International Journal of Engineering and Management Sciences (IJEMS) Vol. 9. (2024). No. 4.
DOI: 10.21791/IJEMS.2024.029.

What Drives The Diffusion of AI Recruitment Systems in Swiss HRM? The Importance of Technological Expertise, Innovative Climate, Competitive Pressure, Employees' Expectations and Contextual Factors

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Abstract. This study examines organizational, environmental, and contextual factors influencing the diffusion of artificial intelligence recruitment systems in human resources management within Swiss organizations. Based on a survey provided to 324 private and public Swiss HR professionals, it explores how some technology-organization-environment theoretical framework predictors' as well as innovative climate provided by organizations influence the three stages – evaluation, adoption, and routinization – of diffusion of this innovation. To do this, the following article is based on a PLS-SEM structural equation model. Its main findings are that technological expertise, innovative climate, competitive pressure, and expectations regarding future use of the tool by organizations working in the same field are directly linked to the spread of this type of AI tool. However, public-sector organizations are more reluctant about using this type of tool. This aversion can, however, be moderated by an innovative climate and the fact that the HR function plays an active part in an organization's strategic direction. This said, this article makes a significant contribution to the literature about the diffusion of emerging technologies in organizations.

Keywords: HR, HRM, Information Systems, AI, Artificial Intelligence, Recruitment

Introduction

Over the past 20 years, the number of scientific publications dealing with the information technologies used in HRM has increased considerably [1]. Indeed, topics such as "*web-based HRM"* [2, p. 364], "*e-HRM*" [3, p. 482], HRM cloud computing [4], and "*HR analytics*" [5, p.20] have been studied extensively. However, access to new generations of structured and unstructured HR databases now makes the further digitalization (sometimes referred to as digitization) of HR possible by introducing information systems based on artificial intelligence[1] (AI) techniques [1, 8]. An increasing number of players view this as an opportunity to improve the effectiveness or efficiency of many HR processes [8], such as recruitment [9, 10], performance management [11, 12], career development [13], and skills development [1].

[1] For an exhaustive list of the latter and their concrete use in the field of HR AI tools, see Strohmeier [1]. However, details are beyond the scope of this article.

The primary goal of this article is to provide a comprehensive understanding of the factors that influence the adoption of HR AI within Swiss organizations. Although there is a clear demand for HR AI, the factors influencing its diffusion remain under-researched in Switzerland. For the time being, they have only been studied qualitatively, and not in the field of HRM [35]. We aim to bridge this gap in the literature and offer valuable insights specific to the Swiss context. More precisely, this study will focus on examining how organizational factors, namely technological expertise and an innovative climate, impact the diffusion of HR AI. Additionally, it will explore how environmental factors, such as competitive pressure and expectations in HR AI, influence its diffusion. Furthermore, it will investigate how the private or public nature of the organization and the role of the HR function serve as contextual factors affecting this diffusion process. By employing the PLS-SEM method [14] to analyze survey data, we seek to validate a theoretical model adapted from Chong and Chan [15], integrating Rogers' [16] diffusion of innovations model and the technology-organization-environment (TOE) theoretical framework [17]. Through this analysis, we aim to answer our overarching research question and provide actionable recommendations for organizations looking to implement HR AI effectively. Our general research question is as follows:

To what extent do organizational, environmental, and contextual factors influence the spread of AI-based CV (pre)selection tools within the Swiss HR function?

The precise choice of this type of instrument is not insignificant. In the literature, HR AI is still widely regarded as an emerging technology [11, 18]. Nevertheless, some HR AI tools are more commonly used than others, as evidenced by the scientific literature [1] as well as our own empirical data collected as part of this work (*Appendix 1*). To minimize any possible bias, we opted to study the spread of one of the most widespread types of HR AI tools in Swiss organizations. In short, this study is in line with ongoing work on the digitization of human resources [19], which represents a major challenge for Swiss organizations, particularly in public administration [20]. The remainder of this paper is organized as follows: Section 2 details our literature review, theoretical framework, and hypotheses; Section 3 describes our method; Section 4 outlines and discusses our results; and finally, Section 5 concludes our work by explaining its limitations and proposing new avenues to explore and deepen our subject.

1. Literature review, theoretical framework, and hypotheses

1.1. AI in HR

The literature on executives[2] and scientists has emphasized for some time now the importance, benefits, and advantages of integrating AI tools to automate, assist, and aid decision-making in HR function tasks [1, 7, 22]. Since the first study of a tool based on AI by Lawler and Elliot [23], a number of academic studies have focused on AI tools in areas such as staff engagement [6, 9, 24, 25, 26], but also within other processes inherent to the HR function [33] such as performance management, skills development

[2] According to Boltanski and Chiapello [21, p. 763], scientific or "*management research*" literature has a "*non-normative*" purpose, and its *"mode of writing presupposes a critical apparatus."* For these authors, it differs from literature "*intended for managers,*" whose "*main objective is to inform managers of the latest innovations in corporate management and human leadership".*

[1], career development [13], and so-called *cross-functional* processes [33], where AI exists that can predict psychosocial risks [34]; specifically, *turnover* [35].

Notwithstanding the aforementioned scientific productions, the understanding of these AI-based HRM tools, instruments, and applications remains limited. Initially, the definition of AI was far from unanimous [30], a fortiori in the field of HRM [1]. However, this did not prevent some authors from attempting a formulation. According to Strohmeier [1], HR AI is defined as a category[3] of software algorithms enabling an information system to perform HRM activities that would normally require the knowledge and intervention of a human. For him [1], an HR AI tool is an information system that, when inserted into an HR process, not only imitates *natural intelligence* but also evolves according to the data that feed it. Its aim is to either completely replace the performance of a task previously performed by the HR function or produce a result that can subsequently be used to inform the choices of the HR function. In the second mode of action, the tool is depicted as a *decision-making aid*.

It is important to note that our work focuses on a specific type of HR AI system, namely an instrument of the (pre)selection type for resumes[4] or application files [10]. In broad terms, this consists of an AI system that studies the correspondence between the CVs received and recruitment criteria using one or more suitable algorithms. When the latter autonomously decides to retain or reject an application, it is considered an automation tool. In contrast, when it simply makes a recommendation concerning a candidate's file, it is a decision-support tool. In this study, we endeavor to capture both modes of use in the administration of our questionnaire.

Therefore, the aim of this work, as no interest has yet been shown in this subject, despite calls to do so [32], is to gain a better understanding of the determinants of the spread of this type of technical system within the personnel hiring process of Swiss private and public organizations. For this purpose, we draw on the two general theoretical frameworks presented in Sections 2.2. and 2.3., as well as on the contributions of Malik and Wilson [33], and Boukamel and Emery [34], which we unify, following the examples of Chong and Chan [15] and Neumann *et al.* [35], in Section 2.4. We present our complete research model and hypotheses.

1.2. Technology diffusion (dependent variables)

The adoption of a technology, especially one marked by a certain complexity, as is the case with HR AI [7], does not occur overnight. Indeed, the scientific literature speaks more readily of *diffusion* than *adoption*, in the sense that the integration of a new technological tool is far more of a *process* than a *rupture* characterized by a *before* and *after* totally changed by the latter [36]. Few organizations can claim to have encountered no obstacles in the search for the best tool for their needs or in the deployment and implementation of a new tool [7]. This is because the introduction of a new technological tool into an organization is far from smooth and is an eminently contextual process. In this

[3] In its simplest sense, an algorithm is a set of instructions, expressed in a particular computer language such as Java, Python or C++, used to solve a well-defined problem. As with a recipe, this then produces a result based on instructions. Depending on the data they are required to process, algorithms are divided into several fields that constitute AI techniques such as natural language processing or machine learning [2, 8].
[4] This tool is deliberately spelled in this manner. In fact, some AI tools of this type preselect, while others select candidates directly. In our questionnaire, we therefore used this term to group these two modalities together.

DOI: 10.21791/IJEMS.2024.029.

sense, the introduction of a tool is always preceded by an *initiation* stage [7], sometimes referred to as *evaluation* [15], which can be understood as a preliminary phase in which the actor(s) in a position to initiate the acquisition of such an object take(s) information and assess/evaluate the potential benefits of using it in their activities [7]. This step involves assessing the potential effectiveness of an instrument in comparison to established processes for performing a task assigned to the HR function [6]. Once the potential effectiveness of a tool has been proven, the organization can decide to initiate its acquisition. The second stage, known as *adoption*, then begins, during which the tool is deployed within the organization. This is followed by a series of adjustments in the form of transformations of work routines, acceleration of operations, resistance, and conflicts, which serve to assess the validity of the decision to adopt the tool [37]. At this point, the tool will be confirmed or, in contrast, eliminated [37]. In the former case, it will enter a phase of *routinization.* In the latter case, its use will have become commonplace in the operations of the organization [37]. To guarantee its long-term use, the organization will then be able to provide training and technical support to the players who will be required to work with or in collaboration with the tool [39]. These two elements will reduce the opacity of the system and, consequently, the aversion of stakeholders to it, as well as the potential dangers inherent in its use, such as problems of confidentiality or management of the collected data [7]. Finally, in a fourth and final stage known as *confirmation* or *extension*, the users of the tool will manage to use its full potential or even innovate thanks to it [7, 40].

The above roughly outlines the complete path of a technical object or innovation until it is fully integrated into an organization, with several variations. Rogers [16] describes five stages, namely (1) *knowledge,* (2) *persuasion,* (3) *decision*, (4) *implementation*, and (5) *confirmation*; Zhu *et al.* [36] and Basole and Nowak [41] detail only three stages: (1) *evaluation*, (2) *adoption*, and (3) *routinization*. The literature is relatively unanimous regarding this process. Therefore, as in Chong and Chan [15] and Neumann *et al.* [35], we base our conceptualization of the dependent variables on the three phases of *evaluation*, *adoption*, and *routinization*. However, we need to understand what presides over the transition from one stage to another. To do so, we draw on the TOE framework [17], recent developments concerning information systems in the public sector [42], on the notion of an *innovative climate* [43, 44], and on the literature concerning innovation levers in the Swiss public sector [34].

1.3. TOE framework and innovation in the public sector (independent variables)

The TOE framework is a theoretical framework that is commonly used to understand why organizations adopt technological innovations [15, 17, 35, 36, 47]. It has already been used to explain the spread of IT tools [46] such as medical devices [15] and HRM information systems (HRMISs[5]) [89] in both the private and public sectors [42]. However, the latter has never been used to study the determinants of the uptake of a particular type of AI tool in Swiss HR. Although the TOE framework is relevant in its entirety, we rely on a limited number of sub-dimensions to remain parsimonious. Therefore, only the organizational factor *technological expertise* is retained in this study. However, we supplement it with another

[5] HRISs constitute systems used *"to acquire, store, manipulate, analyze, retrieve and distribute pertinent information regarding an organization's human resources"* [58, p. 27].

organizational factor, namely the *innovative climate* [43, 44]. We wish to observe whether it directly influences our three diffusion stages and whether it acts as a moderator. In addition, we test both environmental sub-dimensions[6] inherent in the TOE framework. Contextual factors are also considered, namely the position of the HR function within the organization and the public/private dimension. Next sections discuss our independent and moderating variables, describes our hypotheses and concludes with a summary of our theoretical research model. First, we examine the organizational factors (Section 2.3.1). We then present our environmental factors (Section 2.3.2). Thereafter, we describe our contextual factors (Section 2.3.3) and finally, our moderating variable, the innovative climate (Section 2.3.4), which is also considered as an organizational factor. Based on these theoretical developments, we propose our research model (Section 2.3.5).

1.3.1. Organizational factors

Although some authors, such as Chong and Chan [15], detail several organizational factors that are likely to influence the diffusion of innovations, this study focuses solely on technological expertise. Essentially, the concept refers to the level of technological expertise or sophistication of an organization in relation to a technology. This is measured subjectively based on the perspective of the players. They are asked whether they think that employees are aware of the technology behind a technical object (in this case, a tool for (pre)selecting CVs and application files); whether they think that their organization has sufficient technical skills to implement it, if needed; and to provide their opinion on the integration of such a tool into their current HRIS(s). The literature tends to show that the presence of qualified personnel positively influences the diffusion stage of a technical system [7, 15]. We believe that the instrument under investigation is no exception to this rule. Thus, we hypothesize that this factor positively influences all three diffusion stages of our HR AI instruments (*Table 1. Hypotheses h1a, h1b,* and *h1c*).

