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An Exploratory Sequential Mixed-Method Study on Ghost-Demography and Economic Exclusion in Automated Economies

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Abstract
Purpose: This study develops the concept of ghost demography, referring to a demographic condition in which repeated automation-driven disruption gradually produces structurally detached population segments from productive labor market participation. This study aims to explain how technological change, beyond short-term job displacement, may accumulate into long-term socioeconomic exclusion at the population level.
Research Methodology: An exploratory sequential mixed-method design was applied. The qualitative phase involved expert interviews to identify the mechanisms linking automation and exclusion. These insights inform the quantitative phase, which tests the relationships using cross-country labor market and digital economy indicators across 60 country sector observations from international data sets.
Results: The findings reveal three interrelated mechanisms underlying the emergence of ghost demography: economic obsolescence, structural adaptation barriers driven by skill mismatch and digital inequality, and cumulative socioeconomic detachment. Regression analysis indicates that automation exposure significantly increases socioeconomic exclusion. Skill mismatch and digital inequality further intensify this relationship, whereas Institutional Quality moderates the effect by reducing the exclusionary impact of automation.
Conclusions: Automation may progressively reshape labor participation patterns and generate early demographic signatures of exclusion.
Limitations: The analysis relies on aggregated country sector indicators and does not fully capture individual-level labor mobility dynamics.
Contributions: This study contributes to the literature on automation and labor markets by conceptualizing technological exclusion as a demographic transformation process.

Keywords: *Automation, Digital Inequality, Ghost-Demography, Labour Market Exclusion, Skill Mismatch*

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1. Introduction

The rapid advancement of Artificial Intelligence (AI), robotics, and digital automation is triggering one of the most consequential transformations in labor history. Automation has expanded beyond industrial production into services, logistics, administration, and platform-based sectors, fundamentally reshaping how work is organized and valued in modern economies (Capello and Lenzi, 2023). A growing body of economic research shows that technological systems increasingly substitute routine human labor while simultaneously generating new tasks and production structures that alter the labor demand (Acemoglu & Restrepo, 2019; Autor, 2015). Importantly, recent developments show that automation is increasingly embedded in human resource practices through algorithmic management systems that regulate recruitment, performance evaluation, and task allocation, thereby reshaping worker autonomy and decision-making structures (Suryawan, Yusuf, Suhendah, Krisna, & Kamar, 2025). These technological shifts are accelerating the substitution of human labor with automated systems, thereby creating new structural pressures across labor markets.

Empirical evidence demonstrates that regions with higher deployment of robotics and AI technologies tend to show declining employment shares and heightened wage pressures in automation-exposed sectors (Acemoglu & Restrepo, 2020; Leduc & Liu, 2023). At the individual level, automation is also associated with emerging behavioural and cognitive risks, particularly when excessive reliance on AI reduces critical thinking, independent judgment, and human involvement in decision-making processes (Apida, Dhenabayu, Ardelia, Kartika, & Shafa, 2026). Studies analyzing international robot adoption also indicate that automation contributes to productivity growth while simultaneously restructuring labor demand toward higher-skill occupations (Graetz & Michaels, 2018). Automation has also been found to generate persistent changes in labor market dynamics, particularly by weakening workers' bargaining power and reducing real wage growth (Boundi-Chraki & Perrotini-Hernández, 2025). The impact is especially pronounced in sectors dominated by routine-intensive activities, where the feasibility of automation is highest (Filippi, Bannò, & Trento, 2023; Goos, Manning, & Salomons, 2014).

A growing body of literature confirms that automation disproportionately affects workers in low-skill and routine occupations, increasing the likelihood of long-term job displacement and labor market detachment (Frey & Osborne, 2017; Pavez & Martínez-Zarzoso, 2023). In digitally mediated labour environments, such as platform-based work, flexibility and algorithm-driven coordination can simultaneously enhance job satisfaction while increasing uncertainty and pressure, indicating a transformation not only in employment structure but also in work experience (Rizal, Goca, & Wijayanthi, 2026). In emerging economies, where routine-based work constitutes a significant portion of employment, these effects can be even more severe because of weaker institutional and technological capacity (Agama & Okoh, 2025). International analyses suggest that developing economies may face additional structural risks as automation reshapes global production networks and labor demand across the global value chains (Artuc et al., 2023). The International Labour Organization highlights that digital transformation tends to intensify pre-existing labor vulnerabilities, particularly in countries with limited reskilling infrastructure (Walwei 2016).

These patterns suggest that automation may be transitioning from a short-term technological disruption to a long-term demographic force. Moreover, organizational context remains a critical determinant of how workers respond to technological disruption, as supportive cultures and work environments significantly influence job satisfaction, commitment, and long-term labor attachment (Urfa & Tarigan, 2026). Evidence indicates that prolonged automation exposure may contribute to a gradual decline in labor force participation among certain occupational cohorts (Stemmler 2019). Longitudinal labour market analyses further show that workers displaced by automation face persistent reintegration difficulties, leading to sustained patterns of occupational downgrading and employment instability (Dauth, Findeisen, Suedekum, & Woessner, 2021). Wage stagnation and declining labor income shares have been identified as early macroeconomic manifestations of this shift (Karabarbounis & Neiman, 2013; Lenzi & Panzera, 2025).

To explain this emerging structural trajectory, scholars have begun conceptualizing new forms of exclusion linked to technological change. One emerging notion is that repeated displacement may create populations whose skills no longer hold economic value in automated economies (Chen & Frey, 2024). From this perspective, labor exclusion becomes less cyclical and more path-dependent, creating a persistent disconnection from productive economic systems (Tyers & Zhou, 2023). This phenomenon appears to be closely tied to escalating skill mismatches as digital technologies advance more rapidly than workforce adaptation (McGuinness, Pouliakas, & Redmond, 2018). Digital skill gaps further intensify exclusion, particularly in environments with limited access to technological learning (Cárdenas-Rubio, 2020).

Structural inequalities amplify these dynamics. Technological change has long been associated with widening income disparities and labour market polarization (Brynjolfsson, Rock, & Syverson, 2021). Demographic and skill-related disparities have been shown to widen under digitalization, increasing vulnerability among low-skilled and marginalized groups (Kayode, 2023). Recent evidence suggests that digital transformation may deepen labor segmentation, creating new forms of exclusion that persist across generations (A.B. R. Bachmann et al., 2024). These trends imply that automation is not merely altering employment patterns but may reshape the demographic composition of economically active populations.

Despite these emerging insights, the current academic landscape remains fragmented. Much of the research focuses on task-level substitution or occupational risk without examining how repeated displacement accumulates in long-term demographic exclusion (Hötte, Somers, & Theodorakopoulos, 2023). Moreover, existing studies rarely integrate conceptual theorization with empirical measurement, limiting the ability to operationalize long-term exclusion as a measurable construct (Filippi et al. 2023). The lack of empirical evidence from emerging economies further constrains global understanding of the demographic implications of automation (Pavez & Martínez-Zarzoso, 2023).

