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Job Automation in Brazil: Which Consequences for Women's Employment?

Automatización del empleo en brasil: ¿qué consecuencias para el empleo femenino?

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Abstract

The automation of tasks and/or activities that constitute a work process has the potential to replace human labor, raising concerns about technological unemployment. Furthermore, individuals and groups who develop the technology are not gender neutral. This paper explores the relationship between advancements in job automation and gender inequalities within the Brazilian paid labor market. In aggregate terms, the probability of automation is lower for women than for men in Brazil. However, occupations with lower probability of automation generally tend to be lower-skilled and associated with lower pay – this is particularly true for most women's occupations, which are linked to the care economy and reproductive tasks.

Keywords: Gender inequalities, job automation, Brazil, labor market.

Resumen

La automatización de tareas y/o actividades laborales tiene el potencial de reemplazar el trabajo humano, generando así preocupaciones acerca del desempleo tecnológico. El presente artículo busca explorar la relación entre los avances en la automatización laboral y las desigualdades de género en el mercado laboral remunerado en Brasil. A nivel agregado, la probabilidad de automatización para las mujeres es menor que para los hombres en Brasil. No obstante, las ocupaciones con menor probabilidad de automatización suelen requerir menos cualificación y están asociadas con salarios más bajos – allí se encuentran la mayoría de las ocupaciones femeninas vinculadas a la economía del cuidado y a las tareas reproductivas.

Palabras clave: Desigualdades de género, automatización del trabajo, Brasil, mercado laboral.

JEL Classification/ Clasificación JEL: B54; E24; O33.

1. Introduction

The automation of tasks and/or activities that make up a work process (hereinafter also referred to as "automation of jobs or occupations") has the potential to replace human labor, which could lead to concerns about increased technological unemployment or change the characteristics of jobs and the skills necessary for their performance. Furthermore, labor relations can also be significantly impacted by changes in production processes, requiring a new work organization in salaried employment and emerging types of work (Mokyr et al., 2015).

Some authors affirm that automation processes can translate into opportunities and create expectations of improvements in the quality of life of workers (Mokyr et al., 2015). However, they also imply risks concerning a deepening of current inequalities or the emergence of new inequalities. After all, certain social groups (such as women and/or people from lower-income brackets) could be less prepared to take advantage of such potential opportunities (CEPAL, 2019a).

The people and groups who develop automation technology and look for ways to take advantage of it are not gender-neutral (Roberts et al., 2019). Consequently, the development or improvement of automation technologies is also not neutral to gender inequalities in economies or how people integrate into society.

How the automation of tasks in the labor market transforms the economy and who benefits from it depend on several factors, such as the sectors where automation occurs; what skills will be demanded in the future, and how they are valued; who can adapt to new roles; and how gains are distributed (Roberts et al., 2019).

Gender gaps threaten equal participation of women and men in the new work paradigm emerging from technological progress and the introduction of automation at work, to the detriment of female participation (CEPAL, 2019a). Gender gaps also appear in the development of digital skills (Vaca Trigo and Valenzuela, 2022), which are crucial for taking advantage of opportunities that may arise from technological advancements in the labor market. Besides that, people can also differ either by having different colors or races or dedicating more or fewer hours to unpaid work and care, among other factors (Fontana, 2003), which reinforces the gender hierarchy perpetuated by the sexual division of labor.[1]

This paper examines the relationship between advances in job automation and gender inequalities in Brazil's labor market. It is organized into four sections, including the introduction and final considerations. First, we theoretically explore gender inequalities in the labor market under the automation era. Secondly, we discuss job automation and its potential impact on workers. Thirdly, we outline the methodology for assessing the probability of automation in various occupations. Finally, we examine which occupations are most vulnerable to automation through a gender lens, using 2022 Brazilian labor market data.

2. Gender inequalities in the labor market during the automation era

Gender inequalities and the naturalization of the subordinate role of women to men present in societies result from a social construction passed down through generations (Saffioti, 1987). The patriarchal system, which precedes but intensifies during capitalism, is responsible for the formation of gender roles (Lerner, 2019).

Patriarchy often assigns the role of caregivers to women, reinforcing social expectations that direct them towards responsibilities centered on caring for the family and home (Lerner, 2019). While most men direct their time and effort to paid work, most women combine paid and unpaid work. Despite their importance, social reproduction tasks are commonly unremunerated, which contributes to reaffirming their undervaluation in our society (Melo and Castilho, 2009).

The devaluation of women also manifests through disparities in the paid job market. As Elson (1999) points out, the labor market is a "gender-bearing institution", responsible, in many aspects, for reinforcing discrimination against women. Gender stereotypes permeate job market relations and structure, where different types of work are categorized as "men's jobs" and "women's jobs".

The weight of unpaid domestic responsibilities placed on women penalizes them within the labor market and is one of the main determinants of this group occupying an underprivileged position in terms of both salary gains and occupations. For example, given the socially conferred responsibility of carrying out unpaid work, women tend to concentrate on the seasonal workforce and consequently face fewer opportunities to update their human capital or advance in their work (Barrientos, 2001).

1 In summary, oppression varies among women and is shaped by intersecting factors like gender, class, and race (Davis, 2016). In Brazil, due to its history of slavery, racism and sexism are deeply intertwined, disproportionately affecting Black women. Historically, Black women have been responsible for both reproducing the labor force and performing highly exploited labor. Distinct gendered roles have been created for Black and white women, with Black women facing objectification, sexualization, and the denial of their political agency (Gonzalez, 1980).