In his text, inviting academics worldwide to test predictors to understand, from both individual and collective perspectives, why individuals use and why organizations adopt the new generation of AI-based information systems, Venkatesh [32] advises researchers interested in these issues to integrate new predictors into existing explanatory models. Hence, this is the exact approach taken in this study by proposing, in the role of moderator, the perception of an innovative climate within the organizations in our sample. An innovative climate, which is defined as an atmosphere within an organization that fosters creative mechanisms and solutions to achieve the goals defined by the organization [44[7]], is also a necessary condition for the development of new ideas and solutions within organizations. In this respect, we believe that such a climate could also positively influence the diffusion of HR AI tools, such as those we are studying (*Table 1. Hypotheses h2a, h2b,* and *h2c*).

Table 1. Summarizes the hypotheses.

[6] That is, the environment in which organizations operate.
[7] See also Bos-Nehles and Veenendaal [43], and Malik and Wilson [33].

TABLE 1
Hypotheses for organizational factors

Technological expertise (T)	
H1a	The greater the technological expertise of their employees, the more organizations evaluate the possibility of using [the tool].
H1b	The greater the technological expertise of their employees, the more [the tool] is adopted.
H1c	The greater the technological expertise of their employees, the more organizations routinize [the tool].
Innovative climate (IC)	
H2a	An innovative climate positively influences organizations to evaluate the possibilities of using [the tool].
H2b	An innovative climate positively influences organizations to adopt [the tool].
H2c	An innovative climate positively influences organizations to routinize [the tool].

1.3.2. Environmental factors

Competitive pressure leads many organizations to adopt information systems, a fortiori in the private sector [45]. The explanation behind this phenomenon is an open secret: organizations that have implemented a tool and, as a result, achieve higher levels of effectiveness and efficiency than those that have *missed the boat*, and will enjoy a comparative advantage over their competitors [46, 47]. Although this explanation mainly applies to the private sector [48], we should not assume that the public sector is independent of the environment in which it operates. In many countries, the so-called New Public Management reforms have introduced a certain level of competition between public administrations, as well as between the latter and certain private organizations that act, for example, by delegation [49]. Distinguishing oneself by recruiting an employee more quickly or by hiring more diverse profiles, which conventional recruitment methods sometimes have difficulty with and are two advantages of an HR AI tool of the CV (pre)selection type, according to Azoulay *et al.* [50[8]], is, in this sense, as much a concern in private as public organizations. However, Zhu *et al.* [36] show that competitive pressure more strongly affects the early stages of diffusion. According to these authors, it is at the very beginning of a technological innovation that organizations expect to gain comparative advantages by acquiring it. This would explain, at least in the case of organizations with a strong interest in comparative advantages, why the *routinization* stage is subsequently neglected and, consequently, why this sub-dimension explains only a smaller share of the variance. In this case, we believe that the *competitive pressure* sub-dimension positively affects the diffusion stages of the tool considered in this study (*Table 2. Hypotheses h3a, h3b,* and *h3c*). However, we have the same reservation as Zhu *et al.* [36] regarding its influence on the *routinization* stage.

Regarding employees' expectations of the technical object, the first question is whether the tool will be widely used in the future within organizations such as theirs, and the second is whether the same tool will be widely used in the employee engagement process. According to the literature, questioning employees' *expectations* of a technical object reveals their general ideas about the future of information systems [15]. That is, it reflects the trend or fashion [52, 53] in terms of the managerial practices or instruments that are best able to make a difference in terms of HRM. Various empirical studies have shown that employees' *expectations* of a technical object are positively associated with its *evaluation*,

[8] See also Crawshaw *et al.* [51].

adoption, and *routinization* [15, 46]. The same logic applies to the instruments on which we focus. Hence, the HR function's *expectations* of the tool are positively associated with its *evaluation*, *adoption*, and *routinization*. In the case of private organizations, it is easy to imagine "*fashion setters*" [52, p.254] attempting to influence the representations of HR function players through conferences or contacts, which, in turn, would encourage the spread of a new technological tool. Jemine and Guillaume [54] demonstrate that this is indeed the case[9]. Although public-sector organizations are a priori more impervious to these forms of control, there is no doubt that the plethora of inter-municipal and inter-cantonal groupings, as well as the numerous directors' conferences [55], provide opportunities to compare good and bad practices, as well as to exchange ideas about the new must-have tool to be implemented within their respective organizations. According to Troshani *et al.* [42, p. 9], "*local success stories*" and *"champions"* have a positive influence on public sector HRIS adoption. Thus, our hypothesis is that the *expectations* sub-dimension is positively associated with each of the diffusion stages of our technical object (*Table 2. Hypotheses h4a, h4b,* and *h4c*).

Table 2. Summarizes the hypotheses.

TABLE 2
Hypotheses for environmental factors

Competitive pressure (P)	
H3a	The greater the perceived competitive pressure, the more organizations evaluate the possibility of using [the tool].
H3b	The greater the perceived competitive pressure, the more organizations adopt [the tool].
H3c	The greater the competitive pressure, the more organizations routinize [the tool].
Expectations (E)	
H4a	The higher the expectations of the HR function, the more organizations evaluate the possibility of using [the tool].
H4b	The higher the expectations of the HR function, the more organizations adopt [the tool].
H4c	The greater the expectations of the HR function, the more organizations routinize [the tool].

1.3.3. Contextual factors

In the context in which current private and public organizations operate, which is increasingly marked by the need for strategic HRM [33, 56], the success of organizations also depends on the HR function; more precisely, on its ability to optimize resources as well as to contribute to organizational performance [33, 57], which can be understood as reducing costs, improving information processing, or reducing the number of handles required to complete a task or process. In this respect, organizations can be encouraged to equip themselves with an HRIS, which makes it possible not only to access and process data, but also to link them together to derive new information and, consequently, improve personnel management decisions [33, 58]. Indeed, such technical systems have already proven their value in HR processes as diverse as performance management and employee engagement [53, 59]. However, in the literature, the determinants of innovation diffusion in the public sector are, in many respects, different from those that characterize the private sector. First, public organizations pursue a

[9] According to these authors, there are nine types of pressure exerted by HRIS suppliers and consultants on organizations: evaluation, advice, publicity, case development, demonstration, configuration, coaching, support and assistance. Taken as a whole, these demonstrate the systematic presence and active role of external players throughout the HRIS assimilation process in companies.

different goal from private organizations: while the former are interested in producing *public goods* [59] or "*public value*" [60, p. 528], the latter are guided by market signals as well as economic considerations such as profitability and profit seeking [60]. Second, while private organizations *proactively* seek to innovate by acquiring new instruments relatively early on, public organizations, due to their bureaucratic culture [71] or the brakes, particularly the cultural ones, that characterize them [34], generally introduce innovations *reactively*. In most cases, the latter wait until evidence is available to justify their decision to adopt innovations [42]. In addition, public organizations are characterized by the financial and time constraints inherent in budget cycles[10], which also depend on the state of political forces and, more specifically, on changes in priorities depending on who is elected to head the various public administration departments [63]. In addition, legal requirements, particularly in terms of data protection[11], are likely to differ throughout Switzerland depending on federalism [64], which can sometimes prevent or even encourage the spread of new technologies within public organizations. Finally, as the public sector is traditionally characterized by a monopolistic nature, the provision of many of its services is subject to less pressure in terms of efficiency. Thus, it does not necessarily need to seek the latest innovations at all costs, which might enable it to improve its operations [42]. Based on the above, our general hypothesis is that being a public organization has a negative influence on the *evaluation*, *adoption*, and *routinization* stages of our technical object. This hypothesis divided into three hypotheses, one for each diffusion stage (*Table 3. Hypotheses h5a, h5b,* and *h5c*).

Rogers [16] asserts that the way power is concentrated or centralized within an organization is decisive in understanding the process of acquiring and assimilating new technologies. Although certain texts tend to confirm this assertion [65], the influence of this concentration of decision-making power on the diffusion of technical objects remains controversial. Studies have shown that the diffusion of a technology is favored when management alone can decide on the tools it wishes to acquire, independently of the concerns or even resistance of middle managers and employees [66]. However, other studies have demonstrated the negative impact of centralization on decisions to adopt technologies that are nevertheless compatible with the interests of employees [67]. In this case, we believe that, in terms of our instrument, the hierarchical position of the main players concerned by the potential benefits of acquiring such instruments presides over their dissemination. That is, we believe that the position of the HR function – in this case, whether below or at the same level as the main executive body of the organization – positively influences the way an organization *evaluates*, *adopts*, and *routinizes* this type of tool (*Table 3. Hypotheses h6a, h6b,* and *h6c*).

Table 3. Summarizes the hypotheses.

[10] In Switzerland, municipal, cantonal, and federal government budgets are voted on each year by the appropriate parliament. With a degree of flexibility and the possibility of deficits, albeit moderated by the debt brake mechanism (Art. 126 of the Swiss Constitution), the budget is not reviewed until the following year.
[11] Two neighboring cantons, Geneva and Vaud, for example, each have their own legislation on this subject: LIPAD for the former and LPrD for the latter.

DOI: 10.21791/IJEMS.2024.029.

TABLE 3
Hypotheses for contextual factors

Type of organization, private or public (PP)	
H5a	Being a public organization has a negative influence on organizations' assessment of the possibilities of using [the tool].
H5b	Being a public organization has a negative influence on organizations adopting [the tool].
H5c	Being a public organization has a negative influence on organizations routinizing [the tool].
The role of the HR function (R)	
H6a	The closer the HR function is to top management, the more organizations evaluate the possibilities of using [the tool].
H6b	The closer the HR function is to top management, the more organizations adopt [the tool].
H6c	The closer the HR function is to top management, the more organizations routinize [the tool].

1.3.4. Moderator

In addition to directly influencing the diffusion of HR AI instruments, the presence of an innovative climate has the potential to *moderate* the relationship between our independent variables and the diffusion of the HR AI type considered in this study. According to Bolin [68, p. 93]: "*moderation refers to situations when a third variable changes the relationship between two other variables."* In this respect, Gardner *et al.* [69] theorize three types of possible interaction effects: (1) when the moderator strengthens the relationship between IA and VD, (2) when the moderator weakens the relationship between IA and VD, and (3) when the moderator *reverses* the relationship between IA and VD. Indeed, given that AI-based HRM and information systems are still in the early stages of development [1], it is safe to assume that some of the impetus to implement them arises from organizations whose innovative climate favors their diffusion. In this respect, our moderating hypotheses are summarized in *Table 4*.

TABLE 4
Innovative climate moderation hypotheses

Technological expertise (T) X Innovative climate (IC)	
H7a	An innovative climate moderates and reinforces the positive relationship between technological expertise and the [tool] evaluation stage.
H7b	An innovative climate moderates and reinforces the positive relationship between technological expertise and the [tool] adoption stage.
H7c	An innovative climate moderates and reinforces the positive relationship between technological expertise and the routinization stage of [the tool].
Competitive pressure (P) X Innovative climate (IC)	
H8a	An innovative climate moderates and reinforces the positive relationship between competitive pressure and the [tool] evaluation stage.
H8b	An innovative climate moderates and reinforces the positive relationship between competitive pressure and the [tool] adoption stage.
H8c	An innovative climate moderates and reinforces the positive relationship between competitive pressure and the routinization stage of [the tool].
Expectations (E) X Innovative climate (IC)	
H9a	An innovative climate moderates and reinforces the positive relationship between expectations and the [tool] evaluation stage.
H9b	An innovative climate moderates and reinforces the positive relationship between expectations and the [tool] adoption stage.

DOI: 10.21791/IJEMS.2024.029.

H9c	An innovative climate moderates and reinforces the positive relationship between expectations and the routinization stage of [the tool].
Private/Public (PP) X Innovative climate (IC)	
H10a	An innovative climate moderates, by weakening, the negative relationship between being a public organization and evaluating the possibilities of using [the tool].
H10b	An innovative climate moderates, by weakening, the negative relationship between being a public organization and adopting [the tool].
H10c	An innovative climate moderates, by weakening, the negative relationship between being a public organization and routinizing [the tool].
HR place (HR) X Innovative climate (IC)	
H11a	An innovative climate moderates and reinforces the positive relationship between the HR function's proximity to senior management and the evaluation stage of [the tool].
H11b	An innovative climate moderates and reinforces the positive relationship between the HR function's proximity to senior management and the adoption stage of [the tool].
H11c	An innovative climate moderates and reinforces the positive relationship between the HR function's proximity to senior management and the routinization stage of [the tool].

