“Impact of digitalization on the attractiveness of employee recruitment and retention in Moroccan companies”

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IMPACT OF DIGITALIZATION ON THE ATTRACTIVENESS OF EMPLOYEE RECRUITMENT AND RETENTION IN MOROCCAN COMPANIES

Abstract

The relevant evolution of social networks and the expansion of digitalization has led to significant changes in the classical processes used by Moroccan companies in different fields such as marketing, human resources management, etc.

This paper investigates the effects of digitalization on the attractiveness of Moroccan companies in terms of recruitment and safeguarding these constructs by using structural equation models according to the PLS approach. The study was carried out to touch 74 companies in different sectors.

The study showed positive relationships between management support, digitalization, and recruitment performance (defined as the attractiveness of a company for recruitment and federalization of employees). The results show that the T-statistics are equal to 67.55, 6.862, and 5.941, respectively. The Q^2 value is 0.884 for scanning and 0.937 for performance, which means that the model is predictive in nature. The GoF is 1.388, which means that model is sufficiently large for the overall validity of the PLS model.

While jobseeker behavior and competitive intensity did not affect recruitment performance because the test T-statistics is less than 1.64, the two factors have no moderating effect as the p-values are 0.228 and 0.082, respectively, exceeding the threshold of 0.05.

Keywords e-recruitment, SEM-PLS, jobseekers, measurement models, structural models, organizational attractiveness, recruitment process

JEL Classification C51, L25, M15

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INTRODUCTION

The Covid-19 crisis has accelerated the process of digitalization at the level of the various public and private establishments. In fact, it has been observed that there has been an increase in digital commerce, remote service provision, remote recruitment, etc. In addition, digitalization has made it possible to overcome the constraints of the crisis of Covid-19 while maintaining vital activities such as education and health.

For companies, digitalization has become part of daily practice in recent years due to technological developments and the generalization of internet access. Different areas have benefited from this advantage, such as marketing and human resources. However, the crisis has allowed the digitalization process to reach maturity, notably through the introduction of e-work, e-training, and e-services (e.g., e-health).

This shift in traditional processes due to technological innovation is leading to significant changes in the behavior of consumers and

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jobseekers. Indeed, there is a migration toward the use of technology for communication, exchange, payment, etc.

The digitalization of human resources management was one of the priorities for Moroccan companies during the health crisis. Indeed, the implementation of e-work and e-recruitment has enabled companies to maintain their activity and meet their needs in the labor market.

This paper comprises section one dealing with the literature review, section two is reserved for the methodology, section three is devoted to the results, section four presents the discussion, and the paper ends with conclusions.

1. LITERATURE REVIEW AND HYPOTHESES

The study of the impact of certain factors on the performance of a given activity has been the subject of various studies that have used different techniques such as the Chi-square test of independence, structural equations, etc. The following literature review presents the use of structural equation models in management science and the study on the impact of digitalization on various activities.

1.1. Structural equation models

The primary hypothesis of this paper is to test the positive direct relationship between digitization and recruitment performance. Thus, it considers digitization as a mediating and intermediate variable between management support and recruitment performance. It also examines the possible moderating role of the use of digitalization by job seekers and competitive intensity on recruitment performance.

Structural equation modeling assesses causal links between several variables, including moderators and mediators. It allows the simultaneous analysis of assumed linear effects linking several latent independent and dependent variables; the analysis of joint effects on several dependent variables; and testing of construct validity, reliability, and internal validity of instruments such as attitude scales. Bagozzi (1980) presents a theoretical approach to the construction and validation of these models.

The estimation of the parameters of the model is done, in general, by two methods:

- The LISREL method (Linear Structural Relationships), which is based on the analysis of the covariance structure and uses the maximum likelihood approach; it requires the multi-normality of the data; and

- The PLS method (Partial Least Square), which is based on analysis of variance based on the analysis of the variance and uses the partial least squares. Indeed, the introduction of Non-linear iterative partial least squares in the social sciences has been discussed by Wold (1973), while the in-depth theoretical development was done by Wold (1980a, 1980b). For this method, other alternatives have been proposed by Derquenne and Hallais (2004).

Various researchers have studied the PLS and LISREL methods. Indeed, Jöreskog and Wold (1982) evaluated the contributions to systemic risk in the context of US prime institutional money market funds (MMFs) from different sources. They used partial least squares (PLS) for structural equation modeling, in particular, the need to move from simply estimating the model parameters to including measures of predictive relevance. Furthermore, Haenlein and Kaplan (2004) have proposed a guide for beginners in structural equation modeling. The comparison of these two methods was made by Lacroux (2010), who showed that the PLS method works even in the absence of the normality of the variables and in the case of small sample sizes, unlike the LISREL method.

This study uses the PLS method. The choice of the PLS method is dictated by the constraints of conducting the survey. Indeed, according to Chin and Newsted (1999), it can be used even if the sample size is small and even in the absence of normality.

1.2. Choice of items

The choice of items for structural equation modeling depends on the problem to be studied. This study uses items from the literature:

- Digitalization (E-recruitment): A new process in recruitment that recruits candidates to fill vacancies in companies through the Internet. The definition of e-recruitment has been given by Lievens and Harris (2003), Germann et al. (2013), and Sheikh et al. (2018).

- Recruitment performance: Three dimensions are taken, namely efficiency, effectiveness, and adaptability. The objective is to guarantee company's attractiveness and employees' loyalty. Some studies consider that recruitment performance can go through employee loyalty. As such, they must be treated as customers to encourage them to participate in attracting great talents, following Gardner et al. (2011). In marketing, this item is used by Chavey (2010), Trainor et al. (2011), and Morgan (2012).