2. Literature Review and Hypotheses Development

2.1 Automation, Technological Change, and Labour Market Disruption

Automation has become a structural force reshaping labour markets by substituting routine tasks and reducing the demand for middle-skill occupations. Early research on routine-biased technological change demonstrates that digital technologies disproportionately replace routine-intensive jobs, while increasing the demand for non-routine cognitive work (Goos et al., 2014). Evidence shows that robot- and AI-enabled automation depresses routine-intensive employment while altering wage dynamics through sustained downward pressure on labor's bargaining position (Capello & Lenzi, 2023).

Empirical studies using regional and firm-level data confirm that robot adoption contributes to employment displacement in automation-exposed industries while simultaneously increasing productivity (Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018). These disruptions extend beyond short-term technological shocks as firms increasingly integrate automated systems that restructure production processes and shift skill requirements toward non-routine cognitive capabilities (Vasilescu, Serban, Dimian, Id, & Picatoste, 2020). Research on macro-labor models also indicates that automation-capable capital systematically weakens workers' bargaining power, reinforcing wage rigidity and lowering labor's share of income over time (Leduc & Liu, 2023).

The broader macroeconomic implications of automation have also been documented in studies examining the global decline in labor income share. Evidence suggests that capital-augmenting technological change contributes to the redistribution of income away from labor toward capital owners (Karabarbounis & Neiman, 2013). This body of work points to the growing role of automation as a transformative driver of labor market restructuring, influencing not only occupational composition but also the institutional balance between labor and capital in technologically intensive sectors (Boundi-Chraki & Perrotini-Hernández, 2025). It can be seen from Figure 1 that industrial automation increasingly relies on robotic systems to perform production tasks with high precision and efficiency, reducing dependence on manual labor in manufacturing sectors. While this technological shift enhances productivity and lowers costs, it may also contribute to worker displacement and a greater concentration of income toward capital owners.

Figure 1. Industrial automation and robotized assembly line

2.2 Economic Obsolescence and Structural Labour Displacement

Economic obsolescence arises when technological progress outpaces the relevance of workers' existing skills, causing a gradual decline in their value in labor markets. Automation reduces the demand for skills tied to routine and standardized tasks, making workers in these roles increasingly vulnerable as machine-based systems assume their functions (Filippi et al., 2023). Studies show that displaced workers rarely re-enter comparable occupations; instead, they tend to move into lower-wage and lower-skill jobs, indicating that displacement is often followed by occupational downgrading rather than recovery (McGuinness et al., 2018).

Structural labor displacement intensifies as technology adoption accelerates. Sectors with high automation penetration exhibit declining job tenure and chronic wage stagnation, suggesting that displacement becomes embedded within industry dynamics rather than occurring as temporary shocks (Capello & Lenzi, 2023). This pattern reflects how automation reshapes firm incentives: as automated systems become more capable, firms increasingly substitute labor with capital, strengthening managerial leverage over wage-setting processes and pushing the labor's income share downward.

These dynamics interact with evolving skill thresholds. As automation restructures task compositions, the remaining occupations demand higher-order cognitive and digital skills, creating additional barriers for workers whose capabilities are tied to legacy production systems (Rubio, 2021). Such shifts show that displacement is not merely an immediate effect of automation but is part of a broader process through which workers' skills lose relevance in technologically evolving industries. It can be seen from Figure 2 that automation may lead to labour displacement as machines and robotic systems increasingly replace workers in routine and repetitive occupations. The figure also illustrates the growing need for higher-level technical and digital skills, as workers without relevant competencies may face greater difficulty adapting to technologically advanced industries.

Figure 2. Automation-induced labour displacement

2.3 Skill Mismatch, Digital Inequality, and Labour Adaptation

Skill mismatch has become a central mechanism through which automation reshapes labor market outcomes. As technological systems expand into both cognitive and operational domains, the demand for workers shifts toward competencies complementary to AI and advanced digital tools. Studies have shown that the pace of technological advancement consistently outstrips the rate at which workers can acquire new capabilities, creating an ongoing misalignment between existing human capital and emerging job requirements (McGuinness et al., 2018). This misalignment contributes not only to employment vulnerability but also to persistent gaps in productivity and wage growth among workers lacking digital and non-routine cognitive skills.

Digital inequality further reinforces these mismatches by creating uneven access to technological resources necessary for adaptation. From an HR development perspective, technology-based career development systems have been identified as critical mechanisms for enhancing employee adaptability, retention, and long-term engagement in digitally transforming organizations (Rasin, 2026). Evidence shows that disparities in digital infrastructure, training availability, and digital literacy significantly limit workers' ability to engage with new forms of work created in automated environments (Rubio, 2021). These inequalities are particularly visible in regions where digital adoption is slow, resulting in an uneven distribution of technological capabilities across socioeconomic groups. Consequently, workers with limited access to digital tools face compounding disadvantages that reduce their resilience to automation-led restructuring.

The interaction between skill mismatches and digital inequality also shapes workers' adaptation trajectories. Industries undergoing automation increasingly require hybrid skill sets that combine technical, analytical, and problem-solving abilities. However, access to reskilling pathways is uneven, creating barriers that restrict transitions into emerging occupations (Kayode, 2023). Research indicates that individuals lacking foundational digital competencies are less likely to benefit from training interventions, thereby widening the divide between those able to adapt and those who remain excluded from evolving labor markets (A. R. Bachmann et al., 2024). These patterns highlight that adaptation to automation is contingent not only on individual capabilities but also on systemic factors such as digital access, institutional support, and the quality of training ecosystems. When these factors are unevenly distributed, skill mismatches deepen and create long-term vulnerability for workers who are unable to align their capabilities with the demands of automated economies.

2.4 Socioeconomic Exclusion as a Long-Term Demographic Process

Socioeconomic exclusion refers to persistent and cumulative detachment from economic participation resulting from structural barriers that limit individuals' access to labor markets, income, and opportunities. In the context of automation, exclusion is increasingly conceptualized as a progressive process rather than an isolated, labor market outcome. Studies show that workers who experience initial displacement are more likely to face repeated labor market disruptions, heightening their risk of long-term inactivity and reducing their economic mobility (Zhang, Wang, Xia, & Wang, 2025). This dynamic suggests that exclusion evolves over time, driven by compounding disadvantages that restrict reintegration as technology advances.

