A framework for research on the automation of work

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Abstract

Most research on work automation has been conducted using a job-centered approach, which analyzes whether or not a job can be automated. However, this particular perspective can lead to incorrect conclusions. Research has also examined general work activities that do not accurately represent the tasks that workers do. This study proposes a framework for research on work automation that includes multiple scopes of analysis reflecting the scale of technology being analyzed (from technology in general to specific technologies) and the work descriptor being considered (the labor market, occupations, jobs, duties, or tasks). The scope of the analysis determines the type of effects on work and on workers that will be predicted and the relevance and reliability of these predictions. Based on the proposed framework, we assess the impact of technology on an important job in the hotel industry: chambermaids. Compared to other predictions, the results reflect that worker displacement is improbable in this case. Job automation is more likely to occur through a combination of partial automation and work redesign rather than the replacement of entire jobs by technology.

Keywords: work automation, automation technologies, jobs.

Highlights

The accuracy of work automation predictions depends on how work is represented.

The more different tasks a job involves, the lower the risk of job automation.

When there is a high task variety, job automation depends on work redesign.

Industries are less prone to job automation if they involve diverse jobs and tasks.

1 Introduction

Automation technologies are referenced in multiple reports and articles that discuss concerns about the future of employment. These technologies include robotics, artificial intelligence, big data, the Internet of Things, and 3D printing, all of which have demonstrated an impressive capacity to perform tasks previously considered to be within the domain of human skills (Camina et al., 2020). Consequently, numerous studies have endeavored to ascertain the extent to which workers may be displaced by automation technologies (Filippi et al., 2023). Research has not reached a consensus on the severity of this effect. (Willcocks, 2020). Given the potential social consequences of widespread automation, further research is required.

Predicting employment transformation is challenging. Most studies on work automation rely on global evaluations of the content of jobs and seek to predict whether there will be a significant reduction in employment. This approach is relatively straightforward but its results may be unreliable because it does not consider the various tasks that jobs entail. Other research considers common work activities instead of jobs to represent work that could be affected by technological progress. However, technology automates job tasks, and there is virtually no research on automation based on job tasks. Specific evaluations of work through job tasks would allow rigorous predictions about automation consequences but would also complicate the development of these studies due to complex and extensive methodologies.

This study presents a framework for analyzing work automation. This model can be utilized to assess the considerable number of previous studies and reports. Additionally, it can assist future research in determining the most effective approaches to investigate the effects of automation technologies.

As an example, the framework is applied to the tourism industry, specifically to the accommodation activity. Automation technologies are spreading to the tourism industry (Tussyadiah, 2020). As with any industry, the tourism industry can benefit from these technologies (e.g., by reducing costs and improving productivity). Companies in some tourism destinations are facing significant human resource challenges including job vacancies and absenteeism (Hosteltur, 2022). These factors may prompt tourism companies to consider service automation (Tuomi et al., 2020). The tourism industry is an important source of employment in many regions, and there is no evidence of the impact that this technology can have. We focus on of one of the most prevalent occupations in tourism: chambermaids. One of the most cited studies on work automation estimates a probability of automation for this occupation at .69 over 1 (Frey & Osborne, 2017).

The article is structured in five parts. We first focus on how work can be represented. Then we move on to how work has been analyzed up to now in research on the impact automation technologies have on work. This leads us to present a framework for the research of the automation of work that we apply to the job of hotel chambermaids. The article finishes with a discussion and conclusions.

