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Article

Jobless and Burnt Out: Digital Inequality and Online Access to the Labor Market

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Abstract
This article examines how inequalities in digital skills shape the outcomes of online job-seeking processes. Building on a representative survey of Spanish job seekers, we show that people with high digital skill levels have a greater probability of securing a job online, because of their ability to create a coherent profile and make their application visible. Additionally, it is less probable that they will experience burnout during this process than job seekers with low digital skill levels. Given the concentration of digital skills amongst people with high levels of material and digital resources, we conclude that the internet enforces existing material and health inequalities.

Keywords
burnout; digital exclusion; digital inequality; digital skills; online job-seeking; Spain

Issue
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1. Introduction

The diffusion of the internet has deepened social stratification. High levels of material and digital resources foster engagement in online activities, increasing internet users' digital skill levels (Hargittai, 2002; van Dijk, 2020). Digital skills concentrate among more advantaged users and provide additional tangible benefits in their "real life," resulting in the accumulation of material resources and status gain (van Deursen et al., 2017; Helsper, 2021; van Ingen & Matzat, 2018). Furthermore, highly skilled users are better at handling the effects of online problems—such as fraud, identity theft, or privacy violation—in their daily lives (Büchi et al., 2015; Dodel & Mesch, 2019; Helsper, 2021; Micheli et al., 2018; Scheerder et al., 2019).

The internet has also profoundly changed how people access the labour market. Now, job seekers have access to a greater number of vacancies on a global scale while employers gain more and more visibility and can receive more applications (Bonet et al., 2013; Coverdill & Finlay, 2017). This situation creates larger pools of candidates competing for a limited number of vacancies, especially for the most insecure jobs (McDonald et al., 2019). In other words, employment platforms create an unfavourable imbalance in the candidates/vacancy ratio, with negative implications for individual applications. Moreover, regardless of their job-related competencies, those with strong online job-seeking skills increase their visibility and their chances of being hired, while other candidates are much more likely to remain unemployed (Pongratz, 2018). Prolonged periods of unemployment and intensive job-seeking practices generate psychological distress (Bunjak et al., 2021; Gedikli et al., 2022). Distress can be reduced by the availability of material and psychological resources, and by job seekers' perception of themselves as being capable of seeking employment (Chen & Lim, 2012; Fernández-Valera et al., 2020). High levels of digital skills may therefore contribute to reducing psychological distress resulting from the platform-mediated job-seeking process (De Battisti et al., 2016; Gui & Büchi, 2021; Helsper & Smahel, 2020).

In this context, this article examines how persisting inequalities in digital skills shape the outcomes of the platform-mediated job-seeking process. High digital skill levels should help people obtain tangible benefits from the online job-seeking process while avoiding its negative implications (e.g., psychological distress). However, how digital inequalities impact the outcomes of platform-mediated job-seeking processes is unclear (Karaoglu et al., 2021). We address this lack of understanding by proposing that the digitalization of job search fosters social stratification because of the unequal distribution of digital skills among job seekers. We examine this proposition by surveying 1000 Spanish job seekers in a context where high internet access rates coexist with widespread use of employment platforms as well as high unemployment rates among young people (Bolíbar et al., 2019; INE, 2022). In other words, the volume of job seekers is high and most of them use the internet to identify and apply for vacancies.

Our results show that advantaged job seekers with higher educational levels and financial resources do not face significant challenges in the understanding and use of employment platforms. In contrast, job seekers with lower educational levels and limited financial resources struggle with this process and experience psychological distress. Accordingly, the main contribution of this article is to demonstrate that the current theory of socio-digital inequality applies to the sphere of online job-seeking processes and show its implications. Specifically, we contribute to and advance this theory by identifying and analysing some of the key outcomes of inequalities in digital skills in terms of labor market inclusion. More broadly, these findings are important for social exclusion research, given that most job-seeking processes are now digitalized, although we know little about the implications of this digitalization on job seekers with different levels of digital skills. In the remainder of this article, we present and articulate key findings from recent research into digital inequalities and online job-seeking. Subsequently, we present our sample and overall methodology before introducing and discussing our findings as well as their implications for both theory and practice.

2. Theoretical Background

2.1. Digital Inequality

Since the first stages of internet diffusion, academics have been concerned about digital exclusion. Initially, researchers focused on the "first-level digital divide." According to Attewell (2001, p. 252), this phenomenon consisted of "the technological gap between those who have access to information and those who do not have access to it." Early research on this topic focused on the inequalities in internet access that affected traditionally disadvantaged social groups (van Dijk, 2020). In recent years, however, there has been a considerable increase in the number of internet users, especially in Western countries. Thus, academics are now focusing on the "second-level digital divide" derived from the unequal distribution of beneficial internet use and digital skills. Specifically, digital skills concentrate among users with higher levels of education or socio-economic status (Hargittai, 2002; Hargittai & Hinnant, 2008; van Deursen & van Dijk, 2010).