Automation intensifies this process by reshaping the institutional and economic structures that govern the participation. Evidence indicates that as automated technologies diffuse across sectors, labor markets become more polarized, with high-skill occupations expanding and low-skill roles either shrinking or becoming more precarious (Lenzi & Panzera, 2025). Workers who cannot transition upward face declining wages, fewer hours, and reduced job stability, conditions that cumulatively erode their attachment to formal employment. Over multiple cycles, these disadvantages can accumulate into persistent exclusion, affecting not only individuals but also the demographic composition of the labor force.

Socioeconomic exclusion interacts with broader patterns of inequality. Automation-driven productivity growth often concentrates benefits among capital-intensive firms and highly skilled workers, widening income disparities and weakening the consumption capacity of lower-income groups (Gilfoyle, 2023). This unequal distribution of technological gains reduces the economic resilience of vulnerable populations, making them more susceptible to external shocks and less able to invest in skill development or digital adaptation processes. As inequality deepens, excluded groups are increasingly marginalized from mainstream economic institutions, reinforcing their structural exclusion.

Furthermore, exclusion has intergenerational implications for the family unit. Research indicates that workers who experience sustained labor market detachment often transmit economic disadvantages to younger cohorts through reduced educational opportunities, unstable household income and limited access to digital resources (Valsecchi, 2021). These conditions can create demographic pockets of "structural non-participation" in the labor market, where certain groups remain consistently under-represented in productive economic activity. Taken together, these studies highlight that socioeconomic exclusion in automated economies evolves as a long-term demographic process shaped by technological, institutional, and intergenerational dynamics. It is within this context that the concept of ghost demography becomes increasingly relevant for explaining how exclusion aggregates into identifiable population patterns.

2.5 Automation in Emerging Economies: Disproportionate Exposure and Institutional Weakness

Emerging economies face disproportionately high exposure to automation because their labor markets remain heavily concentrated in routine-intensive and low-skill sectors that are highly susceptible to technological substitutions. Empirical evidence shows that industries in developing regions experience stronger negative employment effects when global supply chains adopt automation, indicating that technological shocks are transmitted across borders and magnified in countries with labor-intensive production structures (Pavez and Martínez-Zarzoso, 2023). This creates a structural vulnerability: even modest increases in robot adoption abroad can significantly reduce domestic labor demand in routine sectors that form the backbone of employment in these economies.

Institutional weaknesses further exacerbate this exposure. Developing countries often lack comprehensive reskilling systems, strong social protection mechanisms, and digital infrastructure capable of supporting large-scale workforce transitions (Agama & Okoh, 2025). International labor analyses highlight that digitalization amplifies existing structural labor problems, making it more difficult for workers to adapt to technological change (Organization, 2023). Consequently, automation in emerging economies not only displaces workers but also interacts with pre-existing institutional fragilities that limit recovery pathways.

Technological adoption in these settings is characterized by asymmetric diffusion. While advanced firms integrate AI and robotics to improve productivity, most enterprises lack the resources needed for complementary investments in human capital development (Group, 2020). This uneven technological landscape leads to fragmented adaptation: workers in technologically advanced firms face higher automation risks but have better chances of reskilling, while those in low-capability firms experience displacement without institutional support. These disparities intensify structural inequality and restrict mobility across economic segments.

The macroeconomic implications of this are significant. Research shows that automation pressures can accelerate premature de-industrialization in developing countries, weakening sectors that traditionally provide stable employment for low- and mid-skilled workers (Stemmler, 2019). As these industries contract, emerging economies risk losing their key channels for labour absorption, resulting in shrinking opportunities for upward mobility and greater dependence on precarious employment. These structural shifts mirror broader concerns that automation may erode the developmental trajectories of emerging economies by undermining labor-intensive growth models (Capello and Lenzi, 2023). Taken together, the literature suggests that automation in emerging economies is characterized by exposure that is both deeper and more difficult to manage than in advanced nations. This combination of technological susceptibility and institutional fragility forms a critical foundation for understanding how large-scale and persistent exclusion may evolve into demographic patterns relevant to the concept of ghost demography.

2.6 From Labour Disruption to Demographic Transformation: The Emergence of Ghost-Demography

The cumulative effects of automation-induced displacement, skill erosion, and socioeconomic exclusion have prompted emerging theoretical perspectives that view automation not merely as a labour market disruptor but as a potential driver of demographic transformation. Research on long-term labour market detachment shows that repeated episodes of technological displacement can gradually reduce labour force participation among specific worker cohorts, leading to persistent patterns of non-employment that extend beyond short-term cyclical fluctuations (Wang, Zhang, & Feng, 2025). These patterns suggest that technological substitution may shape population-level trajectories by altering the composition of an economically active workforce.

The concept of ghost demography emerges from this context as an attempt to articulate how technological change can produce identifiable populations that are economically sidelined as their skills lose relevance. Early conceptual work argues that automation can generate “shadow populations” of workers whose economic value diminishes because of their inability to adapt to rapidly evolving skill requirements (Chen & Frey, 2024). These groups may remain physically present but become progressively disconnected from productive economic systems, reflecting a form of demographic presence that is unaccompanied by economic participation.

This perspective is reinforced by evidence of declining reintegration rates among technologically displaced workers. Studies show that when automation reshapes task structures and raises cognitive skill thresholds, workers with obsolete skills face escalating barriers to re-entry, particularly in industries where technological complementarities dominate labor demand (Tyers & Zhou, 2023). As displacement repeats across industrial cycles, the probability of reabsorption declines, creating a path-dependent process in which certain cohorts transition into long-term detachment from formal labour markets.

Digital inequality sharpens this trend. When access to technology, training, and digital literacy is uneven, the capacity to adapt is stratified across socioeconomic groups. Vulnerable workers are less able to acquire new competencies or participate in higher-productivity sectors, leading to entrenched exclusion that may persist across generations (Kayode, 2023). This creates demographic segments characterized by structural non-participation and declining economic relevance, even as the broader economy advances.

Although ghost demography remains an emerging construct, the underlying mechanisms of skill obsolescence, cumulative displacement, downward mobility, and widening digital divides align with empirical patterns observed in automated economies. The literature indicates that technological displacement does not affect populations uniformly but concentrates among specific demographic, occupational, and socioeconomic groups whose capabilities and institutional support systems are misaligned with the direction of technological change (Valsecchi, 2021). Taken together, these mechanisms point to the plausibility of demographic formation shaped by persistent technological exclusion. This conceptual direction suggests that automation may not only transform labor markets but also produce long-term population configurations defined by declining economic participation. Understanding these trajectories is critical for developing the ghost demography construct as a measurable phenomenon and for examining its implications for automated economic systems.