1.3.5. Final research model

Based on the above developments, *Figure 1* summarizes our conceptual or search model.

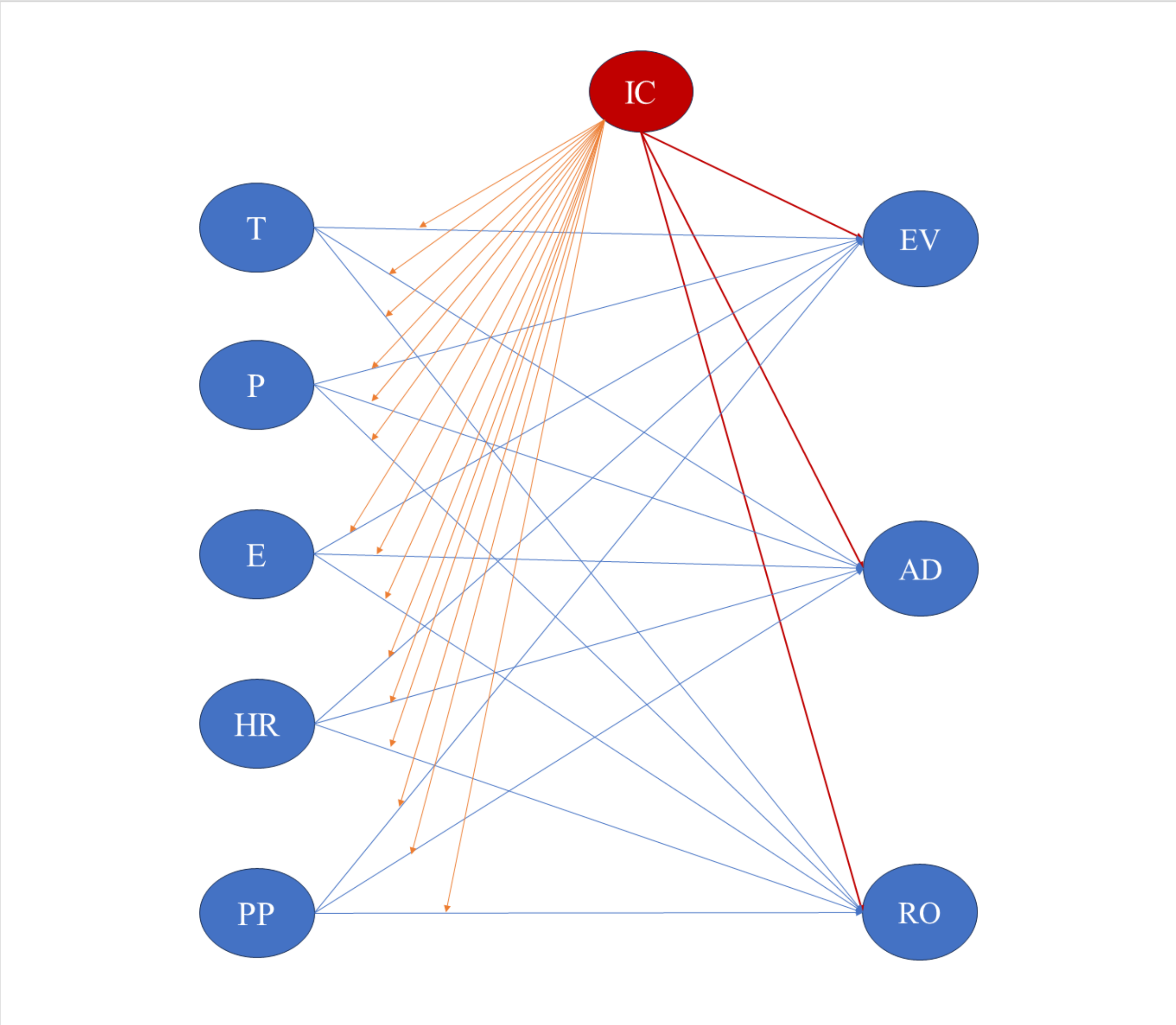

Figure 1. Theoretical model

DOI: 10.21791/IJEMS.2024.029.

In *Figure 1,* the blue lines represent the direct or simple relationships between our IVs and our DPs. Similarly, the red lines represent the direct links between the moderator and the DPs. Finally, the orange lines represent the interaction or moderation effects that we hypothesize. With the aim of empirically testing this model, we present our method and analytical procedure in the following section.

2. Method

2.1. Data collection and organizations characteristics

This study is based on a survey of private and public HR professionals in Switzerland that was conducted between November 2022 and March 2023. The associations HR Vaud (N = 777), HR Tessin (N = 270), and the ZGP[12] (N ≃ 600) all agreed to distribute the questionnaire to their networks and to carry out at least one follow-up survey at three-week intervals after the first distribution of the questionnaire. The HR Genève (N = 720) and HR Valais (N = 330) chapters distributed the questionnaire to their networks only once. The questionnaire was first tested by three professors working in the field of HRM in Switzerland. After the necessary reformulations were incorporated, the questionnaire was tested a second time. A few final adjustments were then necessary before sending it out. As anonymized questionnaire research does not fall within the scope of the Swiss Federal Law on Research Involving Human Subjects [96], we did not need to consult an ethics committee before administering it.

Since 1848, the Swiss federal political system has consisted of three levels of governance: the federal state, cantons, and communes. The principle of subsidiarity [64] confers on each level a broad autonomy in politics and the way they organize their public administration, particularly in terms of infrastructure and information systems [70]. However, contextual differences can be observed in this area, which is why we also surveyed the Federal Personnel Office (N = 1), the 26 cantonal HR departments, and 168 of Switzerland's 2136 municipalities. Regarding the latter, we deliberately chose to restrict ourselves to those with more than 10,000 inhabitants [90]. The size of a municipality also generally determines whether it has an HR department [71]. This arbitrary threshold allowed us to ensure that the respondents were proven HR function members. Each public authority was invited to participate in our questionnaire three times, at three-week intervals, by e-mail and post. Finally, 324 responses were received with a return rate of 11.20%[13]. As Swiss HR professionals are very busy, this rate is acceptable. To respect the linguistic diversity of Switzerland, the questionnaire was translated[14] into three of the four languages that are officially recognized by the Swiss Confederation: German, French, and Italian, in addition to the English version. The characteristics of the organizations that responded are shown in *Table 5*.

[12] *Zürcher Gesellschaft für Personalmanagement.*
[13] To calculate: 324*100/2892 = 11.203%, where 324 is the total number of responses out of a potential 2892 respondents.
[14] The items, initially in English, were translated by native speakers of German, French and Italian. The questionnaire was then tested by at least three native speakers of each language.

DOI: 10.21791/IJEMS.2024.029.

TABLE 5
Sample (N=324)

Variable	*Percentage*	*Variable*	*Percentage*
Size of organizations		**Language area**	
Less than 10 jobs	4.94	French Switzerland	44.44
10 to 49 jobs	6.17	German Switzerland	42.90
50 to 249 jobs	10.80	Italian Switzerland	6.17
250 to 499 jobs	11.73	NA	6.48
500 to 999 jobs	25.31		
1000 to 9'999 jobs	21.60		
More than 10'000 jobs	17.28		
NA	2.16		
Maximum activity level		**Private/public**	
International	30.86	Private	48.46
Federal	27.47	Public	47.53
Cantonal	14.51	NA	4.01
Communal	20.06		
NA	7.10		

2.2. Preventing bias

Organizational behavior research is often plagued by methodological bias, particularly when researchers rely on self-administered questionnaires [73]. In some cases, this can threaten the validity of the observed relationships between variables, as well as the conclusions inferred from them [72, 89]. Good questionnaire design, a clear data collection strategy, and post-hoc data analysis are three means of mitigating and verifying that potential measurement biases are neither present nor influential within the data [73]. To this end, we guaranteed complete anonymity for all respondents [72]. The invitation to complete the questionnaire was accompanied by a description of the aims of our study and a reminder of the essential rules of scientific ethics. The respondents were also asked to answer freely and were informed that none of the information gathered would be passed on to anyone else. Although not necessarily required when using the PLS-SEM method [14], post-hoc statistical tests of skewness and kurtosis were carried out to ensure the normality of our variables. The results are presented in *Appendix 2*. Subsequently, our measurement and structural models were tested to ensure that our results met the standards for using PLS-SEM in HRM [74].

2.3. Measurements

2.3.1. Dependent variables

Our dependent variables, namely the *evaluation*, *adoption*, and *routinization* stages, are latent constructs [14]. Their items were measured on a four-point Likert scale, from (1) "*strongly disagree*" to (4) "*strongly agree.*" For each of these variables, this is a type of ordinal scale that, as in Blaikie [75] and Anderfuhren-Biget *et al.* [76], we assume to be continuous when applying the PLS-SEM analysis method [14].

DOI: 10.21791/IJEMS.2024.029.

2.3.2. Independent and moderating variables

Most of our independent variables were also measured on a four-point Likert scale, from (1) "*strongly disagree*" to (4) "*strongly agree*." Some of these constructs, such as *technological expertise*, *competitive pressure*, and *expectations*, are latent. Others, such as the private/public dimension and location of the HR function, are single constructs [14]. Finally, the innovative climate construct was measured on a five-point Likert scale ranging from (1) "*strongly disagree*" to (5) "*strongly agree*," as in Bos-Nehles and Veenendaal [43] and Malik and Wilson [33]. Similar to the dependent variables, the independent variables are presented in *Appendix 2*.

2.4. Analysis procedure

This section briefly summarizes our analyses, which are presented in full in *Appendix 3*, using the PLS-SEM method [14].

2.4.1. Preliminary considerations

Statistically, the use of PLS-SEM structural equations is justified when a theoretical model includes latent constructs and involves testing the complex relationships between them as proposed from a theoretical framework [14, 77]. This was the case in the present study. However, the data used must meet certain requirements if the PLS-SEM method is to retain sufficient statistical power, and the results thus obtained should be generalizable beyond the simple sample under consideration [14]. The 10-time rule and inverse square root method are respected in this case [14]. The number of iterations required for the model to converge must also be less than 300 [14], which was the case here with a value of six.

Note that we proceeded in two steps[15]: the first consisted of specifying a measurement model and a structural model, and then estimating the main structural equation model without introducing our interaction terms. This first step assessed the quality of the model in accordance with commonly accepted PLS-SEM standards. The second step consisted of specifying new measurement and structural models, incorporating the interaction terms formed from the product of the latent constructs or single items validated in step 1 and our moderator variable. Thus, we estimated a second auxiliary structural equation model. We then analyzed the significance and importance of the moderations that occurred, or if no interaction was significant, the absence of moderation within our model [14].

2.4.2. Evaluation of the main measurement model

First, the evaluation of the measurement model depends on the type of latent constructs used. In our case, these are reflective latent constructs, as they exist independently of the items used to measure them [79]. In general, perceptual, attitudinal or personality trait measurement scales are reflective constructs [80]. Second, reflective constructs assume that causality runs from the concept to the

[15] That is, we base our work on the *two-stage approach* initially formulated by Chin *et al.* [96]. Although there are others, such as the *product indicator approach* or the *orthogonalizing approach* [17], we naturally selected the latter. Indeed, not content with enjoying the methodological credibility of the aforementioned authors, simulation studies have demonstrated that the latter excels in terms of parameter recovery and statistical power [17].

DOI: 10.21791/IJEMS.2024.029.

indicators [80]. They must also share a common theme and be interchangeable [80], which was the case in our study.

Empirically, the evaluation of a model formed from reflective constructs involves various tests, for which we referred to the different commonly accepted thresholds in the literature [14].

2.4.3. Evaluation of the main and auxiliary structural models

Hair *et al.* [14, 77] also propose a systematic approach to assessing the quality of our main and auxiliary models. Our full analysis is detailed in Appendix 3 where we see that there is no reason to suspect that our results are unreliable.

3. Results

3.1. Direct effects

Table 6 summarizes the results of our main structural equation model.