While it is true that the quality of an internet connection and the type of technology available for navigation are important, internet users' digital skills are essential if they are to obtain tangible benefits from the use of the internet as a tool. Many authors have therefore attempted to build reliable and accurate tools to measure them (DiMaggio & Hargittai, 2001; van Deursen et al., 2016; van Dijk, 2006). In this vein, van Dijk (2006) suggested utilizing the distinction between operational skills, which are needed to handle computer hardware and software, and the informational skills required to search and filter online information. Van Deursen and colleagues have also added several dimensions to the digital skills construct, such as strategic skills, formal skills, and internet communication skills (van Deursen et al., 2016; van Deursen & van Dijk, 2008). These dimensions have been successfully assessed and validated using representative samples of the British and Dutch populations (van Deursen et al., 2016; van Deursen & van Dijk, 2014). They reveal that high levels of digital literacy are associated with advanced internet use. However, general navigational skills do not guarantee effective and beneficial internet use in all its applications and must be coupled with specific skills for each advanced internet use if they are to foment the obtention of tangible benefits (Arroyo, 2018).

Scholars have also studied the mechanisms by which people develop high digital skill levels. Internet users with higher levels of digital resources (i.e., technological resources available at home) and those who benefit from the possibility of connecting from multiple locations and with greater frequency, demonstrate advanced internet use (Hassani, 2006; Peter & Valkenburg, 2006; van Deursen & van Dijk, 2015). In addition, better digital resources increase both digital proficiency and users' confidence in their ability to evaluate and filter online information (Robinson, 2009, 2012). The concept of “digital capital” (Ragnedda, 2018; Ragnedda et al., 2022) describes the accumulation of internet users’ digital skills and resources. It represents a link between online and offline opportunities, as it can increase internet users’ material resources when actioned through internet use.

The “third-level digital divide” revolves around the differences between users based on the tangible benefits they derive from the same internet use (van Deursen & Helsper, 2015). Different levels of resources correspond to different levels of digital capabilities, raising different levels of online engagement (Scheerder et al., 2017). Increased offline resources lead to increased levels of digital capital, which are manifested, amongst other things, in increased levels of digital skills, particularly those of an instrumental nature. Consequently, internet users differ in terms of the tangible social, economic, and professional outcomes of internet use. Thus, people with more resources have a greater ability to minimize the impact of the negative effects of internet use (Scheerder et al., 2019). As such, the third-level digital divide acts as a reinforcer of social stratification because it allows people with higher levels of offline resources to increase these further via their digital resources and skills, thus obtaining higher levels of tangible benefits and avoiding the negative effects of internet use (Calderón Gómez, 2020). This model would be in line with the concept of “credential rents” (Sørensen, 2000; Wright, 2000), which refer to the greater economic outcomes enjoyed by the advantaged social classes that access and hoard higher levels of education, expertise, or (digital) skills.

2.2. Online Job-Seeking

Among the uses of the internet that can bring tangible benefits to people’s lives is platform-mediated job search. Job seekers have a better chance of finding employment via internet and of that job being better paid (Lindsay, 2005). Using the internet may reduce the time involved in finding a new job by 25% compared to traditional, offline, channels (Kuhn & Mansour, 2014). Furthermore, recruiters and prospective employers have access to large databases of potential candidates for their selection processes, which is important at a time when online job-seeking has penetrated most sectors and is especially popular among young people who are more confident in using the internet (Kroft & Pope, 2014; Piercy & Kyong Lee, 2019).

However, these benefits also have significant downsides. For low-skilled workers, the digitalization of job-seeking has led to an imbalance between the number of job seekers and the number of online vacancies (OECD, 2022). This situation raises fierce competition among job seekers with similar profiles. In contrast, for high-skilled workers in the IT sector, high demand and a limited number of job seekers have shifted competition to labour market intermediaries, who struggle to find candidates (McDonald et al., 2019). The fact that highly skilled IT employees can potentially benefit from a “privileged location” within the labour market is again related to credential/skill rents from the social class theories by Sørensen (2000) and Wright (2000).

In the current digitalized labour market, creating and presenting an image as a competent professional on job-seeking platforms is extremely important in obtaining employment (Dumont & Ots, 2020; Gandini, 2016; Pongratz, 2018). Furthermore, the ability to instrumentally use personal and professional information has become key to successfully seeking employment online (Sharone, 2017). Accordingly, van Deursen et al. (2017) have suggested a link between digital skills and the ability to use the internet instrumentally to achieve personal goals, emphasising the role of instrumental and communication skills. Likewise, Karaoglu et al. (2021) found that strategic online job-seeking skills facilitated the use of social networks for job-seeking purposes. This type of skill would involve intuiting how algorithms sort and present applications received by recruiters, and then using this intuition to tailor CVs, profiles, or applications to make them more visible (Smythe et al., 2021).

Specific types of digital skills are concentrated among people with higher levels of material and educational resources (Karaoglu et al., 2021; van Dijk et al., 2017). Consequently, job seekers with lower levels of material and educational resources and online job-seeking skills will experience greater difficulties in finding employment via internet, building on the employability problems already suffered by the more disadvantaged social classes in pre-digitalized contexts (Goldthorpe & McKnight, 2006). This triggers unemployment and lower-paid jobs for low-skilled job seekers, with consequent negative implications for gaining new material resources. Additionally, the psychological well-being of job seekers may suffer because of prolonged periods of unemployment and job-seeking. In fact, unemployment has a negative impact on both mental health and life satisfaction, i.e., the longer the duration of the employment search, the greater the impact (Gedikli et al., 2022). Paul and Moser (2009) also found that the severity of psychological distress resulting from unemployment accumulates over time, leading to a continuous decline in mental health.