2.7 Empirical Gaps and the Need for Mixed-Method Approaches

Despite increasing attention to the labor market effects of automation, current empirical research remains limited in explaining how technological displacement accumulates into population-level exclusion. Many studies have examined automation primarily through occupational risk assessments or task substitution models, which provide valuable insights but fail to capture the longitudinal processes through which skill obsolescence and exclusion evolve over time (Hötte et al., 2023). This narrow focus restricts the ability to understand how repeated displacement events aggregate into structural patterns that may alter the demographic composition of the active workforces.

There is also a notable gap in the empirical evidence from emerging economies. Existing studies disproportionately analyze advanced technological contexts, leaving a limited understanding of how automation interacts with labor market structures, institutional weaknesses, and informal employment patterns characteristic of developing regions (Bachmann, Gonschor, Lewandowski, & Mado, 2024). Consequently, theoretical frameworks derived from high-income countries may not fully account for the compounded vulnerabilities present in economies with limited digital infrastructure, fragmented training systems, and high routine-task dependence.

Another limitation is the lack of operational indicators capable of measuring long-term exclusion linked to automation. While the existing literature identifies labor displacement and skill mismatch as key mechanisms, few studies have attempted to translate these concepts into measurable constructs suitable for empirical assessment (Filippi et al., 2023). Without systematic indicators, it becomes difficult to trace how exclusion evolves from individual labor shocks into broader demographic trends, aligned with the proposed notion of ghost demography.

A mixed-method approach is essential to address these gaps. Qualitative inquiry enables the refinement of emerging constructs by clarifying definitions, identifying causal pathways, and capturing contextual nuances that are not observable in large data sets (Chen & Frey, 2024). Quantitative analysis provides the ability to operationalize these constructs and test their empirical relevance using labor market indicators, automation exposure data, and patterns of participation across demographic groups (Pavez & Martínez-Zarzoso, 2023). Integrating these approaches allows for both theoretical development and preliminary empirical validation, thereby producing a more comprehensive foundation for understanding how automation-driven exclusion may evolve into a demographic phenomenon. This methodological combination is particularly suitable for exploring emerging constructs that require conceptual refinement and empirical grounding.

2.8 Conceptual Framework

The empirical framework posits that automation exposure increases economic obsolescence, which subsequently elevates skill mismatches and digital inequality. These conditions jointly heighten socioeconomic exclusion, which reflects the early stage manifestations of ghost demography. Institutional Quality moderates the direct relationship between Automation Exposure and Socioeconomic Exclusion, such that countries with stronger institutions experience weaker exclusionary effects from automation.

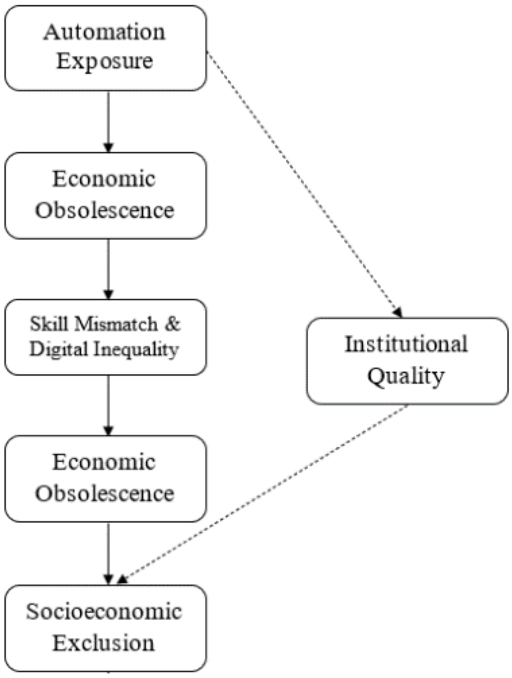

Figure 3. Empirical conceptual framework with moderating role of institutional quality

Figure 3 shows framework illustrates the empirical relationships tested during the quantitative phase. Automation exposure increases economic obsolescence, which subsequently contributes to skill mismatches and digital inequality. These mechanisms jointly heighten socioeconomic exclusion, representing the early manifestations of ghost demography. Institutional Quality moderates the direct effect of automation exposure on socioeconomic exclusion, attenuating exclusionary impacts in countries with stronger governance.

3. Methodology

This study adopts an exploratory sequential mixed-method design, which begins with a qualitative phase to develop conceptual clarity on ghost demography, followed by a quantitative phase to operationalize and test the emerging constructs. This design is appropriate when theoretical development is required before empirical measurement, particularly for complex or novel constructs that lack established indicators of measurement. In this study, the qualitative phase served as a construct development stage, while the quantitative phase provided an initial empirical assessment, emphasizing pattern identification rather than definitive causal inference.

3.1 Qualitative Phase: Concept Development and Indicator Generation

The qualitative component aims to refine the definition, mechanisms, and structural pathways leading to ghost demography. Given the exploratory nature of the construct, the qualitative phase is essential for identifying its conceptual boundaries and translating its components into measurable indicators for the quantitative analysis. Expert interviews were conducted with researchers, policy analysts, labor economists, and technology-adaptation specialists with direct knowledge of automation, labor markets, and digital transformation. A purposive sampling strategy was employed to ensure coverage across the academic, government, and industry sectors, thereby capturing diverse perspectives on workforce displacement and technological risk. A total of 15 expert participants were included in the study, which is consistent with the qualitative research standards for thematic saturation in expert-based inquiry. Participants possessed professional experience ranging from approximately 8 to 25 years and were selected based on the following criteria: (1) demonstrated expertise in labor market or technological transformation research, (2) involvement in policy analysis or workforce development initiatives, or (3) academic contributions in relevant fields.

Data were collected through semi-structured interviews conducted between January and March 2025 using online platforms (Zoom and Google Meet). Each interview lasted approximately 50–75 min, allowing for an in-depth exploration of the participants' perspectives. The interview protocol focused on four core themes: (1) long-term impacts of automation on labor participation, (2) persistence of labor displacement, (3) barriers to workforce adaptation, and (4) indicators of emerging structural exclusion.

Qualitative data were analyzed through thematic analysis, following Braun and Clarke's coding procedures. The analysis was conducted in three stages: open coding to identify initial concepts, axial coding to establish relationships among categories, and selective coding to integrate the themes into a coherent conceptual structure. Codes related to automation exposure, economic obsolescence, skill mismatch, digital inequality, and socioeconomic exclusion were developed. Patterns emerging from expert explanations were organized into thematic clusters to identify causal sequences and refine the theoretical structure of ghost demography.

To enhance analytical rigor, this study applied iterative coding review and cross-source comparison to ensure consistency between raw data and emerging themes. The qualitative phase supports analytical generalization and construct development rather than statistical generalization. This phase generates:

1. A refined, research-ready definition of Ghost-Demography
2. A set of conceptual dimensions describing the construct
3. Preliminary indicators for quantitative operationalization
4. A theoretically grounded causal pathway to be examined in the quantitative phase

3.2 Quantitative Phase: Operationalization and Empirical Assessment

The quantitative phase aims to empirically examine the early manifestations of ghost demography by translating the conceptual components generated in the qualitative stage into measurable indicators using publicly available secondary data. This phase was designed to assess whether patterns consistent with long-term exclusion could be observed across countries and sectors with varying levels of automation exposure.