- Management support: It is a positive or proactive attitude in which management supports the process of recruiting talented applicants by allocating the necessary resources and means. Several researchers have studied the use of this item in marketing, such as Germann et al. (2013) and Sheikh et al. (2018).

- Jobseekers' behavior towards digitalization: It is the impact of the digital environment on the adoption and use of digitalization by jobseekers. Several researchers have studied the use of e-recruitment (digitalization) by jobseekers, such as Galanaki (2002), Khan (2010), and Ekanayaka and Gamage (2019). In marketing, this item is used by Kannan and Hongshuang (2017).

- Competitive intensity: It is the impact level that competitors have on the company that could be modified by adopting new information systems. Several researchers have studied the use of competitive intensity, such as Zhou et al. (2020) and Giantari et al. (2022). In marketing, this item is used by Zhu et al. (2006).

1.3. Impact of digitalization

In literature, research has shown that new technologies generate value and improve performance at the level of organizations (Deltour & Lethiais, 2014; Chae et al., 2014). In addition, a new technology-performance relationship is impacted by other factors such as the level of complementary resources and management support (Sheikh et al., 2018).

In marketing, this relationship has been studied by Kannan and Hongshuang (2017). They proved the positive impact of new technologies, in general, and digitalization and the internet, in particular, on changing customer behavior through digital channels.

The positive relationship between digitalization and marketing performance is demonstrated by Trainor et al. (2011). They examined the integration of information technology with marketing capabilities and other resources at the enterprise level and their performance implications. Moreover, Olomu and Irefin (2016) examined the relationship between increased sales and e-marketing performance.

From human resources management perspective, various studies have dealt with the contribution of new technologies, digitalization, the Internet, and social networks to attracting good talents. For example, Faliagka et al. (2011) showed that jobseekers increasingly use Web 2.0, such as LinkedIn and job search sites. Furthermore, Rafiq et al. (2013) found that companies have adopted the online environment following the increasing use of the Internet. Finally, Sylva and Mol (2009) showed that companies use commercial recruitment sites to find qualified people to conduct their online recruitment process.

According to Fong et al. (2011), digitalization is defined as a hiring process that uses various electronic tools and technologies to recognize, attract, and select potential employees. The use of e-recruitment by companies is explained by Thielsch and Hirschfeld (2012), who consider that the observed change is due to two reasons. First, it is considered the most effective means of

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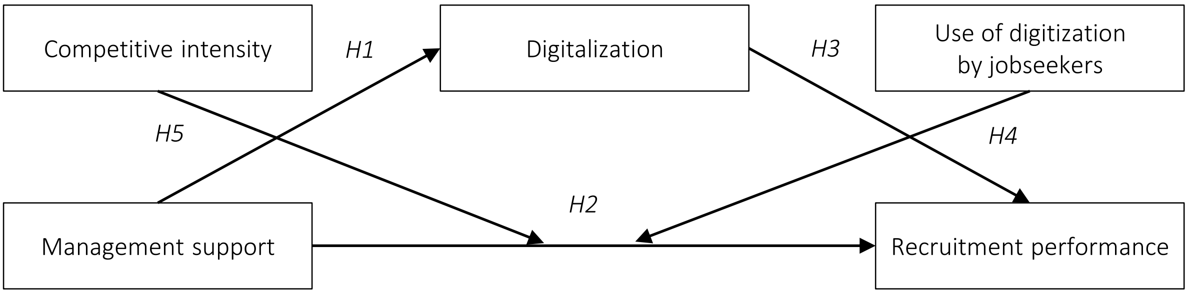

Figure 1. Research framework

reaching the target group of candidates. Second, it is preferred because of its cost-savings benefits and dealing with competitive pressure in the market.

Research shows that e-recruitment sites play a crucial role in determining whether companies attract qualified candidates. Indeed, Fong et al. (2011) deduced that the advancement of technology in the recruitment industry represents a strategic advantage in the marketplace. The impact of technology on recruitment efficiency has been studied by Kamalasaravanan (2019), who found the positive effect of technology on the recruitment process.

This paper uses a structural equation model to estimate the impact of digitalization (e-recruitment) on recruitment performance. Indeed, according to Davcik (2014), digitalization is considered a mediating variable, and researchers in management increasingly use this model. For human resources, several studies have used structural equation models, such as Bhanugopan et al. (2013), Piening et al. (2013), and Juera (2020).

In the case of Morocco, the use of media in human resources practices has been studied by Boudi and Qachar (2018). El Ouizgani (2020) conducted a qualitative study on the effect of e-recruitment among recruitment firms. Therefore, this study differs from the previous study on human resource management by using modeling to determine the impact of digitalization on recruitment performance and by using a sample of companies and jobseekers.

The objective of this study is to determine the impact of digitalization on recruitment performance. Therefore, this study formulates the following hypotheses:

H_1: *Management support has a positive relationship with the use of the Internet in recruitment.*

H_2: *Management support has a positive relationship with recruitment performance.*

H_3: *Internet use in recruitment has a positive relationship with recruitment performance.*

H_4: *The use of information and communication technology (ICT) by jobseekers moderates the relationship between internet use in recruitment and recruitment performance.*

H_5: *The pressure of competitive intensity moderates the relationship between management support and the use of the Internet in recruitment.*

The framework of this study is presented in Figure 1.