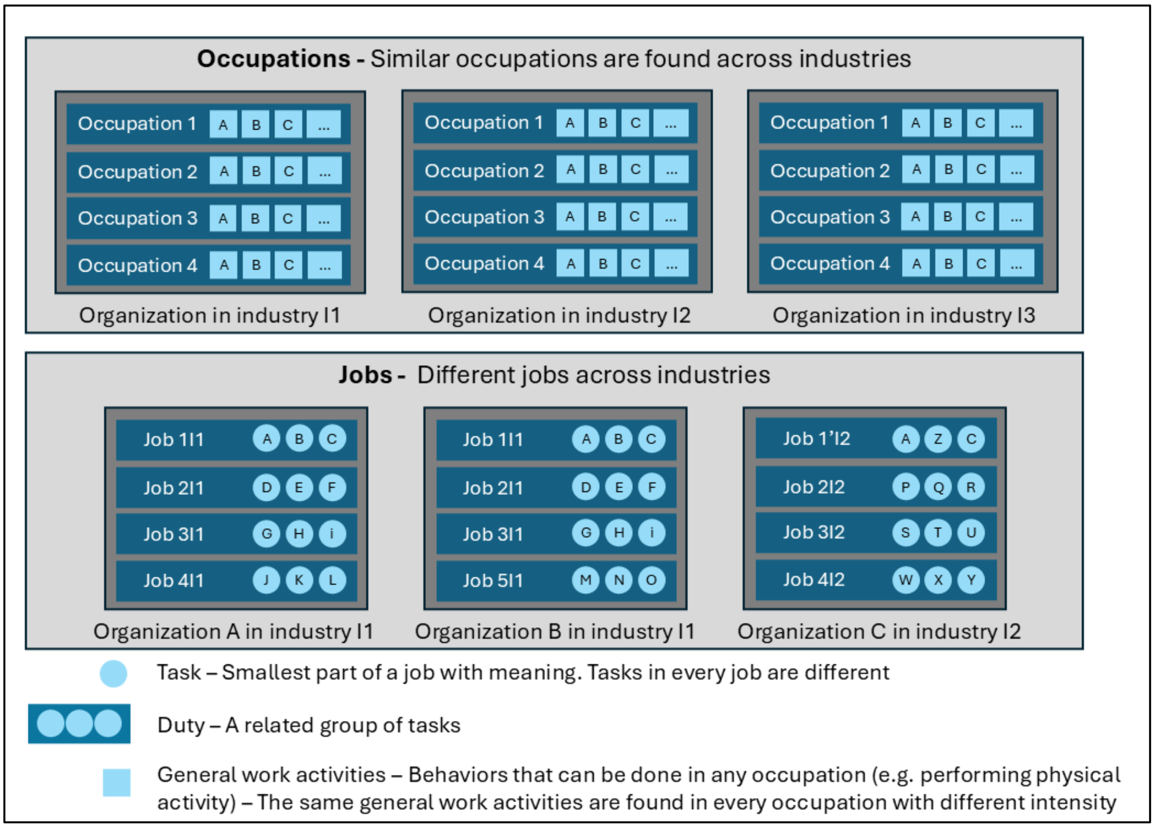
2 Work analysis

In general, work analysis is conducted based on data provided by job incumbents and subject matter experts (Sanchez & Levine, 2012). Dierdorff and Morgeson (2009) stated that the analysis of work is often regarded as a relatively straightforward process, whereas in fact, it involves making complex inferences on the part of those who evaluate the jobs. These authors used the term "descriptors" to represent the features of work examined in a work analysis.

The terms tasks, work activities, duties, responsibilities, jobs, and occupations are descriptors representing people's work with different levels of specificity (Cunnigham, 1996) (see Figure 1). Of these, *tasks* are the most specific (Dierdorff & Morgeson, 2009). Altman and Gagne (1966) defined a task as the smallest part of a job having a meaningful unitary goal or purpose. Tasks are specific and job-contingent. Because many jobs (and their tasks) are industry-specific, tasks cannot be used for cross-occupational comparisons comparing jobs across industries or sectors. Therefore, there was a need for a more generic descriptor that would allow comparisons between jobs. The term *general work activities*, less specific than tasks, was conceived to serve as a unified metric for the content of all occupations (Sanchez & Levine, 2012). A general work activity is a set of similar actions done in different jobs and applicable across a range of jobs and occupations (Dierdorff & Wilson, 2003). An example of a task would be "cleaning the windows of a room" which is specific to the job of a hotel chambermaid. A general work activity would be "performing general physical activities," which allows for the comparison of different jobs.

Cunnigham (1996) mentioned the alternative concept of duties. *Duties* or *responsibilities* are employed to categorize related groups of tasks. Continuing with the previous example, a duty would be "cleaning a room". *Jobs* are comprised of various tasks or duties. The delineation between job and occupation is not always discernible. According to Cunnigham (1996), jobs are a group of similar positions within an organization (e.g., hotel chambermaid), whereas *occupations* are a group of similar jobs found in multiple organizations (e.g. cleaners and helpers).

Figure 1: Occupations, jobs, tasks, duties and work activities



Source: Own elaboration

To represent the work involved in jobs or occupations it is necessary to consider their specific content: tasks or general work activities. A work analysis based on tasks relies on the idiosyncratic tasks of a job, whereas one based on general work activities relies on a set of behaviors or actions applicable to a wide range of jobs or occupations. Based on the Occupational Information Network (O*NET), the main database about occupations content (Jeanneret et al., 1999), Table 1 shows a sample of job content descriptors for the O*NET occupation Maids and Housekeeping Cleaners at the three levels that this database includes: (general) work activities, detailed work activities, and tasks.

Table 1. Examples of Job Content Descriptors for the Occupation Maids and Housekeeping Cleaners from O*NET

General work activities	Detailed work activities	Tasks
• Handling and moving objects • Performing general physical activities • Assisting and caring for others	• Clean facilities or sites • Clean furniture or fixtures • Move furniture • … [17 other detailed work activities]	• Clean rooms, hallways, lobbies, lounges, restrooms, corridors, elevators, stairways, locker rooms, and other work areas so that health standards are met • Keep storage areas and carts well-stocked, clean, and tidy • Wash dishes and clean kitchens, cooking utensils, and silverware

• … [4 other general work activities]		• … [22 other tasks]

Source: O*NET (n.d.)

