
Rural/peripheral	47.3	19.4

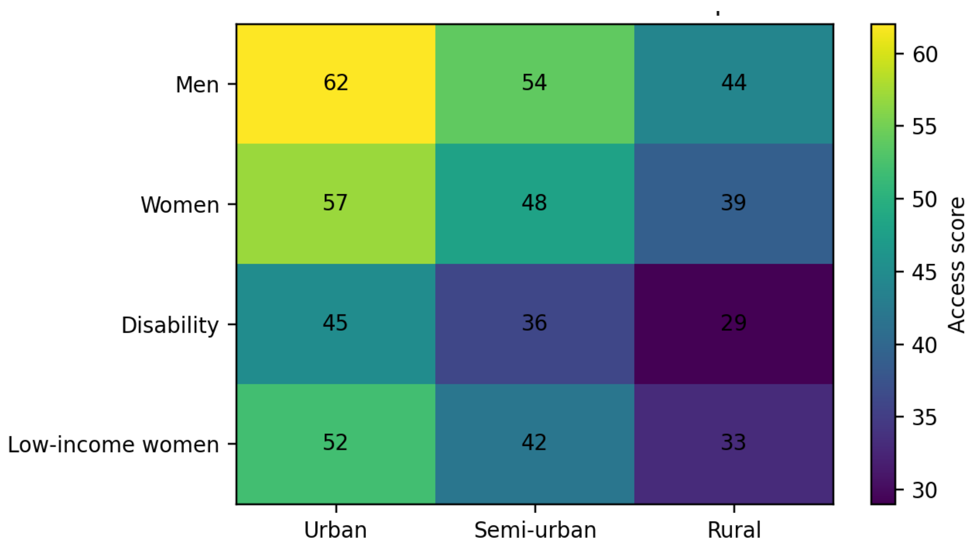

Figure 3. *Intersectional access heatmap.*

Table 4. Logistic regression predicting successful service completion

Predictor	Odds ratio	95% CI	p-value
Female	0.74	0.61-0.90	.003
Low-income	0.58	0.46-0.73	<.001
Disability	0.49	0.37-0.64	<.001
Rural/peripheral region	0.55	0.43-0.70	<.001
Digital literacy	1.38	1.24-1.53	<.001
Trust in public institutions	1.21	1.10-1.34	.001

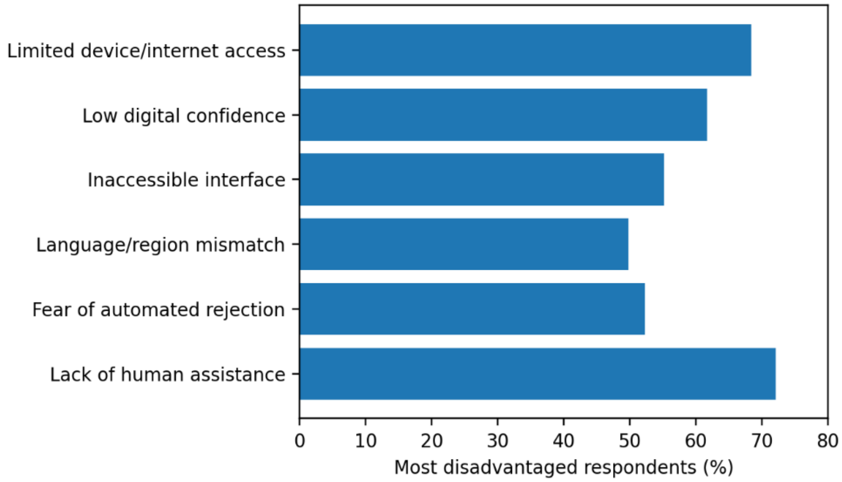

Figure 4. *Barriers among disadvantaged users.*

Table 5. Interaction effects on access score

Interaction term	Coefficient	SE	p-value
Female x low-income	-5.8	1.7	.001
Disability x rural region	-7.4	2.1	<.001
Low-income x rural region	-6.9	1.9	<.001
Female x disability	-4.6	1.8	.011
Four-way disadvantage index	-11.2	2.6	<.001