The material and psychological resources of job seekers, however, have been described as being very helpful in preventing psychological distress associated with job-seeking. In fact, financial hardship and social exclusion can lead to job-seeking fatigue and negatively affect the quality of subsequent re-employment (Lim et al., 2016). At the same time, psychological capital can reduce job seekers’ fatigue and prevent these negative outcomes. For example, job seekers with less confidence in their job-seeking skills are likely to be pessimistic, see themselves as unemployable, give up on reemployment more easily, and be less resilient to setbacks (Chen & Lim, 2012). Hence, we would expect that job seekers with less material and online job-seeking skills would have more difficulty finding a job online. Additionally, online job-seeking skills should be useful in reducing psychological distress related to online job-seeking.

Our literature review highlights the importance of digital skills in deepening social stratification. Digital skills generate tangible benefits and allow the avoidance of side effects on internet users' lives. This should also be the case for online job-seeking. Online job-seeking skills should help internet users find employment and avoid psychological distress related to long-term job-seeking. These skills should be concentrated mostly among users with higher levels of material resources, thus increasing the differences between them and people with fewer resources. Despite the importance of this topic, there is a lack of empirical work that analyses the relationship between material resources, digital skills, and online job search outcomes.

3. Methodology

3.1. Sample

Spain provides a valuable setting for this inquiry given the high number of internet users in the country, reaching a rate of over 90% (see Figure 1). This includes non-nationals and individuals residing in rural areas, with the only exception being people older than 75. Spain also provides an excellent case study because of a combination of high unemployment rates and the widespread adoption of employment platforms.

We conducted a survey using a sample of 1000 subjects aged between 18 (legal age for signing a work contract) and 65 (retirement age in Spain). All participants were part of the active population, were internet users, and had at least minimal levels of upper-secondary education. We utilized a panel of 2,722.476 Spanish people and used random sampling. To ensure representation of the Spanish active population by age and education level, we introduced quotas based on percentages provided by the Spanish National Statistics Institute (INE). Our sample included both employed and unemployed individuals actively seeking jobs across a wide range of job sectors, including both lower and higher positions, to provide a comprehensive picture of Spanish online job seekers. Participants had to have been actively seeking employment within the last year, to ensure the inclusion of a sufficient number of participants who used the internet to seek employment. Table 1 shows the sociodemographic characteristics of the respondents. The age variable divides the sample into four groups, with the 18–29 age group being the largest (32.6%) and the 51–65 age group the smallest (12.9%). The sample is made up of approximately the same number of women (54.1% of the sample) and men (45.9%). Furthermore, participants can be grouped into 4 levels via the educational attainment variable. The largest group represents people whose highest level of education is upper secondary (26.9%) and the smallest group represents people with a doctorate (6.8%).

3.2. Analysis

We used structural equation modelling (SEM) because it enables the transfer of a theoretical model with latent variables to a testable statistical model (Kline, 2015) and the comparison of nested models (Ullman, 2006). Specifically, we employed the diagonally weighted least squares (DWLS) estimation method using a polychoric correlation matrix to manage the combination of continuous and categorical variables (Li, 2016, 2021).

We performed all analyses in the free statistical environment R (version 4.2.2) with the *lavaan* package (version 0.6–11). We assessed model adequacy through a comparison of the following goodness-of-fit indices: the Comparative Fit Index (CFI), the