The three job content descriptors vary in their level of specificity. For example, the general work activity "Handling and moving objects" is included in most occupations in O*NET. Out of the total number of 1,006 occupations, 873 (86%) include this activity. Instead, the detailed work activity, "Clean facilities or sites" is more specific and appears in only seven occupations (0.7%). Last, the three tasks shown in the third column of Table 1 are only present in the occupation Maids and Housekeeping Cleaners.

Research has indicated that the reliability of work analysis based on tasks is higher than that based on general work activities (Sanchez & Levine, 2012). The job descriptor chosen can influence the result of an assessment of the probability of work automation. Many robots can handle and move objects, but few machines can "clean rooms, hallways, lobbies, lounges, restrooms, corridors […]." The latter task involves different worker actions (e.g., cleaning rooms vs. cleaning corridors). Thus, a simplification of the representation of workers' actions can cause a failure in estimating the probability of work automation. Consequently, tasks should be correctly represented if a precise assessment is to be achieved.

3 Work analysis in the research on the impact of automation technology on work

Most predictions about work automation are based on two perspectives on what drives automation: the routinization hypothesis (Autor, Levy & Murnane, 2003) and the bottleneck approach (Frey & Osborne, 2017). The routinization hypothesis posits that technology will automate routine work and complement workers performing non-routine tasks. The bottleneck approach posits that automation will displace jobs that are not affected by the bottlenecks that hinder work automation. According to this approach, jobs that are safe from automation are those that include tasks that require a) complex perception and manipulation actions, b) creative intelligence, or c) social intelligence.

In general, research on the impact of automation technology on work has been conducted based on a job-based approach (Filippi et al., 2023). The entire occupation is considered to be affected by technology through, for example, the estimation of the extent to which the occupation is highly routine (Autor & Dorn, 2013). This view has been criticized because jobs include multiple tasks that differ in terms of the skills and behaviors that workers are required to perform (Autor, 2013; Willcocks, 2020). Autor and Handel (2013) have shown that within occupations, the heterogeneity of tasks performed at different workplaces is considerable. Finally, a basic premise about automation is that technology fundamentally automates tasks rather than jobs (Bessen, 2016; Huang & Rust, 2018).

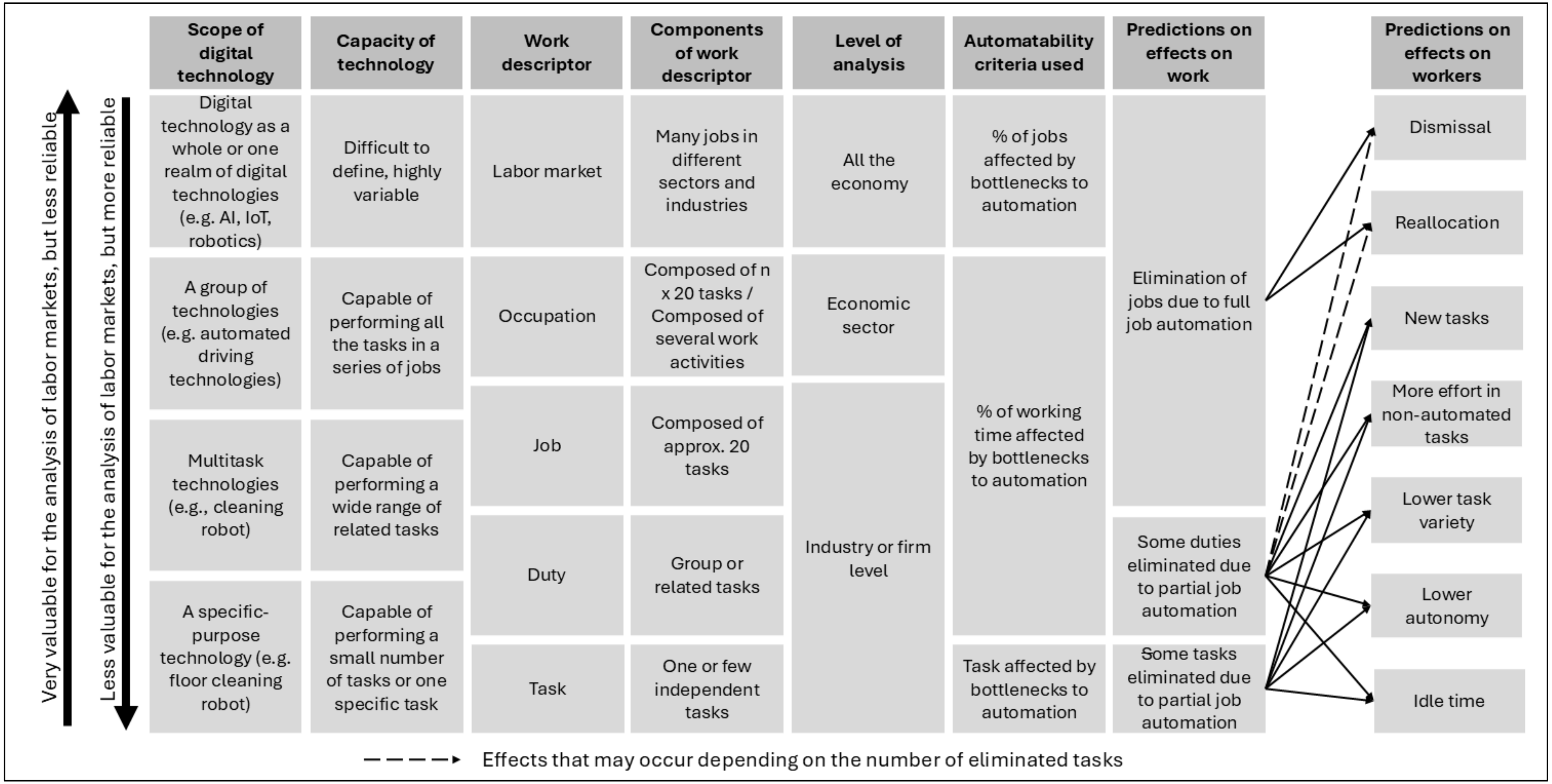
Therefore, a task-based approach that considers the multiple activities or tasks that jobs involve has been proposed. Studies based on this approach (Arntz, Gregory, & Zierahn, 2016; Chui, Manyika, & Miremadi, 2015; Manyika et al., 2017; Nedelkoska & Quintini, 2018; Georgieff & Milanez, 2021) provide figures of workers that could be displaced by technology as much lower than studies based on the job-centered approach. However, the previous studies done under the task-based approach really rely on general work activities and are based on sources such as the Programme for the International Assessment of Adult Competencies (PIACC), BIBB/IAB- BIBB/BAuA (the German employment surveys on qualifications and working conditions), and O*NET. Studies on work automation that consider tasks as such are scarce. One is Sampson (2021), who showed that the tasks that compose the job of business teachers have significant variance when analyzed from the perspective of the bottlenecks to automation, specifically, the bottlenecks of creative intelligence and social intelligence. Sampson (2021) proved that there were differences at the task level and that analysis at a more general level was misleading.