TABLE 6
Path coefficients, Significance and R^2

	Evaluation	Adoption	Routinization
R^2	.283	.171	.063
R^2 adjusted	.270	.156	.045
T	.165***	.133**	.130*
P	.323***	.213***	.074
E	.277***	.202***	.124*
RH	.056	.093	.126*
PP	-.129**	-.137**	-.050
CI	.193***	.169**	.056

T: Technological expertise; CI: Innovative climate; P: Competitive pressure; E: Expectations; PP: Private/Public; RH: Place of HR function; EV: Evaluation; AD: Adoption; RO: Routinization.

t Table (two-tailed):
- 95% confidence interval: t-value ≥ 1.960 (*)
- 99% confidence interval: t-value ≥ 2.576 (**)
- 99.9% confidence interval: t-value ≥ 3.291 (***)

It can be observed that 27.0% of the variance is explained in the dependent variable *evaluation*, compared with 15.6% for *adoption* and 4.5% for *routinization*. According to commonly accepted thresholds in the literature, our model explains a reasonable share of the variance in our dependent variables [14]. In addition, there is no reason to suspect, as high R^2 values would indicate, that our model overfits the data [14].

Considering the path coefficients – or direct effects – and their significance, our model shows that the variables T, IC, P, and A are significantly linked to the *evaluation* and *adoption* stages of our technical object. This confirms hypotheses H1a, H1b, H2a, H2b, H3a, H3b, H4a, and H4b. However, only two independent variables of our HR AI instrument, namely technological expertise (T) and expectations (E), are linked to its *routinization*. Thus, H1c and H4c are confirmed. In terms of contextual variables, only the position of the HR function is significantly linked to *routinization*, thereby confirming H6c.

DOI: 10.21791/IJEMS.2024.029.

Finally, being a public organization is significantly and negatively linked to the first two stages of diffusion, which confirms H5a and H5b. Conversely, the hypotheses h2c, h3c, h5c, h6a, h6b, h7a, h7b and h7c are rejected.

3.2. Interaction effects

From our auxiliary structural equation model which is detailed in full in *Appendix 3*, among the moderations formulated within our hypotheses, three are statistically significant. These are PP*IC → EV, PP*IC → AD, and HR*IC → RO. However, only the moderation hypotheses H11a, H11b, and H12c are confirmed, whereas all the others are invalidated. Thus, their interpretation requires reference to the simple effect, as well as the interaction effect inherent in each of the moderations [14]. In addition, f^2 metrics were used to assess the contribution of each of these interaction terms to their respective dependent variables [14].

*3.2.1. PP*IC → EV*

The PP*IC term has an interaction effect of .105 on EV, whereas the simple effect of PP on EV is -.125. These results suggest that the relationship between the private/public dimension and the *evaluation* of our HR AI instrument is -.125 for an average level of innovative climate. For a higher level of innovative climate; that is, for each increase of one unit in this variable, this relationship varies by -.125 + .105; that is, -.020. Conversely, for each decrease of one unit in the innovative climate, the relationship between PP and EV varies by -.125 + (-.105) = -.230. In an orthonormal graph, this yields *Figure 2.*

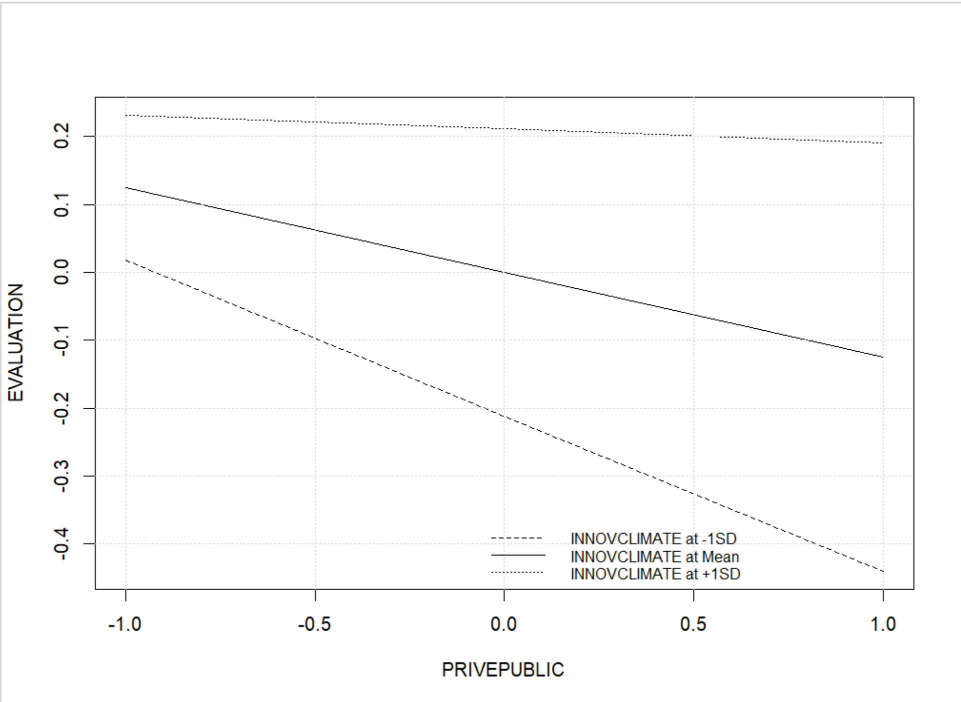

*Figure 2. Simple slope analysis: PP*IC → EV*

It can be observed from the slope of the first line in *Figure 2* that for an increase of one unit in the moderator variable innovative climate, the negative relationship between the private/public dimension and the evaluation of our instrument is weakened. Thus, a public organization with an innovative

DOI: 10.21791/IJEMS.2024.029.

climate is more inclined to evaluate the possibility of being equipped with AI-based CV (pre)selection instruments. However, the relationship remains negative in the sense that this would not be sufficient to reverse the lower propensity of public organizations to evaluate the possibility of using these AI tools. Other would therefore be necessary to arouse the interest of public organizations and players in this type of tool. Conversely, when the organization in question is public and its climate is one unit below average, this reinforces its lower propensity to *evaluate* the possibility of being equipped with this type of tool.

In terms of the relevance of this moderation, which is provided by the f^2 metric, we observe that this interaction term contributes moderately to the variance of our dependent variable *evaluation*: f^2 (PP*IC → EV) = .014[16].

*3.2.2. PP*IC → AD*

The PP*IC term also has a statistically significant effect of .111 on AD, while the simple effect of PP on AD is -.135. These results suggest that the relationship between the private/public dimension and adoption of our AI instrument is -.135 for an average level of innovative climate. For a higher level of innovative climate; that is, for each one-unit increase in this variable, this relationship varies by -.135 + .111, i.e., -.024. Conversely, for each unit decrease in the innovative climate, the relationship between PP and EV varies by -.135 + (-.111) = -.246. In an orthonormal graph, this yields *Figure 3.*

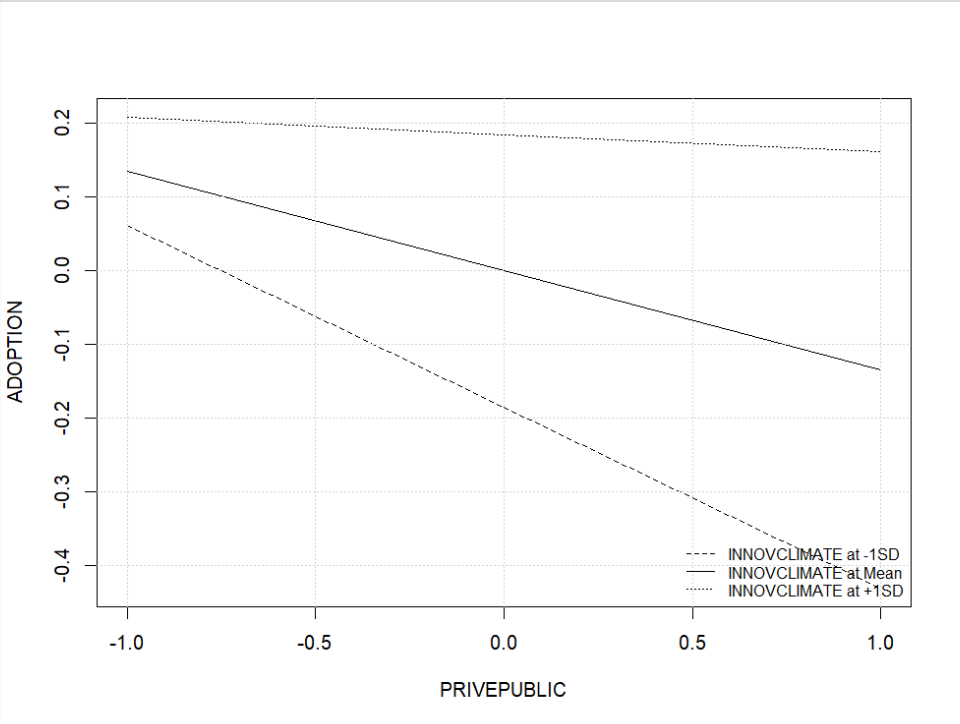

*Figure 3. Simple slope analysis: PP*IC → AD*

[16] Indeed, although Cohen [81] suggests referring to thresholds of .02, .015 and .35, which correspond respectively to a small, medium and large contribution of an interaction term to the variance of a dependent variable, i.e., its R^2, Aguinis *et al.* [82] nevertheless demonstrate that the average effect of an interaction term, in the context of a moderation analysis, is .009. In this context, Hair *et al.* [17] suggest being more flexible and lowering these three thresholds for the contribution of interaction terms to .005, .01 and .025. In this case, we refer to the latter. All f^2 values of our auxiliary structural equation model are available in *Appendix 3*.

DOI: 10.21791/IJEMS.2024.029.

As with the previous interaction effect, an innovative climate reinforces the propensity of public organizations to *adopt* instruments such as the (pre)selection of CVs and application files by diminishing the effect of PP on AD. Its contribution to the variance of this dependent variable is also moderate: f^2 (PP*IC → AD) = .014.

*3.2.3. HR*IC → RO*

Thus, the HR*IC term has a statistically significant interaction effect of .147 on RO, whereas the simple effect of HR on RO is .137. These results in combination suggest that the relationship between the location of the HR function and the *routinization* of our AI instrument is .137 for an average level of innovative climate. For a higher level of innovative climate (i.e., for each one unit increase in this variable), the relationship between HR and RO varies according to the size of the interaction effect; that is, by .137 + .147 = .284. Conversely, for each one unit decrease in innovative climate, the relationship between HR and RO varies by .137 + (-.147) = -.010. Graphically, this yields *Figure 4.*

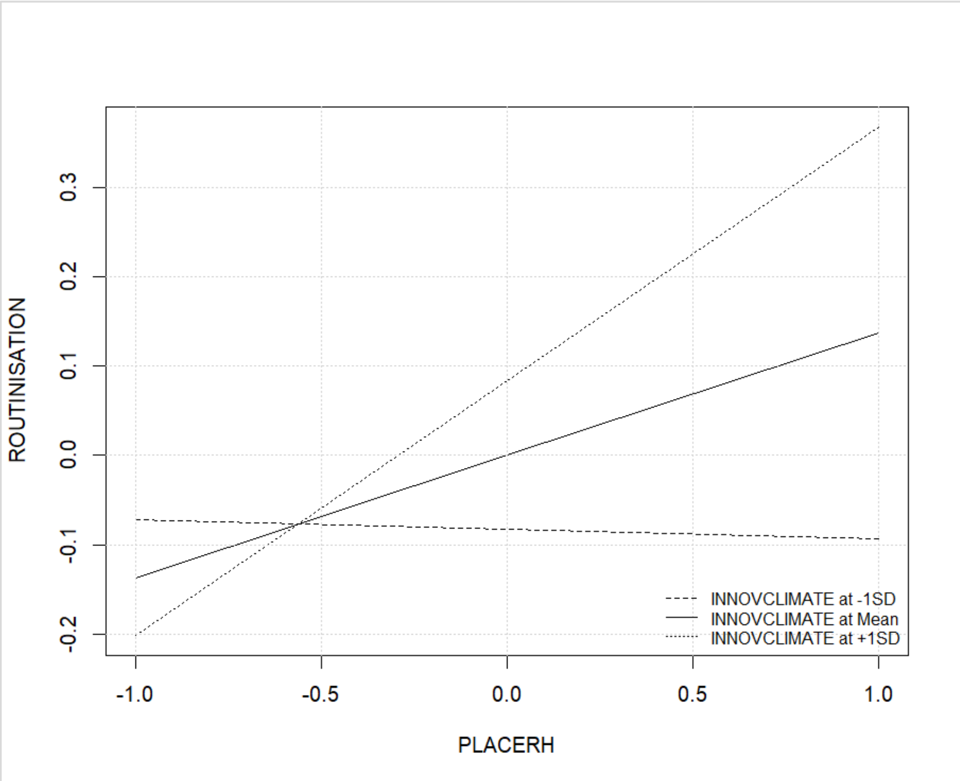

*Figure 4. Simple slope analysis: HR*IC → RO*

The solid line in the middle of *Figure 4* represents the relationship between HR and RO for an average IC level. The other two lines represent the relationship between HR and RO for higher levels (i.e., the mean IC value plus one standard deviation unit) and lower levels (i.e., the mean IC value minus one standard deviation unit). It can be observed that the relationship between HR and RO is positive in the first two cases and negative in the third. In this case, we can conclude that, in addition to being positively linked to the routinization of HR AI tools for (pre)selecting CVs and application files, the influence of the position of the HR function on this dependent variable is reinforced when the prevailing climate within an organization is more innovative than average. Conversely, when the climate is less innovative than average, the influence of the position of the HR function on the routinization of the type of instrument under consideration deteriorates. Therefore, with reference to Gardner *et al.* [69], we affirm that an innovative climate *strengthens* the ability of the HR function to influence the routinization of this type of HR AI instrument. Its contribution to the variance of this dependent variable is, as with our two previous interaction terms, also mean: f^2 (HR*IC → RO) = .021.