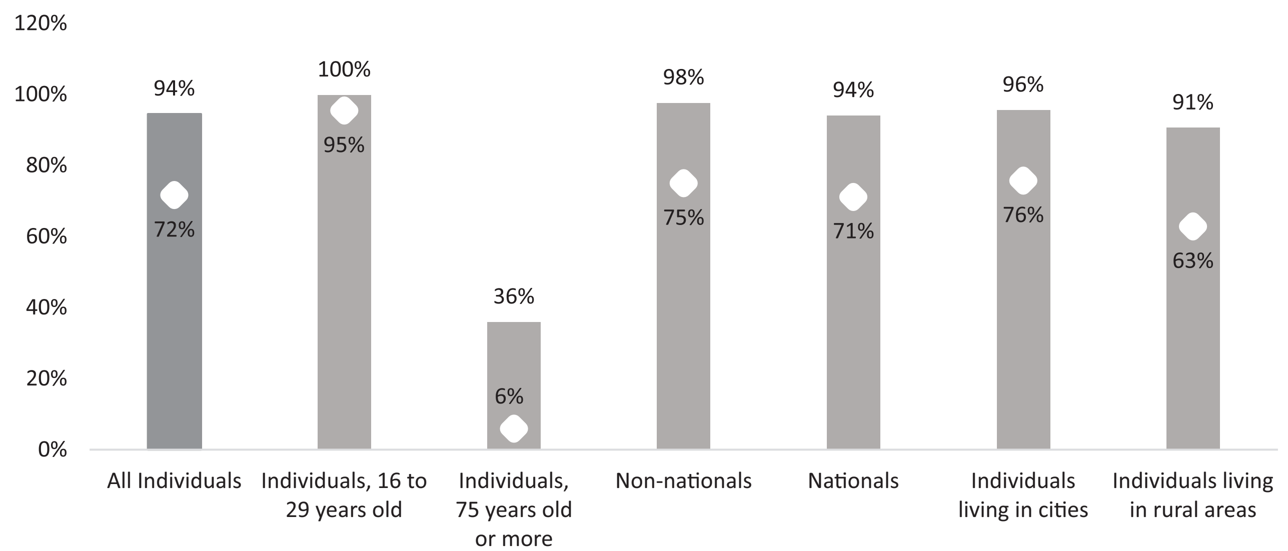

Figure 1. Evolution of internet users in Spain (2013–2022). Source: Eurostat (n.d.).

Table 1. Sociodemographic characteristics of the sample.

Categories	Frequency	Percentage
Age		
18 to 29 years	326	32.6%
30 to 39 years	274	27.4%
40 to 50 years	271	27.1%
51 to 56 years	129	12.9%
Gender		
Male	459	45.9%
Female	541	54.1%
Level of Education		
Second stage of secondary education and similar	269	26.9%
Higher vocational training (FP II) and university degrees of 2 years or more	265	26.5%
Diploma, first cycle of undergraduate degree, technical engineering, degree, and similar	154	15.4%
Undergraduate degree, higher engineering degree, bachelor's degree of more than 4 years, master's degree, or equivalent	244	24.4%
Higher university studies at the doctorate level or equivalent	68	6.8%
Total	1000	100.0%

Tucker–Lewis Index (TLI), the Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMR).

However, when using estimation methods such as DWLS that do not belong to the "maximum likelihood" family, the common cut-off criteria for these indices (in the TLI and CFI this is greater than 0.90; in the RMSEA and SRMR it is lower than 0.08 and 0.06, respectively; see Hu & Bentler, 1999) may not provide clear guidance (Xia & Yang, 2019). To show that the hypothesized model fits the data to a high degree of approximation, we also report the parsimony ratio (cut-off point: 0.85; see Carlson & Mulaik, 1993; Mulaik, 2007). Additionally, following Barrett's (2007) recommendations, we provide the results of the χ^2 goodness-of-fit test—despite its potential sensitivity to large sample sizes.

Furthermore, we have examined two mediational chains: (a) material and educational resources—digital resources—digital skills and (b) material and educational resources—digital resources—online job-seeking skills. Subsequently, indirect effects and their corresponding 95% confidence intervals were estimated using 5,000 bootstrap samples. Moreover, to better understand these mediational chains, we estimated an alternative model with direct paths from *material and educational resources* to *digital skills* and from *material and educational resources* to *online job-seeking skills*.

Finally, we worked with full information. No data imputation has been carried out (*listwise deletion*) because the construction of some variables (such as *digital skills* and *online job-seeking skills*) required this. Nonetheless, in the worst case, sample attrition was low (17.1%) and the sample size continues to meet the requirements for SEM estimation: It exceeds the minimum requirement of 200 participants (Barrett, 2007) and the number of indicators per latent variable is high (Wolf et al., 2013).

3.3. Measures

We introduced three blocks of independent variables to our model. First, we introduced the variables that assess internet users' resources, including *level of education*; an ordinal variable with 5 categories running from *upper secondary* to *doctorate* (M = 4.58, SD = 1.30). Lower levels of education were not included because a low level of education corresponds to a reduced, or near zero, use of online platforms for job-seeking (see Baruffaldi et al., 2017). Even so, there are differences among internet users with higher levels of education depending on their skills and their material resources at home. Next, we introduced a *weighted household income* indicator (M = 2.67, SD = 1.37), because people who live with others benefit from economies of scale in consumption, which individuals living alone do not have access to (Browning et al., 2013). Following Eurostat's (2021) recommendations, we computed this indicator by dividing the household monthly income by the equivalised household size, by assigning a value of 1 to the first household member and 0.5 to each additional person (either adult or child).

Another set of independent variables includes indicators that assess internet users' digital resources. First, we introduced the *technology present in the household* variable, calculated by adding up the number of pieces of technological equipment that a participant declared to have in their home. The result was a numerical variable ranging from 0 to 11 (M = 7.84, SD = 2.10). Secondly, we introduced the *variety of internet access points* variable; a numerical variable with a range from 0 to 6 (M = 4.22, SD = 1.61), constructed by summing up the number of places from which the respondent had connected to the Internet in the six months prior to the survey.