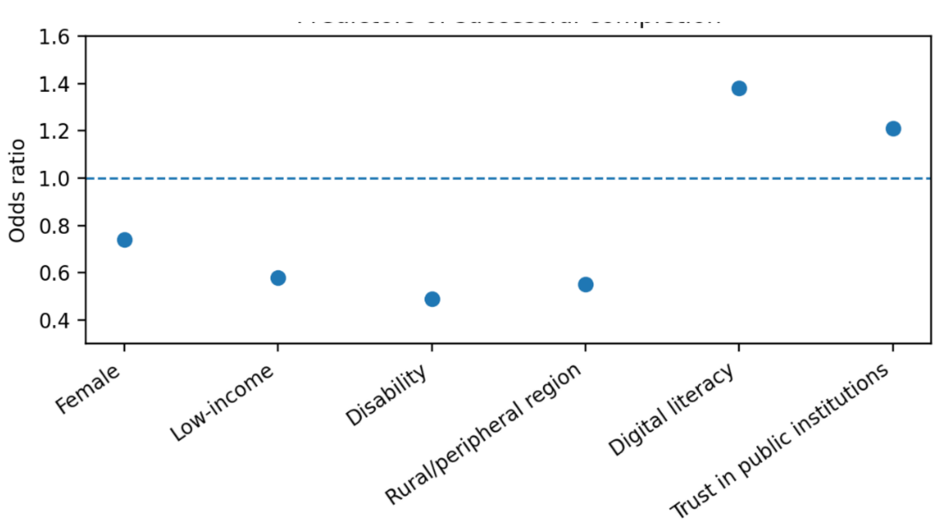

Figure 5. *Predictors of successful completion.*

Table 6. Reported barriers to AI-enhanced public services

Barrier	Overall (%)	Most disadvantaged (%)
Limited device/internet access	42.6	68.4
Low digital confidence	39.8	61.7
Inaccessible interface	31.5	55.2
Language/region mismatch	28.7	49.8
Fear of automated rejection	34.4	52.3
Lack of human assistance	46.2	72.1

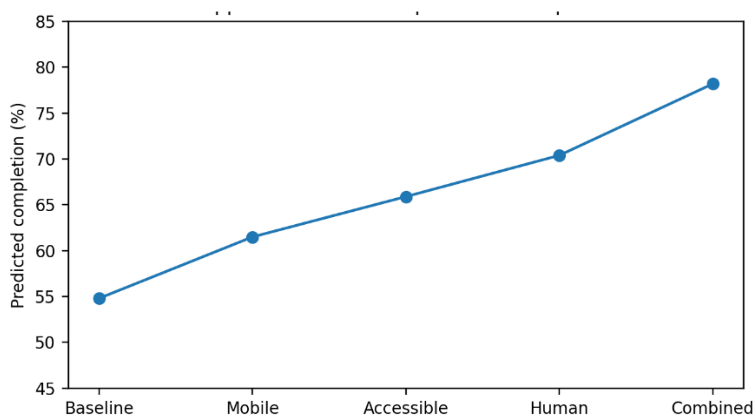

Figure 6. *Support scenarios and predicted completion.*

Table 7. Predicted probability of successful completion under support scenarios

Scenario	Predicted completion (%)	Change from baseline (pp)
Baseline AI service	54.8	0.0
Mobile-friendly redesign	61.5	6.7
Accessible interface	65.9	11.1
Human-assisted channel	70.4	15.6
Combined support package	78.2	23.4