3.3. Discussion of results

3.3.1. Organizational factors

Following Chong and Chan [15] and Garrison *et al.* [83], the technological expertise of private and public employees is positively associated with each dependent variable. This confirms that the greater the technological expertise of their employees, the more organizations not only *evaluate* the possibility of using the type of instruments studied, but also *adopt* and *routinize* it. As indicated by our results, they would also look more closely at whether their HR can judiciously use a new tool at the *evaluation stage* rather than at the *adoption* or *routinization stage of* the technical object. Therefore, we can state that H1a, H1b, and H1c are confirmed in our sample. Empirically, this result makes perfect sense: when an organization *evaluates* the possibility of acquiring an information system, it must also consider that it has sufficient employees that can use it. The same applies to the *adoption* stage, where organizations must judge their staff to be sufficiently competent to use our tool, and the *routinization* stage, where the daily use of our tool as part of the hiring process necessarily requires minimum competence in the field.

Next, innovative climate was found to have a statistically significant relationship with the first two dependent variables. Although this variable has never before been tested as a predictor of innovation diffusion, this result is nonetheless interesting insofar as it demonstrates the direct and positive influence of a climate that is conducive to innovation on the *evaluation* and *adoption of* the type of AI instruments considered in this study. Thus, our hypotheses H2a and H2b are confirmed.

3.3.2. Environmental factors

Our results also show that a certain competitive pressure would indeed be exerted on Swiss organizations in the race to disseminate HR AI. More specifically, the fear of seeing other organizations become better at recruiting would prompt the organizations in the sample to *investigate* the possibility of using AI and even to *adopt* it, but not to *routinize* it. This result is consistent with those of Chong and Chan [15] and Wang *et al.* [45]. Moreover, this finding concurs with that of Zhu *et al.* [36], who suggest that competitive pressure affects the early stages of diffusion more strongly. However, according to the literature, the influence of this sub-dimension on innovation assimilation is contextual. Chen *et al.* [47] found no significant relationship between this variable and the *adoption of* AI systems in China's telecoms sector. Thus, in our case, it can be stated that its influence depends in part on the relevance of our tool to Swiss organizations. Therefore, we can assume that Swiss organizations face competitive pressure to *evaluate* and *adopt* this type of tool because they find it useful. However, this would need to be tested empirically using a mediation analysis.

In addition, expectations; that is, the belief that CV (pre)selection tools will be widely used in organizations in the future or the belief that, in the near future, the recruitment process will be largely aided by this type of tool, positively influence the three diffusion stages. When we contrast very enthusiastic view of AI of the Swiss HR function with the feedback from experimentation, which is still sparse at present [1], this result suggests a certain penchant for the AI-in-HR fad previously identified by Bondarouk *et al.* [53] in relation to *electronic HRM*. The latter also leads us to believe that we would currently be in the *overenthusiam* described by Strohmeier [1]. However, further empirical studies, focusing directly on this dimension, would be necessary to confirm or invalidate this intuition.

3.3.3. Contextual factors

In our model, the type of organization has a significant but negative influence on the first two dependent variables. As this variable is coded in binary form, public organizations are more reluctant than private ones to *assess* the relevance of this type of HR AI instrument, as well as to *adopt* it. Given the nature of this variable, we cannot explain this result, but there is every reason to believe that the various theoretical elements presented in the relevant section play a role in the spread of HR AI tools within Swiss organizations. This result is consistent with the literature on the assimilation of technical objects within public organizations, where players are portrayed as relatively pessimistic and sometimes reticent towards technological innovations [84]. The many obstacles to innovation [71], particularly cultural obstacles [34], could also explain the lower propensity of public organizations in our sample to disseminate this type of tool. However, as our moderation analysis shows, an innovative climate can attenuate the reluctance of public organizations to adopt this type of instrument. Conversely, this could encourage the *evaluation* and *adoption* of this type of tool. From a managerial perspective, these results imply that public decision-makers who wish to implement such tools would be well advised to first develop a climate conducive to innovation within their organization. By doing so, public organizations can become more proactive in disseminating new information systems[17]. This could also reduce the inertia inherent in their budgetary constraints and power struggles, as well as the specific regulations and sometimes contradictory political injunctions that characterize them [63]. In short, highlighting this interaction effect makes it possible to identify a lever (the innovation climate) that Swiss public organizations can act on to mitigate their lower propensity to disseminate HR AI tools. This could enable public organizations to foster the development of strategic HRM, which includes, but is by no means limited to, equipping themselves with relevant HRISs for personnel management [7, 33, 85].

Finally, in line with the hypothesis that the HR function, in proximity to power, exerts pressure on the diffusion process of our technical object, our results show that it positively and significantly influences the *routinization* stage of our instrument. In our view, this can be explained by a certain appetite on the part of the HR function for HR AI instruments, which is expressed empirically at the *routinization* stage of our AI instrument in this case. From a managerial perspective, this result underlines the importance of the HR function in the dissemination of this type of innovation. This influence is further strengthened by the moderation of an innovative climate, which reinforces the influence of the proximity of the HR function to management on the *routinization* of our type of instrument.

[17] They tend to be reactive [42].

DOI: 10.21791/IJEMS.2024.029.

4. Limitations and prospects

In short, our work has enabled us to identify several organizational, technological, and contextual factors that govern the evaluation, adoption, and routinization of CV and application file (pre)selection tools within their organizations according to the Swiss HR function. Although almost all of them are directly involved in the intention to use this type of HR AI tool and many of them also explain the decision to adopt this type of tool, only three are significantly associated with the routinization variable. In our view, as the first limitation of this work, this could be because, within our sample (Appendix 1), few organizations declare that they always use this type of tool in their engagement process. In this case, the statistical power of the model is reduced for the dependent variable. Therefore, we would like to repeat this study in several years, when a greater number of organizations have adopted these information systems. We can then observe whether our predictors influence this dependent variable or whether they continue not to be significantly associated with them. At present, as HR AI is still a nascent technology [1], we are satisfied with the very low share of reasons for the *routinization* of these instruments: R^2 adjusted: .043.

Our work also has the advantage of incorporating a new explanatory predictor, namely the innovative climate, for the diffusion of our type of instrument. In addition to significantly influencing the *evaluation* and *adoption* of the latter, it also acts as a moderator for three predictors. Not only does it reinforce the propensity of public organizations to *evaluate* and *adopt* this type of instrument, but it also reinforces the positive influence of the HR function on their *routinization* when it is located close to general management. In this case, public organizations that are interested in implementing this type of tool would be well advised to ensure that they develop an innovative climate. Similarly, the position of the HR function within the hierarchy appears to be a key issue in asserting the interests of the appropriate function regarding AI-based information systems.

In terms of replication, our study suffers from the weaknesses that are inherent in all cross-sectional studies [86], the main one being the impossibility of drawing causal inferences. Therefore, our results are limited to describing the relationships observed between our variables at a given time, which makes it difficult to predict how the various factors studied will influence the *evaluation*, *adoption*, and *routinization* of CV and application file (pre)selection tools in the future. However, our model is characterized by relatively strong predictive power (*Appendix 3*), which suggests that the findings are generalizable beyond the sample. However, we invite researchers who are interested in related topics to replicate this work by testing other explanatory factors such as trust in HRISs [57], trust in technology [87], and algorithmic aversion [88].

Another potential limitation of this study is the presence of potential selection bias caused by the greater involvement of organizations that already use AI within their HR processes. However, this bias is controlled insofar as, as shown by the level of use of the CV and application file (pre)selection tools studied (*Appendix 1*), approximately half of the organizations surveyed never use this type of information system during their hiring process.

Notwithstanding these limitations, our study has the advantage of laying the foundation for new research avenues. The main results are that almost all independent variables included in our structural equation model are significantly associated with the fact that organizations *evaluate* the possibility of using them; almost all of the same predictors are associated with their *adoption*; very few of them are linked to their *routinization*; and an innovative climate not only directly influences our first two stages of diffusion, but also moderates several of our exogenous variables. These findings help us to better understand the factors that drive the diffusion of AI tools for CV (pre)selection within Swiss organizations, as well as the overall spread of HR AI.

Therefore, researchers could consider exploring the subject in greater depth by studying, for example, the factors behind the spread of other HR AI tools, such as chatbots that are sometimes inserted into the recruitment process, by integrating other independent variables into similar structural equation models or by conducting case studies on the reasons behind the spread of these AI instruments within organizations; for example, the influence of private players who are active in promoting this type of instrument, sometimes purely for monetary reasons, despite empirical evidence of their effectiveness or efficiency [54]. In short, this study establishes a basis from which researchers who are interested in the diffusion processes of AI in both private and public HR will have ample opportunity to develop their own research questions.

Funding

This research received no external funding.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Due to confidentiality guarantees given to respondents and to comply with the legal requirements for the storage of scientific data in the canton of Vaud, complete data are only available on request.

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DOI: 10.21791/IJEMS.2024.029.

Appendix 1
Level of use of CV (pre)selection AI tools in Switzerland

TABLE 1

Variable	*Percentage*
AI-based CV (pre)selection tools	
Not used at all	48.77
Occasionally used	24.69
Frequently used	9.88
Always used	11.42
NA	5.25

DOI: 10.21791/IJEMS.2024.029.

Appendix 2
List and details of variables and latent constructs

1. AI-based CV (pre)selection tools

Dependent variables	*Item*	*Mean*	*SD*	*Skewness*	*Kurtosis*	*Wording*
Evaluation	evaluationcv_1	2.58	.975	.227	1.90	My organisation intends to use [the tool] if possible.
	evaluationcv_2	2.52	.981	.260	1.96	My organisation collects information about [the tool] for possible intention of using it.
	evaluationcv_3	2.50	.990	.253	1.96	My organization conducts a pilot test to evaluate [the tool].
Adoption	adoptioncv_1	2.54	1.00	.187	1.90	My organization invests resources to adopt [the tool].
	adoptioncv_2	2.54	1.00	.158	1.87	HR activities of my organisation requires to use [the tool].
	adoptioncv_3	2.53	1.04	.121	1.79	The HR function of my organisation asks to use [the tool].
Routinization	routinecv_1	1.87	1.05	.894	2.48	It was not difficult for my organization to integrate [the tool] to our existing systems.
	routinecv_2	1.83	1.04	.989	2.68	The recruitment process is now always carried out with the help of [the tool].
Independent variables	*Item*	*Mean*	*SD*	*Skewness*	*Kurtosis*	*Wording*
Organisational factors & moderator:						
Technological expertise	techcv_1	2.01	.941	.577	2.38	In my organisation, we know the technology behind [the tool].
	techcv_2 (**R**)	3.36	.855	-1.56	5.03	My organisation doesn't have the technical knowledge and skills to implement [the tool].
	techcv_3	2.12	.992	.440	2.11	My organisation knows how to integrate [the tool] with the existing systems.
Innovative climate	ic_1	3.05	1.21	.020	2.00	My organization is always moving toward the development of new answers.

