

# **Searching for a Job in the Digital Age: Using Metered Data to Explore Digital Divides in Job Search Patterns in Spain**

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## **Disclosures and declarations**

### Author contributions

Maiki Estevez Cano conducted the literature review and wrote the initial draft of the paper. Melanie Revilla contributed to the conceptualization and methodology of the study, to the writing (review and editing), project administration and funding acquisition. Carlos Ochoa performed data preparation and analysis in R.

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**Abstract:** Employment is a crucial determinant of individual and societal well-being, yet access to job opportunities remains unequally distributed. In today's digital labour market, job search has increasingly moved online, raising concerns about digital inequalities in employment access. This study investigates how online job search behaviour varies across sociodemographic groups in Spain—a country marked by persistently high unemployment rates. To move beyond the limitations of self-reported measures, we leverage metered data—a form of digital trace data that captures the URLs of the webpages visited on participants' tracked devices. Our analyses examine differences in participants' actual online job search patterns by gender, age, education, income, migrant background and job status. Using data from the Netquest metered panel in Spain (n = 600) collected between March and November 2023 (nine months), the results highlight the existence of limited digital divides. By leveraging an innovative data source and focusing on a country with a high share of active job seekers, this study contributes to a better understanding of online job search dynamics and informs the design of employment and digital inclusion policies.

**Keywords:** Digital divide, digital traces, job search patterns, metered data, online employment seeking, socioeconomic inequality.

**Data availability and online resources:**

The anonymized dataset, scripts used for the analyses, and Supplementary Online Materials (SOMs) are available at:

[https://osf.io/qrzmg/overview?view\\_only=03dbe8ac5ccb419ea7a9d99bcc07e192](https://osf.io/qrzmg/overview?view_only=03dbe8ac5ccb419ea7a9d99bcc07e192).

## 1. Introduction

Work constitutes a fundamental aspect of human life, exerting a profound influence on psychological, economic, and social well-being (Damaske, 2020). Employment not only provides individuals with the financial means to maintain a decent and autonomous standard of living, but also contributes to self-esteem, self-worth, self-confidence, and a stable self-image. In contrast, unemployment can significantly deteriorate these dimensions of personal and societal well-being. As such, employment outcomes have become a central concern for public administrations due to their critical role in shaping macroeconomic indicators such as consumption, investment, and social stability (Cortés et al., 2023). Consequently, enabling individuals to access and retain employment has become an essential objective not only for personal fulfilment but also for public policy and social cohesion.

Given that most individuals engage in job-seeking activities at some point in their lives, understanding the dynamics of job search is both practically and theoretically essential (Chapple, 2001). The mechanisms and conditions under which people search for jobs merit close examination, especially in light of recent transformations in how job searches are conducted.

Over the past few decades, the process of job search has been significantly transformed by digital technologies. Initially a tool to facilitate access to job information, the internet has evolved into the primary means through which job searches are conducted. Online applications have become standard practice, and today the vast majority of job-seekers rely on internet-based platforms (Karaoglu, Hargittai & Nguyen, 2022).

This study focuses on Spain, where already 98% of unemployed job seekers searched online in 2016 (Adecco, 2016). A figure that has at least remained the same since then, particularly as online-only application systems have become more prevalent. Spain presents a compelling case for analysing job search behaviour due to its persistently high unemployment rates, among the highest in the European Union (ILO, 2025) resulting in a large pool of active job-seekers.

In this context, job search is of paramount importance in Spain for both individuals and institutions. The formulation of job-related policies and the reduction of unemployment have been consistent priorities for successive Spanish governments, particularly following the 2008 financial crisis. Job loss and employment instability have deleterious effects on individual well-being and quality of life and can even precipitate severe outcomes, such as substance abuse and homelessness (Damaske, 2020).

While enhancing job search mechanisms cannot, on its own, resolve the structural conditions underpinning Spain's high unemployment, studying the nuances of job-seeking behaviour—and its variation across sociodemographic groups—can contribute to more effective policy design and to improvements in public well-being, by reducing the time or effort required to secure new employment and improving the match between job seekers and suitable positions or employers.

This study also introduces a key methodological innovation: rather than relying on conventional data sources such as surveys, it uses metered data to capture actual online behaviours. Metered data represent a kind of digital traces collected through tracking software (called a “meter”) installed by participants on their browsing devices that registers

at least the URLs of the websites visited (Revilla et al., 2021). Depending on the capabilities of the specific meter used, the data may include not only visited URLs but also search queries, app usage, content of web and app pages, and behavioural metrics such as time spent on specific activities.

While metered offer important advantages for both participants (e.g., reduced effort) and researchers (e.g., elimination of recall bias). This is particularly valuable for studying job search activity, which often consists of numerous short, repetitive interactions—making it especially prone to inaccurate recall (Tourangeau, 2000). Moreover, social desirability bias may lead individuals to overreport the effort they put into job searching, due to perceived social pressure. Metered data might help reduce these issues, capturing real-time, objective information about online behaviours.

Author and Author (2025) began exploring the use of metered data to study online job search patterns, drawing on data collected between March and November 2023 from the Netquest metered panel in Spain ( $n = 600$ ). However, their focus is primarily methodological. This study builds on the work of Author and Author (2025) and uses the same dataset, but takes it a step further by focusing on substantive differences in online job search patterns and considering a broader range of variables that may contribute to the digital divide.

Our main goal is to explore how online job search behaviours vary by gender, age, education, income, migrant background and job status, thereby contributing to a deeper understanding of potential inequalities in job search patterns.

## **2. Background**

### **2.1. Duration of job search as the classic measure**

The study of job search has long been a central topic in labour economics. Foundational contributions (Stigler, 1962; McCall, 1970) conceptualized the search process as an optimization problem where unemployed individuals face random job offers and must decide the optimal point to accept an offer based on their reservation wage—the minimum wage at which they are indifferent between accepting a job and continuing to search.