Thirdly, we used a set of indicators assessing internet users' digital skills, variables that we developed based on the work of van Deursen et al. (2016). It comprises 12 items measuring *operational internet skills*, *content creation skills*, *informational internet skills*, and *communication skills*. Each item has a five-point response scale (acceptable reliability values: α = 0.82, ω = 0.83). The punctuation of each subject on this scale is calculated by adding the answers given to each one of the 12 items. Consequently, the values of this variable range from 0 to 65 (M = 47.93, SD = 7.47). Additionally, we have developed and introduced a new scale to assess digital skills for online job-seeking. Items for this new scale have been generated based on 77 semi-structured interviews: 44 with people actively using the Internet to search for employment and 33 with recruiters at employment agencies or in human resources positions for large companies.

We built both samples to cover the widest possible range of profiles and areas of job-seeking. We asked research participants about actions that would make it more likely for a job application to be noticed during a selection process, hence increasing a candidate's chances of being contacted for an interview. We identified 11 actions related to job-seeking and we transformed them into items to be included on the scale (see Table 2; M = 41.79, SD = 7.94, α = 0.91, ω = 0.92).

In addition, our model included two dependent variables. The first was a variable that measured the success of the online job search. To this end, we used the following item: *In the last 6 months, I have been offered a job interview* (M = 2.20, SD = 1.05). This allows us to measure the frequency with which participants were invited to be contacted for an interview after having applied for a job online in the six months prior to the survey (Table 3).

Table 2. Items that make up the digital skills for online job-seeking scale.

Below is a series of things that can be done with a professional network profile or in a job search. Indicate to what extent the following statements about using the Internet to look for a job are true for you [reply options: *totally false* (1); *quite false* (2); *neither true nor false* (3); *somewhat true* (4); *totally true* (5); *I don't know* (66); *I don't want to answer* (99)].

Item 1	I know how to choose a profile picture appropriate to apply for a job.
Item 2	I know how to ask for recommendations from people so that recruiters can judge my job potential.
Item 3	I know at what time to send a job application so as to make it more visible.
Item 4	When I search for a job, I know how to check that I am using the same terms or keywords used by companies offering jobs that interest me.
Item 5	I know how to describe my skills in my profile to make them more visible.
Item 6	I know how to describe the positions I have held.
Item 7	I understand how the algorithms that sort applications on job search platforms work.
Item 8	I know how to make an application that catches recruiters' attention.
Item 9	I know what information to prioritize in my CV
Item 10	I know how to use the keywords included in job postings to describe my profile/CV.
Item 11	I know how to upload information to my public profile about events or things of professional interest to demonstrate my experience.

Table 3. Frequency table for the *contacted for a job interview* variable.

In the last 6 months, I have been invited for an interview after sending an application for a position advertised on the Internet.

Categories	Frequency	Percentage
Never	268	26,8%
A couple of times	425	42,5%
Monthly	154	15,4%
Weekly	110	11%
Daily	30	3%
Missing	13	1,3%
n	1000	

The second dependent variable was *job-seeking burnout* (M = 2.96, SD = 1.76), used as a measure of psychological distress. We obtained this variable through a Spanish version of the Maslach Burnout Inventory emotional exhaustion subdimension (Maslach et al., 1996), adapted to the job-seeking field. This subscale consists of nine items (e.g., *I feel emotionally drained by the job search*) which are assessed with a seven-point Likert scale from 0 (*never*) to 6 (*every day*). Internal consistency values were excellent (α = 0.97, ω = 0.97).

3.4. Hypotheses

Levels of material resources are related to levels of access to digital technologies that enable internet connections (Ragnedda, 2018; Ragnedda et al., 2022). Also, people with high levels of material and educational resources show greater autonomy of use, assessed as the variety of places from which a person can connect to the internet (Hassani, 2006; Peter & Valkenburg, 2006). Both digital technology and autonomy of use are part of the "digital resources" construct (Robinson, 2009). Accordingly, our first hypothesis is:

> H1. Material and educational resources have a significant and positive impact on internet users' digital resources.

High levels of technology at home facilitate the acquisition of high levels of digital skills by internet users (Robinson, 2009, 2012). Also, autonomy leads to higher levels of digital skills (van Deursen & van Dijk, 2015). However, general navigation skills cannot be applied to categories of advanced internet use (Arroyo, 2018). People need a specific set of skills for each one of these categories; however, generic digital skills can still help develop specific digital skills (van Deursen et al., 2017). Accordingly, we hypothesize that:

> H2. Internet users' digital resources have a significant and positive impact on their digital skills.

> H3. Internet users' digital resources have a significant and positive impact on their online job-seeking skills.

> H4. Internet users' digital skills have a significant and positive impact on their online job-seeking skills.

Likewise, we explored two possible mediational chains: (a) material and educational resources—digital resources—digital skills and (b) material and educational resources—digital resources—online job-seeking skills. This approach allows us to conceptualize *digital resources* as a kind of conduct through which the presumed positive impact of the material and educational resources can be transferred.

For online job-seeking results, job-seeking skills should help internet users give more visibility to their applications, thus helping them find a job (Karaoglu et al., 2021; Sharone, 2017). Hence:

> H5. Internet users' online job-seeking skills have a positive and significant relationship with the frequency with which they are offered job interviews.