Female segregation is a crucial factor of gender inequality in the labor market, highlighting the limitations that women face when seeking employment opportunities. Occupational segregation is divided into horizontal segregation, associated with feminized and masculinized sectors, and vertical segregation, when women are excluded from positions or occupations associated with better wages or decision-making.

Compared to men, women typically face wage gaps and fewer opportunities for advancement. It is worth noting that, for women, wage gaps are often associated with the low value attributed to women's work, reflecting the historical sexual division. This disparity is a result of discrimination rather than productivity differentials (Teixeira, 2016).

Technological changes and advancements are not inherently neutral to gender inequalities. On the one hand, technological changes reflect and reinforce preexisting distinctions and socio-economic structures in our society. On the other hand, gender inequalities influence the ways women can take advantage of digital innovations, placing them at a disadvantage in a scenario of increasing technological advances in the labor market. Thus, we can consider a bidirectional relationship between gender inequalities and technological changes.

In the first direction, as pointed out by Howcroft and Rubery (2019), when automated eligibility systems and predictive analytics are built using data that contains gender biases, they can incorporate, perpetuate, and amplify these biases within software design and operation. The authors refer to this phenomenon as "bias in, bias out" and illustrate it with two examples: (i) women being less likely to be shown ads for high-paid jobs on Google, and (ii) Amazon's recruitment AI penalizing resumes that included the word "women."

In the second direction, the overload of unpaid care tasks affects women's digital skills development, as they have less time than men to explore cyberspace. This disparity translates into higher rates of digital illiteracy among women, meaning they have fewer skills to understand, control, and establish trusting relationships with technology (Vaca Trigo and Valenzuela, 2022). In several countries in Latin America, women make more limited use of digital technologies and engage in activities that require less technological skills, which puts them at a disadvantage compared to men. The gender gap in digital skills is significant, with women having 1.6 times less chance than men of possessing such skills (UNESCO, 2019).

The low participation of women as internet users and in the fields of information and communication technology (ICT) is closely related to a patriarchal culture that discourages the development of digital skills. Gender stereotypes manifest in norms, family pressures, and the lack of role models, leading to the perception of technology as a predominantly male field. This perception contributes to girls' insecurity regarding their own digital skills from an early age, affecting the inclusion of women and girls in science, technology, engineering, and mathematics (STEM). Furthermore, the lack of female representations in the tech sector, in educational materials, media and advertising reinforces this perception (CEPAL, 2019b).

3. Job automation and its possible impacts on workers

Technological innovations occur exponentially and cause transversal transformations in economies and societies, impacting complete production, management, and governance systems (CEPAL, 2018). Innovations, including automation technologies, can translate into opportunities for economies and imply risks regarding the increase or emergence of inequalities (CEPAL, 2019b).

The continuous advancement of artificial intelligence and robotics has allowed machines to perform and automate more and more tasks, whether routine, non-routine, physical, or cognitive.[2] Activities previously considered exclusive to humans can be performed more efficiently and economically by machines (CEPAL, 2019b; McKinsey Global Institute, 2019; Roberts et al., 2019). Although automation is not a new phenomenon - sectors such as agriculture and manufacturing have experienced major replacements of labor by machines in the past - the computerization of white-collar services (associated, for example, with bureaucratic or management activities) in advanced economies has accelerated (Acemoglu and Restrepo, 2018; Frey and Osborne, 2016).

In recent decades, the replacement of several jobs by computers has been evident, including functions as supermarket cashiers, clothing retail store cashiers, and telephone operators. In general, labor-saving automation is already eliminating many jobs that involve routine tasks requiring low and medium skills, and task automation is expected to have an even broader scope in the medium term (Brussevich et al., 2019). Progress in machine learning has further expanded the set of activities that can be performed more efficiently by computers than by humans (Brynjolfsson et al., 2018). Currently, automation already goes beyond routine tasks associated with manufacturing. One example is driverless autonomous cars, which indicate how manual tasks in transportation and logistics could soon be automated (Brynjolfsson and McAfee, 2011).

As machine-learning techniques progress, such as advances in digitalization and artificial intelligence, the number of automatable tasks in the workplace is increasing. These technological innovations could change how the production

2 Tasks can be classified into non-routine analytical, non-routine interactive, routine cognitive, routine manual, and non-routine manual. Some examples of non-routine analytical tasks include research and planning, while non-routine interactions involve negotiation and management. Routine cognitive tasks cover activities like accounting, while routine manual tasks involve operating machines. Non-routine manual tasks include repairing machines or restoring art. In this sense, routine manual tasks are more susceptible to automation than non-routine analytical or interactive tasks (Black and Spitz-Oener, 2010).

process is carried out, leading to increased productivity and growth. However, they can also transform the nature of work itself (Brussevich et al., 2018).

Another way the automation of activities can affect the job market is through the precariousness of working conditions. In situations where there is no evidence of job losses, wages may decrease or stagnate due to a loss of employee bargaining power. In developing economies, for example, the relocation of industrial production can pressure wages (CEPAL, 2019b). On the other hand, as Boddy et al. (2015) found, the automation of tasks in developed countries has caused the average wages of workers to stagnate while the wages of high-skilled workers continued to grow.

Precariousness can also manifest in more flexible work arrangements, with weaker links between employers and workers, often restricting access to traditional social protection mechanisms. Furthermore, varied atypical forms of work many also emerge or be adopted, with new determinations of spaces and working hours, such as intermittent work and variable hours (Novick, 2018).