2. METHODOLOGY

The structural equation model uses two types of variables, namely observed and latent variables. The relationship between the latent variables and the observed variables on the one hand and the latent variables between them, on the other hand, is determined respectively by two types of models, namely:

- Measurement model (outer) is a sub-part of the full model, including the relationships between observed and latent variables.

- Structural model (inner) is a subpart of the full model, including the relationships between the latent variables.

The measurement (outer) models can be formative or reflective models. The distinction between the two depends on the pattern linking the latent variable and the observed variable. For this reflective model, which is the most common in research, each observed variable is related to its latent variable by simple regression.

Let be A_k, $k = 1, \ldots l$ is a latent variable and p_k is a number of observed variables associated with A_k and X_{ik}, $i = 1, \ldots p$ the observed variable associated with A_k.

The relationships of the outer model are said to be reflective if, for each latent variable A_k, the relationship between this variable and each observed variable X_{ik} associated with it is written:

$$X_{i_k} = \beta_{i_k} A_k + \varepsilon_{i_k}, \tag{1}$$

where β_{ik} is a loading associated with X_{kj} and ε_{ik} is an error term; $\mathrm{Cov}(\varepsilon_{ik}, A_k) = 0$, $\forall\ k = 1, 0, \ldots l$ and $\forall\ i = 2, 1, \ldots$ p; $\mathrm{Cov}(\varepsilon_{ij}, \varepsilon_{ml}) = 0$, $\forall\ i, j, m, l, (i, j) \neq (m, l)$.

The values taken by the observed variables are "consequences" of the latent variable. The causal relationship runs from the latent variable to the observed variables.

For the formative model, it is assumed that each latent variable is a linear combination of its corresponding manifest variables. Indeed, each latent variable A_k is related to the set of manifest variables associated with it:

$$A_k = \sum_{i=1}^{p} \beta_{ki} X_{ki} + \varepsilon_k, \tag{2}$$

with β_{ki} is a weight of X_{ki} and et ε_k is an error term; $\mathrm{Cov}(X_{ki}\varepsilon_k) = 0$, $\forall\ i = 2, 1, \ldots p$.

The structural model (inner): is defined by linear equations linking the latent variables. For any endogenous A_k, the model is written:

$$A_k = \sum_{i=1}^{p} \beta_{ki} A_i + \tau_k, \tag{3}$$

where p is a number of A_i exogenous in relation to A_k; $\mathrm{Cov}(\tau_k, A_i) = 0$, $\forall\ i \neq k$; $\mathrm{Cov}(\tau_k, \varepsilon_{kj}) = 0$, $\forall\ k = 1, 0, \ldots K$ and $\forall\ i = 2, 1, \ldots p_k$; β_{ki} is the structural coefficient associated with the relationship between the variables A_k and A_i; τ_k is an error term associated with the endogenous latent variable A_k.

The estimation of the latent variables A_k can be done by the internal model or the external model. Indeed, A_k can be estimated either from the inner model or from the outer model.

The estimate from the outer model noted A_k^* of the standardized latent variables is equal to the linear combination of their centered observed variables:

$$A_k^* \propto \mp X_k w_k = \sum_{i=1}^{p} X_{ki} w_{ki}, \tag{4}$$

where $\propto$ signifies that the left-hand term is equal to the standardized right-hand term; $\pm$ shows the ambiguity of the sign. The sign is chosen so that A_k^* is positively correlated with as many columns of X_k as possible. w_k are called outer weights.

The inner model estimate of A_k^{**} is defined by

$$A_k^{**} \propto \sum_i h_{ki} l_{ki} A_i^*, \tag{5}$$

where $H = (h_{ki})$ is a matrix of 0 and 1 such that $h_{ki} = 1$ if $A_i \to A_k$ or $A_k \to A_i$; $L = (l_{ki})$ is the matrix of inner weights defined by three methods detailed in Appendix A, the Centroid method, the Factorial method and the Structural method.

The update of the outer weights w_{ki} is done by two methods defined in Appendix A, namely: Mode A and Mode B. Wold (1982) associated mode A with the reflective model and mode B with the formative model. This formalization is the most widespread in practice but has no robust mathematical basis. In reality, modes are associated with the subject of the study. Thus, the choice of mode may be motivated by different factors:

- if the study wants to give more weight to the outer model, mode A should be used;
- if the study wants to give more weight to the inner model, mode B should be used;
- if the number of observed variables per block is high, mode A should be used.

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The average extracted variance (AVE) can be used as a convergent and divergent validity test. The AVE measures the average commonality of each latent variable in a reflection model.

Chin (1998) and Höck and Ringle (2006) show that the measurement model is adequate if the AVE is greater than 0.5. According to Fornell and Larcker (1981), AVE of less than 0.50 means that the explained variance is less than the error variance.

The validity of the measurement model is made in two steps:

- The first step concerns discriminant validity, which is measured using the criterion of Fornell and Larcker (1981). It indicates that the construct must share more variance with its indicators than with any other construct (Hair et al., 2014).
- The second part of validity refers to the degree of differentiation of one construct from another by examining their potential overlap or cross-loading.

To evaluate structural models, one must measure the hypothetical relationships in the structural model. Therefore, the direct effect must be determined via the criteria of Hair et al. (2014), the indirect effect, including mediation (bootstrapping resampling method), and moderating variable moderation.

The evaluation criteria used in this study are those defined by Hair et al. (2014).

The Trajectory coefficients represent the hypothetical relationships between the constructs. The significance of this relationship depends on the p-value, which must be less than 5%, in accord with Henseler et al. (2014). To judge the importance of the relationship, this study uses the statistical value that must be, according to the recommendations of Hair et al. (2014), greater than 1.64 for a significant relationship.