DOI: 10.21791/IJEMS.2024.029.

	ic_2	3.07	1.24	-.016	1.91	My organization can be described as flexible and continually adapting to change.
	ic_3	3.06	1.26	-.011	1.91	People in my organization are always searching for fresh, new ways of looking at problems.
	ic_4	3.08	1.25	-.064	1.92	Creativity is encouraged here.
	ic_5	3.12	1.27	-.049	1.93	My organization seems to place a high value on taking risks, even if there are occasional mistakes.
Environmental factors:						
Competitive pressure	pc1_cv	2.46	1.08	.068	1.71	My organization experiences competitive pressure to implement [the tool].
	pc2_cv	2.57	1.07	.030	1.73	My organization will be at a disadvantage compared to similar organizations if we don't implement [the tool].
Expectations	expect1_cv	2.45	1.07	.099	1.76	In the future, [the tool] will be widely used in organizations like mine.
	expect2_cv	2.52	1.04	.057	1.82	In the future, the recruitment process will be greatly helped by [the tool].
Contextual factors:						
Private/Public	PP	1.49	.500	.019	1.00	Your organization is : 1 : Private 2 : Public or semi-public
HR function place	HR	2.32	.669	.048	2.23	What is the place of the HR function within your organization? 1 : The HR function is two levels below general management (=N–2) 2 : The HR function is one level below general management (=N–1) 3 : The HR function is at the level of general management (=N)

DOI: 10.21791/IJEMS.2024.029.

Appendix 3
Complete analysis procedure

1. Analysis procedure

1.1 Preliminary considerations

We use the open-source software R Studio to specify our measurement and structural models to respect the association links proposed from our theoretical framework. According to Hair *et al.* [14], the number of iterations required for the model to converge should be less than 300. In our case, it is 6.

Note that we proceed in two stages. The first consists of specifying a measurement model and a structural model, and then estimating a principal structural equation model without introducing our interaction terms. This first step is also used to assess the quality of the model in accordance with commonly accepted PLS-SEM standards [14]. Visually, this results in *Figure 1*.

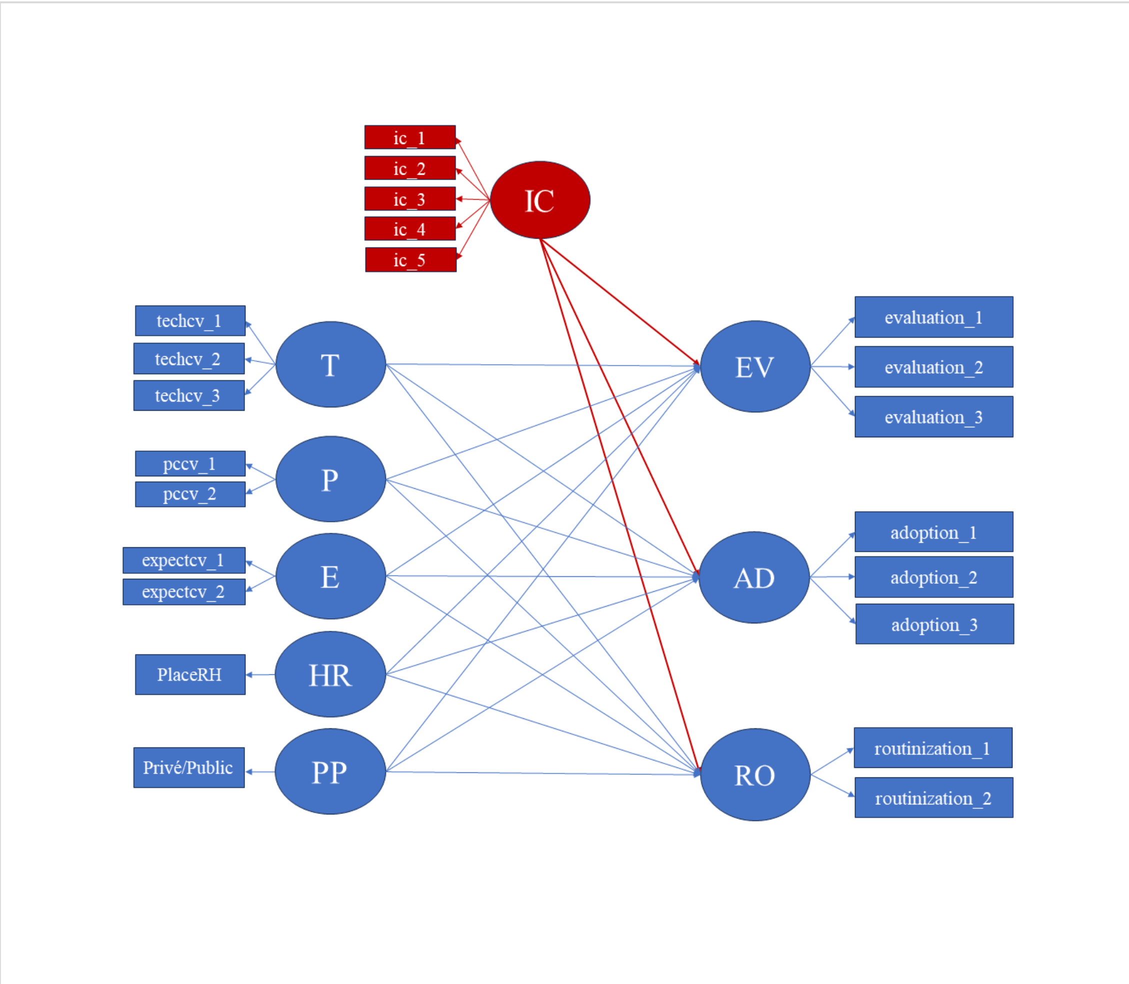

Figure 1. Main structural equation model: Step 1

Step 2 consists of specifying a new measurement model and a new structural model, incorporating our interaction terms that are formed from the product of the latent constructs or single items validated in step 1 and our moderator variable, which is also a latent construct. In this manner, we estimate a second auxiliary structural equation model [14], analyzing the significance and importance of moderations or, if no interaction is significant, the absence of moderations within our model. The auxiliary structural equations are visually summarized in *Figure 2*.

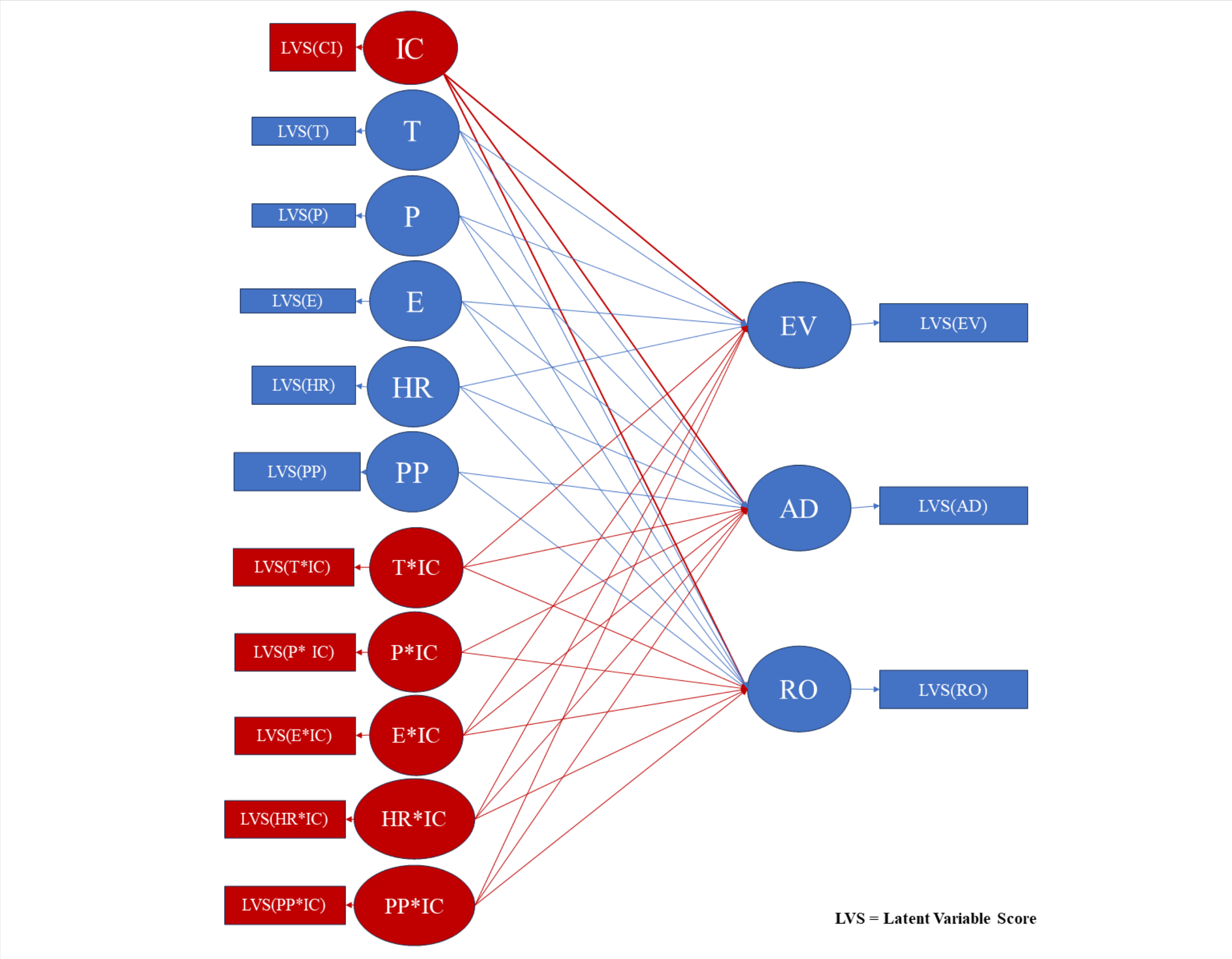

Figure 2. Auxiliary structural equation model: Step 2

This approach corresponds to that of Hair *et al.* [14], originally formulated by Chin *et al.* [96], which is known as the *two-stage approach*. Although other approaches exist[18], we selected this one. Indeed, not only does it benefit from the methodological credibility of the aforementioned authors, but simulation studies have demonstrated that it excels in terms of parameter recovery and statistical power.

1.2 Assess the main measurement model

The evaluation of our measurement model first depends on the type of latent constructs used. In our study, these are reflective latent constructs [78, 80].

Theoretically, a reflective construct must meet several criteria. First, it must exist independently of the items that are used to measure it [79]. Typically, scales measuring perceptual, attitudinal, or personality traits are reflective constructs [80]. According to this criterion, our latent constructs are indeed reflective. Reflective constructs assume that causality runs from the concept to the indicators [80]. That is, a reflective construct *causes* covariation in the variables or items of which it is composed [14]. This

[18] As in, for example, the *product indicator approach* or the *orthogonalizing approach* [14].

DOI: 10.21791/IJEMS.2024.029.

second criterion is also met in our work. Finally, the indicators of a reflective construct must share a common theme and be interchangeable [80], which is the case in our study.

Empirically, the evaluation of a model that consists reflective constructs involves various tests, for which we refer to the different thresholds, or *rules of thumb*, commonly accepted in the literature [14].

1.2.1. Displaying indicator loadings and assess indicator reliability

Indicator reliability is examined in two stages. In the first, the indicator loadings are produced to observe whether they comply with the thresholds commonly accepted in the literature, which recommends retaining an item only if its weight is > .708 [14]. In the second stage, indicator reliability is examined. The commonly accepted threshold here is > .50 [14]. For reasons of economy, we do not provide details of the reliability of our indicators. Mathematically, when a loading is > .708, then its squared value - which is how we produce the reliability of our indicators according to Hair *et al.* [14] - is higher than .50 anyway. *Tables 2* and *3* show our loadings and reliability values, respectively.