Long-term job-seeking can generate psychological distress (Gedikli et al., 2022), even when using online job-related platforms (Bunjak et al., 2021). This relationship can be explained through the job resources and demands model (Bakker & Demerouti, 2007). We conceptualize job-seeking as an activity requiring a high number of ordered tasks, which are structured, coercive, and have specific goals. According to the job resources and demands model, job-seeking can be considered a demanding activity that requires the use of personal resources. High pressure in job-seeking and the emotional demands associated with unemployment both play a role in reducing personal resources and have an impact on job seekers' burnout. Specifically, the concept of burnout can be used to study emotional responses to work-like activities (Schaufeli & Taris, 2005), where job seekers with low resource levels can experience a dysfunctional response (like burnout). On the contrary, job seekers with more personal resources are less at risk, hence, a key resource for job seekers can be found in their digital skills.

Additionally, digital skills can help internet users avoid psychological distress related to internet use (De Battisti et al., 2016; Helsper & Smahel, 2020). Candidates' material and psychological resources, together with a high level of self-confidence, should help in reducing their psychological distress (Chen & Lim, 2012; Fernández-Valera et al., 2020). As such, we would expect online job-seeking digital skills to help internet users reduce the probability of suffering burnout related to the search process. Accordingly, our last hypothesis is:

> H6. Online job-seeking skills reduce the probability of suffering burnout in relation to job-seeking.

Figure 1 includes all the relationships between the constructs discussed above.

4. Results

4.1. Model Fit

As shown in Table 4, our data had a good fit with the proposed theoretical model (CFI = 0.974, TLI = 0.971, RMSEA = 0.053, SRMR = 0.060, parsimony ratio = 0.905). The only fit index that resulted below the acceptance criterion was SRMR, which was just at the limit. Regarding χ^2 (975.071, df = 294, p-value = 0.000), we ought to refuse model fit, but, as stated before, these results may be caused by the large sample size. In fact, the ratio between the χ^2 value and the degrees of freedom is acceptable (less than 5; see Jöreskog, 1969).

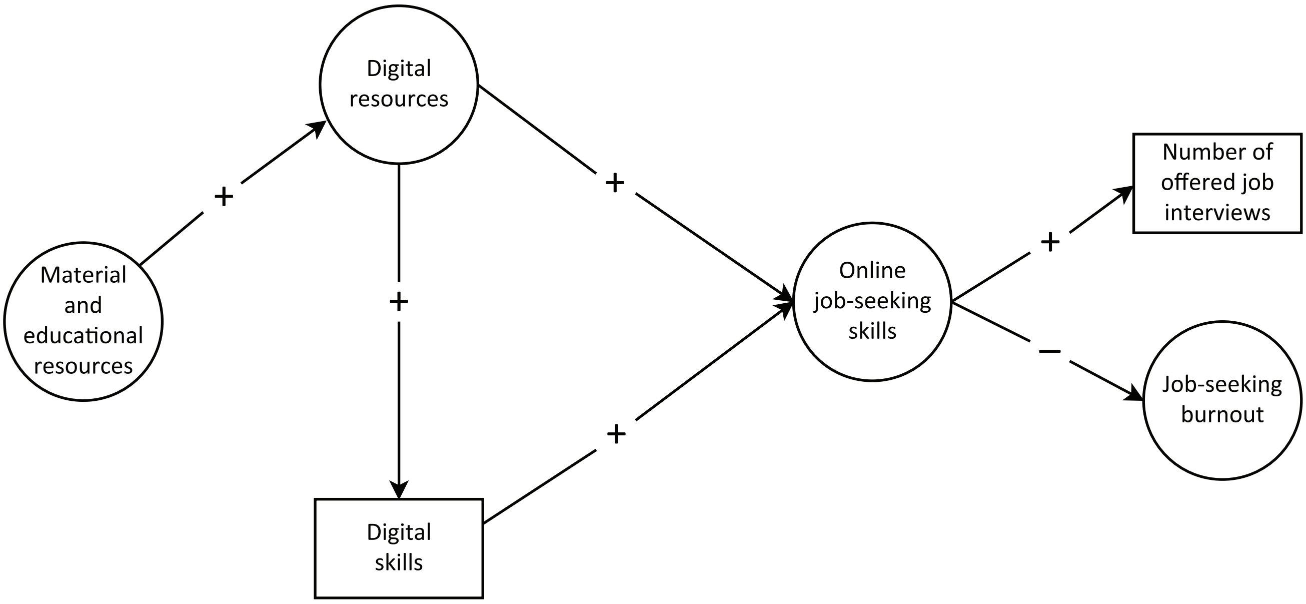

Figure 2. Proposed theoretical model. Circles represent latent variables, while rectangles represent observed variables.

Table 4. Model goodness-of-fit indices.

Model	*N*	χ^2	*df*	χ^2/df	χ^2 *p*-value
Proposed theoretical model	829	975.071	294	3.317	0.000
Alternative model	829	974.544	292	3.337	0.000
Model	CFI	TLI	RMSEA (a)	SRMR	Parsimony score (b)
Proposed theoretical model	0.974	0.971	0.053 (0.049, 0.057)	0.060	0.905
Alternative model	0.974	0.971	0.053 (0.049, 0.057)	0.060	0.898

Notes: (a) 90% CI in brackets; (b) parsimony score = model *df*/null model *df*.