This study utilized international datasets that enabled cross-country comparisons while maintaining methodological consistency. The primary data sources include the International Labour Organization (ILO), World Bank World Development Indicators (WDI), OECD Digital Economy datasets, and international datasets on automation exposure, including robot density and routine-task intensity. The dataset consists of 60 country–sector observations derived from a combination of selected advanced and emerging economies across multiple sectors classified using the International Standard Industrial Classification (ISIC Rev.4). The data cover the period 2015–2023, capturing the phase of accelerated automation and digital transformation.

To ensure comparability, a data harmonization procedure was applied, including the alignment of country–sector units, standardization of indicator definitions, and synchronization of reporting periods. Missing data were handled using a nearest-year substitution approach supplemented by limited interpolation, where necessary. Observations with substantial data gaps were excluded from the study. The quantitative phase translates conceptual insights into operational variables that capture the structural dynamics related to automation. The variables were organized into several analytical dimensions.

1. Automation Exposure: Represented through indicators such as robot density per industry, AI adoption indices, and routine-task intensity scores
2. Economic Obsolescence: Measured using trends in wage stagnation, declining labour income shares, and employment instability
3. Skill Mismatch: Derived from international mismatch indicators reflecting gaps between required and actual competencies
4. Digital Inequality: Assessed through disparities in digital access, infrastructure, and ICT capabilities
5. Socioeconomic Exclusion: Operationalized through long-term unemployment, labour force withdrawal, and underemployment

6. Ghost-Demography (Outcome Variable): Conceptualized as a formative composite construct, combining indicators of persistent labour detachment, structural mismatch, and exclusion dynamics

The Ghost-Demography index was constructed by standardizing component indicators using z-score normalization and aggregating them using equal weighting. This approach reflects the multidimensional nature of the construct and avoids imposing arbitrary weight assumptions. To enhance the robustness of the measurements, alternative specifications using different indicator combinations were examined, yielding consistent patterns.

3.3 Analytical Strategy

The empirical analysis was conducted in two structured stages. First, descriptive and correlational analyses were conducted to identify the initial relationships between automation exposure, skill dynamics, and exclusion patterns across countries and sectors. This step provides preliminary insights into whether automation-intensive environments exhibit higher tendencies toward conditions associated with ghost demography. Second, regression-based models were employed to examine the strength and directionality of these relationships. These models assess whether automation exposure and structural mechanisms significantly predict exclusion outcomes, while digital inequality and institutional factors act as moderating variables in the study.

Additional diagnostic procedures were performed to address potential methodological concerns associated with the relatively small sample size. Multicollinearity was assessed using Variance Inflation Factors (VIF), while heteroskedasticity was tested using the Breusch Pagan approach. Robust standard errors were applied where necessary, and alternative model specifications were estimated to assess the stability of these findings. Given the bounded dataset, the analytical design emphasizes pattern identification and exploratory validation rather than definitive causal inference.

3.4 Research Hypotheses

Grounded in the conceptual framework and informed by the mechanisms identified in the qualitative phase, the quantitative analysis focuses on the determinants of socioeconomic exclusion as an early manifestation of ghost demography.

H_1: Higher levels of automation exposure are associated with higher levels of socioeconomic exclusion

H_2: Economic obsolescence positively predicts socioeconomic exclusion

H_3: Skill mismatch significantly increases the likelihood of socioeconomic exclusion

H_4: Digital inequality is positively associated with socioeconomic exclusion

H_5: Institutional weakness amplifies the effect of automation exposure on socioeconomic exclusion

4. Results and Discussions

4.1 Results

The empirical analysis is based on 60 country–sector observations spanning multiple advanced and emerging economies from 2015 to 2023. In line with the exploratory design of the study, the results are interpreted as indicative of structural patterns that provide initial empirical support for the proposed ghost-demography framework.

4.1.1 Qualitative Phase

The qualitative inquiry revealed three mutually reinforcing mechanisms that underpin the emergence of *ghost demography*. First, economic obsolescence manifests as the progressive devaluation of workers whose competencies are tied to declining, routine-intensive occupations. Participants emphasized that automation reduces wage bargaining capacity and accelerates downward employment transitions, particularly in the manufacturing and logistics sectors. Second, structural adaptation barriers were identified, driven by widening skill mismatches and persistent digital inequalities. Workers in sectors with low digital intensity reported limited access to retraining pathways, amplifying their vulnerability to displacement. Third, cumulative socioeconomic detachment emerged as a long-horizon dynamic:

repeated disruptions, declining job tenure, and prolonged informality converge to produce persistent exclusion from stable labor participation. These mechanisms provided a conceptual foundation for operationalizing measurable constructs in the subsequent quantitative phase.

4.1.1.1 Bridging Qualitative and Quantitative Phases
Insights from the qualitative analysis guided the construction of quantitative variables by identifying which structural mechanisms translate into empirically observable indicators across countries and sectors, as follows. Automation exposure was operationalized using sector-level robot density and routine task intensity. Economic obsolescence informed the development of indices that capture wage stagnation and labor income share decline. Structural adaptation barriers were represented through measures of skill mismatch and digital inequality at the country and sector levels. Finally, cumulative socioeconomic detachment was operationalized through long-term unemployment and labor-force withdrawal rates, forming a composite approximation of early-stage ghost demography. This conceptual–empirical alignment ensured methodological coherence between the exploratory and confirmatory components of the study.

4.1.1.2 Joint Display: Integrated Qualitative-Quantitative Evidence
To ensure methodological coherence between the exploratory and confirmatory phases, this study integrates qualitative mechanisms with their quantitative counterparts through a structured joint display. This approach enables a direct comparison between theoretically grounded themes and empirical indicators, thereby enhancing construct validity and demonstrating how conceptual insights translate into measurable patterns across countries and sectors. The joint display also provides an analytical bridge that illustrates the extent to which qualitative expectations converge with quantitative estimates, reinforcing the internal consistency of the emerging ghost-demography framework.