Finally, although workers spend differing amounts of time on each of the tasks or activities in their jobs, only Manyika et al. (2017) considered this issue in their analysis of work automation. Based on general work activities, these authors find that occupations in accommodation and food services spend most of their time on predictable physical tasks whereas occupations in agriculture spend most of their time on unpredictable physical tasks.

4 A framework for research on the automation of work

Based on the various ways of representing work analyzed in previous sections, we present a framework for addressing and understanding the research of work automation (Figure 2).

Figure 2. Framework for the Research of Job Automation



Source: Own elaboration

When analyzing the impact of technology on work, the first issue to consider is the level of the analysis of the study. As shown in Figure 2, technology can be analyzed at four levels: global and generic, groups of technologies, one multipurpose or multitask technology, and specific-purpose technology. For each, there will be several work descriptors associated that have different levels of specificity: the labor market as a whole when considering technologies globally; occupations or jobs when considering groups of technologies; jobs or duties when analyzing multipurpose technologies; and tasks when analyzing specific-purpose technologies.

The scope of technology chosen in the research will determine the level of work affected. Starting at the top of Figure 2, assessing the impact of general technologies implies that global work analyses such as changes in the labor market are conducted (e.g., whether technology will eliminate jobs). At this level, results will provide valuable information about labor market transformation. However, the reliability of these results will be low, since many jobs in different industries at a global level are being considered, probably without taking into consideration the tasks that are done in each job.

Analyzing the impact of a group of related technologies narrows the effect on the work descriptor. This level allows assessment of changes in occupations (e.g., whether technology will eliminate cleaning staff). To be as precise as possible, we recommend considering all the tasks done in each of the jobs in the various sectors (e.g., chambermaids, building cleaner). If occupations are analyzed on the basis of general work activities, results will be imprecise. The framework we propose does not include general or detailed work activities because these do not represent accurately what workers perform in their jobs. According to O*NET, in the case of Maids and Housekeeping Cleaners, a detailed work activity such as "clean facilities or sites" involves the task of cleaning rooms. The same activity, in the case of Landscaping and Groundskeeping Workers, involves the task of trimming or picking flowers and cleaning flower beds. The work activity is the same, but the tasks differ in terms of the behaviors they demand.

The following level is to consider technologies that perform various tasks. This type of technologies is usually aimed at automating whole jobs or duties. When analyzing jobs (e.g., whether the job of chambermaids will be eliminated), it is important to consider that jobs are composed of multiple tasks. The O*NET database provides approximately twenty core tasks for each occupation. If the work descriptor is a duty (e.g., whether the duty of cleaning bathrooms will be performed by technology), the object of the analysis would be a group of related tasks. The number of tasks that a duty encompasses depends on the tasks' content. No database of duties exists that can be used as a reference.