Multiple R^2 measures the predictive behavior of the model. Indeed, if R^2 is greater than 10%, the model is significant. If R^2 is 5%, 10%, the model is tangent, and if R^2 is less than 0.05, the model is not significant.

Effect size (F_k^2) is the quality of the structural model (internal model) evaluated with the statistic F_k^2 called redundancy, which measures the quality of the structural model for each endogenous block k taking into account the measurement model. It is defined in Appendix A. It starts from the same idea as communality, but the latent variable is replaced by its estimation from neighboring latent variables. The effect size of the omitted construct for a particular endogenous construct can be determined such that 0.02, 0.15, and 0.35 represent small, medium, and large (significant) effects, respectively.

The Stone-Geisser Q^2 coefficient (cross-validation redundancy index), defined in Appendix A, is the test of cross-validation between the manifest variables of an endogenous latent variable and the set of manifest variables of the latent variables explaining said endogenous latent variable using the estimated structural model.

The quality of the measurement model for each block is measured by communality. The quality of each structural equation is calculated according to the Q^2 Stone-Geisser index. Significance levels can be calculated using Student's t-test or methods such as bootstrap or jackknife.

The quality of the measurement model (external model) is evaluated by the statistic H^2 called communality defined in Appendix A. H^2 represents the proportion of the variance of the manifest variables explained by their associated latent variable.

The GoF Fit Index (Goodness-of-fit) is a global validation index. It is equal to the geometric mean of both the AVE and the mean of R^2 of the endogenous variables. Therefore, this index must be greater than 0.25. Indeed, it is considered medium if it is higher than 0.25, and very large if it is higher than 0.36, according to the classification of Wetzels et al. (2009).

The measurement items are defined in Table 1; they are borrowed from the literature review mentioned in Table 1 and operationalized through seven-point Likert scales.

Table 1. Item definitions

Constructs	Items
Digitalization (E- REC) items used in marketing adapted to human resources. Sheikh et al. (2018)	E-R1: Your company uses internet resources (site, web, email, social networks...) to attract candidates. E-R2: Your company uses digitalization resources as a communication medium on potential income (salary grid, benefits, working conditions, skills management). E-R3: Your company uses internet resources (social networks, job boards, company website) to receive feedback from candidates. E-R4: Your company uses internet resources to facilitate recruitment. E-R5: Your company has the infrastructure and skills to implement digitalization (server for data storage, an IT team, outsourcing). E-R6: Your company allocates a budget for the development of digitalization.
Recruitment performance (PERFO) items used in marketing adapted to human resources. Chavey (2010), Morgan (2012), and Trainor et al. (2011)	PR1: The Internet has a significant effect on the quality of the recruitment action. PR2: The Internet makes it possible to attract the best profiles and to succeed in the recruitment action. PR3: The Internet has a positive effect on employee loyalty.
Management support (SUPDIR) items used in marketing adapted to human resources. Germann et al. (2013) and Sheikh et al. (2018)	S1: Your top management has a favorable attitude toward using the Internet in the recruitment process. S2: Your top management is aware of the benefits of using ICT in recruitment. S3: Your top management sees internet channels as levers for attracting the right talent. S4: Your top management encourages the use of the Internet in the recruitment process.
The behavior of job seekers concerning digitalization (COMDEM) items used in marketing adapted to human resources. Kannan and Hongshuang (2017)	CD1: Candidates use the Internet intensely. CD2: Candidates prefer to contact you via the Internet. CD3: Potential recruits learn and interact with your company through internet channels.
Competitive intensity (INTCON) items used in marketing adapted to human resources. Zhou et al. (2020), Giantari et al. (2022), and Zhu et al. (2006)	CI1: The use of the Internet in recruitment by your sector is very intense. IC2: The Internet is used intensely in recruitment and by your competitors. IC3: Using the Internet is a competitive advantage for recruiting the right talents.

3. RESULTS

The empirical study was carried out on a sample of 74 companies distributed in several sectors. Indeed, 2.9% are telecommunications companies, 7.1% are banks, 14.3% are training establishments, 5.7% operate in the insurance sector, 14.3% in the industry, 28.6% in services, 17.1% from the tourism sector, and 15.7% in various other sectors.

The data analysis by the smartPLS software made it possible to determine the measurement models. Therefore, the measurement models, factor loadings, and coefficient values are represented in Figure 2.

The measurement model equations for each latent variable are as follows:

- Digitalization (*E-REC*)

$$\begin{cases} E-R1 = 0.911 \cdot E-REC + \varepsilon_{11} \\ E-R2 = 0.925 \cdot E-REC + \varepsilon_{12} \\ E-R3 = 0.899 \cdot E-REC + \varepsilon_{13} \\ E-R4 = 0.930 \cdot E-REC + \varepsilon_{14} \\ E-R5 = 0.863 \cdot E-REC + \varepsilon_{15} \\ E-R6 = 0.840 \cdot E-REC + \varepsilon_{16} \end{cases}; \tag{6}$$

- Recruitment performance (*PERFO*)

$$\begin{cases} PR1 = 0.922 \cdot PERFO + \varepsilon_{21} \\ PR2 = 0.952 \cdot PERFO + \varepsilon_{22} \\ PR2 = 0.907 \cdot PERFO + \varepsilon_{23} \end{cases}; \tag{7}$$