The likelihood of automating work activities and thus eliminating jobs or changing labor relations depends on the type of occupation performed by workers and the associated responsibilities (Brussevich et al., 2018). The risk of job destruction depends on the technological feasibility of replacing human labor, but other economic, political, and social factors will also shape the future of work. In short, economic, political, and social actors will decide the future of work, but their actions are conditioned by the characteristics of new technologies and their competitive use (Weller et al., 2019).

Furthermore, the impacts on jobs and labor relations are uncertain and may vary across countries and population groups (CEPAL, 2018). According to McKinsey Global Institute (2019), emerging economies are expected to experience lower levels of automation relative to the size of their employed population than mature economies, given the feasibility of technological implementation. Developing countries usually face a range of barriers to the absorption of innovations, which can result in a slower adoption of new technologies (CEPAL, 2019b). The introduction of technological changes in Latin America and the Caribbean, for example, is subject to a series of barriers. The region lacks the necessary supply of skills and capabilities to meet the demand of the ongoing technological revolution, thus preventing the adoption of new technologies. Furthermore, the presence of smaller companies and low wages in some occupations in the region limit innovation due to the high costs of technology (CEPAL, 2019b).

The literature also suggests that, while jobs can be eliminated due to advances in automation, demand is created for workers in non-automated tasks due to productivity gains (Acemoglu and Restrepo, 2018; CEPAL, 2019a). In practice, the automation of activities would have two competing effects on employment. First, as technology replaces labor, there is a knock-on effect, requiring male and female workers to reallocate their labor supply. Secondly, there is the capitalization effect, as more companies enter industries where productivity is relatively high, causing employment in these industries to expand (Frey and Osborne, 2016). In short, jobs maintained and/or created are expected to be those most intensive in technical skills, cognitive skills, creative activities, decision-making, managerial, and care functions (Brussevich et al., 2018; Roberts et al., 2019).

Nevertheless, the potential positive impacts of automation in the labor market on the economy and specific groups depend on several factors: who can access the new jobs that may arise, what will happen to wages, what changes to job conditions will occur or remain, and how "abundance"[3] created by increased productivity will be distributed (Roberts et al., 2019). In short, the balance between job conservation and technological progress reflects the balance between the distribution of power in society and the gains from technological progress (Frey and Osborne, 2016).

As automation reconfigures the labor market, one relevant phenomenon to observe concerns the "polarization of the labor market." Since it affects mostly routine tasks in "intermediary" occupations regarding remuneration and qualification, the advance of automation can induce a concentration of jobs in the extremes of employment based on qualification. This phenomenon has been identified in many countries, from developed to developing ones.[4] Rocha and Vaz (2023) found that the technologies adopted by manufacturing industries in Brazil replace low-skilled workers in performing routine tasks while complement workers with higher qualifications. Finally, other hypotheses help explain such phenomenon, such as the Skills-Biased Technological Change (SBTC) and the Routine-Biased Technological Change (RBTC) ones. The SBTC, as discussed by Acemoglu and Autor (2011) and Goos et al. (2014), highlights the increasing demand for workers with higher education levels, while the RBTC, as explored by Fernández-Macías and Bisello (2020), classifies jobs based on the proportion of routine or generic tasks that can be automated. Both perspectives complement the analysis by showing how technology influences the demand for different skills in the labor market.

4. Methodology adopted to estimate the probability of job automation in Brazil

Several studies seek to estimate the probability of automation (from now on, p(auto)) of occupations in an economy, among which the seminal work by Frey and Osborne (2016). They developed a methodology to estimate the probability of automation in the set of occupations in the United States (U.S.), based on data from the O*NET survey, the primary source of information about occupations in that country, for the year 2010.

3 Automation could result in a "paradox of abundance", in which society would become richer in aggregate terms, but technological change could reinforce inequalities in power and reward for many individuals and communities,"schema":"https://github.com/citation-style-language/schema/raw/master/csl-citation.json"}. (Roberts *et al.*, 2019).

4 A panoramic reference to this ample literature that comprises both country studies and different methodological approaches is the cross-country study from OECD (2017).

Although many studies replicate the vector of the p(auto) of occupations estimated by Frey and Osborne (2016), labor market characteristics in the U.S. differ from those in Latin American countries, so adjustments may apply to conduct estimates for this region. This is what Espíndola and Suárez (2023) did, they adapted the Frey and Osborne (2016) estimation strategy and data source, as described ahead[5], to build a vector of the probability of automation of occupations to analyze the labor market of LA countries that have internationally homologous occupation data (CIUO-08).

Espíndola and Suárez (2023) build on Frey and Osborne's (2016) categorization of occupations as automatable and non-automatable ones but consider only two of the three original "bottlenecks to automation": (i) social intelligence and (ii) creative intelligence. Bottleneck (iii) perception and manipulation was discarded based on the study by Lassébie and Quintini (2022), who assessed the automation potential of certain activities and occupations in light of recent advances in artificial intelligence. They found that most skills related to the "perception and manipulation" bottleneck are now automatable with current technologies. Therefore, Espíndola and Suárez (2023) considered only the bottlenecks (i) and (ii), which included a set of 15 non-automatable skills that served as the main predictive variables for automation probability, such as "collaborating with other workers", "advising", and "solving complex problems". Additionally, the authors incorporated social indicators to enhance the predictive capacity of the algorithms by considering important factors to better reflect task structures. Thus, it was assumed that the variation in tasks within an occupation could be related to the worker's education, gender, and the sector in which they operate, among other factors. As for the data source, Espíndola and Suárez (2023) used data from the Programme for the International Assessment of Adult Competencies (PIAAC) survey for four countries in Latin America (Chile, Ecuador, Mexico, and Peru). This survey provides information about workers' skills in their respective countries.