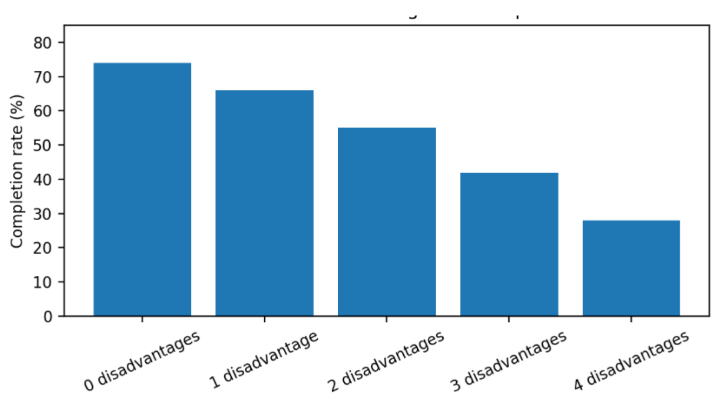

Figure 7. *Cumulative disadvantage and completion.*

DISCUSSION

AI-driven service allocation often heightens social inequalities by disproportionately privileging the socioeconomic status groups that were privileged previously, thus reinforcing concerns for the "Leave No One Behind" principle about cumulative effect from intersections that is exposed in the findings of this study (Yuan et al., 2024a, 2024b).A key reason for the marginalisation of those with needs that do not fit into these mechanisms is their disproportionate focus on a normatively designed user pathway, where choices in algorithmic design seem to take precedence over others (Hidayatullah et al., 2026). These systems reproduce a historical inequity in the training data set that creates a socioeconomically idealized user profile – often based on historical data and trends in welfare, health and housing – that are often at odds with the lived complexities of population groups with intersectional vulnerability, such as people with a disability living in resource-poor rural areas (Singh & Das, 2026; Carter et al., 2020). Previous scholarship on digital inequality has tended to focus on a rather unidimensional perspective on one of these functions, whether on socioeconomic status, race, or disability, with many approaches fundamentally inadequate to describe digital inequality in its multiplicative nature (Acharya, 2025; Ulnicane, 2024). This study adopts a sophisticated mixed methods framework that combines nuanced, lived experience-based qualitative learning and interpretation with quantitative Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy and Latent Class Analysis, thereby presenting a novel, holistic lens that moves away from a focus on individual shortcomings to structural barriers in the algorithmic architecture (Evans et al., 2024; Yuan & Pang, 2024). This methodological shift is critical in recovering the non-additive, heterogeneous effects of the interplay between social categories that are reified as algorithmic systems, and the resulting service delivery deficits (Hoben et al., 2024). AI-supported public services, for example, do not function in isolation but are part of a social framework: the large differences found when comparing the service delivery of disabled people in low-income urban and rural areas illustrate this well as services reflect how far existing power and inequality structures can adapt to the technological progress of AI (Robertson et al., 2024). Our findings suggest that, without a fuller social understanding embedded in the algorithmic design, AI-powered automation will only reinforce and further deepen existing sociotechnical inequalities, thereby reinforcing and widening the sociotechnical gap of those whose identities are multiple and vulnerable (Chiariello & Frondizi, 2024). Our results thus make a significant contribution to the still emerging and more critically discussed evidence base of algorithmic accountability, as we show that the "Leave No One Behind" principle is not just a symbolic commitment, but a call for a systemic data re-engineering of data representation, objective function of algorithms, and systemic pathways that regulate equitable access to vital public goods (Yuan et al., 2024, 2025). The concluding argument of this research is that a fair transition from the "fairness-by-design" normatively based approach to design that can appreciate, validate, and accommodate human diversity is necessary to attain fairness. We expand on current frames of research regarding automation, highlighting that both qualitative and computational techniques are essential to build what we term an automatic sensate ethnography.In drawing out these intersectional dynamics, we extend current discussions on automation research by showing that computation and qualitative techniques should be combined to capture the lived frustrations of diverse populations (Robertson et al., 2024a, 2024b). By doing so, we contribute to the urgent methodological requirement to examine how to take into account social difference in more fluid and complex ways, such that algorithmic governance accounts for the complex, interdependent nature of marginalised groups (Robertson et al., 2022).

CONCLUSION

This paper finds that the access to the AI-enhanced public services is not only dependent on the pool of technology but also on general social, economic and institutional inequalities. The empirical analysis reveals that the interdependencies of gender, class, disability and region are complex and needs to be taken into account in considering who can access and benefit from AI-driven welfare, education, health, and administrative systems. It can increase the efficiency of providing services, enhance public awareness, but can also generate new spheres of exclusion, if an artificial system is not designed taking into account the life conditions of disadvantaged groups.

These findings suggest that digital literacy, technology access (Internet), and access to digital technology (Internet device) may be disadvantageous to lower income groups. Access may be limited for women because of physical constraints, child-care duties, and the fact that men often have access to more technology. AI platforms that are not built to provide access to persons with disabilities pose issues for everyone with disabilities, and access to AI in the rural context is complicated by issues of connectivity, institutional support, and service infrastructure. When these disadvantages overlap, it is clear that inequality in AI facilitated public services cannot be captured in isolation in one category.

The study underscores the fundamental role that inclusive governance of AI goes beyond simply adopting technologies. Public institutions need to ensure that the aspects of transparency, accountability, accessibility and responsiveness in AI systems are part and parcel of their core. Ensure that there is still human intervention for when citizens are unable to use digital systems completely. To avoid algorithmic exclusion, it is essential to regularly audit algorithms, consult with communities, design them to be disability inclusive, provide them in more than one language and invest in infrastructure at the local level. In conclusion, the paper suggests that to make these assisted public services a catalyst for social justice, equality must be integrated into their design, creation and assessment. If properly executed, AI can appreciate that can perpetuate the very disparities that public service is designed to mitigate.

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