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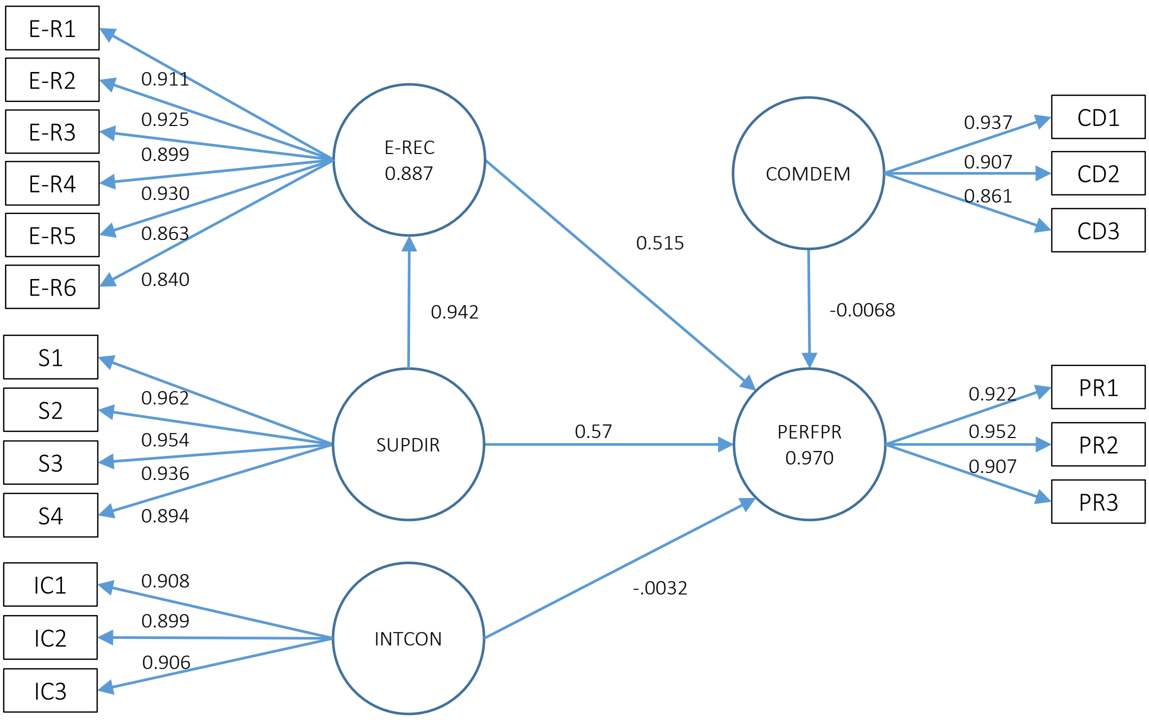

Figure 2. Measurement models, factor loadings, and coefficient values

- Management support (*SUPDIR*)

$$\begin{cases} S1 = 0.928 \cdot SUPDIR + \varepsilon_{31} \\ S2 = 0.933 \cdot SUPDIR + \varepsilon_{32} \\ S3 = 0.956 \cdot SUPDIR + \varepsilon_{33} \\ S4 = 0.871 \cdot SUPDIR + \varepsilon_{34} \end{cases}; \quad (8)$$

- The behavior of jobseekers concerning digitalization (*COMDEM*):

$$\begin{cases} CD1 = 0.938 \cdot COMDEM + \varepsilon_{41} \\ CD2 = 0.907 \cdot COMDEM + \varepsilon_{42} \\ CD3 = 0.860 \cdot COMDEM + \varepsilon_{43} \end{cases}; \quad (9)$$

- Competitive intensity (*INTCON*):

$$\begin{cases} IC1 = 0.908 \cdot INTCON + \varepsilon_{51} \\ IC2 = 0.899 \cdot INTCON + \varepsilon_{52} \\ IC3 = 0.906 \cdot INTCON + \varepsilon_{53} \end{cases}. \quad (10)$$

The validity of the measurement models is made by three elements, which are Cronbach's Alpha, Composite Reliability, and Average Variance Extracted. Indeed, for digitalization, the Cronbach's Alpha is 0.950, the Composite Reliability (CR) is 0.960, and the Average Variance Extracted (AVE) is 0.802. For recruitment performance, the Cronbach's Alpha is 0.918, the Composite Reliability (CR) is 0.948, and the Average Variance Extracted (AVE) is 0.959. For management support, the Cronbach's Alpha is 0.953, the Composite Reliability (CR) is 0.966, and the Average Variance Extracted (AVE) is 0.878. For behavior of jobseekers concerning digitalization, the Cronbach's Alpha is 0.937, the Composite Reliability (CR) is 0.907, and the Average Variance Extracted (AVE) is 0.861. Finally, for competitive intensity, the Cronbach Alpha is 0.889, the Reliability of the composite (CR) is 0.931, and the average variance extracted (AVE) is 0.818.

The convergent validity (reliability of the composite) is greater than the threshold value of 0.7, which signifies the reliability of the items. The discriminant validity (AVE) is between 0.802 and 0.878 for all the constructs, which means that they fulfill the statistical condition, which is to be greater than 0.5. Therefore, the measurement scales are valid. The calculation of R^2 of endogenous latent variables shows that the digitalization variable is explained by 88.7% of the management support variable. Next, the recruitment performance variable is explained by 97% of the digitalization variable.

Table 2. Fornell and Larcker criterion

Variable	*COMDEM*	*E-REC*	*INTENCONCU*	*PERFO*	*SUPDIR*
COMDEM	0.902	–	–	–	–
E-REC	0.696	0.895	–	–	–
INTENCONCU	0.888	0.810	0.904	–	–
PERFO	0.633	0.806	0.775	0.927	–
SUPDIR	0.667	0.802	0.809	0.907	0.937

The discriminant validity of all the constructs is verified by the Fornell and Larcker criterion. The results are shown in Table 2.