4.2. Direct Effects

Figure 2 and Table 5 show that all relationships are significant and in line with our theoretical model. Material and educational resources positively impact digital resources (H1). Moreover, the higher the digital resources, the higher the digital (H2) and online job-seeking skills (H3). These job-seeking skills are also positively predicted by digital skills (H4), while, in turn, they predict a higher frequency of offered job interviews (H5) and a lower level of job-seeking burnout (H6).

4.3. Indirect Effects

Before examining indirect effects estimations, we must look at the alternative model. This model is almost identical to the proposed theoretical model but includes two new paths: (a) from *material and educational resources* to *digital skills* and (b) from *material and educational resources* to *online job-seeking skills*. Its fit is also acceptable (see Table 4), but the added paths are not significant (see Table 5). It seems then, that internet users' material and educational resources do not have a direct effect on their digital and online job-seeking skills. Nevertheless, considering a 95% confidence level, both the indirect effect of *material and educational resources* on *digital skills* (b = 1.755, SD = 0.377, β = 0.248, p-value = 0.000) and that of *material and educational resources* on *online job-seeking skills* (b = 0.157, SD = 0.061, β = 0.117, p-value = 0.010) are statistically significant. In other words, digital resources not only have a direct positive effect on digital and job-seeking skills, but they also represent a transfer mechanism that connects internet users' material and educational resources with the outcomes of online job-seeking and burnout.

5. Conclusions and Discussion

This article has examined how inequalities in digital skills shape the outcomes of online job-seeking processes. With this aim, we used Spanish data, as this country boasts a high percentage of internet access, along with a pronounced use of online platforms for job search and high unemployment rates, particularly among youth (Bolíbar et al., 2019; INE, 2022). In other words, many working-age individuals are actively seeking

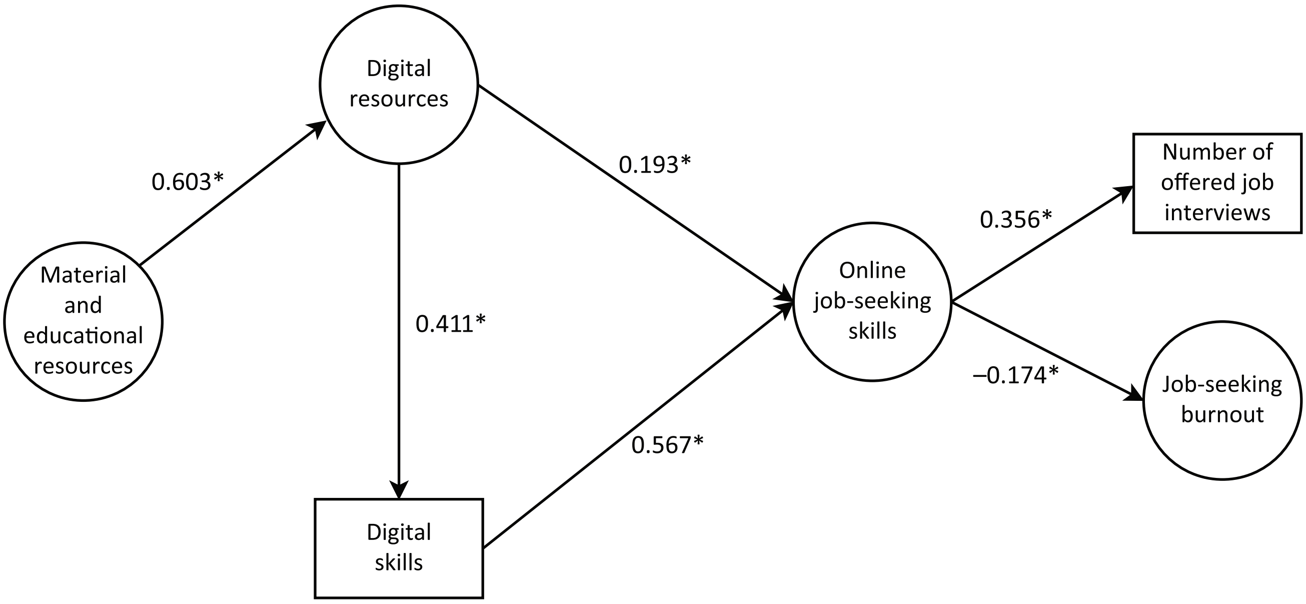

Figure 3. Proposed theoretical model results. Notes: * statistically significant standardized estimates (95% confidence level); circles represent latent variables, while rectangles represent observed variables; path values are standardized weights.

Table 5. Results for the proposed theoretical model and the alternative model.