It is important to mention that the vector of probability of automation of occupations is based solely on the demand for work skills that can (or cannot) be automated. Also, each occupation is made up of several tasks. Therefore, the vector p(auto) for each occupation will consider how automatable the set of activities that make up that occupation is. The vector consists of probabilities of automation of occupations common to all workers who exercise the same profession in any country in the region, even though the structure of tasks can vary within the same occupation.

Even though the framework has been adapted considering the characteristics of occupations in Latin America, it still stems from an initial structure developed with the U.S. economy in mind. Therefore, it may not fully reflect aspects of the Brazilian labor market, which is marked by strong informality. Furthermore, it

5 Consult Espíndola and Suárez (2023) for a complete review.

also does not consider people belonging to the armed forces and sex workers. In summary, the vector should not be interpreted literally but as indicative of underlying trends and patterns.

In this work, we will use the vector p(auto) estimated by Espíndola and Suárez (2023) and employ the Brazilian 2022 labor market data from the Continuous National Household Sample Survey (Pnad Contínua, according to its Portuguese acronym) released in 2023. Notably, the results can be different for women and men given gender differences rooted in occupational of activities and sectoral structures. Consequently, we will analyze the data disaggregated by sex to examine the impacts of the automation of occupations on women. Additionally, as Pnad Contínua data allows identification of the weight of each occupation within the economic sectors, we also present a sectoral analysis.

5. Job automation and gender inequalities in Brazil

5.1. Aggregate and sectoral results

In Brazil, according to the occupational structure evidenced in the job market in 2022, there is an average probability of automation of 50%. This probability is more pronounced for men (56%) than for women (42%).[6] This pattern is similar to the results reported by Espíndola and Suárez (2023) for Latin American countries, where men have an average probability of automation of 56%, while women have an average of 43%.

Conversely, Lima et al (2019) specifically estimated the probability of automation for Brazilian jobs and found that women are in a more vulnerable situation to automation than men, with probabilities of automation of their jobs being 69.7% and 62.5%, respectively. It is important to note that this study relied solely on formal employment data from the Annual Report of Social Information (RAIS, according to its Portuguese acronym) database and used the original automation probability vector created by Frey and Osborne (2016). This raises concerns about the accuracy of applying the same vector to Brazil, as the tasks performed in similar occupations can differ significantly between the two countries.

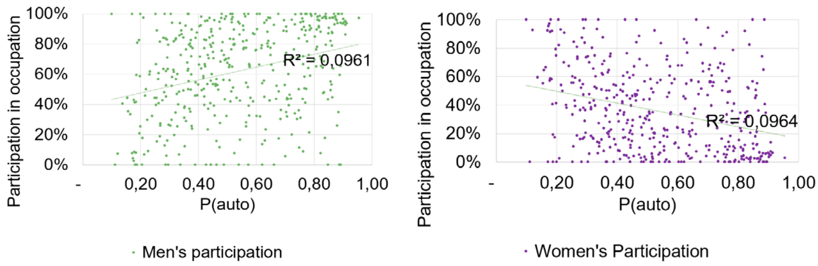
Furthermore, we found a negative correlation between p(auto) and female participation in occupations. In other words, the occupations with the highest rate of female participation tend to be those with the lowest probability of automation. However, the coefficient of determination is low; that is, the relationship between the variables is weak (Figure 1).

In a sectoral analysis, we identified that the four sectors with the lowest probability of automation are precisely the feminized sectors (where women represent more than 50% of employed individuals). These sectors are domestic services, which have a low p(auto); education; accommodation and food; and

6 Own elaboration based on data from Espíndola and Suárez (2023) and Pnad Contínua (2023).

health, which have a with low to medium p(auto). Conversely, the sectors with the lowest female participation are construction, which has a medium to high p(auto); and transport, which has a high p(auto) (Table 1).

FIGURE 1. DISTRIBUTION OF EMPLOYED WOMEN'S AND MEN'S PARTICIPATION BY PROBABILITY OF AUTOMATION



Source: Own elaboration based on data from Espíndola and Suárez (2023) and Pnad Contínua (2023).

TABLE 1. PROBABILITY OF AUTOMATION AND PARTICIPATION OF MEN AND WOMEN BY SECTOR

Sector	P(auto)	Participation	
		Men	Women
Domestic services	0.16	9%	91%
Education	0.37	26%	74%
Accommodation and Food	0.38	44%	56%
Health	0.42	26%	74%
Agriculture	0.48	80%	20%
Other services	0.49	56%	44%
Professional activities	0.53	53%	47%
R&D	0.55	59%	41%
Telecommunications and Information Services	0.55	70%	30%
Financial and Insurance Services	0.60	53%	47%
SIUP	0.64	78%	22%
Construction	0.64	96%	4%
Extractive industry	0.66	86%	14%
Transformation industry	0.69	65%	35%
Transport	0.77	88%	12%

Source: Own elaboration based on data from Espíndola and Suárez (2023) and Pnad Contínua (2023). Note: P(auto) is categorized as low [0, 0.3), low-medium [0.3, 0.5), medium-high [0.5, 0.7) and high [0.7, 1].