The criterion of Fornell and Larcker (1981) confirms the discriminant validity of all the constructs making up the model because the average extracted variance (AVE) of the three constructs is greater than the square of the correlations of these constructs with the other latent variables of the model.

Table B1 in Appendix B confirms the discriminant validity of latent variables, as they do not overlap and share more variance with their indicators than other latent variables.

The structural equations between the latent variables are defined as follows:

$$\begin{cases} E-REC = 0.942 \cdot SUPDIR + \tau_k \\ PERFO = 0.557 \cdot SUPDIR + 0.515 \cdot E- \\ -REC - 0.068 \cdot COMDEM - \\ -0.032 \cdot INTENCONCU + \tau_2 \end{cases} \quad (11)$$

To evaluate the structural models, the following paragraph presents the empirical results of the direct effect and the tests of the hypotheses. To evaluate the trajectory coefficients (β_i), the values of the T-statistics, and the regressions coefficient of the 74 responses, it is necessary to perform 5,000 iterations (Hair et al., 2014). This study contains three hypotheses based on the direct link of the relationships. Figure 3 presents the direct relationships from the bootstrap.

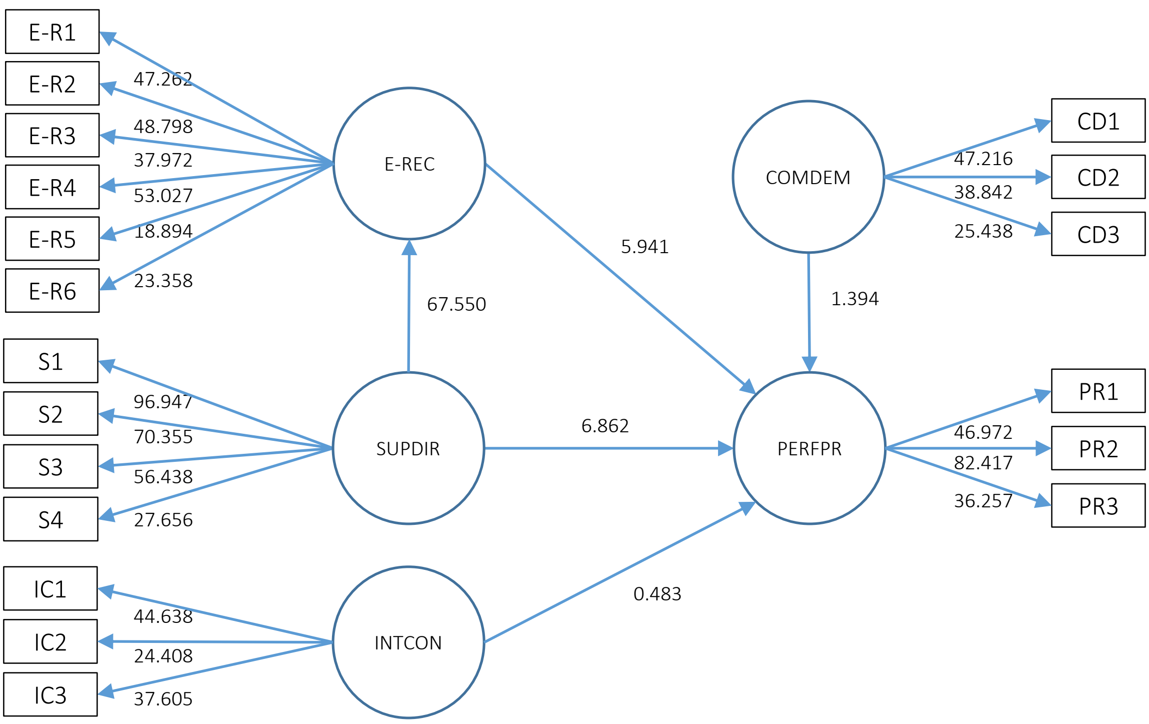

Figure 3. Direct relationships from the bootstrap

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Table 3. Determining BETAs and test results

Relationships	BETA	Standard deviation	*T* Value	*p*-values
H_1: SUPDIR → E-REC	0.942	0.014	67.925	0.000
H_2: SUPDIR → PERFO	0.557	0.081	6.886	0.000
H_3: E-REC → PERFO	0.515	0.086	5.990	0.000
H_4: COMDEM → PERFO	–0.068	0.049	1.385	0.166
H_5:INTENCONCU → PERFO	–0.032	0.064	0.493	0.622

The analysis of the tests based on the T-statistics shows that the relationships defined by the hypotheses H_1, H_2, and H_3 are significant, and the hypotheses are confirmed. T-statistics equal respectively to 67.55, 6.862, and 5.941 are higher than 1.64, with a strong significance in the relationship between management support and digitalization. It means that management support has a positive relationship with digitalization and recruitment performance. Moreover, digitalization has a positive relationship with recruitment performance.

On the other hand, the hypotheses H_4 and H_5 are not confirmed because the test T-statistics is less than 1.64.

The results of the statistical tests based on the T-statistics are shown in Table 3.

For the coefficient R^2 of the endogenous random variables, the values of the two dependent constructs, presented in Table 4, are greater than 0.67, which, according to Chin (1998), is a significant result.