*Unemployment duration* plays a central role in these models, serving as the primary empirical indicator of job search outcomes. Longer durations typically signal difficulties in job matching due to weak labour demand, high reservation wages, insufficient search effort, or skill mismatches (de Koning & Mosley, 2001). This reliance on unemployment duration persisted for decades, forming the backbone of empirical job search literature (Devine & Kiefer, 1991; van den Berg, 2001). However, not all job seekers are unemployed. In fact, at least 33% of workers in Spain were actively seeking another job (Obregón, 2025; Servimedia, 2025).

Therefore, some literature has extended the classical measure of unemployment duration to the broader concept of *job search duration* (Faberman & Kudlyak, 2019). This measure includes both individuals who are currently unemployed and those who are employed but seeking new opportunities—whether to improve working conditions, earn higher salaries, or change occupations.

Still, with digital technologies transforming how individuals engage with the labour market, the limitations of duration-based approaches have become increasingly apparent. Even the broader measure of job search duration primarily reflects outcomes rather than the behaviours and decisions that lead to them.

## 2.2. Newer contributions

In response, newer contributions have shifted attention toward the process of job search itself. Recent work in the job search literature has highlighted novel aspects of the phenomenon, beyond the duration-based measures.

First, various studies investigate *job search effort*, defined as the time and resources individuals invest in job-seeking activities (Wanberg, Zhu, & Van Hooft, 2010). Effort is shaped by several factors, including perceptions of progress, emotional responses, and self-regulation strategies, many of which are influenced by social dimensions. For example, perceived progress tends to enhance effort, whereas its absence can lead to disengagement. Yet perception of progress itself might be influenced by factors like gender, as women are more likely to undervalue their own achievements than men (Kling, Hyde, Showers, & Buswell, 1999). Furthermore, social feedback and support networks also shape job search effort (Wanberg, Zhu, & Van Hooft, 2010). Additionally, Faberman and Kudlyak (2019) showed that aggregate search effort is responsive to macroeconomic conditions, indicating that labour supply is more elastic than previously assumed.

Second, several studies link these efforts to the duration of the job search process, introducing *search intensity* as a key variable. Search intensity refers to the level of effort job seekers devote to the search, considered in relation to the length of the process. Krueger and Mueller (2010, 2011), using time-use data, found that unemployed US job seekers spent approximately 40 minutes per day on average searching for jobs. Crucially, they demonstrated that search intensity significantly declines over unemployment duration, falling by about 30 minutes over 12 weeks. The authors discuss several possible explanations including discouragement, exhaustion of suitable job opportunities, or increasing search efficiency, but emphasize that distinguishing among these mechanisms remains an open question.

Building on the aforementioned, Faberman and Kudlyak (2019) used online job application data to examine both the variation in search duration and intensity. They found significant diversity in job search duration, with some job seekers searching for just one week while others continued for six or more months. Moreover, they exemplified that even among individuals with similar unemployment durations, there is substantial variations in the number of applications sent per week and the pattern of search effort over time. This finding challenged classical assumptions and highlighted the diversity in job-seeking behaviour, even among individuals experiencing similar unemployment durations.

Wanberg et al. (2010) also introduced the metric of *average time per job offer*, referring to the time a job seeker spends viewing a single job posting. Longer viewing times may indicate more effort, and more selective consideration, while shorter ones could reflect browsing fatigue or superficial engagement. This measure offers a new lens through which to assess search quality and job-seeking strategies.

Moreover, some authors examine effort in relation to outcomes. Wanberg et al., (2010) consider successful employment outcomes, such as job finding and job quality, while Author and Author (2025) investigate *job search effectiveness*, which refers to the extent to which search activities result in job applications.

Effectiveness is influenced by both external factors (e.g., platform usability, labour market match quality) and internal factors (e.g., motivation, perceived fit), which are themselves shaped by psychological and sociodemographic characteristics (Dolado, Jansen & Jimeno, 2009; Van Hooft et al., 2021). As such, search effectiveness provides a behaviourally grounded measure of job-seeking success that complements and enhances traditional metrics.

Finally, Author and Author (2025) propose broadening the analysis of the job search process to include additional dimensions, such as the specific platforms visited, the type of device employed to search for a job (e.g., PC or smartphone), the search terms used immediately before accessing a job platform, or the temporal patterns of job search activity (e.g., day of the week or time of day). These aspects allow for a more nuanced understanding of the phenomenon. Such an approach is enabled by recent advances in passively collected data, which provide continuously generated information for studying these processes.

Overall, these indicators offer valuable and more granular insights into what job seekers actually do—how much time, how often, and with what results they search for jobs— that traditional duration-based metrics cannot capture.

### **2.3. Social differences in job search**

While early research conceptualized job search as a uniform process governed by rational optimization, more recent studies reveal heterogeneity in how individuals search for work. Not all job seekers exhibit the same levels of search effort or intensity—even when experiencing similar job search durations. These variations are often shaped by socio-demographic factors (Doposo-Fernández, Kucel & Raya, 2025).

Incorporating these factors into job search research is essential, especially in the context of the digital divide. As job search increasingly shifts online, disparities in digital access—which are still salient even if narrowing (Marz & Abendroth, 2025)—, platform familiarity, and psychological resources can exacerbate existing labour market inequalities.

This subsection examines how key social variables influence job search behaviour, emphasizing differences not only in the amount of search effort but also in the manner and outcomes of that search.

First, gender differences in job search behaviour remain the subject of ongoing debate. Some studies find minimal gender disparities (Krueger & Mueller, 2011; Caliendo et al., 2015), whereas others report significant differences in effort or outcomes (Kuhn & Shen, 2013; Belot et al., 2019). These divergent findings may stem from variations in measurement methods, the inclusion of variables that mediate the relationship or the specific dependent variable considered (duration, effort, etc.). Psychological mechanisms, like risk aversion and optimism, are central to understanding these gender differences. Research suggests that men tend to be more risk-tolerant (Croson & Gneezy, 2009; Eckel & Grossman, 2008), potentially leading to broader application patterns. Optimism may also vary by gender, influencing persistence and expectations (Kling et al., 1999). Women’s greater risk aversion (Charness

& Gneezy, 2012) might prompt more thorough and careful search efforts, possibly offsetting the effect of applying to fewer positions. The numerous factors affecting gender differences in behaviour render the theoretical explanation of job-search disparities and interpretation of empirical results complex. Moreover, some evidence suggests that gender differences in employer contact rates may partly reflect differences in personality traits, especially risk aversion, that shape job search behaviour —such as search radius— rather than direct discrimination (Eriksson & Lagerström, 2012).