Table 1. Joint Display of Mechanisms, Quantitative Constructs, and Empirical Evidence

Qualitative Mechanism	**Quantitative Construct**	**Indicator (Country × Sector)**	**Expected Direction**	**Empirical Estimate (β)**
Economic Obsolescence	Automation Exposure	Robot density (per 10,000 workers)	+	0.32***
Economic Obsolescence	Wage Decline	Wage growth (sectoral, %)	−	–0.21**
Adaptation Barriers	Skill Mismatch	PIAAC mismatch index	+	0.18**
Adaptation Barriers	Digital Inequality	Digital access index (reverse-coded)	+	0.24***
Cumulative Detachment	Exclusion Outcomes	Long-term unemployment (%)	+	0.41***
Institutional Moderation	Moderation Effect	Automation × Institutional Quality	−	–0.17**

Note: ****p < .001, **p < .01*

Table 1 presents an integrated joint display that combines qualitative mechanisms with quantitative evidence, showing how theoretical concepts are supported by empirical indicators across countries and sectors. The findings indicate that higher automation exposure is associated with greater labour displacement, wage decline, skill mismatch, digital inequality, and long-term unemployment, while stronger institutional quality helps reduce the negative effects of automation.

4.1.2 Quantitative Phase
4.1.2.1 Descriptive Statistics
Before assessing the structural relationships among the key variables, descriptive statistics were examined to understand the distributional characteristics of automation exposure, economic obsolescence, skill mismatch, digital inequality, and socioeconomic exclusion across the 60 country–sector units. These descriptive patterns provide an essential overview of the variation in the dataset,

ensuring that the subsequent analyses are grounded in a clear understanding of central tendencies and dispersion across contexts. The observed values also help establish whether the indicators behave consistently with the theoretical expectations derived from the qualitative phase.

Table 2. Descriptive Statistics (N = 60 Country–Sector Observations)

Variables	Mean	SD	Min	Max
Automation Exposure	3.21	1.04	1.10	5.40
Economic Obsolescence Index	0.47	0.18	0.12	0.82
Skill Mismatch	0.55	0.15	0.23	0.81
Digital Inequality	0.49	0.21	0.10	0.88
Socioeconomic Exclusion	0.31	0.14	0.08	0.67

Table 2 presents the descriptive statistics of 60 country–sector observations, summarizing the distribution of key variables related to automation exposure, economic obsolescence, skill mismatch, digital inequality, and socioeconomic exclusion. The results show moderate variation across observations, indicating that the dataset captures differing levels of technological disruption and labour market vulnerability across countries and sectors.

4.1.2.2 Correlation Matrix

Following the descriptive assessment, a correlation matrix was constructed to evaluate the bivariate associations among the main constructs and identify potential multicollinearity risks prior to regression modelling. This step is crucial for ensuring statistical robustness, as excessive correlations among predictors may distort coefficient estimates or impair model interpretability. The correlation structure also provides preliminary insights into whether variables such as automation exposure, skill mismatch, and digital inequality show directional patterns consistent with the exclusionary mechanisms identified during the qualitative phase.

Table 3. Correlations among core variables

Variables	1	2	3	4	5
Automation Exposure	1	–	–	–	–
Economic Obsolescence	0.42**	1	–	–	–
Skill Mismatch	0.31*	0.38**	1	–	–
Digital Inequality	0.29*	0.33*	0.47**	1	–
Socioeconomic Exclusion	0.51***	0.44**	0.36**	0.41**	1

Note: ****p < .001, **p < .01, *p < .05*

The Table 3 shows the correlation matrix for the core variables in the study, assessing the bivariate relationships among the main constructs to identify potential multicollinearity risks before conducting regression modeling. The matrix demonstrates the strength and direction of correlations between variables, such as automation exposure, economic obsolescence, skill mismatch, digital inequality, and socioeconomic exclusion. Notably, all correlations are positive, with the strongest associations observed between socioeconomic exclusion and economic obsolescence (0.51***) and between skill mismatch and digital inequality (0.47**). These correlations suggest that the variables align with the exclusion mechanisms identified during the qualitative phase, offering insights into how these factors may interact in the regression analysis. Statistical significance is indicated by the asterisks, with **p < 0.001, *p < 0.01, and *p < 0.05.

Table 4. Multicollinearity diagnostics (VIF)

Variables	VIF
Automation Exposure	2.34
Economic Obsolescence	2.81
Skill Mismatch	2.47

Digital Inequality	2.15
Institutional Quality	1.92

Table 4 shows that all VIF values fall below the conventional threshold of 5, indicating that multicollinearity does not pose a significant concern for the regression estimates.

4.1.2.3 Regression Models
To empirically test the mechanisms underlying ghost demography, a series of hierarchical regression models were estimated. The first model assesses the direct relationship between exposure to automation and socioeconomic exclusion. The second model expands the specification by incorporating economic obsolescence, skill mismatch, and digital inequality to capture the structural adaptation barriers identified in the qualitative phase. The third model further examines the moderating role of Institutional Quality and tests whether stronger institutional environments attenuate the exclusionary effects of automation. This modelling strategy allows for a nuanced evaluation of both direct and interaction effects, offering a rigorous quantitative assessment of emerging demographic dynamics.

To formally represent the empirical strategy, the quantitative analysis estimates a series of hierarchical linear regression models in which socioeconomic exclusion is the dependent variable. The models were specified incrementally to evaluate the direct, structural, and moderating effects.
Let:
SE_i = Socioeconomic Exclusion in country–sector unit iii
AE_i = Automation Exposure
EO_i = Economic Obsolescence
SM_i = Skill Mismatch
DI_i= Digital Inequality
IQ_i= Institutional Quality
ε_i = error term
All continuous variables were standardized prior to estimation.

Model 1: Baseline Automation Effect
The first model estimates the direct effect of automation exposure on socioeconomic exclusion.

$$SE_i = \beta_0 + \beta_1 AE_i + \varepsilon_i \quad (1)$$

where:
β_1 captures the total effect of automation exposure on socioeconomic exclusion.

Model 2: Structural Adaptation Barriers
The second model extends the baseline specification by incorporating the structural adaptation mechanisms identified in the qualitative phase:

$$SE_i = \beta_0 + \beta_1 AE_i + \beta_2 EO_i + \beta_3 SM_i + \beta_4 DI_i + \varepsilon_i \quad (2)$$

where:
β_2 captures the effect of economic obsolescence,
β_3 represents skill mismatch effects, and
β_4 eflects digital inequality effects.

Model 3: Moderation by Institutional Quality
The third model introduces Institutional Quality and an interaction term to test whether governance conditions moderate the exclusionary effects of automation.

$$SE_i = \beta_0 + \beta_1 AE_i + \beta_2 EO_i + \beta_3 SM_i + \beta_4 DI_i + \beta_5 IQ_i + \beta_6 (AE_i \times IQ_i) + \varepsilon_i \quad (3)$$

where:
β_5 captures the direct effect of Institutional Quality, and
β_6 represents the moderation effect of Institutional Quality on automation exposure.