5.2. MAIN RESULTS ACCORDING TO LARGE OCCUPATION GROUPS

Notably, within each of the sectors previously examined, a vast set of activities are carried out, associated with specific occupations whose p(auto) can also be highly dispersed. For example, in the telecommunications and information services sector, one finds directors and call-center workers among the occupations with the greatest weight in the sector's structure. Furthermore, gender segregation goes beyond the concentration of women and men in certain sectors (horizontal segregation); there is also an unequal distribution in terms of which occupations will be performed in each sector (vertical segregation). Therefore, understanding the potential impacts of automation on women and men requires carrying out the analysis at the level of occupations.

First, we will conduct an analysis at the level of large groups of occupations,[7] categorized into high, medium, and low qualifications, following the classification adopted by the International Labor Organization. In this classification, the qualification is based on the level of skills required, which in turn is associated with the complexity and variety of tasks demanded by each occupation. Operationally, qualification is measured by considering the nature of the work, the level of formal education, and the amount of informal training or previous experience necessary for the competent performance of tasks (ILO, 2023).

Highly qualified occupations – directors and managers, science and intellectual professionals, and technicians and mid-level professionals – are precisely among those with the least probability of automation. Furthermore, these occupations are associated with better pay. However, there is a considerable difference between the p(auto) and remuneration for technicians and mid-level professionals concerning the other two occupations: p(auto) tends to be higher, approaching what we consider to be a medium-high probability of automation, and the remuneration is approximately half of that for directors and managers (Table 2).

Together, these three occupations represent a greater weight in the female occupational structure than in the male one; however, only science and intellectual professionals show a higher participation of women. Furthermore, despite the strong female participation in this occupation, it displays the biggest salary gap for women. When analyzing director and management positions, the concept of a "glass ceiling" is reinforced, as it prevents women from reaching such positions (Table 2).

In the case of medium-skilled occupations, including service workers, salespeople in shops and markets, qualified agricultural, forestry, hunting and fishing workers, qualified workers, laborers and artisans in construction, mechanical arts and other trades, administrative support workers, and plant and machine operators and assemblers, the distribution of p(auto) is not so homogeneous, varying from low-medium to high. Salaries, in turn, also vary, despite remaining below average. Among those occupations, the only feminized ones are service workers, salespeople in shops and markets (p(auto) low-medium), and administrative support workers (p(auto) high). The two have,

7 According to the Classification of Occupations for Brazilian Household Surveys, which is compatible with CIUO-08, occupations are organized into four groups: Large Group (1 digit), Main Subgroup (2 digits) Subgroup (3 digits) and Base Group (4 digits).

respectively, the first and fourth largest weight in the female occupational structure (Table 2).

Low-skilled occupations, which include elementary ones, have a medium-high probability of automation. In this occupational group, women represent almost 50% of employed individuals. These occupations offer both lower remuneration and a smaller salary gap: women, in general, earn R$1,164 per month, which is equivalent to 89% of the remuneration received by men in the same occupation (Table 2).

Table 2. Probability of automation by major occupational groups and selected characteristics

CIUO-08	Occupations (Large Group)	P(auto)	Participation		Proportion		Remuneration (R$)	
			Men	Women	Men	Women	Men	Women
1	Directors and Managers	0.34	61%	39%	4%	3%	7,867	5,650
2	Science and intellectuals professionals	0.39	41%	59%	9%	17%	6,862	4,439
5	Service workers, salespeople in shops and markets	0.43	42%	58%	17%	30%	2,438	1,594
3	Technicians and mid-level professionals	0.49	56%	44%	8%	9%	3,988	2,861
9	Elementary occupations	0.53	52%	48%	15%	18%	1,303	1,164
6	Qualified agricultural, forestry, hunting and fishing workers	0.69	80%	20%	8%	3%	2,059	1,494
7	Qualified workers, laborers and artisans in construction, mechanical arts and other trades	0.73	83%	17%	20%	5%	2,176	1,433
4	Administrative support workers	0.74	39%	61%	6%	12%	2,325	1,998
8	Plant and machine operators and assemblers	0.82	86%	14%	14%	3%	2,226	1,622
Total		0.57	57%	43%	100%	100%	2,926	2,301

Source: Own elaboration based on data from Espíndola and Suárez (2023) and Pnad Contínua (2023). Note: P(auto) is categorized as low [0, 0.3), low-medium [0.3, 0.5), medium-high [0.5, 0.7) and high [0.7, 1]. CIUO-88 groups are classified as high (1-3), medium (4-8), and low (9) qualifications.

5.3. Main results by detailed occupational groups

Analyzing the main subgroups of occupations (2 digits) according to the probability of automation, we found that women are the vast majority in occupations with low p(auto). Of the four occupations that make up this group, three include medium-skilled occupations and have a female participation rate exceeding 60%. Together, they account for 20% of employed women (versus 7% in the case of men) and are commonly judged as "more feminine." These occupations include Health professionals; Teaching professionals; and Personal service workers. The fourth occupation in this group is Executive directors, public administration directors, and members of the executive and legislative branches (Table 3).

Health professionals are the occupation with the highest remuneration for men and the fifth highest for women, resulting in a salary gap exceeding R$4,000 to the detriment of women. Among the occupations that make up the subgroup (3 digits), women constitute the majority in nursing and childbirth professionals, traditional and alternative medicine professionals, and veterinarians. However, remuneration for these occupations is less than 50% of that for doctors in general, regardless of gender. Among these occupations, nursing and childbirth professionals have the lowest p(auto), equivalent to 0.19 (Table 3).

In the case of Teaching professionals, women only are not the majority in the occupations of Vocational training teachers, and other music teachers (4 digits). However, there is a notable difference in female participation in occupations such as professors at universities and higher education teachers (55%) compared to preschool teachers (96%). Within this group, the latter is the occupation with the lowest p(auto), equal to 0.17, and the remuneration for women is equivalent to only 33% of that of professors at universities and higher education (Table 3).