	Proposed theoretical model				Alternative model			
Path	Estimate	*SD*	Standardized Estimate	*p*-value	Estimate	*SD*	Standardized Estimate	*p*-value
Material and educational resources → Digital resources	0.756*	0.223	0.603	0.001	0.758*	0.185	0.604	0.000
Material and educational resources → Digital skills	—	—	–	—	0.420	0.778	0.059	0.589
Digital resources → Digital skills	2.321*	0.369	0.411	0.000	2.012*	0.597	0.357	0.001
Material and educational resources → Online job-seeking skills	—	—	—	—	−0.063	0.107	−0.046	0.557
Digital resources → Online job-seeking skills	0.208*	0.066	0.193	0.002	0.254*	0.086	0.235	0.003
Digital skills → Online job-seeking skills	0.108*	0.009	0.567	0.000	0.109*	0.011	0.567	0.000
Online job-seeking skills → Number of offered job interviews	0.281*	0.025	0.356	0.000	0.279*	0.014	0.356	0.000
Online job-seeking skills → Job-seeking burnout	−0.131*	0.031	−0.174	0.000	−0.131*	0.006	−0.174	0.000

employment and utilizing the internet for this purpose, making Spain an ideal context for examining the impact of digital inequality on labour market access.

We first examined the relationship between material and digital resources and found that income and educational level significantly and positively impact digital resources. Higher levels of offline resources enable better internet access and autonomy. Secondly, we tested the relationship between digital resources and digital skills, conceived as both navigational and online job-seeking skills, and found that high levels of digital resources promote high levels of digital skills (Ragnedda, 2018; Ragnedda et al., 2022; Robinson, 2009, 2012). Hence digital resources enable the transfer of the positive benefits of existing materials, and educational resources are transferred. Furthermore, we found a qualitative difference between generalist navigation and specific skills and suggest that navigation skills are not a one-size-fits-all set of abilities because advanced internet use requires specific skills (Arroyo, 2018). Thirdly, we tested the relationship between online job-seeking skills, the frequency with which candidates are offered a job interview, and their psychological distress during this process. According to our model's predictions, we found that online job-seeking skills have a positive relationship with the frequency of job interview invitations received and a negative relationship with psychological distress. Online job-seeking skills also help reduce the burnout related to online job-seeking above and beyond search outcomes, and positively impact the likelihood of being contacted for an interview. Thus, independently of internet users' psychological resources, online job-seeking skills reduce the psychological distress related to online job searching.

These findings advance social inclusion research in an area that remains relatively unexplored despite its current importance. Specifically, this relates to research into digital exclusion that has yet to examine how persisting digital inequalities shape access to work and employment, with particular reference to platform-mediated job-seeking. Building on these findings, we argue that the unequal distribution of digital skills across specific segments of the population strongly shapes the development of online job-seeking skills. Because these online job-seeking skills are critical in searching for and securing work in the current platform-mediated employment landscape, their unequal distribution contributes to enforcing the digital exclusion of the most vulnerable in an additional yet critical domain, namely, work and employment.

Our findings also have implications for both public and private employment services and job seekers. Since job seekers with higher levels of digital skills are more likely to get a job online, prospective employers face a risk of loss of human capital. Indeed, candidates with high levels of competencies, but little ability to make their online applications visible, are more likely to be discarded. Therefore, it would be advisable for human resources services, as well as temporary employment agencies and employment offices, to provide users with a training plan for online job-searching. Secondly, our findings provide important insights into designing inclusive labour market policies for the most vulnerable groups. They outline the critical need to implement active policies that aim to facilitate the development of online job-seeking skills across all population segments. Achieving this goal would help in supporting labour market integration and prevent public health problems related to burnout and psychological distress.

As digital resources are not equally distributed among the population, the internet has become a vector of inequality. In fact, the most advanced internet uses, as well as the tangible benefits that arise from them, are concentrated among those segments of the population with the greatest levels of material and digital resources. As in the case of reading and writing skills in 20th-century societies, digital skills should be a universal objective in education. They should be taught as mandatory in schools since they shape the outcomes of public and social life today. This study also demonstrates the need to learn not only generic navigation skills but also those that specifically convert beneficial internet uses into tangible benefits. Consequently, it is important to address this issue by bringing to the fore the need to act against digital illiteracy.

5.1. Limitations

Firstly, our sample has some limitations when it comes to representation, because we decided not to include people with lower levels of education. The reason lies in empirical evidence, which shows that people with lower levels of education usually use "real world" contacts to find a job. While this choice may bias the results, as we don't consider the impact of digital literacy on psychological distress in all population groups, we believe that our findings are still highly relevant to this area of research. Secondly, due to the design and aims of this study, our survey did not include information about offline job-seeking. Whilst this limits the possibility of comparing offline and online processes, it also raises a stimulating path for future research in this direction. Furthermore, while 30 out of 1000 subjects reported receiving an invitation for a job interview daily, we do not have information about the number of applications that each subject submitted. However, we found that 16% of the sample (N = 159) was sending at least one application every day. This makes it less improbable that 30 subjects would be contacted for an interview with this frequency, though this may also very well depend on qualification levels and sectors. The design of data collection for future research in this area may benefit from the inclusion of indicators pertaining to the number of applications submitted per day. Finally, the exclusive use of Spanish data may be a limitation in terms of the generalisability of our results. Therefore, we believe that further research should be carried out in countries other than Spain.

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Conflict of Interests

The authors declare no conflict of interests.

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