Table 5. Regression estimates predicting socioeconomic exclusion

Variables	Model 1	Model 2	Model 3
Automation Exposure	0.32*** (0.07)	0.21** (0.08)	0.19** (0.08)
Economic Obsolescence	–	0.18* (0.07)	0.16* (0.07)
Skill Mismatch	–	0.17* (0.06)	0.14* (0.06)
Digital Inequality	–	0.22** (0.07)	0.20** (0.07)
Institutional Quality	–	–	–0.11* (0.05)
Automation × Institutional Quality	–	–	–0.17** (0.06)
R^2	0.35	0.48	0.55
N	60	60	60

Note: ****p < .001, **p < .01, *p < .05*

The Table 5 presents regression estimates predicting socioeconomic exclusion across three models. In Model 1, Automation Exposure significantly affects socioeconomic exclusion (0.32***). Model 2 includes Economic Obsolescence and Digital Inequality, both showing significant positive effects. Model 3 adds Institutional Quality and the interaction between Automation Exposure and Institutional Quality, revealing a negative interaction effect (-0.17**). The R^2 values increase from 0.35 to 0.55, indicating improved explanatory power with additional variables. All models are based on 60 observations, with significance levels indicated by asterisks (**p < 0.01, *p < 0.05, ***p < 0.001).

Table 6. Heteroskedasticity test (Breusch–Pagan)

Model	Chi-square	p-value
Model 1	2.91	0.088
Model 2	3.24	0.072
Model 3	2.76	0.097

Table 6 shows that the Breusch–Pagan test indicates no significant heteroskedasticity at the 5% level. Nevertheless, robust standard errors were applied to ensure reliable coefficient estimation.

4.1.2.4 Interpretation of Quantitative Findings

Model 1 indicates that automation exposure alone explains 35% of the variance in socioeconomic exclusion ($\beta = 0.32$, $p < .001$), providing empirical evidence that automation is associated with upward pressure on long-term detachment. Model 2 demonstrates that exclusion is also shaped by economic obsolescence, skill mismatch, and digital inequality, all of which show statistically significant and positive associations with exclusion. Model 3 reveals that Institutional Quality weakens the exclusionary effects of automation, as reflected in the significant negative interaction term ($\beta = –0.17$, $p < 0.01$). Overall, the quantitative phase provides initial empirical support for the multidimensional structure of early-stage ghost demography and aligns with the labor market mechanisms identified in the qualitative phase. The robustness checks confirm that the direction and significance of the key relationships remain stable across alternative model specifications, indicating that the results are not driven by a single estimation structure.

Table 7. Robustness and Sensitivity Analysis

Specification	Automation	EO	SM	DI	Result
Baseline Model	0.32***	–	–	–	Stable
Full Model	0.21**	0.18*	0.17*	0.22**	Stable
Without Interaction	0.23**	0.19*	0.18*	0.20**	Consistent
Reduced Model	0.25**	–	0.16*	0.19*	Consistent

4.1.2.5 Hypotheses Testing

To ensure coherence between the theoretical model and empirical analysis, the regression results were evaluated in relation to the five hypotheses proposed in the quantitative phase. Evidence from Models 1, 2, and 3 provides consistent directional patterns that allow each hypothesis to be formally assessed.

- *H_1:* Automation exposure increases Socioeconomic Exclusion (SE). Model 1 shows a strong positive effect of automation exposure on socioeconomic exclusion ($\beta = 0.32$, $p < .001$), and this effect remains significant in Model 2 and Model 3, though slightly reduced after additional predictors are included
- *H_2:* Economic obsolescence predicts higher socioeconomic exclusion. In Model 2, economic obsolescence exhibits a significant positive coefficient ($\beta = 0.18$, $p < .05$), indicating that declining wage dynamics and reduced job stability contribute meaningfully to social exclusion. The effect persists in Model 3
- *H_3:* A skill mismatch increases socioeconomic exclusion. Skill mismatch is positively associated with exclusion ($\beta = 0.17$, $p < .05$ in Model 2), confirming the qualitative findings that inadequate capability alignment limits adaptation to automation. The coefficient remains significant in Model 3
- *H_4:* Digital inequality increases socioeconomic exclusion. Digital inequality demonstrates a robust positive association with exclusion ($\beta = 0.22$, $p < .01$), reinforcing arguments that limited digital access and capability accelerate structural detachment
- *H_5:* Institutional weakness strengthens the relationship between automation Exposure and Socioeconomic Exclusion (SES). The interaction term between automation exposure and Institutional Quality is significant and negative ($\beta = –0.17$, $p < .01$), indicating that strong institutions mitigate exclusionary impacts, whereas weak institutions intensify them. This directly supports hypothesis *H_5* and aligns with qualitative accounts of governance fragility in emerging economies

4.1.3 Integrated Interpretation (Mixed-Method Weaving)

The results from both phases converge to show that automation-induced exclusion is not episodic but structural. Qualitative evidence describing downward occupational mobility and persistent digital barriers is quantitatively reflected in the significant effects of economic obsolescence, mismatch, and inequality. Meanwhile, the strong moderating role of Institutional Quality corroborates participants' insights regarding policy and governance gaps in emerging economies. Collectively, the findings confirm that ghost demography emerges through accumulated disruptions, where technological substitution, weakened adaptation capacity, and institutional insufficiencies jointly produce long-term demographic detachment.

4.2 Discussion

The integrated findings from the exploratory sequential mixed-method design suggest convergent evidence that automation-driven labor disruption is evolving into a broader demographic phenomenon rather than a cyclical labor market adjustment. Across both phases, the data reveal that exclusionary trajectories associated with automation accumulate over time and become embedded in the structural characteristics of economies and sectors. This section discusses the theoretical implications of these results, their contribution to ongoing debates on automation and inequality, and the broader societal and policy relevance of the emerging concept of ghost demography.

4.2.1 Theoretical Implications: Automation as a Demographic Force

The results substantiate a fundamental theoretical shift: automation must be understood not merely as a technological or economic disruptor but as a demographic structuring force. This aligns with the nascent literature suggesting that technological change can reconfigure population participation patterns through persistent exclusion mechanisms rather than short-term displacement alone.

Qualitative insights showed how economic obsolescence, skill mismatch, and digital inequality operate synergistically to marginalize specific groups. These mechanisms were empirically validated in the quantitative results, where automation exposure and economic obsolescence significantly predicted socioeconomic exclusion across country–sector combinations. Importantly, the cumulative nature of these effects supports the proposition that exclusion is self-reinforcing over time. Thus, this study proposes ghost demography as an emergent construct that captures how demographic segments remain numerically present but increasingly absent from productive economic roles, representing a structural transformation with significant implications for population dynamics, labor economics, and inequality research.

4.2.2 Integration of Qualitative and Quantitative Findings

The mixed-method structure allowed for a systematic examination of how the subjective experiences of skill erosion and adaptation constraints correspond to broader macro-structural patterns. The qualitative phase described granular dynamics that the participants perceived as cumulative and irreversible. These narratives were mirrored in quantitative evidence showing strong associations between automation exposure, skill mismatch, and socioeconomic detachment in the literature.