Regarding personal service workers, the occupation accounts for 9% of employed women, where they are mainly concentrated in two occupations: cooks (3 p.p.) and Hairdressers, beauty treatment specialists and similar (5 p.p.), with these being the two with the lowest p(auto) within the group, at 0.20 and 0.18, respectively. Conversely, within the same group, the occupation of Direct service workers for passengers can be highlighted, as its p(auto) and remuneration are considerably above average, and the composition is predominantly male (Table 3).

Executive directors, public administration directors, and members of the executive and legislative branches perform highly qualified activities. These positions have the highest paying for men and the second highest for women, with a salary gap of R$1,658 to the detriment of women. This occupation is commonly perceived as "more masculine," and, indeed, women make up only 29% of employed individuals in this field. In this group, men are the majority regardless of the level of disaggregation (Table 3). One explanation could be the stereotypes related to leadership qualities such as assertiveness, rationality, risk-taking, firmness, and strategic vision, which are generally considered masculine traits.

In the group of occupations with a low-medium probability of automation, women are the majority in one-third of the 18 occupations that make up the group. This group is quite diverse and includes low, medium, and high qualification activities, which correspond to 54% and 44% of employed women and men, respectively. Among these occupations, the two with the greatest weight in the female occupational structure are sellers; and domestic workers and other building interior cleaning workers (Table 3).

Even though the occupation of sellers is considered to have a low-medium p(auto), it is among the six with the least p(auto) and includes everything from street vendors (whether street or home-based, for example) to store supervisors. Notably, even though salaries and p(auto) are generally low, when analyzing the supervisory category, where salaries and p(auto) are higher, men are the majority (Table 3).

In the case of people employed as domestic workers and other building interior cleaning workers, the dynamics are similar. In a 4-digit analysis, there is great granularity in the p(auto) of the occupation group. For instance, p(auto) is 0.12 for domestic service workers in general, on the other, 0.74 for workers cleaning the interior of buildings, offices, hotels, and other establishments, and 0.70 for vehicle washers. Female participation in these occupations is, 93%, 70%, and 8% respectively, and, for women, the average remuneration in these occupations is R$1,034, R$1,344, and R$1,527 (compared to R$1,309, R$1,538 and R$1,398 for men) (Table 3).

Still, regarding the group of occupations with a low to medium probability of automation, in terms of female participation in the group of employed people, the overrepresentation stands out in the case of personal care workers (93%) and domestic workers and other building interior cleaning workers (80%), considered, respectively, of medium and low qualification. Both are among the 10 lowest-paying occupations (Table 3).

On the other hand, in the highly qualified occupations that make up the group, associated with directors and management, the maximum level of female participation reached was 43%. Notably, female participation in executive positions exceeding 40% only occurs when these positions are in the hotel, food, and commercial sectors, which are the categories of directors and management positions with the lowest remuneration. If the occupation is associated with production and operation, the participation of women decreases (Table 3).

In fact, within the basic occupations that make up the subgroup of directors and production and operation managers, only managers of childcare services, health service managers, managers of care services for elderly people, and directors of education services have female participation exceeding 40% (Table 3).

In the case of occupations with medium-high p(auto), women are the majority in only one of the six occupations that make up the group, direct customer service workers, corresponding to 73% of the employed individuals in this occupation. This is the second lowest-paid occupation among medium-high p(auto) occupations. This group includes telephone operators; receptionists; and call-center workers. In a 4-digit analysis, women only do not for the majority as hotel receptionists, where they represent 45% (Table 3).

Altogether, medium-high p(auto) occupations represent 9% of the female occupational structure (versus 13% in the male case). This group mainly consists of medium-skilled activities, except for garbage collectors and other elementary occupations. In this latter occupation, women represent 22% of employed individuals, a participation rate also found in the other basic occupations that comprise the group (for example, garbage and recyclable material collectors; and Waste classifiers), except for sweepers and similar, where they represent 44% (Table 3).

Finally, in the group composed of occupations with high p(auto), only medium-skilled activities are concentrated. Among them, two occupations have greater female representation: clerks, and artisans and graphic arts workers. Both have below-medium pay, but only the latter is among the worst-paid occupations, behind only the skilled forestry workers, fishermen and hunters. Considering the proportion of these occupations in the occupational structure, the weight is relatively greater for men (35%) than for women (16%) (Table 3).

Table 3. Probability of automation by main occupational subgroup and selected characteristics