Findings are more consistent with respect to age. Age shapes job search behaviour through life-cycle effects, cohort experiences, and technological adaptation. Older job seekers generally search less intensively and face longer unemployment spells (Krueger & Mueller, 2011; Wanberg et al., 2020), often due to higher reservation wages or adjusted job expectations. Indeed, evidence shows that higher reservation wages are associated with longer unemployment durations among older workers (Axelrad, Luski & Malul, 2017). The digital divide is especially pronounced among older workers (typically defined as those over 50), who are less likely to use online job platforms or digital tools effectively (DiMaggio et al., 2004). This divide arises not only from access issues but also from differences in motivation, digital skills, and prior exposure to technologies.

Socioeconomic status (SES) also influences job search behaviour and outcomes. Lower-SES individuals face more structural barriers and possess fewer social connections, making them more reliant on online platforms due to limited social capital, especially the so-called “job boards” (Nikolaou, 2014). Several authors (Granovetter, 1973; Holzer, 1988) argue that social capital is a critical factor in securing employment, with higher-SES individuals being more likely to find jobs through interpersonal networks rather than formal credentials. Consequently, higher-SES job seekers typically experience shorter unemployment durations (Bonoli & Turtschi 2015), whereas lower-SES individuals often exhibit higher search effort out of necessity (Kanfer, Wanberg & Kantrowitz, 2001). However, this increased effort does not always translate into better outcomes, particularly when digital literacy or confidence is lacking (van Deursen & van Dijk, 2014) or in highly competitive labour markets with elevated unemployment rates (Krueger & Mueller, 2011). These dynamics may result in better search outcomes for higher-SES individuals, reflecting the advantages of social capital and networking in job acquisition. Such inequalities at the entry stage may resemble what some authors describe as “sticky floors,” where initial disadvantages shape long-term trajectories (Baker, 2003). They have traditionally been linked to gender, but recent studies have shown that its impact is especially salient for economic disadvantages.

Migrant background is another critical factor in digital inequality, intersecting with gender, age and SES. In Spain, migrants constitute approximately 19% of the population and tend to be younger and socioeconomically disadvantaged compared to natives (Instituto Nacional de Estadística [INE]; González-Enríquez, 2024). Migrants encounter structural labour market barriers such as non-recognition of credentials, language difficulties, and discrimination (Dustmann et al., 2009; Lancee, 2016). Digitally, migrants are more prone to experience access and skill deficits, often relying on smartphones and public Wi-Fi instead of home computers (van Deursen & van Dijk, 2014). This limits their ability to use formal online job platforms effectively and may lead to an underestimation of digital inequality if migrant background is not accounted for in analyses. Moreover, migrants may be less familiar with

Spanish digital platforms and rely more on ethnic networks or informal job channels, further reducing engagement with online search tools.

Overall, previous research suggests that sociodemographic variables have an impact on job search patterns. However, empirical evidence remains limited, particularly regarding aspects of the job search beyond its duration and for potential explanatory variables such as migrant background (Dopeso-Fernández, Kucel & Raya, 2025).

## **2.4. Job status**

Besides the sociodemographic profile of the job-seekers, substantial evidence from labour economics and behavioural studies (Van Hoof et al., 2004; Faberman et al., 2022) shows that job search behaviour varies between unemployed and employed individuals. Differences arise from variations in available time, search incentives, urgency, and constraints related to current employment (Faberman, Mueller, Şahin, & Topa, 2022).

Due to the urgency of securing income and the absence of work-related obligations, unemployed job seekers typically devote more hours to job search activities. For instance, (Faberman et al., 2022) found that unemployed individuals spend approximately 4.8 hours more per week searching compared to their employed counterparts.

In contrast, employed job seekers tend to search more selectively and strategically. Their behaviour is characterized by lower intensity but greater targeting, often motivated by career advancement, improved working conditions, or better wages (Burgess, 1994; Kuhn & Skuterud, 2004). Because they must balance job search with current responsibilities, employed individuals often conduct searches during after-hours or use discreet, mobile-enabled channels (Faberman et al., 2022).

Empirical research using online job search data confirms that employed seekers browse more but submit fewer applications compared to unemployed ones (Hall & Krueger, 2012; Kroft et al., 2013).

Additionally, perceived costs and risks associated with job transitions differ by job status. Employed individuals face opportunity costs and job security concerns, making them more cautious about applying, especially for uncertain positions. Conversely, unemployed individuals are more willing to accept lower match quality or wage offers, consistent with declining reservation wages over time (Kaas & Kircher, 2015; Mortensen, 1986).

Together, these results suggest that online job search behaviour is not uniform but is significantly conditioned by employment status. Understanding these differences is crucial for interpreting online job search patterns, designing effective platforms, and evaluating policies aimed at improving job search efficiency.

## **3. Research question, contribution and hypotheses**

### **3.1. Research question and contribution**

While online job search is now the dominant mode of employment seeking in Spain, prior research highlights persistent inequalities in digital skills, access, and strategies (van Deursen

& van Dijk, 2014; Wanberg et al., 2020). These divides may reinforce broader labour market inequalities if disadvantaged groups search less effectively or rely on more limited online strategies. Against this background, we propose the following research question:

**RQ.** *To what extent do gender, age, education, income, migrant background, and employment status influence online job search behaviours in Spain?*

By addressing this research question, this study contributes to the literature in several ways. First, it examines a comprehensive set of job search dimensions, including some more habitual ones, namely duration, effort, intensity, and effectiveness, average time spent per job offer and per application, but also some rarely studied: the platforms visited, the type of device used for both searching and applying to jobs, the search terms employed immediately before accessing a job platform, the channel used (web or app), and the temporal patterns of activity (day of the week and time of day). This breadth of measures allows for a richer and more nuanced understanding of how individuals engage in job search.