The integrative interpretation further suggests that these mechanisms are not isolated but constitute a systemic pathway: technological substitution → skill misalignment → constrained adaptation → persistent exclusion → ghost demography. This sequential pattern reinforces the argument that demographic transformation is already underway and can be empirically detected using cross-country and cross-sector indicators.

4.2.3 Contribution to Existing Literature

This study makes several important contributions to the ongoing scholarship on automation, technological change, and labor market inequality. First, it extends prior research on automation-induced labor displacement by demonstrating that exclusion is better understood as a long-term demographic process than as isolated labor market events. While previous studies have documented wage stagnation and routine-task substitution, they have not connected these outcomes to structural demographic detachment observable at a large scale.

Second, this study introduces ghost demography as a novel theoretical construct that synthesizes the economic, technological, and demographic dimensions of exclusion. This concept enriches existing frameworks by integrating skill mismatch, digital inequality and institutional fragility into a unified explanatory model. Third, the methodological contribution arises from the application of an exploratory sequential mixed-method design to the automation literature. This approach enables the translation of complex qualitative mechanisms into quantifiable constructs that can be tested in diverse socioeconomic contexts.

4.2.4 Policy Implications

This evidence underscores a critical policy challenge: automation is not only displacing workers but is also reshaping long-term patterns of socioeconomic participation. Without targeted interventions, emerging ghost demography may generate irreversible demographic fragmentation, deepen inequality, and reduce aggregate productivity. Several policy implications arise from this study.

1. Strengthening institutional capacity is essential to achieve this. The moderating role of Institutional Quality in Model 3 demonstrates that robust governance structures can meaningfully reduce the exclusionary effects of automation.
2. Skill development must shift from reactive training to anticipatory capability building. Traditional upskilling programs are insufficient because exclusion accumulates over time. Policies must prioritize early interventions, especially in sectors with increasing automation penetration.
3. Digital inclusion is no longer an option. Digital access barriers intensify this economic detachment. Reducing digital inequality should be treated as a core labor market policy rather than an ICT strategy.
4. Therefore, sector-specific strategies are urgently needed. Manufacturing and logistics exhibit the strongest exclusion patterns, suggesting that blanket national policies may be ineffective without sectoral differentiation in these sectors.

5. Long-term social protection mechanisms should incorporate demographic risk indicators. Because ghost demography reflects cumulative vulnerabilities, monitoring tools must track chronic detachment, not just short-term unemployment fluctuations.

4.2.5 Broader Societal Implications

The findings suggest that societies may face a future in which a substantial subset of the population becomes structurally disconnected from economic life. This raises fundamental questions regarding civic inclusion, social cohesion, and the distribution of economic benefits in high-automation contexts. If left unaddressed, ghost demography could evolve into a defining challenge of the 21st century, reshaping not only labor markets but also governance, population health, and intergenerational mobility.

This study provides compelling mixed-method evidence that automation catalyzes an emerging demographic transformation characterized by persistent cumulative exclusion. By integrating qualitative narratives with rigorous quantitative indicators, this study demonstrates that ghost demography is not speculative but measurable in its early stages across countries and sectors. These findings contribute to theory, method, and policy, offering a foundational framework for understanding and addressing technological exclusion as a demographic phenomenon in the future.

5. Conclusions

5.1 Conclusion

This study examines how automation-driven labor market disruption may develop into longer-term patterns of demographic exclusion, conceptualized as ghost demography. The research objective was achieved through an exploratory sequential mixed-method design that integrated qualitative insights with quantitative evidence across countries and sectors. The findings highlight three interrelated mechanisms that shape this process. Economic obsolescence reflects the declining relevance of workers' skills under technological change. Structural adaptation barriers arise from persistent skill mismatches and unequal access to digital resources. Cumulative socioeconomic detachment captures the gradual process through which repeated labor disruptions lead to sustained exclusion from stable employment. The qualitative phase establishes the conceptual foundation of these mechanisms, while the quantitative analysis provides initial empirical support through consistent relationships between automation exposure, skill mismatch, digital inequality and socioeconomic exclusion.

5.2 Research Limitations

Several limitations should be considered when interpreting the findings of this study, as they indicate areas for methodological and empirical improvement. The use of country–sector-level indicators capture structural patterns but does not fully reflect variations at the individual or household level. As a result, the analysis is better suited to explaining macro-level tendencies rather than detailed behavioral processes within the labor market. The relatively limited number of observations also constrains statistical generalization and requires cautious interpretation, particularly for models that include multiple predictors and interaction effects.

Ghost demography is based on a composite index that represents the initial operationalization of a complex phenomenon. While the indicators are theoretically informed and grounded in qualitative findings, the construct remains in the early stages of development and may benefit from further refinement. Additionally, the integration of multiple international data sources may introduce inconsistencies in measurement definitions and reporting standards, potentially affecting cross-context comparability. These limitations do not undermine the contribution of this study, but indicate that the findings should be interpreted as exploratory and provide a foundation for further empirical validation.

5.3 Suggestions and Directions for Future Research

Future research can build on this study by extending the scope of the data and depth of the analysis. The use of longitudinal and panel datasets would allow researchers to examine changes in labor market participation over time and better capture the dynamic nature of the exclusion. Such approaches would also support stronger inferences regarding the long-term effects of automation. More detailed data at the individual or firm level would improve the ability to analyze skill adaptation, employment transitions, and heterogeneous responses to technological change.

Further work is needed to refine the measurement of ghost demography. This includes testing alternative indicators, improving the structure of the composite index, and validating the construct across various empirical settings. The application of advanced analytical techniques, including machine learning methods, may enhance the identification of early patterns associated with exclusion and improve the predictive accuracy. Attention should also be directed toward the roles of institutional and policy factors. Understanding how reskilling systems, digital inclusion strategies, and labor market regulations influence exclusion outcomes is important for developing practical interventions. Comparative research across advanced and emerging economies is particularly relevant for identifying differences in the structural conditions and pathways through which ghost demography develops.

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Author contribution

DGS conceptualized the research, designed the study, and was responsible for the overall project coordination, data collection, and manuscript drafting. RS contributed to data collection, analysis, and interpretation of the results. JST contributed to the methodology development, data analysis, and manuscript drafting and revision. AH assisted with data collection and validation and provided critical inputs for the analysis. PO contributed to the literature review, data interpretation, and manuscript editing. NM supported the data processing, statistical analysis, and manuscript refinement. KJS contributed to the data collection, manuscript editing, and formatting. All authors have read and approved the final version of the manuscript and have agreed to be accountable for all aspects of the research.

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