The last level is the most specific. Specific-purpose technologies will usually be able to perform one task or a small number of tasks. Therefore, the type of effect that can be predicted are also very specific (e.g., whether the "cleaning the floor" task will be performed by technology). This level of analysis can produce reliable results although they have a low relevance in terms of labor market consequences.

The automatability criteria used in Figure 2 can be used to assess the extent to which the work descriptor can be automated. Research has predominantly relied on two premises about what drives work automation: the routinization hypothesis (Autor, Levy & Murnane, 2003) and the bottleneck approach (Frey & Osborne, 2017). As previously explained, evaluating jobs without considering their tasks can lead to misleading results. For example, an O*NET item used in research to determine whether a job is routine (e.g., Acemoglu & Autor, 2011) is: How important to your current job is being very exact or highly accurate? The tasks grouped in a job can be very different in this regard, so it is necessary to analyze each task separately. On the other hand, some characteristics of routine work, such as repetitiveness (Fernández-Macías & Bisello, 2022), are difficult to determine when an analysis at the task level is conducted. If the item: How much time in your current job do you spend making repetitive motions? is adapted for a task-level analysis (i.e., asking for a task instead of the job), the result would be that most of the tasks would probably be considered repetitive. The reason is that tasks are specific worker actions, so any task involves repeated motions or intellectual processes.

Assessing whether tasks present bottlenecks that prevent work automation does not have this inconvenience. Therefore, for all the work descriptors, a straightforward option to assess their automation probability is to consider to what extent tasks require a) complex perception and manipulation actions, b) creative intelligence, and c) social intelligence. The impacts of each of these three bottlenecks have been estimated using a series of items from O*NET (Frey & Osborne, 2017). The first, complex perception and manipulation actions, is measured using three items of the O*NET variables: finger dexterity, manual dexterity, and cramped workspace and awkward positions. The second, creative intelligence, is based on the O*NET items of originality and fine arts. The third, social intelligence, is measured through the O*NET items social perceptiveness, negotiation, and persuasion.

Depending on the work descriptor that is analyzed, different effects on work will be predicted. When the analysis is carried out at the level of a job, occupation, or labor market, job automation is often predicted. When the analysis is done at the duty or task level instead, partial automation is usually predicted. Partial automation means that only a part of a job is automated, with various possible consequences.

The rightmost part of Figure 2 presents the predictions on consequences for workers. Job automation implies the elimination of jobs. Workers may be fired or, if there are job vacancies, they may be reassigned to other jobs. These vacancies can be new jobs required by the technology or vacancies in other jobs in the company. The impact of duty automation on workers varies depending on the time that the duties involve. If technology automates duties that require significant work time, some workers could be fired or relocated to vacant jobs.

These are the same as for the case of job automation, with the additional possibility of new jobs that result from combining non-automated tasks with other jobs' tasks (Ivanov, 2020). Another possibility is that companies integrate new tasks into the job. If this is not the case, workers would experience lower task variety (Peeters & Plomp, 2022) with an increase in the frequency of the non-automated tasks. Alternatively, there could be an increase in idle time. Another possible consequence is that workers' behavior becomes dependent on the technology introduced to the job, which would reduce their autonomy (Cirillo et al., 2021). Job autonomy and task variety are job characteristics important for worker attitudes and behavior (Grobelna, 2019).

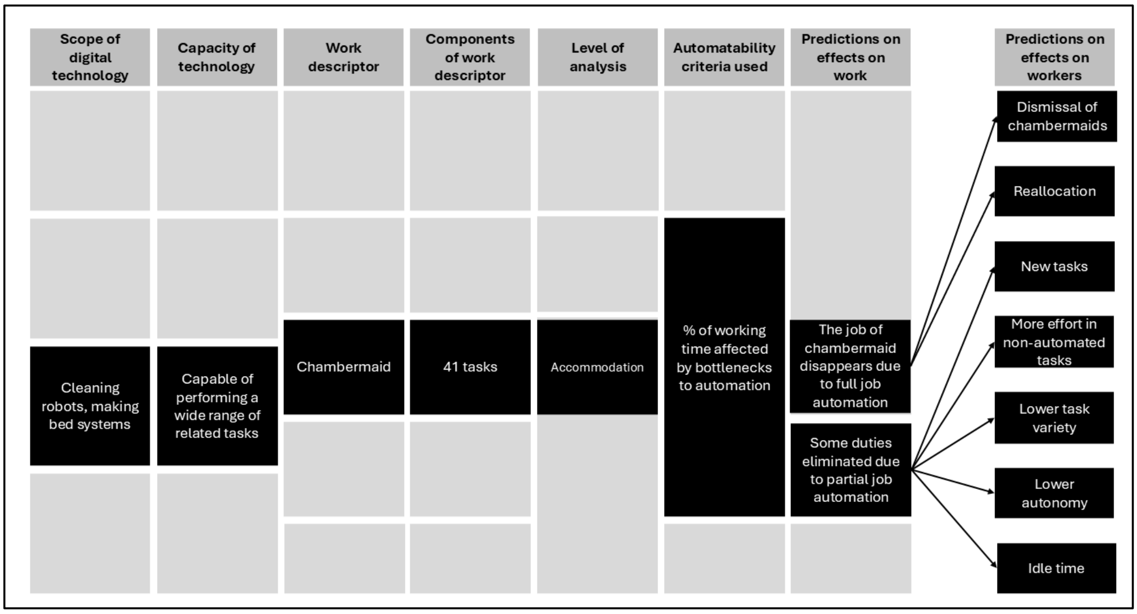
Finally, the partial automation of one or several independent tasks will not, in general, affect the staff number, unless it is an extreme case of a task that takes up a large amount of workers' time and many workers perform the same job. The impact on workers would be the same as that of duties automation when employees are not displaced.