Second, while previous research focused mainly on gender, age, and education, this study extends the analysis to income and migrant background—two dimensions that remain underexplored despite their relevance to digital inequality. In addition, it differentiates by employment status, capturing the distinct constraints and strategies associated with each group.

Third, the study leverages metered data to observe actual online job search behaviours. Unlike surveys, which are vulnerable to recall error and satisficing, the metered data used is not affected by memory limitations or lack of effort. Although these data do suffer from other errors (see Section 6.2), they provide highly detailed and continuous information over a nine-month period, offering a more objective, granular, and temporally rich perspective on job search activity.

### **3.2. Hypotheses**

Overall, we expect online job search behaviours in Spain to differ across sociodemographic groups, reflecting digital divides in access to employment opportunities.

More precisely, we propose the following hypotheses:

*H1a:* Men show higher effectiveness than women, consistent with evidence of greater male risk tolerance (Croson & Gneezy, 2009).

*H1b:* Women spend more average time per job offer or application than men and exhibit higher search effort and intensity, reflecting a more careful and selective evaluation of opportunities (Kling et al., 1999; Charness & Gneezy, 2012).

*H1c:* Search duration is similar for men and women, as men may submit more applications, but these tend to be of lower quality and fit compared to those of women.

*H1d:* Men rely more on platforms that can be classified as Social Networking Websites (SNWs), consistent with findings showing that men tend to use LinkedIn more extensively than women (Nikolaou, 2014).

*H2a:* Job seekers aged 30 to 50 have shorter search durations than both younger and older candidates, because younger job seekers usually have limited experience and weaker professional networks, while older job seekers encounter age-related discrimination, which can prolong their job search.

*H2b:* Job seekers over 50 rely less on apps and more on SNW platforms, consistent with findings showing that older job seekers tend to use LinkedIn more than younger individuals (Nikolaou, 2014).

*H3a:* Lower-educated job seekers show higher search effort but lower effectiveness and search duration, reflecting necessity-driven but less efficient strategies (Kalleberg, 2011).

*H3b:* Higher-educated job seekers rely more on SNW platforms such as LinkedIn (Nikolaou, 2014), and use more PCs than lowed-educated ones, due to their higher digital skills.

*H4a:* Lower-income job seekers display higher search effort and intensity and lower job search duration, reflecting necessity-driven strategies.

*H4b:* Higher-income job seekers rely more on SNW platforms such as LinkedIn and use more PCs, consistent with their stronger social capital (Granovetter, 1973) and digital access (Marz & Abendroth, 2025).

*H5a:* Migrants job seekers show lower effectiveness and average time per offer and per application than non-migrants, due to necessity-driven strategies (Dustmann et al., 2009).

*H5b:* Migrants job seekers rely more on job boards, on mobile devices, and on apps than non-migrants.

*H6a:* Unemployed job seekers show higher effort and intensity and lower search duration than employed individuals, driven by greater urgency (Krueger & Mueller, 2011).

*H6b:* Employed individuals tend to search for jobs more frequently in the evenings, after finishing work, and rely more on mobile devices, which provide a more discreet channel for job search activities (Faberman et al., 2022).

Other potential effects cannot be fully ruled out; however, we did not formulate specific hypotheses for them due to the lack of sufficient theoretical justification. To nonetheless capture possible additional relationships, we adopt an exploratory approach to assess whether further patterns or effects emerge.

## **4. Data and method**

### **4.1. Data collection**

We use data from the Netquest metered panel in Spain (netquest.com). Membership in the metered panel is not based on random selection; instead, Netquest employs an internal predictive model to identify survey respondents who are most likely to install the meter, taking into account the panel's composition and research needs (Revilla et al., 2021). Participants receive points for their contributions, which can be redeemed for rewards.

The sample was drawn from 18,980 active panel members. Eligibility criteria required: (1) metered data sharing across the nine-month period of interest (March 1–November 30, 2023), (2) prior provision of gender, age, region, and social class information, and (3) having visited at least one of Spain’s major job search platforms (see SOM1) on five or more separate days during the nine months. From this pool, 600 individuals were randomly selected.

In adherence to the principle of data minimization, Netquest was asked to extract for these 600 panellists only the activity directly related to job search: visits to relevant platforms and search queries immediately preceding those visits. Profiling variables obtained from routine panel surveys were also provided by Netquest for each sampling unit (see SOM2).

## 4.2. Analyses

First, descriptive analysis was performed for 13 variables measuring different aspects of job search. These are divided in three groups, depending on the nature of the variable.

The first group includes variables that are treated as continuous indicators, and that correspond to the most usual measures of job search behaviours:

- *Duration*: Total days engaged in active job search.
- *Effort*: Total hours invested in job search.
- *Intensity*: Average daily time spent on job search (in minutes per day).
- *Effectiveness*: Proportion of visits resulting in an application.
- *Average time per offer* and *Average time per application*: Measures of time allocation per search task (in seconds).

The second group is based on categorical variables where the focus is on the proportion of panellists for whom each level of the variable applies—thus, these proportions do not sum to 100%. These variables are less commonly studied, but have been proposed by Author and Author (2025), except the last one:

- *Platform*: Proportion of panellists who visited at least once each of the following platforms: InfoJobs, indeed.com, and linkedin.com/jobs. While LinkedIn is classified as a SNW, InfoJobs and Indeed are considered job boards. The key difference is that SNW platforms go beyond simply listing job offers; they function as social media environments focused on professional networking (Nikolau, 2014).
- *Device for visits*: Proportion of visited job offers from PCs vs. mobile devices (smartphones and tablets) among panellists sharing metered data from both types of devices.
- *Device for applications*: Proportion of job applications from PCs vs. mobile devices among panellists sharing metered data from both types of devices.
- *Search terms*: Proportion of terms used in (1) search engines (e.g., Google) before accessing job search platforms and (2) internal search engines inside job search platforms (information not recordable by the used meter for all the sites) that refer to different aspects: Specific search, Job search platform name, Job related searches, Generic employment query. The search terms have been coded into these categories by a native speaker.
- *Channel*: Proportion of the visits done through Web, App, or Both.