Table 4. R^2-values

Quality criteria	R^2	Result
E-REC	0.887	The model is significant
PERFO	0.970	The model is significant

The values of F_k^2 presented in Table B2 of Appendix B show that each exogenous variable explains the endogenous variable. However, the size effects vary because digitalization and management support variables have a significant effect, while the behavior of jobseekers and the intensity of competition has a small effect.

The Q^2 value was greater than zero, i.e., 0.884 for digitalization and 0.937 for performance, which means the model is predictive in nature.

Table B3 in Appendix B calculates the GoF (Goodness-of-fit) fit index. Indeed, the GoF value is equal to 1.388, which means that model is large enough for the overall validity of the PLS model (Wetzels et al., 2009).

The situation in which a variable absorbs to some extent the effect of an exogenous variable (management support) on an endogenous construct (recruitment performance) represents mediation. The variable in question is called the mediating variable. The measurement of the median role of a variable by the PLS approach is made by the bootstrapping resampling method. To consider that there is a median effect of a variable, Preacher and Hayes (2008) provide two conditions:

- The relationship between management support and recruitment performance must be significant (p-value < 0.05) based on the Bootstrap indirect effect (total effect).
- The lower leverage and the upper leverage should not cross 0 based on the bootstrap confidence interval.

For the Bootstrap indirect effect (total effect), there must be an indirect relationship between management support and recruitment performance that includes digitalization to be significant, which represents the specific indirect effect, and that the three relationships between the latent variables are significant, which represents the total effect.

For the specific indirect effects, the indirect relationship between management support and recruitment performance is significant because the *p*-value tends towards 0 ($P = 0.000$), which is equivalent to a very high statistic (5.845). The results are summarized in Table 5.

Table 5. Specific indirect effects

Specific indirect effects	Beta	Standard deviation	*T* Value	*p*-values
SUPDIR → E-REC → PERFO	0.485	0.083	5.845	0.000

The total effects are significant for the 3 relationships with $p < 0.01$. The values of the betas, the *T*-statistics, and the p-values are presented in Table B4 of Appendix B.

The second condition of Preacher and Hayes (2008) is fulfilled. Indeed, the lower leverage is equal to 0.334, and the upper leverage is equal to 0.660, as presented in Table B5 of Appendix B, and does not cross the 0. As a result, this result affirms that digitalization plays a significant median role (Value = 5.845) between management support and recruitment performance.

Borau et al. (2015) define the moderating role as the existence of one or more variables that modulate the influence of a variable *X* on a variable *Y* by impacting the nature, direction, and/or strength of this influence which would vary depending on the values of the moderating variable.

The analysis of the moderating effect of the variable behavior of jobseekers concerning digitalization (*COMDEM*) on the influence of the variable digitalization (*E-REC*) on the dependent variable recruitment performance (*PERFO*) rejected the existence of a moderation effect because the p-value equal to 0.228 is greater than 0.05. Hypothesis *H4* is rejected. Table 6 presents the results of the analysis of the moderating effect.

The analysis of the moderating effect of the competitive intensity variable (*CONC*) on the influence of the digitalization variable (*E-REC*) on the dependent variable recruitment performance (*PERFO*) rejected the existence of a moderation effect because the p-value is greater than 0.082 to 0.05. The hypothesis *H5* is rejected. Table 7 presents the results of the analysis of the moderating effect.

4. DISCUSSION

In this study, digitalization was found to be a factor influencing the success of the recruitment process and the attraction of good talent. Indeed, T-statistics showed the existence of this relationship with T-statistic values (67.55, 6.862, and 5.941) higher than the critical value (1.64).

This result is in line with previous research that has addressed e-recruitment, including Fong et al. (2011), Sylva and Mol (2009), and Kamalasaravanan (2019). However, in the absence of a study on the impact of digitalization on recruitment performance in Morocco, this study becomes the first in this field.

Assessing the moderating role of jobseekers' behavior, this study did not conclude the existence of such an effect, as the *p*-value (0.228) is above the critical value (0.05). As studies such as Faliagka et al. (2011) have confirmed this moderation relationship, this result needs to be confirmed by a more specific study dedicated to jobseekers only.

Regarding the intensity of competition, this study rejects the existence of direct and moderation effects with a p-value of (0.082) above the critical value (0.05). However, this result needs to be confirmed by other studies as the digital performance of firms can generate a competitive advantage. Davcik (2014) and Piening et al. (2013) have confirmed the moderating role of digitalization on organizational performance.

This study can be enriched by studying other internal factors that may be determinants of performance, such as recruitment knowledge management and the human resources information system, as well as external factors such as recruitment agencies.

Table 6. Moderating effect of the behavior of jobseekers

Moderating Effect	Beta	Standard deviation	*T* Value	*p*-values
Moderating Effect1 → *PERFO*	0.026	0.019	1.206	0.228

Table 7. Moderating effect of competitive intensity

Moderating Effect	Beta	Standard deviation	*T* Value	*p*-values
Moderating Effect1 → *PERFO*	0.039	0.022	1.739	0.082

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CONCLUSION

This study aims to determine the impact of changes in management processes due to technological change, particularly the digitalization of treatment and communication. Indeed, in recent years Morocco has seen radical changes in the behavior of individuals, enterprises and the administration, which are taking a positive stance towards digitalization and communication at a distance.

The results of this study confirm the positive effect of digitalization on recruitment management and employee retention. Thus, digitalization moderates the positive relationship between the enterprise's commitment to recruitment and good talents' attraction and retention.

This study could not confirm the existence of a direct relationship between the positive behavior of job-seekers toward the use of digital recruitment processes and talent recruitment or talent retention in a company. Indeed, this relationship needs to be confirmed in a larger sample size.