CIUO-08	Occupations (Main Subgroup)	P(auto)	Participation		Proportion		Remuneration (R$)	
			Men	Women	Men	Women	Men	Women
2	Health professionals	0.23	33%	67%	1%	3%	9,775	5,598
2	Teaching professionals	0.26	24%	76%	2%	7%	4,563	3,468
1	Executive directors, public administration directors and members of the executive and legislative branches	0.28	71%	29%	0%	0%	9,614	7,956
5	Personal service workers	0.28	36%	64%	4%	9%	1,948	1,536
1	Managers of hotels, restaurants, shops and other services	0.32	57%	43%	1%	1%	5,101	3,948
5	Sellers	0.32	45%	55%	10%	16%	2,612	1,715
5	Personal care workers	0.34	7%	93%	0%	5%	1,793	1,227
1	Administrative and commercial managers	0.35	60%	40%	1%	1%	9,200	6,250
1	Production and operation directors and managers	0.35	65%	35%	1%	1%	8,260	6,272
2	Professionals in law, social and cultural sciences	0.35	46%	54%	2%	3%	6,437	5,296
9	Domestic workers and other building interior cleaning workers	0.36	20%	80%	3%	14%	1,467	1,131
9	Itinerant service workers and the like	0.37	63%	37%	0%	0%	1,328	999
9	Food preparation helpers	0.39	30%	70%	0%	1%	1,726	1,375
9	Elementary workers in mining, construction, manufacturing and transport	0.40	88%	12%	7%	1%	1,353	1,482
3	Mid-level healthcare and related professionals	0.44	28%	72%	1%	4%	3,293	2,208
6	Farmers and qualified agricultural workers	0.44	79%	21%	7%	3%	2,144	1,556
2	Science and engineering professionals	0.45	67%	33%	1%	1%	7,526	4,818
3	Mid-level science and engineering professionals	0.45	83%	17%	2%	1%	3,595	2,816
3	Mid-level professionals in legal, social, cultural and related services	0.47	55%	45%	1%	1%	4,689	3,542
2	Information and communications technology professionals	0.48	77%	23%	1%	0%	7,090	5,658

CIUO-08	Occupations (Main Subgroup)	P(auto)	Participation		Proportion		Remuneration (R$)	
			Men	Women	Men	Women	Men	Women
6	Skilled forestry workers, fishermen and hunters	0.49	82%	18%	1%	0%	1,064	706
9	Elementary agricultural, fishing and forestry workers	0.49	80%	20%	3%	1%	1,040	953
2	Specialists in the organization of public administration and companies	0.50	51%	49%	2%	2%	7,019	4,563
3	Mid-level professionals in financial and administrative operations	0.54	56%	44%	3%	3%	4,654	3,514
3	Mid-level information and communications technology technicians	0.59	85%	15%	1%	0%	3,301	3,394
9	Garbage collectors and other elementary occupations	0.64	78%	22%	1%	0%	1,250	1,138
4	Direct customer service workers	0.66	27%	73%	1%	4%	1,968	1,617
7	Qualified workers and workers in metallurgy, mechanical construction and similar areas	0.68	95%	5%	6%	0%	2,478	2,521
4	Numerical calculation workers and material recorders	0.70	69%	31%	2%	1%	2,309	2,175
7	Workers specializing in electricity and electronics	0.71	95%	5%	2%	0%	2,235	2,297
7	Workers and officials in food processing, wood, clothing and similar areas	0.72	52%	48%	3%	4%	2,034	1,358
4	Clerks	0.76	33%	67%	2%	7%	2,466	2,176
4	Other administrative support workers	0.77	59%	41%	0%	0%	2,492	2,048
5	Protection and security services workers	0.77	89%	11%	3%	0%	2,594	2,818
7	Artisans and graphic arts workers	0.78	45%	55%	1%	1%	1,820	946
7	Skilled workers and construction workers exclusive electricians	0.80	97%	3%	9%	0%	2,037	2,304
8	Operators of fixed installations and machines	0.80	60%	40%	3%	2%	1,885	1,448
8	Assemblers	0.88	82%	18%	1%	0%	2,212	1,949
8	Vehicle drivers and operators of heavy mobile equipment	0.88	96%	4%	11%	1%	2,307	2,201
Total		0.53	57%	43%	100%	100%	2,926	2,301

Source: Own elaboration based on data from Espíndola and Suárez (2023) and Pnad Contínua (2023). Note: P(auto) is categorized as low [0, 0.3), low-medium [0.3, 0.5), medium-high [0.5, 0.7) and high [0.7, 1]. CIUO-08 groups are classified as high (1-3), medium (4-8), and low (9) qualifications.

5.4. Unpacking the challenges

In short, the weight of low and low-middle p(auto) occupations is noticeably greater for women (74%) than for men (52%), which is reflected in a higher aggregate p(auto) in the male case, as evidenced at the beginning of the previous section. However, one must consider how positive this fact is.

On the one hand, in the case of occupations with low p(auto), the only high-skilled occupation in the group has a female representation of less than 30% and a negligible weight in the female occupational structure. On the other hand, although occupations with low-medium p(auto) represent 54% of the female occupational structure, the low-skilled occupations within this group correspond to 18pp of this 54%, while high-skilled occupations correspond to just 3pp (Table 3).

Furthermore, a disaggregated analysis allows for a more nuanced examination of the gender pay gap, as illustrated in the box below.

Box 1. Gender pay gap across occupations

The gender pay gap is a clear and persistent reality. On the one hand, there is a significant discrepancy in the average wages of female-dominated occupations compared to male-dominated ones. On the other hand, it is evident that, overall, women tend to earn less than men.

At the main subgroup level (or 2 digits), we find a set of 39 occupations, of which only 12 are feminized. These feminized occupations are, on average, precisely the ones with the lowest remuneration: the average monthly remuneration for masculinize occupations is R$2,837, while for feminized ones is R$2,412. In other words, remuneration in feminized occupations represents only 85% of the average remuneration in masculinized occupations.

In an analysis of the wage gap within these two groups, in feminized occupations, women tend to earn less than 70% of what men earn, while in masculinized occupations, women's remuneration tends to be slightly higher (equivalent to 103% of male remuneration).

In an analysis considering a more disaggregated level of occupations (4 digits), the results are similar, but the discrepancy between men and women is accentuated. The average salary for masculinized occupations is R$2,929, while for feminized occupations, it is R$2,251. In percentage terms, the remuneration of feminized occupations now represents 77% of the remuneration of more masculinized occupations, compared to the 85% it represented in a 2-digit analysis.