Finally, the last group of indicators is also based on categorical variables, but the interest lies in the distribution, i.e., how the activity of panellists is distributed across the levels of these variables:

- *Weekday*: Proportion of job search sessions per day of the week. This is defined not by the proportion of panellists using job search platforms each weekday but by how the activity on these platforms is distributed over weekdays, so the proportions add to 100%.
- *Part of day*: Proportion of visited job offers per time of the day: Night (0:00-5:59), Morning (6:00-11:59), Afternoon (12:00-17:59) and Evening (18:00-23:59).

For the first group of variables (continuous indicators), we first calculated the individual mean per panellist, then averaged across all panellists. For the second group (proportions), each level was recoded as a binary variable. For example, for the variable platform, we created three binary indicators for *platform-infojobs*, *platform-indeed.com*, and *platform-linkedin.com/jobs*. We report the percentage of positive cases for each binary variable. For the last group (distributions), the focus was on the distribution of activity across levels (e.g., proportion of visits per weekday), since nearly all panellists were active in all categories. For each panellist, we calculated the proportion of visits in each level and then averaged this across panellists.

All descriptive results are presented by groups based on their:

- *Gender*: We present the results for male versus female.
- *Age*: We consider three groups: 18–29, 30–50, >50.
- *Education*: We distinguish between low (compulsory studies), middle (high secondary studies) and high (college) education levels.
- *Income*: We consider the household gross monthly income and divide in three groups: less than 2,000€, from 2,000 to 3,000€ and more than 3,000€.
- *Migrant background*: We divide between migrant and non-migrant using a profiling question about whether the panellist was born outside of Spain.
- *Job Status*: Panellists were grouped into three levels (Unemployed, Employed, or Other) because distinctions among the various “Other” categories were not of interest, and the small sample sizes within these subgroups did not permit reliable analysis.

Differences were assessed using t-tests for means and Fisher’s exact tests for proportions. Distributional variables (weekday and part of day), treated as individual-level compositions summing to 100%, were analysed using ILR-transformed compositional data and compared across groups using PERMANOVA (Euclidean/Aitchison distance; 9,999 permutations).

Next, regression models were estimated to examine the potential influence of the explanatory variables on the various measures of job search behaviour. Continuous indicators were examined using linear regressions and binary indicators using logistic regressions, with each level entered as the dependent variable and sociodemographics as predictors. For the weekday and part-of-day variables, categories were collapsed into two groups: weekday vs. weekend and daytime vs. nighttime, respectively. Accordingly, two mixed-effects logistic regression models with a random intercept at the panellist level were fitted to account for repeated observations per individual. The dependent variables were binary indicators of whether a browsing observation occurred on the weekend (Saturday/Sunday) rather than a

weekday, and whether it occurred during nighttime (evening/night) rather than daytime. Coefficients from the logistic models are reported as odd ratios, and statistical inference is based on Wald standard errors. A sensitivity analysis using alternative model specifications is provided in SOM3. Statistical significance was set at  $\alpha = 0.05$ .

## 5. Results

Tables 1 and 2 present descriptive results, respectively for continuous (means) and categorical variables (proportions and distributions). Tables 3, 4 and 5 present the results of the regression analyses.

Comparing the descriptive and regression analyses, mixed patterns emerge. Regarding gender, the regression coefficient for women on job search effectiveness is negative but not statistically significant, confirming the descriptive finding that men and women display similar levels of effectiveness and providing no support for *H1a*. Although descriptive analyses suggest that women spent more time per application than men, partially supporting *H1b*, the regressions show no significant gender effects on average time per offer, application, effort, or intensity. Consistent with *H1c*, search duration does not differ significantly by gender in either analysis. No evidence is found to support the claim that men rely more on SNW (*H1d*) in either analysis.

For age, *H2a* is not supported in either analysis: the coefficient for job seekers aged 30–50 on search duration is positive but non-significant. However, *H2b* receives partial support. In the descriptive analyses, older job seekers rely less on apps than job seekers in both younger age groups (variable *Channel*). In the regressions, older job seekers are significantly less relying on apps compared to the 18-29 group.

Considering education, *H3a* and *H3b* receive partial support in the descriptive analyses, since low-educated job seekers exhibit significantly shorter search durations than mid-educated ones, and higher-educated individuals use LinkedIn more than lower and mid-educated ones. Nevertheless, they are not supported in the regressions, where no significant effects are found for these variables.

Regarding income, *H4a* receives partial support descriptively as lower-income job seekers show significantly shorter search durations than higher-income ones. However, this is not supported in the regression analyses. Likewise, *H4b* is partially supported in the descriptive analyses (middle-income job seekers use LinkedIn significantly more than lower-income ones) but not in the regressions.

Next, migrants spend significantly less time per job offer but do not differ concerning time per application or effectiveness, offering partial support to *H5a*. Migrants also use InfoJobs more frequently, although they do not rely more on mobile devices or apps, again only partially supporting *H5b*. In the regressions, *H5a* is not supported while *H5b* receives partial support, as migrants are significantly more likely to use InfoJobs.

Finally, for job status, in contrast to the descriptive results that do not support *H6a*, the regressions indicate that employed individuals have significantly longer search durations compared to unemployed, suggesting lower urgency and partially supporting *H6a*. *H6b* is not supported in either analysis.

Beyond the hypotheses tested, several additional significant patterns emerge, as summarized in Table 6. However, they are in general different between the descriptive and regression analyses.

## **6. Discussion**

### **6.1. Summary of results**

Using metered and profiling data, this study provides new empirical evidence about job search patterns across sociodemographic groups. Overall, both descriptive and regression analyses revealed modest differences in job search behaviour across groups. Table 7 presents a summary of the support for all hypotheses tested.

Overall, fewer differences emerged in the regression models than in the descriptive analyses, and most findings were non-consistent across both methods. This suggests that job search behaviours are more similar across groups than initially expected, with only few factors—primarily age, income and migration background—showing isolated consistent associations.

### **6.2. Limitations and future research**

While this study provides novel insights into the patterns of online job search in Spain, several limitations should be acknowledged.