4.1 Application of the framework

Although automation technologies are expanding rapidly in the tourism industry, research on work automation in this field has mostly been limited to descriptions of existing applications and potential implementations and consequences (Tussyadiah, 2020). The tourism industry includes several economic activities (e.g. accommodation, restaurants, travel agencies, passenger transport) with many different jobs. The framework suggests that it is very difficult to obtain reliable results without taking into account the tasks of these jobs. In the case of accommodation alone, the Spanish National Labor Agreement for Hospitality Companies includes 42 different jobs. Therefore, the possibility of carrying out a global analysis in which the impact of technologies on the workforce is carried out would produce imprecise results. Thus, we decided to focus on the accommodation activity and to assess the impact of specific technologies (e.g., cleaning robot) on one of the most frequent jobs in the accommodation activity: chambermaids. Chambermaids are among the most numerous workers in many hotels (Cañada, 2018).

In this analysis, the results will be less relevant for labor market analysis, but these will be more reliable. There are some estimates of the probability of automation of the chambermaid job. Frey and Osborne (2017) estimated the probability of automation to be .69 over 1. For cleaners and helpers, Pouliakas (2018) predicted an average probability of automation of .54, with 13% of workers having a probability of automation over 70%. Ivanov (2019) stated that the number of chambermaids can be significantly reduced by automation technologies. We present in Figure 3 marked in black the level at which we decided to carry out our analysis: multitask technologies capable of performing a wide range of related tasks, taking into account all the tasks that constitute a job at the industry level and using the bottleneck approach. Therefore, the type of results that this analysis will provide will be the total automation of this particular job or a partial automation based on the elimination of some duties or tasks. The effects on workers could be dismissals, reallocations, the introduction of new tasks for the job, the need to dedicate more time and effort to non-automated tasks, a reduction in task variety and a lower autonomy of the chambermaids.

Figure 3. Level of analysis in this research



Source: Own elaboration

We based our study on a sample of sixteen four- and five-star sun-and-beach hotels with at least 200 rooms located in the Canary Islands. In 2023, in these hotels, around 43% of the employees were in three jobs: chambermaids, cooks, and waiters. All the interviews and data gathering took place in 2023.

Our objective was to analyze the extent to which the chambermaid job could be automated. The initial step was to identify an appropriate representation of the tasks that chambermaids carry out. An initial list of tasks was obtained from three sources: the Spanish National Labor Agreement for Hospitality Companies, the O*NET database, and the European Skills, Competences, Qualifications and Occupations (ESCO) Classification of Skills, Competences and Occupations. This initial list was composed of 20 tasks.

Some of the tasks in this initial list needed a greater level of specification. For example, the task “Cleaning the rooms” involves various behaviors that needed to be explicitly addressed, as they differed significantly from one another. Based on interviews with six housekeeping supervisors, we disaggregated those 20 tasks into a total of 41 tasks. Then, 33 structured interviews with chambermaids were conducted to assess the time that workers spent on tasks in the final list. A typical eight-hour (480 minutes) workday was considered to determine the amount of time that these tasks involved. Interviewees were unable to calculate the number of hours spent on each of the 41 tasks because they performed a high number of different tasks during each workday. Therefore, working time was estimated at the duty level. Table 3 presents the tasks, duties, and the percentage of working time of the chambermaid job.