TABLE 2
Indicator loadings & (reliability) - Dependent variables

	Evaluation	Adoption	Routinization
evaluation1_cv	.961		
evaluation2_cv	.932		
evaluation3_cv	.882		
adoption1_cv		.881	
adoption1_cv		.923	
adoption1_cv		.865	
routinization1_cv			.932
routinization2_cv			.959

TABLE 3
Indicator loadings & (reliability) - Independent variables

	T	IC	P	A
tech1_cv	.877			
tech2_cv	.867			
tech3_cv	.766			
ic1		.971		
ic2		.842		
ic3		.875		
ic4		.846		
ic5		.867		
pc1_cv			.884	
pc2_cv			.946	
expect1_cv				.853
expect2_cv				.934

T: Technological expertise; IC: Innovative climate; P: Competitive pressure; E: Expectations.

DOI: 10.21791/IJEMS.2024.029.

Note that, for the sake of parsimony, our single-item constructs [14], namely *HR place* and *private/public*, are not presented in these tables. The loading is always 1.00[19]. Our measurements indicate that all of our items are reliable.

1.2.2. Assess internal consistency reliability and convergent validity

The internal consistency assessment step consists of examining the extent to which the items that make up the same latent construct are associated with each other. To do this, we use the following indices: rhoC and rhoA, which must be between .70 and .95 and Cronbach's alpha, which must be greater than .70 [14]. Convergent validity is assessed via the average variance extracted (AVE), which represents the average amount of variance that a construct explains in its indicators relative to their overall variance [14]. For a construct to be validated, the AVE must be > .50 [14]. *Table 4* lists the values for each of our constructs.

TABLE 4

Internal consistency reliability - α, rhoC, rhoA & Convergent validity - AVE

Latent constructs	Alpha (α)	RhoC	RhoA	AVE
Dependent variables				
Evaluation	.917	.947	.934	.857
Adoption	.873	.920	.915	.792
Routinization	.884	.944	.924	.895
Independent variables				
Technological expertise	.792	.876	.828	.703
Competitive pressure	.812	.912	.889	.838
Expectations	.758	.889	.835	.800
Innovative climate	.928	.946	.938	.777

As shown in *Table 4*, all our constructs are valid in terms of the thresholds that are commonly accepted in the literature.

1.2.3. Discriminant validity

Construct discriminant validity, which is the extent to which our constructs are distinct from one another within the model, is measured by the heterotrait-monotrait ratio of correlations (HTMT) [14, 91]. Henseler *et al.* [91] propose two maximum thresholds: .90 and .85. The first is used for models within which the latent constructs are conceptually close and where, therefore, the constructs are more likely to capture the same part of reality. The second, which is more conservative, is used for models in which the constructs are relatively distinct. In this study, the constructs are conceptually distinct. That said, we can afford to be stricter and adopt the second criterion. *Table 5* present the HTMT scores for each construct.

[19] The same applies to steps 2 and 3 of this section.

DOI: 10.21791/IJEMS.2024.029.

TABLE 5
Heterotrait-monotrait ratio (HTMT)

	T	P	E	HR	PP	IC	EV	AD
P	.094							
E	.054	.025						
HR	.053	.027	.160					
PP	.049	.032	.010	.095				
IC	.078	.020	.072	.058	.024			
EV	.213	.381	.342	.079	.137	.216		
AD	.163	.241	.255	.115	.136	.197	.788	
RO	.148	.091	.166	.139	.044	.073	.438	.290

T: Technological expertise; IC: Innovative climate; P: Competitive pressure; E: Expectations; PP: Private/Public; HR: Place of HR function; EV: Evaluation; AD: Adoption; RO: Routinization.

Given that our HTMTs are systematically below the .85 threshold, there is no reason to suspect that one latent construct in our model measures the same dimension as another. In a complementary manner, Henseler *et al.* [91] suggest using bootstrap confidence intervals to determine whether HTMTs are significantly different from 1 and our .85 threshold. We use the procedure described by Hair *et al.* [14] for this purpose. For the sake of brevity, however, the results of this procedure are not reported here. The confidence intervals that emerge confirm the discriminant validity of our various constructs.

1.3. Assess the main structural model

1.3.1. Examining collinearity issues

Potential collinearity problems are examined using the variance inflation factor (VIF). Ideally VIF values should be below 3 [14]. As our VIF values are systematically below 3, there is no reason to suspect any collinearity problems in our structural model.

1.3.2. Assess significance and relevance of the structural model

The second phase in the evaluation of our main structural model is examining the significance of the path coefficients and their relevance [14]. Hair *et al.* [14] recommend inspecting bootstrapped paths and setting the number of bootstraps to 10,000, which is the approach we follow. Note that, in certain situations, bootstrapping non-normal data can affect PLS-SEM results by producing peaked and skewed distributions [77]. However, on the understanding that our data are normal[20] (*Appendix 2*), this does not appear to be the case in our work. Thus, the significance of the structural model is assessed using two indicators: the t-value and inspection of the confidence interval within which the path coefficients lie [14]. For a confidence interval of 95%, as is common in the social and management sciences, the t-value of each path coefficient must exceed 1.960. Below this threshold, the relationship between the two variables is not significant [14]. Alternatively, a confidence interval indicated for each path coefficient by the values provided in the "*2.5% CI*" and "*97.5% CI*" boxes that would pass through 0 is problematic. However, when the t-value is above 1.960, the confidence interval never passes through 0 [14].

For relevance, we need to examine the path estimate coefficients, which are provided in the *Original Est.* column. These values generally lie between -1 and +1. A negative value close to -1 indicates a strong

[20] According to Kline [95] a variable is *normal* when its skewness does not exceed ±3 and its kurtosis is within ±10.

DOI: 10.21791/IJEMS.2024.029.

negative relationship between an exogenous variable and an endogenous variable, while a positive value close to +1 indicates a strong positive relationship between two variables. The path coefficients represent the direct effects of our model. A direct or main effect [14] characterizes the relationship between an independent variable, whether a latent construct or a single item, and a dependent variable when the link between these two variables does not depend on any moderating variables. The method for interpreting them is as follows: a path coefficient, for example, of 0.505 means that when the value of the predictor increases by one unit compared to its mean value, that of the dependent variable increases by 0.505. *Table 6* summarizes the values obtained using this procedure.

TABLE 6
Bootstrapped paths, nboot = 10'000

Paths	Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	2.5% CI	97.5% CI
T → EV	.164	.166	.044	3.718***	.080	.253
T → AD	.132	.136	.047	2.788***	.042	.230
T → RO	.129	.134	.054	2.357**	.024	.240
P → EV	.322	.323	.048	6.644***	.229	.417
P → AD	.213	.213	.053	3.974***	.105	.316
P → RO	.073	.074	.051	1.419	-.026	.174
E → EV	.276	.278	.050	5.527***	.178	.374
E → AD	.201	.203	.054	3.685***	.095	.309
E → RO	.124	.125	.056	2.196*	.013	.235
HR → EV	.055	.055	.048	1.149	-.038	.149
HR→ AD	.092	.093	.053	1.729	-.010	.198
HR → RO	.125	.126	.053	2.365*	.018	.227
PP → EV	-.129	-.127	.046	-2.777**	-.216	-.035
PP → AD	-.136	-.134	.050	-2.733**	-.230	-.036
PP → RO	-.050	-.049	.055	-.899	-.157	.059
IC → EV	.193	.194	.045	4.220***	.105	.283
IC → AD	.168	.171	.051	3.264**	.069	.271
IC → RO	.055	.057	.053	1.034	-.048	.159

T: Technological expertise; IC: Innovative climate; P: Competitive pressure; E: Expectations; PP: Private/Public; HR: Place of HR function; EV: Evaluation; AD: Adoption; RO: Routinization.

t Table (two-tailed):
- 95% confidence interval: t-value ≥ 1.960 (*)
- 99% confidence interval: t-value ≥ 2.576 (**)
- 99.9% confidence interval: t-value ≥ 3.291 (***)

1.3.3. Assess the explanatory power of the model

The next step is examining the coefficient of determination *(R^2)*. As this step is already detailed in the article, we won't go any further here.

At this point, and since we perform several moderations, we must observe the f^2 values of our main structural model to identify how each predictor influences its R^2 [14]. This is shown in *Table 7*.

DOI: 10.21791/IJEMS.2024.029.

TABLE 7

f^2

Latent constructs	Evaluation	Adoption	Routinization
Technological expertise	.038	.019	.015
Competitive pressure	.143	.057	.006
Expectations	.103	.049	.016
Private/Public	.024	.023	.003
Place of HR function	.004	.008	.016
Innovative climate	.052	.032	.003

Cohen [81] suggests thresholds of .02, .15 and .35, which correspond to *small*, *medium*, and *large* contributions of an interaction term to the variance of a dependent variable (R^2), respectively. However, Aguinis *et al.* [82] demonstrate that the average effect of an interaction term in a moderation analysis is .009. Hair *et al.* [14] suggest being more flexible and lowering these thresholds for the contribution of the interaction terms to .005, .01, and .025.

Regarding the dependent variable *evaluation*, the most influential predictors are as follows: Competitive pressure contributes strongly to its variance, with a value of f^2 = .143. Next is expectations (f^2 = .103), innovative climate (f^2 = .052), technological expertise (f^2 = .038), and the private/public dimension (f^2 = .024), with a moderate contribution to *evaluation* variance. The HR function makes a low contribution (f^2 = .004).

Regarding the dependent variable *adoption,* the most influential predictors are competitive pressure (f^2 = .057), expectations (f^2 = .049), innovative climate (f^2 = .032), the private/public dimension (f^2 = .023), and technological expertise (f^2 = .019). All of them make a moderate contribution. Finally, the position of the HR function makes a low contribution (f^2 = .008).

The contributions of our independent variables to *routinization* can be ranked as follows: HR function position (f^2 = .016), expectations (f^2 = .016), and technological expertise (f^2 = .015), all of which make a moderate contribution to the variance of this final endogenous construct. These are followed by competitive pressure (f^2 = .006) and private/public (f^2 = .003), with a low contribution.

1.3.4. Assess the predictive power of the model

Many researchers interpret the R^2 statistic as a measure of the predictive power of their models [92]. This is not completely accurate, as R^2 only indicates the explanatory power of the model for the sample under consideration [14] and does not indicate its predictive power in the population [93]. Researchers can rely on several indicators that quantify prediction errors, such as the root mean square error (RMSE) or the mean absolute error (MAE) to assess the predictive power of their PLS-SEM models [14]. In general, when the prediction error distribution is highly asymmetric; that is, characterized by a long tail to the left or right in the prediction error distribution, the MAE is a more appropriate metric than the RMSE [14]. Our visuals indicate relatively symmetric prediction error distributions for our first six items and highly asymmetric ones for the last two:

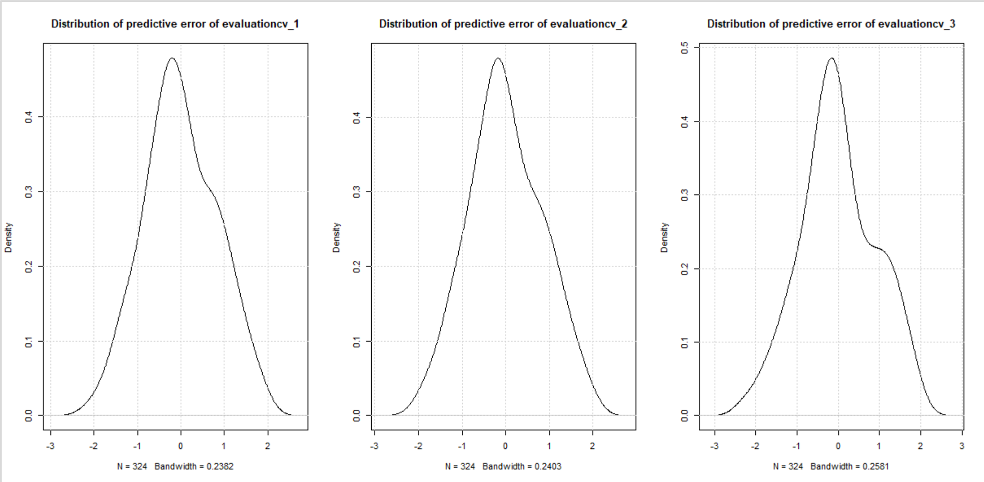

Figure 3. Prediction error distribution for evaluation.