First, the Netquest metered panel is composed of participants who voluntarily installed a tracker, which may introduce self-selection bias. Individuals willing to install tracking software are likely more digitally literate and privacy-tolerant than the general population, potentially underestimating the true extent of digital divides in job search. To mitigate this limitation, future research could implement weighting procedures.

Second, although Spain represents a valuable case study, results may not generalize to other countries. Cross-national research is needed.

Third, while metered data offer detailed behavioural traces, they are inherently restricted to online activity and cannot capture offline job search strategies. Since job seeking is often a hybrid process, the findings reflect only one component. Future studies could complement metered data with survey or qualitative data to assess how online and offline job search strategies interact.

Finally, metered data are not free from error. Undercoverage (Bosch et al., 2024) may result in certain traces not being captured, while shared devices might introduce noise, as some of the recorded traces may not originate from the intended person (e.g., the partner of the panellist might use the PC where the meter is installed). This type of measurement error could partially explain why only limited differences were observed. Furthermore, decisions regarding how to collect the metered data and how to operationalize the concepts using such data may also affect the results (Author and Author, 2025). Further methodological research is therefore needed to clarify how best to adjust for these potential sources of error.

### **6.3. Practical implications and conclusions**

The results of this study suggest that while digital divides in online job search remain observable in Spain, their magnitude is smaller and more nuanced than anticipated.

From a public policy perspective, this indicates that traditional digital inclusion policies—focused mainly on access and basic literacy—may be reaching their limits. The key disparities may now lie in search strategies, intensity, and effectiveness rather than in simple connectivity. Public administrations could therefore shift emphasis toward “second-generation” digital policies, aimed at improving effective use, strategic search, and evaluation skills. This might include training programs that help individuals interpret job offers critically, use professional networks like LinkedIn effectively, and tailor applications more strategically to reduce effort–outcome gaps.

For private companies and digital job platforms, the implications are equally relevant. The data show that users’ behaviours differ subtly across groups, indicating that “one-size-fits-all” algorithms may overlook valuable segments of candidates.

The relatively weak effects observed across many sociodemographic variables also suggest that the most relevant divides may no longer be demographic but motivational. Consequently, future research and policy could look beyond structural indicators, considering other dimensions of the digital divide.

Finally, the study underscores the value of metered data for both public and private decision-making. For companies, these data provide insights into user engagement patterns across different platforms that can inform the design of fairer, more efficient recruitment processes. For governments, such data could help evaluate the effectiveness of active labour market policies in real time, while ensuring strong data protection standards.

By integrating behavioural evidence into public policy, Spain—and other countries facing similar labour market conditions—could move toward a more inclusive, data-informed, and user-centred digital employment environment.

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## 8. Tables

**Table 1. Descriptive Statistics for Continuous Variables**

	Gender		Age			Education			Income			Migrant		Job Status		
	Male	Fem.	18-29	30-50	>50	Low	Mid	High	<2k€	2-3k€	>3k€	No	Yes	Unem.	Em.	Other
<b>Duration</b> (days)	164.6	160.5	164.9	162.2	161.4	141.1 <sup>a</sup>	166.8 <sup>a</sup>	164	152.5 <sup>b</sup>	168.9	185.3 <sup>b</sup>	148.1	163.7	162.2	163.8	156.3
<b>Effort</b> (hours)	4.1	2.4	2.8	3.6	2.7	2.1	3.8	2.9	4.7	3.3	1.6	2.3	3.4	3.2 <sup>b</sup>	3.5	1.8 <sup>b</sup>
<b>Intensity</b> (min./day)	1.5	0.8	0.8	1.5	0.7	0.6	1.6	0.8	2.3	0.9	0.5	1	1.2	1.1 <sup>b</sup>	1.3	0.5 <sup>b</sup>
<b>Effectiveness</b> (%)	8.6	8.5	9.9	8.9	7.4	8.7	10.3	7.2	7.1	6.7	4.5	9.2	8.6	12.8 <sup>a</sup>	7.2 <sup>a</sup>	6.8
<b>Avg. time / offer</b> (sec.)	51.8	45	56.7	44.3	51.7	39.9	43.4	53.5	51.6	55.9	33.2	80.1 <sup>a</sup>	44.3 <sup>a</sup>	40.5	51.9	44.4
<b>Avg. time / appli</b> (sec.)	80.1 <sup>a</sup>	122.7 <sup>a</sup>	93.6	98.9	111.4	88.5	98.7	106.9	115.9 <sup>a</sup>	47.4 <sup>a</sup>	92	94.6	104.7	118.1	91.8	110.1

*Note:* “Fem.” denotes *Female*, “k€” denotes *thousands of €*, “Unem.” denotes *Unemployed*, “Em.” denotes *Employed*, and “appli.” denotes *application*. Superscripts <sup>a</sup> and <sup>b</sup> indicate statistically significant differences between groups sharing the same letter. For example, for *Duration*, the *Low* and *Mid* education groups differ significantly, as shown by the superscript <sup>a</sup> next to the values 141.1 and 166.8.