Table 2. Tasks, duties, and working time of the Chambermaid job

Tasks	Duty	Time
• Placing or removing decorations or furnishings • Folding towels in specific shapes (e.g., swan) • Cleaning furniture and fixtures • Cleaning floors and carpets • Cleaning windows, screens, and mirrors • Moving furniture in rooms or between rooms • Notifying the need for repairs • Dusting furniture • Emptying trash • Emptying and cleaning ashtrays • Replenishing amenities	Cleaning and preparing the rest of the room	26.12%
• Placing and/or replacing towels • Folding paper (hand and toilet paper) into specific shapes • Cleaning the floor • Cleaning the bathtub or shower, including the enclosure • Cleaning mirrors • Cleaning the toilet fixtures in the bathroom • Cleaning and preparing the sink area in the bathroom • Replenishing amenities in the bathrooms	Cleaning and preparing the bathrooms of the rooms	25.09%
• Flipping mattresses • Making beds • Removing the dirty bedding	Making the beds	21.09%
• Cleaning furniture and fixtures • Cleaning floors and carpets • Cleaning windows, screens, and mirrors • Moving furniture • Notifying the need for repairs • Dusting furniture • Emptying trash • Emptying and cleaning ashtrays • Placing or removing decorations or furnishings	Cleaning and preparing the rest of the common areas of the hotel (stairs, furniture, corridors, etc.)	8.70%
• Cleaning and carrying out maintenance of work tools and equipment • Replenishing cleaning carts with necessary material • Taking dirty laundry to the laundry room • Receiving training and attending employee briefings	Other tasks	8.50%
• Folding paper (hand and toilet paper) into specific shapes • Cleaning the floor • Cleaning mirrors • Cleaning toilets • Replenishing hygiene products	Cleaning and preparing bathrooms in the common areas of the hotel	6.65%
• Waiting and travel time between rooms	Waiting and travel time between rooms	3.85%

NOTE: Sorted based on the time dedicated to each duty.

Source: Own elaboration

The three duties that demanded the most time (cleaning and preparing the bathrooms of the rooms; making the beds; and cleaning and preparing the rest of the room) accounted for a total of 72.30% of the workday. We selected five tasks with different characteristics included in these duties (Table 3) to assess to what extent they presented any of the bottlenecks to automation. None of them require creative intelligence or social intelligence, so we focused on the bottleneck of complex perception and manipulation actions. We asked thirteen tourism university professors to assess the extent to which these tasks could be affected by this bottleneck. The assessment was conducted using a five-point Likert scale, based on the O*NET variables used by Frey and Osborne (2017), which includes three items that measure the aforementioned bottleneck. Table 3 presents the results of the answers we received. We consider an item of the bottleneck to be relevant when its mean is above 4.

Table 3. Chambermaid tasks components to the bottleneck "Complex perception and manipulation actions"

		Bottleneck "complex perception and manipulation actions"		
		Finger dexterity	Manual dexterity	Cramped workspace, awkward positions
Tasks	Placing and/or replacing towels	3.33 (0.94)	**4.25 (0.72)**	2.50 (1.38)
	Cleaning the bathtub or shower, including the enclosure	3.46 (1.08)	**4.46 (0.63)**	**4.54 (0.75)**
	Making beds	2.92 (0.62)	**4.38 (0.74)**	**4.38 (0.62)**
	Cleaning floors and carpets	2.69 (0.91)	3.62 (0.92)	3.85 (0.77)
	Emptying trash	3.23 (1.31)	3.92 (0.92)	3.15 (1.23)

NOTE: Numbers in cells represent the mean with the standard deviation in parenthesis

Source: Own elaboration

The task "Placing and/or replacing towels" presented the bottleneck to automation of manual dexterity. The tasks "Cleaning the bathtub or shower, including the enclosure" and "Making beds" presented two bottlenecks: manual dexterity and cramped workspace, awkward positions. Finally, the tasks "Cleaning floors and carpets" and "Emptying trash" appeared to be less susceptible to the bottlenecks of automation.

An Internet search of automation technologies related to cleaning in hotels was conducted. The keywords used were: automation technologies, robotics, housekeeping, and hotels. Three main types of technologies were found: autonomous cleaning robots (with various capabilities), robotic beds, and robotic cleaning trolleys. Regarding the tasks characterized by having bottlenecks to automation (the first three in Table 3), no technology was found that could perform any of these tasks. The same was true for the task "Emptying trash," which presented lower bottlenecks to automation. However, vacuum robots were identified as capable of doing the task "Cleaning floors and carpets".

The technologies found, whether individually or jointly, were not able to execute a large proportion of the tasks outlined in Table 2. Thus, currently, the chambermaid job seems to be far from being eliminated by technology. However, partial automation seems to be possible. We identified specialized technologies that can automate a significant portion of the tasks associated with two duties. The Jingwu 3D cleaning robot[1] can perform three of the eight tasks associated with the duties of cleaning and preparing the bathrooms of the rooms: cleaning the floor, cleaning mirrors, and cleaning the toilet fixtures in the bathroom. The Somatic Robot[2] can perform three of the five tasks associated with the duty of cleaning and preparing common area bathrooms: cleaning the floor, cleaning mirrors, and cleaning toilets. Therefore, this type of technology could partially automate the chambermaid job.