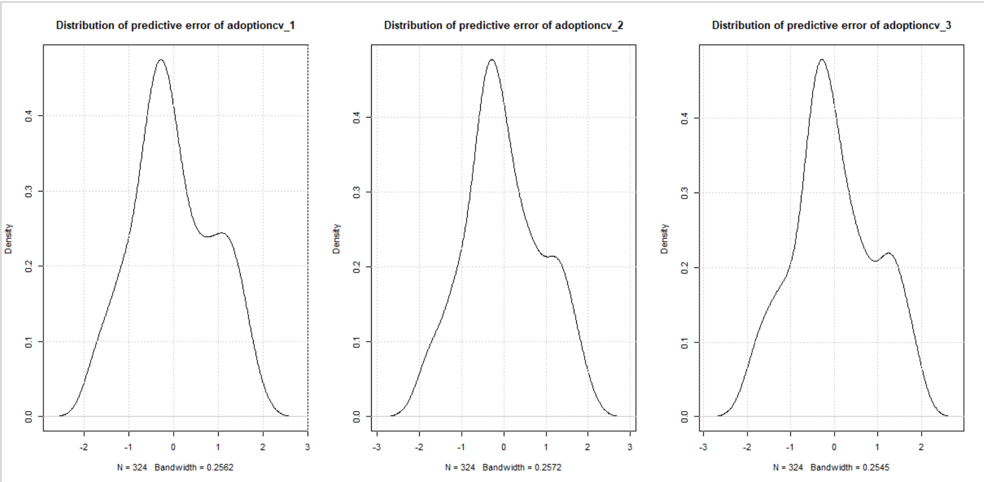

Figure 4. Prediction error distribution for adoption.

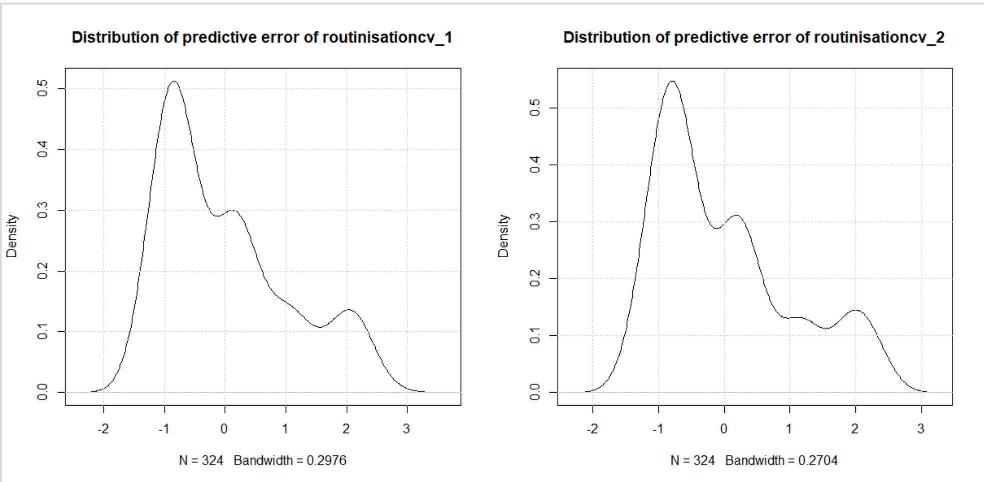

Figure 5. Prediction error distribution for routinization.

We use the RMSE for the first six and MAE for the final two. Thus, their interpretation depends on their comparison with another indicator, the linear regression model (LM) benchmark [14]. In this respect, Hair *et al.* [14] formulate the interpretation rules presented in *Table 8*.

DOI: 10.21791/IJEMS.2024.029.

TABLE 8
RMSE (MAE) and LM benchmark - General rules of interpretation

Configuration	General rules
1	If *all the* dependent variable indicators have RMSE (or MAE) values less than or equal to those of the LMs, the model has high predictive power.
2	If *the majority* (or the same number) of the dependent variable indicators have RMSE (or MAE) values less than or equal to those of the LMs, the model has average predictive power.
3	If *a minority of* the dependent variable indicators have RMSE (or MAE) values less than or equal to those of the LMs, the model has poor predictive power.
4	If all the indicators of the dependent variables have RMSE (or MAE) values greater than those of the LMs, then the model has no predictive power.

To produce these values, predictions must first be generated using the *predict_pls()* function. We perform this procedure with *k = 10* folds and 10 repetitions. For this purpose, we set *noFolds = 10* and *reps = 10*. In addition, we use the *predict_DA* approach [14]. The generated predictions place us in the first configuration, where all of the indicators have values below the corresponding LM values (*Table 9*). Therefore, our model has very high predictive power. In addition, although our study is cross-sectional, this information suggests that our results are generalizable beyond the considered sample.

TABLE 9
Evaluation of the predictive power of our model - RMSE and MAE values

	PLS out-of-sample metrics:							
	ecv_1	ecv_2	ecv_3	acv_1	acv_2	acv_3	rcv_1	rcv_2
RMSE:	.498	.585	.617	.524	.768	.817	.941	.902
MAE:	.330	.398	.395	.300	.577	.633	.795	.766
	LM out-of-sample metrics:							
	ecv_1	ecv_2	ecv_3	acv_1	acv_2	acv_3	rcv_1	rcv_2
RMSE:	.542	.638	.662	.569	.834	.891	1.040	1.000
MAE:	.361	.435	.427	.331	.627	.690	.873	.842

ecv_1 + ecv_2 + ecv_3 = *evaluation*
acv_1 + acv_2 + acv_3 = *adoption*
rcv_1 + rcv_2 = *routinization*

Having completed the evaluation of our main measurement and structural models, we run our moderator model and interpret all of our results to determine whether our hypotheses are validated or invalidated. As a reminder: "*Measurement and structural model evaluation criteria (...) also apply to moderator models. For the interaction term, however, there is no requirement to assess its measurement model since it represents an auxiliary measurement that incorporates the interrelationships between the moderator and the exogenous construct in the path model*" [14, p. 161]. Thus, in the following section, only our auxiliary structural model, and not the measurement model, is assessed.

1.4. Assess the auxiliary structural model

1.4.1. Examining collinearity issues

As our VIF values are systematically below 3 here, there is no reason to suspect any collinearity problems in our structural model.

1.4.2. Assess significance and relevance of the structural model

To determine the presence or absence of moderation effects, we must first bootstrap this second structural model to observe the significance of its path coefficients [14]. We proceed by replicating it 10,000 times. *Table 10* summarizes the obtained values.

TABLE 10
Bootstrapped paths, nboot = 10'000

	Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	2.5% CI	97.5% CI
T → EV	.173	.174	.046	3.758***	.085	.265
T → AD	.141	.145	.049	2.842**	.045	.242
T → RO	.120	.125	.055	2.160*	.012	.234
P → EV	.323	.325	.048	6.640***	.230	.420
P → AD	.212	.213	.053	3.997***	.106	.315
P → RO	.062	.063	.051	1.217	-.036	.163
A → EV	.278	.280	.049	5.636***	.181	.377
A → AD	.210	.212	.053	3.924***	.106	.317
A → RO	.114	.117	.055	2.053*	.008	.225
HR → EV	.048	.049	.048	1.002	-.044	.142
HR → AD	.083	.084	.052	1.591	-.016	.188
HR → RO	.136	.136	.054	2.521*	.029	.239
PP → EV	-.124	-.121	.046	-2.662**	-.212	-.028
PP → AD	-.134	-.131	.050	-2.658**	-.229	-.030
PP → RO	-.052	-.050	.055	-.941	-.157	.057
IC → EV	.211	.211	.048	4.373***	.116	.305
IC → AD	.184	.186	.052	3.495***	.083	.289
IC → RO	.082	.082	.054	1.514	-.027	.186
P*IC → EV	-.024	-.020	.055	-.442	-.129	.088
P*IC → AD	.003	.007	.059	.053	-.104	.123
P*IC → RO	-.022	-.021	.049	-.446	-.119	.076
E*IC → EV	.041	.039	.050	.814	-.058	.137
E*IC → AD	.065	.061	.056	1.147	-.050	.172
E*IC → RO	-.018	-.018	.053	-.337	-.121	.089
T*IC → EV	.022	.022	.046	.488	-.070	.112
T*IC → AD	-.012	-.014	.053	-.224	-.118	.090
T*IC → RO	-.051	-.054	.052	-.990	-.157	.049
HR*IC → EV	-.056	-.056	.050	-1.117	-.154	.045
HR*IC → AD	-.105	-.105	.055	-1.908	-.213	.003
HR *IC → RO	.147	.147	.051	2.854**	.046	.249
PP*IC → EV	.104	.104	.049	2.130*	.009	.201
PP*IC → AD	.111	.111	.053	2.068*	.007	.214
PP*IC → RO	.101	.102	.054	1.885	-.003	.207

T: Technological expertise; IC: Innovative climate; P: Competitive pressure; E: Expectations; PP: Private/Public; HR: Place of HR function; EV: Evaluation; AD: Adoption; RO: Routinization.

t Table (two-tailed):
- 95% confidence interval: t-value ≥ 1.960 (*)
- 99% confidence interval: t-value ≥ 2.576 (**)
- 99.9% confidence interval: t-value ≥ 3.291 (***)

As shown in *Table 10*, many predictors are significantly related to the dependent variables. This indicates the presence of the following three interaction effects:

- Place of the HR function * innovative climate on the dependent variable routinization.
- Private/Public * innovative climate on the dependent variable evaluation.
- Private/Public * innovative climate on the dependent variable adoption.

1.4.3. Assess the explanatory power of the model

We investigate the R^2 metrics that emerge from this structural model, as presented in *Table 11*.

TABLE 11
Path coefficients, significance and R^2

	Evaluation	Adoption	Routinization
R^2	.298	.193	.100
R^2 adjusted	.273	.165	.069
T	.173***	.142**	.121*
P	.323***	.212***	.063
E	.279***	.211***	.115*
HR	.049	.084	.137*
PP	-.125**	-.135**	-.052
IC	.211***	.185***	.083
P*IC	-.024	.003	-.022
E*IC	.041	.065	-.018
T*IC	.023	-.012	-.052
HR*IC	-.057	-.105	.147**
PP*IC	.105*	.111*	.102

T: Technological expertise; IC: Innovative climate; P: Competitive pressure; E: Expectations; PP: Private/Public; HR: Place of HR function; EV: Evaluation; AD: Adoption; RO: Routinization.

t Table (two-tailed):
- 95% confidence interval: t-value ≥ 1.960 (*)
- 99% confidence interval: t-value ≥ 2.576 (**)
- 99.9% confidence interval: t-value ≥ 3.291 (***)

As in our first structural model, many of the relationships between our predictors and dependent variables are statistically significant and no relationships are altered by the introduction of our interaction terms. However, as our moderation model is only an auxiliary to our main model, the aim here is not to interpret the direct effects between our independent and dependent variables, but to focus on the interaction effects, which we do in the following section.

1.4.4. Assess the relevance of moderations

The relevance of moderation is assessed using the f^2 metric and, as before, Aguinis *et al.* [82] as well as Hair *et al.* [14] thresholds. The f^2 values are listed in *Table 12*. This table also shows the effect of each interaction term on each dependent variable.

TABLE 12
f^2

Interaction terms	EV	AD	RO	Contribution to EV/AD/RO
P*IC	.001	.000	.001	NS/NS/NS
E*IC	.002	.005	.000	NS/NS/NS
T*IC	.001	.000	.003	NS/NS/NS
HR*IC	.004	.012	.021	NS/NS/Average**
PP*IC	.014	.014	.011	Average*/Average*/NS

DOI: 10.21791/IJEMS.2024.029.

T: Technological expertise; IC: Innovative climate; P: Competitive pressure; E: Expectations; PP: Private/Public; HR: Place of HR function; EV: Evaluation; AD: Adoption; RO: Routinization.

t Table (two-tailed):
- 95% confidence interval: t-value ≥ 1.960 (*)
- 99% confidence interval: t-value ≥ 2.576 (**)
- 99.9% confidence interval: t-value ≥ 3.291 (***)

NS = Not significant.

It can be observed from *Table 12* that HR*IC contributes .021 of the *routinization* explanation of our HR AI instrument. That is, it explains .021 of its variance. Given the thresholds presented above, their contributions can be qualified as *average*. PP*IC contributes .014 to the explanation of the *evaluation* of our HR AI instrument. Its contribution can also be described as *average*. Finally, PP*IC contributes .014 to the explanation of the *adoption* of our HR AI instrument. Its contribution can also be considered as *average*.