Regarding the salary gap, in feminized occupations, women continue to earn less than 70% of what men do. However, unlike the previous case, the salary gap in more masculine activities continues to be to the detriment of women, even though it is considerably smaller: women now earn 93% of men's remuneration.

From these facts, we can conclude that men tend to work in activities considered "more prestigious" and that pay better. In addition to a clear concentration of women in occupations that have, on average, lower pay, when men work in these same occupations (feminized), they tend to receive considerably higher pay than women.

For example, we can consider occupations associated with domestic service, which are clearly feminized and associated with low pay. In this case, while women receive, on average, R$1,131, men receive R$1,467. Furthermore, looking at the basic occupations that make up the group, male participation will be greater in activities that have above-average remuneration, such as Workers cleaning the interior of buildings, offices, hotels and other establishments, where they represent 30% of employed individuals. Conversely, their participation as Domestic service workers in general, the occupation with the lowest pay within this group, is only 7%.

Source: Own elaboration based on data from Pnad Contínua (2023).

Another important issue is that most occupations held by women are associated with the care economy and life reproduction tasks (with a weight equivalent to 36% for women versus 10% for men), such as Domestic work and health, which require cognitive skills – such as empathy, attention to the needs of individuals who require care, communicative skills, or creativity – and thus tend to be more difficult to automate. Additionally, these also tend to be more invisible and poorly paid (or unpaid) activities, which discourages their automation (Table 4). As highlighted by Castilho and Ferreira (2024), 95% of employed women tend to balance paid work with household chores and/or caregiving, whereas only 85% of men face similar conditions. Moreover, most women dedicate more than 14 hours per week to such tasks, while most men contribute a maximum of 14 hours.

Table 4. Probability of automation of selected occupations associated with the care economy and selected characteristics

Selected Occupations (Base Group)	P(auto)	Participation		Proportion		Remuneration (R$)	
		Men	Women	Men	Women	Men	Women
Domestic service workers in general	0.12	7%	93%	1%	9%	1,309	1,034
Child caregivers	0.18	3%	97%	0%	2%	1,598	1,009
Cooks	0.20	21%	79%	1%	3%	2,248	1,489
Manual clothes washers and ironers	0.22	30%	70%	0%	0%	1,499	1,241
Personal care workers at home	0.29	6%	94%	0%	2%	1,480	1,340
Housekeepers and domestic butlers	0.35	12%	88%	0%	0%	5,740	2,101
Community health workers	0.36	29%	71%	0%	1%	2,347	2,007
Total	0.25	11%	89%	2%	17%	2,317	1,460

Source: Own elaboration based on data from Espíndola and Suárez (2023) and Pnad Contínua (2023).
Note: P(auto) is categorized as low [0, 0.3), low-medium [0.3, 0.5), medium-high [0.5, 0.7) and high [0.7, 1].

Besides the points highlighted in sections 5.1, 5.2, and 5.3, it should be noted that women may face greater difficulties adapting to the jobs that may arise with the advancement technological innovations and the introduction of automation in the labor market, in addition to taking less advantage of the potential of ICT.

According to Lawrence, Roberts, and King (2017, p. 24), "automation is more likely to accelerate wealth and income inequalities than to create a future of mass unemployment", and these are shaped by people's class, race, age, and gender (Roberts et al., 2019). In this sense, the economic benefits of automation are likely to be concentrated among technology and business owners, as well as highly skilled workers, while the labor market is polarized between high-skilled and low-skilled jobs (Lawrence et al., 2017).

Several factors contribute to this scenario, including women's limited access to the internet (ITU, 2021), the prevalence of a large digital gender gap (CEPAL, 2019b), the underrepresentation in STEM careers (Weller et al., 2019), and the disproportionate burden of unpaid work and care for women (Vaca Trigo and Valenzuela, 2022).

6. Final considerations

As new technologies that encourage the automation of activities are introduced, several authors indicate the potential for job substitution, job precariousness, and/or job creation. These effects can occur isolated or simultaneously, and the net effect is uncertain. Given the gender differences rooted in both the sectoral structure of activities and the occupational structure, these effects may vary for women and men, raising concerns about the potential effects of the automation of occupations for women in Brazil.

Employing the vector of the probability of automation of occupations developed by Espíndola and Suárez (2023) for Latin American countries, the present study found that, in Brazil, the p(auto) in the job market for women (42%) is lower than that for men (56%). However, one must consider the underlying complexity: occupations with lower p(auto) tend to be lower-skilled and associated with lower pay.

Additionally, most women's occupations are linked to the care economy and reproductive tasks, such as domestic work and healthcare. These activities require specific cognitive skills, such as empathy, attention to individual needs, and communicative or creative skills, making them less prone to automation. However, these occupations are often informal, poorly paid, or unpaid, which poses challenges for valuing work and disincentivizes their automation. It is worth noting that such results should not be interpreted literally but as indicative of underlying trends and patterns.

Furthermore, the gender pay gap is a persistent issue. In general, men tend to work in activities considered "more prestigious" and that pay better. In addition, when working in feminized occupations, men tend to get considerably higher pay than women.

Finally, it should be noted that women currently face greater hardships in entering jobs created by automation in the labor market. Factors such as limited access to connectivity, lower digital skills, underrepresentation in STEM careers, and the responsibility for carrying out unpaid domestic and care work represent crucial bottlenecks for women and make it more difficult for them to enter these potential jobs.

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