**Table 2. Descriptive Statistics for Categorical Variables**

	Gender		Age			Education			Income			Migrant		Job Status		
	Male	Fem.	18-29	30-50	>50	Low	Mid	High	<2k€	2€-3k€	>3k€	No	Yes	Unem.	Em.	Other
<b>Platform</b>																
InfoJobs	87.0	91.1	95.8 <sup>b</sup>	90.1 <sup>c</sup>	83.5 <sup>bc</sup>	84.4	92.4	87.4	90.2 <sup>b</sup>	90.0	73.9 <sup>b</sup>	70.6 <sup>a</sup>	90.4 <sup>a</sup>	92.1	88.6	86.8
Indeed	44.0 <sup>a</sup>	53.5 <sup>a</sup>	50.0	48.8	48.8	45.3	47.0	51.6	44.7	50.0	60.9	62.8	50.4	54.7	47.8	44.1
linkedin	44.7	40.5	38.5	44.6	40.6	26.6 <sup>b</sup>	31.5 <sup>c</sup>	55.8 <sup>bc</sup>	39.4 <sup>a</sup>	56.0 <sup>a</sup>	60.9	39.2	46.3	35.3 <sup>a</sup>	45.3 <sup>a</sup>	41.2
<b>Device visits</b>																
PC	85.5	77.0	82.1	79.3	84.3	74.1	78.2	84.6	85.9	81.5	90.0	72.7	81.1	81.1	81.6	77.8
Mobile	37.7	48.0	35.9	45.1	42.2	55.6	46.4	38.3	35.9	37.0	50.0	59.1	41.8	40.5	43.2	48.2
<b>Device appli.</b>																
PC	85.9	82.7	82.6	85.2	83.3	78.6	82.0	87.3	86.2	73.3	100.0	72.7	84.0	84.3	84.3	83.3
Mobile	26.8	32.0	26.1	25.9	38.1	28.6	31.2	28.2	24.1	26.7	75.0	45.5	28.8	29.4	28.9	33.3
<b>Search terms</b>																
Specific search	68.2	65.2	64.9	67.2	66.3	77.8 <sup>a</sup>	54.9 <sup>ac</sup>	74.7 <sup>c</sup>	62.3	75.0	66.7	72.0	66.9	70.7	66.7	57.1
Platform name	48.4	53.4	52.6	52.9	46.1	48.2	48.6	53.6	54.6	50.0	38.9	44.0	53.2	53.3	51.1	45.7
Job related searches	48.4	44.9	50.9	43.9	49.4	33.3	49.3	46.4	44.2	46.4	44.4	40.0	46.8	49.3	45.8	45.7
Generic em. query	11.5	18.0	19.3	13.2	15.7	14.8	16.2	13.9	15.6	25.0 <sup>c</sup>	0.0 <sup>c</sup>	16.0	15.9	13.3	15.1	17.1
<b>Channel</b>																
Web	92.1	93.4	89.2	91.9	96.1	92.9	94.3	91.4	92.7	92.1	100.0	94.6	92.7	92.9	92.5	93.8
App	41.2	40.3	60.0 <sup>ab</sup>	44.3 <sup>ac</sup>	24.2 <sup>bc</sup>	42.9	47.2 <sup>c</sup>	35.3 <sup>c</sup>	46.9 <sup>b</sup>	36.8	13.6 <sup>b</sup>	37.8	39.0	45.9	39.6	37.5
Both	33.3	33.7	49.2 <sup>b</sup>	36.2 <sup>c</sup>	20.3 <sup>bc</sup>	35.7	41.5 <sup>c</sup>	26.7 <sup>c</sup>	39.6 <sup>b</sup>	29.0	13.6 <sup>b</sup>	32.4	31.7	38.8	32.1	31.3
<b>Weekday</b>																
Monday	17.9	16.7	16.3	17.7	17.0	16.1	16.7	18.0	15.5	22.0	19.2	16.9	17.2	17.0	17.6	15.8
Tuesday	16.5	17.2	16.2	17.3	16.5	16.0	16.8	17.2	16.7	17.8	20.1	18.9	16.7	16.4	16.7	19.0
Wednesday	19.0	17.8	19.1	18.4	17.9	17.2	17.2	19.7	18.4	16.2	17.3	20.3	18.4	17.7	18.4	19.4
Thursday	16.0 <sup>a</sup>	18.1 <sup>a</sup>	17.8	17.5 <sup>c</sup>	15.9 <sup>c</sup>	16.5 <sup>b</sup>	16.7 <sup>c</sup>	17.7 <sup>bc</sup>	16.5	17.5	15.2	14.0	16.9	17.7	17.0	16.7
Friday	13.2	13.5	13.8	13.7	12.4	13.5	14.3	12.4	13.9	13.1	12.6	12.6	13.5	13.6	13.6	11.2
Saturday	8.4	8.4	8.0	7.7	10.0	10.5	8.5	7.8	9.4	5.9	6.8	8.5	8.4	8.9	8.3	7.9
Sunday	9.1	8.3	8.8	7.8	10.3	10.2	9.9	7.3	9.5	7.5	8.8	8.8	8.8	8.7	8.4	10.0
<b>Part of day</b>																
Night	6.2	4.9	5.5	5.7	5.1	6.8	5.8	5.0	7.1	5.3	3.8	6.9	5.2	5.5	5.5	5.7
Morning	27.8	27.8	24.3	28.3	28.7	25.4	27.8	28.3	25.2 <sup>b</sup>	28.5 <sup>b</sup>	30.9	26.3	28.3	25.6	28.8	26.5
Afternoon	40.2	40.2	44.1	40.7	37.2	38.1	39.0	41.8	39.6	37.6	41.1	45.8	39.6	42.0	39.7	39.8
Evening	25.8	27.1	26.1	25.3	29.0	29.8	27.4	25.0	28.1	28.6	24.2	21.1	26.8	26.9	26.1	28.0

Note: “Fem.” denotes *Female*, “k€” denotes *thousand of €*, “Unem.” denotes *Unemployed*, “Em.” denotes *Employed* or *Employment*, and “appli.” denotes *application*. Superscripts <sup>a</sup>, <sup>b</sup> and <sup>c</sup> indicate statistically significant differences between groups sharing the same letter.

**Table 3. Regression Analyses for Continuous Indicators (coefficients)**

	Job search duration (days)	Job search effort (hours)	Job search intensity (min./day)	Job search effectiveness (%)	Average time per job offer (sec.)	Average time per job application (sec.)
<b>Gender</b>						
Female	-2.28	-4.51	-2.27	-4.30	-10.98	34.29
<b>Age</b>						
30-50 y.old	17.07	3.43	2.02	-7.29 *	-68.54 *	-30.84
>50 y.old	44.15	0.73	-0.12	-8.23 *	-36.48	-36.65
<b>Education</b>						
Mid	21.93	4.51	3.36	-5.45	3.18	-29.86
High	44.46	1.19	0.71	-8.31	13.82	21.33
<b>Income</b>						
2-3k€	7.13	-3.5	-2.29	0.45	-4.44	-74.05
>3k€	13.28	-3.33	-1.55	-0.16	-15.08	-66.61
<b>Migrant</b>						
Yes	20.6	1.96	1.02	-2.80	2.07	-46.36
<b>Job status</b>						
Employed	54.31 *	1.24	0.47	-1.02	3.77	-49.72
Other	47	1.44	0.22	0.56	-42.28	-116.08