The same goes for the competitiveness of enterprises to provide technology to make their digitized processes more efficient, which gives them a competitive advantage in the labor market. Indeed, the positive relationship between the intensity of competition and the performance of the recruitment process has not been validated by this study. Therefore, a study to confirm this finding should be conducted on a larger sample.

AUTHOR CONTRIBUTIONS

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APPENDIX A

The Centroid method, in this case the l_{ki} coefficients are expressed as La méthode

$$l_{ki} = \mathrm{sgn}\left(A_k^{*\prime} A_i^*\right), \tag{1A}$$

The Factorial method, in this case the l_{ki} coefficients are expressed as:

$$l_{ki} = A_k^{*\prime} A_i^*, \tag{2A}$$

The Structural method, in this case the l_{ki} coefficients are expressed as:

$$l_{ki} = \begin{cases} \text{regression coefficient in the regression of } A_k^* \; on \; A_i^* \; if \; A_i \to A_k \\ cor\left(A_k^*, A_i^*\right) \;\; \text{if} \;\; A_k \to A_i \end{cases}, \tag{3A}$$

Mode A: in this case the coefficients are written as:

$$w_k = \frac{1}{A_k^{**\prime} A_k^{**}} X_k{}' A_k^{**}, \tag{4A}$$

Mode B: in this case the coefficients are written:

$$w_k = \left(X_k{}' X_k\right)^{-1} X_k{}' A_k^{**}, \tag{5A}$$

with $w_k^{\prime Xk^\prime Xkwk} = N$ (number of observations)

The statstic $F_k^{\,2}$ is défined by:

$$F_k^2 = H^2 \cdot R^2\left(A_k^*, \left[\, les \; A_i^* \; qui \; \exp liquent \; A_k^* \right]\right), \tag{6A}$$

For a latent variable A_k, the Q^2 Stone-Geisser coefficient is calculated by:

$$Q_k^2 = 1 - \frac{\sum_{j=1}^{kp} \sum_{i=1}^{N} \left(x_{kji} - \overline{x_{kj}} - m_{kj}^* pred\left(A_k^*\right)\right)^2}{\sum_{j=1}^{kp} \sum_{i=1}^{N} \left(x_{kji} - \overline{x_{kj}}\right)^2}, \tag{7A}$$

where x_{kji} is the ith e observation of the jth variable of block k, $m_{kj}^{\;*}$ is the estimator of m_{kj} and

$$pred\left(A_k^*\right) = \sum_{i, A_i \to A_k} \beta_i^{\prime} A_i^*, \tag{8A}$$

the prediction of the latent variable A_k obtained from the latent variables that explain it in the structural model.

If $Q_k^{\,2} > 0$, the model is said to have predictive validity (Fernandes, 2012).

The statistics H^2:

$$H^2 = \frac{\sum_{i=1}^{kp} cor^2\left(X_{ki}, A_k^*\right)}{kp}. \tag{9A}$$

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APPENDIX B

Table B1. Discriminant validity – cross-loading

Items	COMDEM	E-REC	INTENCONCU	PERFO	SUPDIR
CD1	**0.937**	0.585	0.812	0.537	0.557
CD2	**0.907**	0.541	0.725	0.506	0.529
CD3	**0.861**	0.725	0.845	0.646	0.689
E-R1	0.693	**0.911**	0.819	0.870	0.864
E-R2	0.604	**0.925**	0.740	0.900	0.880
E-R3	0.654	**0.899**	0.750	0.867	0.844
E-R4	0.647	**0.930**	0.748	0.904	0.889
E-R5	0.613	**0.863**	0.674	0.830	0.809
E-R6	0.520	**0.840**	0.608	0.814	0.767
IC1	0.749	0.709	**0.908**	0.677	0.707
IC2	0.833	0.740	**0.899**	0.679	0.707
IC3	0.826	0.746	**0.906**	0.743	0.778
PR1	0.595	0.903	0.736	**0.922**	0.893
PR2	0.661	0.928	0.760	**0.952**	0.936
PR3	0.500	0.853	0.656	**0.907**	0.868
S1	0.606	0.922	0.773	0.940	**0.962**
S2	0.671	0.907	0.777	0.934	**0.954**
S3	0.693	0.876	0.802	0.900	**0.936**
S4	0.523	0.820	0.678	0.860	**0.894**

Table B2. F_k^2 values

Constructs	*E-REC*	*PERFO*	Result
E-REC	–	0.918	Important effect
SUPDIR	7.832	1.041	Important effect
COMDEM	–	0.031	Weak effect
INTCONC	–	0.004	Weak effect

Table B3. GoF calculation element

Latent variable	*AVE*	R^2
SUPDIR	0.802	–
E-REC	0.959	0.887
PERFO	0.878	0.97
COMDEM	0.861	–
INTCONC	0.818	–
Moyenne	0.8636	0.9285

Note: $GoF = \sqrt{\overline{H^2} \cdot \overline{R^2}} = 1.338.$

Table B4. Total effects

Total effects	Beta	Standard deviation	*T* Value	*P*-values	Decision
E-REC → PERFO	0.515	0.086	5.990	0.000	Supported*
SUPDIR → E-REC	0.942	0.014	67.925	0.000	Supported*
SUPDIR → PERFO	1.041	0.033	31.751	0.000	Supported*

Note: * $p < 0.01$.

Table B5. Lower leverage and upper leverage

SUPDIR → E-REC	*E-REC → PERFO*	Indirect effect	Standard deviation	*T*	LL	UL
0.942	0.515	0.485	0.083	5.845	0.334	0.660