The duty "Cleaning and preparing the bathrooms of the rooms" accounts for 25.09% of the working time of chambermaids. However, the Jingwu 3D cleaning robot is unable to execute most of the related tasks. If this technology is implemented, it will not displace workers. A potential outcome is that one chambermaid will be able to clean more rooms in the same amount of time, as some of the tasks they currently do would be done by robots. Another possible outcome is that chambermaids would experience a reduction in autonomy, as they would need to adapt their behavior to the robot's activity.

Some large hotels had two types of chambermaids, one that specialized in cleaning the rooms and another that specialized in cleaning the common areas. While this was not the most common scenario, when it is the case, the duty "Cleaning and preparing common area bathrooms" represents approximately 27% of the working time of chambermaids in charge of cleaning common areas, instead of the 6.65% mentioned in Table 2. If hotels lack alternative opportunities for these employees, the automation of this duty using a robot such as Somatic that can execute most of the tasks required to clean the bathrooms in common areas could result in the dismissal of some employees. Furthermore, the range of tasks of the chambermaid in charge of common areas would be reduced, which could negatively affect workers due to a low task variety.

5 Discussion

The analysis of the potential automation of work is complex. Generic analysis can easily lead to incorrect conclusions that overestimate the possibility of job substitution. Most of the research on work automation and its consequences in terms of employment is based on the job approach, which ignores the specific content of jobs. The high number of tasks inherent in many jobs presents bottlenecks to automation. In the case of chambermaids, previous estimates of the probability of automation seem to have neglected this issue. Therefore, concerns about the displacement of workers may be unfounded or, at the very least, may be an issue with nuances.

In general, to effectively substitute jobs with technology, it would be necessary to have general-purpose automation technologies capable of conducting a wide range of tasks.

[1] https://en.jwai-tech.com/product/clean/
[2] https://getsomatic.com/

Developing this type of technology is challenging due to economic and technical constraints (Wirtz et al., 2018). Thus, the more jobs and tasks involved in an industry, the lower the risk of worker displacement.

For example, and for the specific case analyzed in this manuscript, the accommodation industry, we analyzed the following technologies that are often cited as examples of work automation in this field: robot concierges Mario, Connie, and Pepper; delivery robots Botlr and Dash; and the bellboy robot Yobot (Ali et al., 2023; Shin & Jeong, 2020; Tussyadiah, 2020). These technologies can perform just a few tasks and enable companies to deliver specific services that usually are low-frequency tasks in one or two hotel jobs. Thus, according to the automation technology cited in the literature about work automation in tourism, we can state that, currently, there are no available technologies capable of executing most of the tasks that hotels need to provide their services.

In contrast, although still within the service sector, fast-food restaurants present a completely different case. Compared to hotels, this industry provides a lower variety of services, based on a low number of jobs whose content is highly standardized, simple, and repetitive (Allan et al., 2006). Tuomi and Ascenção (2023) found that frontline food service jobs mostly require mechanical intelligence. This type of intelligence is applied to tasks that are simple, standardized, repetitive, rule-based, and routine. These characteristics facilitate job automation (Huang & Rust, 2018). Thus, many tasks in the fast-food activity do not present the bottlenecks to automation of creative intelligence and social intelligence. These jobs that mostly rely on a short range of physical tasks have an equivalence to chef robots that cook hamburgers and more complex meals (Fusté-Forné, 2021). Berezina et al. (2019) identified numerous options for automation in fast-food operations that range from specific activities to large activities such as menu production and food delivery. Consequently, because the fast-food industry relies on a) a small number of different jobs; b) jobs with a low variety of tasks; and c) jobs with simple and repetitive tasks, automation technologies have the potential to reduce the number of employees required.

From this, we can conclude that, in general, economic activities based on multiple jobs that perform several types of activities are more immune to automation than activities based on a lower number of jobs that perform a smaller set of tasks. In the absence of powerful multipurpose automation technologies for activities such as accommodation, the most realistic scenario is partial automation. To predict the impact of the latter on workers, two factors should be considered: the number of automated tasks (i.e., duties) and the time that these tasks consume of the total work time. However, the risk of unemployment due to technologies exists because companies can redesign processes and jobs to take advantage of technological progress. Firms can combine the technology that automates duties with operations redesign, which can result in some workers being displaced and dismissed.

5.1 Conclusion

Before trying to predict the effect of technology on work, it is important to consider the level of analysis, as shown in the framework presented in Figure 2. While generic levels can generate more relevant information in labor market terms, the results will probably be imprecise and unreliable. Instead, more detailed levels (i.e., tasks, duties) allow for more precise and reliable results at the cost of being less relevant for the future of the labor market. We believe and have shown in this manuscript with a case that an intermediate analysis can be a good compromise. This is, analyzing groups of related technologies or multitask technologies, which can automate specific jobs or occupations. We suggest considering the tasks in each of the jobs and occupations and using the bottleneck approach. This type of analysis leads to relevant conclusions with a good level of reliability while allowing for methodologies that can be feasibly addressed.

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