Note: y.old = years old; “k€” = thousand of €; \* if p < 0.05

**Table 4. Regression Analyses for Categorical Indicators (odd ratios)**

	Platform			Device visit		Device appl.		Search terms				Channel		
	Infojobs	Indeed	Linkedin	PC	Mobile	PC	Mobile	Specific search	Platform name	Job related	Generic query	Web	App	Both
<b>Gender</b>														
Female	0.94	1.55	0.91	0.35	1.75	2.13	1.43	0.95	0.85	0.48	2.01	0.73	0.85	0.75
<b>Age</b>														
30-50 y.old	1.97	0.49	0.57	1.91	1.25	9.51	0.34	6.04 *	0.97	0.65	1.05	0.95	0.66	0.65
>50 y.old	0.84	0.7	0.46	1.00	4.19	3.47	2.87	3.62	0.74	1.48	1.66	1.99	0.24 *	0.24 *
<b>Education</b>														
Mid	4.19	1.89	0.49	0.00	1.57	0.00	5.00	0.71	3.63	2.91	0.44	0.00	1.89	1.63
High	4.01	1.83	1.01	0.00	1.30	0.00	2.31	1.10	5.46	2.76	1.00	0.00	0.90	0.52
<b>Income</b>														
2-3k€	0.85	1.51	1.90	0.58	1.50	0.39	2.22	2.30	0.57	0.77	2.7	1.24	0.69	0.70
>3k€	0.21 *	1.93	1.65	1.53	1.91	9.90	15.47	0.69	0.33	0.84	0.00	9.79	0.25 *	0.42 *
<b>Migrant</b>														
Yes	5.08 *	0.54	0.94	0.47	0.53	0.22	6.79	0.40	0.96	0.76	0.32	0.00	1.40	1.08
<b>Job status</b>														
Employed	0.66	0.98	0.93	0.63	0.93	9.79	0.33	0.34	0.41	0.34	1.03	0.00	0.86	0.61
Other	0.52	1.66	4.80	1.73	9.91	6.46	0.35	1.71	0.58	0.54	1.08	1.36	0.29	0.34

Note: y.old = years old; “k€” = thousand of €; \*if p < 0.05

**Table 5. Regression Analyses for Temporal Distributions (odd ratios)**

	<b>Weekend (%)</b>	<b>Nighttime (%)</b>
<b>Gender</b>		
Female	1.12	1.14
<b>Age</b>		
30-50 y.old	0.68	1.11
>50 y.old	1.03	0.96
<b>Education</b>		
Mid	1.23	0.86
High	0.80	0.73
<b>Income</b>		
2-3k€	0.70	0.86
>3k€	0.67	0.46
<b>Migrant</b>		
Yes	1.81	1.22
<b>Job status</b>		
Employed	0.90	0.73
Other	0.54	1.04

*Note:* y.old = years old; “k€” = thousand of; \* if  $p < 0.05$

**Table 6. Other significant differences found**

<b>Relationship</b>	<b>Descriptives</b>	<b>Regressions</b>
Gender – Platform	Yes (Indeed)	No
Gender – Day of the week	Yes	No
Age – Effectiveness	No	Yes
Age – Time per offer	No	Yes
Age – Platform	Yes (InfoJobs)	No
Age – Search terms	No	Yes (Specific terms)
Age – Channel	Yes (Both)	Yes (Both)
Age – Weekday	Yes	No
Education – Search terms	Yes (Specific terms)	No
Education – Channel	Yes (App, Both)	No
Income – Average time per application	Yes	No
Income – Platform	Yes (InfoJobs, LinkedIn)	Yes (InfoJobs)
Income – Search terms	Yes (Generic em. query)	No
Income – Channel	Yes (App, Both)	Yes (App, Both)
Income – Part of day	Yes	No
Job Status – Effectiveness	Yes	No
Job Status – Intensity	Yes	No
Job Status – Effort	Yes	No
Job Status – Platform	Yes (LinkedIn)	No

**Table 7. Summary of support for our hypotheses**

<b>Name</b>	<b>Hypothesis</b>	<b>Supported descriptives</b>	<b>by</b>	<b>Supported regressions</b>	<b>by</b>
<i>H1a</i>	Men show higher effectiveness than women.	No		No	
<i>H1b</i>	Women spend more average time per job offer or application than men and exhibit higher search effort and intensity.	Partial (Time per application)		No	
<i>H1c</i>	Search duration is similar for men and women.	Yes		Yes	
<i>H1d</i>	Men rely more on SNW platforms.	No		No	
<i>H2a</i>	Job seekers aged 30 to 50 have shorter search durations than both younger and older candidates.	No		No	
<i>H2b</i>	Job seekers over 50 rely less on apps and more on SNW platforms such as LinkedIn.	Partial (Channel)		Partial (Channel compared to 18-29)	
<i>H3a</i>	Lower-educated job seekers show higher search effort but lower effectiveness and search duration.	Partial (Duration)		No	
<i>H3b</i>	Higher-educated job seekers rely more on SNW platforms and use more PCs.	Partial (LinkedIn)		No	
<i>H4a</i>	Lower-income job seekers display higher search effort and intensity and lower job search duration.	Partial (Duration)		No	
<i>H4b</i>	Higher-income job seekers rely more on SNW platforms and use more PCs.	Partial (LinkedIn: 2-3k€ vs <2k€)		No	
<i>H5a</i>	Migrants job seekers show lower effectiveness and average time per offer and per application.	Partial (Average time per offer)		No	
<i>H5b</i>	Migrants job seekers rely more on job boards, on mobile devices, and on apps.	Partial (InfoJobs)		Partial (InfoJobs)	
<i>H6a</i>	Unemployed job seekers show higher effort and intensity and lower search duration.	No		Partial (Duration)	
<i>H6b</i>	Employed individuals tend to search for jobs more frequently in the evenings and rely more on mobile devices	No		No	