Journal of Human Resource Management
--
HR Advances and Developments

ISSN 2453 – 7683 www.jhrm.eu

Implementation of AI Recruitment Systems in Swiss HRM: The Importance of Technological and Organizational Factors

Guillaume REVILLOD

ABSTRACT

Purpose – There are no studies on the factors involved in the spread of AI recruitment tools in Swiss HR.
Aims(s) – The aim of this paper is to understand the determinants of AI diffusion in Swiss human resources recruitment process. In addition to the usual factors such as relative advantage, costs, security, financial resources or organizational size, this paper also looks at factors such as red tape or the innovative climate of organizations.
Design/methodology/approach – This article is based on a quantitative method, PLS-SEM. Our database consists of 324 private and public respondents working in Swiss HR. They were selected through a survey based on their membership of the various regional sections of the HR Swiss association.
Findings – The main findings of this article are that relative advantage, compatibility, complexity, cost reduction, size of organization, technological expertise of employees, innovative climate, and red tape are directly related to the evaluation and adoption stages of this type of AI tool. Security, for its part, is only linked to the evaluation of these tools. Compatibility and technological expertise are also directly linked to the routinization of these tools.
Limitations of the study – First, this is a longitudinal study that needs to be replicated to offer causal explanations. There may also be a selection bias in favor of optimistic respondents who already have HR AI in their organization. This bias is nevertheless controlled, as few of our respondents already use this type of tool. In the future, other predictors could be added to our model, including environmental or individual predictors.
Practical implications – HR decision-makers now know what levers they can use to successfully implement HR AI in their recruitment process.
Originality/value – This article makes a significant contribution to the literature about the diffusion of nascent HR information systems in the specific context of Switzerland and provides decision-makers with levers on which to act to encourage the introduction of this type of AI-based information systems within their organization. No other study has identified the factors behind the spread of HR AI tools in the specific context of Switzerland, as they are still in their infancy.

KEY WORDS

HR, HRM, management, information systems, AI, artificial intelligence, recruitment, hiring process, innovative climate, private and public sectors

JEL Code: J24, M15, O33, M51

DOI: 10.46287/YDNH4362

1 INTRODUCTION

Over the last twenty years, the number of scientific publications dealing with human resources management information technologies has grown considerably (Bondarouk et al., 2017; Strohmeier, 2022). Widely studied topics include web-based HRM (Ruël et al., 2004), e-HRM (Strohmeier and Kabst, 2009), HRM cloud computing (Wang, 2016), and HR analytics (Gerber *et al.,* 2023; Strohmeier and Piazza, 2015). However, access to new generations of structured and unstructured HR databases now makes it possible to take the digitalisation—sometimes called digitisation—of human resources even further by introducing information systems based on artificial intelligence (AI) techniques (Prikshat et al., 2023; Strohmeier, 2022).[1] An increasing number of actors see this as an opportunity to improve the effectiveness or efficiency of many HR processes[2] (Mohamed et al., 2022), such as recruitment (Schuetz and Venkatesh, 2020; Zu and Wang, 2019), performance management (Jia et al., 2018, Johnson et al., 2022), career development (Höddinghaus et al., 2020), or skills development (Gross, 2022).

Although Neumann et al.'s (2022) case study focuses on the diffusion of certain AI tools within eight public organizations, the reasons behind their assimilation, a fortiori in the Swiss context, are still largely unknown. Consequently, this study's interest is twofold: it examines the spread of AI in Swiss human resources and, using the PLS-SEM method, quantitatively analyses questionnaire survey data on the spread of AI-based CV (pre-)selection tools (Hair et al., 2021). The study relies on a theoretical model adapted from Chong and Chan (2012), who unified the diffusion of innovations model formulated by Rogers (1995) and technology-organization-environment theoretical framework (Tornatzky and Fleischer, 1990).

Our research question is as follows:

To what extent do technological and organizational factors influence the spread of AI-based CV (pre-)selection tools within Swiss public and private organizations?

The choice of this type of tool is not insignificant. In the literature, HR AI is still widely considered an emerging technology; that is, it is at an early stage of development in both private and public organizations (Strohmeier, 2022: 2; Young et al., 2021). Some HR AI instruments are nevertheless more commonly used than others, as evidenced by the scientific literature (Strohmeier, 2022) and empirical data collected in this study (Appendix 1). To minimise any possible bias, we therefore chose to study the dissemination of one of the most widespread types of HR AI tools in Swiss organizations. This research is in line with the ongoing work on human resources digitisation (Malik et al., 2020), which represents a major challenge for Swiss organizations and public administration (Emery and Giauque, 2023).

The remainder of this article is organised as follows: Section 2 details the literature review, theoretical framework, and hypotheses. Section 3 describes the methodology, while Section 4 transcribes and discusses the results. Finally, Section 5 concludes by explaining study limitations and proposing new avenues to explore to advance our subject.

2 LITERATURE REVIEW, THEORETICAL FRAMEWORK, AND HYPOTHSES

2.1 AI IN HUMAN RESOURCES

For some time, the literature aimed at managers[3] and scientists has emphasized the importance, benefits, advantages, and challenges of integrating AI tools into human resources management to automate, assist, or help with decision-making in HR function tasks (Strohmeier, 2022; Priskhat et al., 2023). Since Lawler and Elliot's (1993) first study of a tool based on AI, numerous academic studies have focused on AI tools in inherent HR processes (Emery and Gonin, 2009). Examples include staff engagement (Jantan et al., 2010a; Rodney et al., 2019; Strohmeier and Piazza, 2015), performance management (Johnson et al., 2022; Palishkar et al., 2018), skills development (Gross, 2022), and career development (Höddinghaus et al., 2020). Studies also consider the so-called '*cross-functional*' processes (Emery and Gonin, 2009: 46), where AI uses machine learning techniques applied to textual data (Karami et al., 2021) to predict psychosocial risks (Merhbene et al., 2022) like turnover (Kang et al., 2020) or to detect cases of workplace harassment (Karami et al., 2021).

[1] For an exhaustive list of the latter and their concrete use in the field of HR AI tools, see Strohmeier (2022). However, the details are not the subject of this study.

[2] For an exhaustive list of all HR processes that take place within an organisation, see Emery and Gonin (2009), who propose a nomenclature. Other nomenclatures are possible; however, we chose to base our study on the latter because it is largely based on the work of these researchers in Switzerland. Our field of investigation is limited to Switzerland.

[3] According to Boltanski and Chiapello (1999: 763) scientific management research literature is not prescriptive, and its mode of writing presupposes a critical apparatus. For these authors, scientific management research differs from literature intended for managers, whose main objective is informing managers of the latest innovations in company and human resources management (Boltanski and Chiapello, 1999: 100).

Notwithstanding these scientific productions, there is nevertheless a limited understanding of what these AI-based HRM tools, instruments, or applications are (Prikshat et al., 2023: 5). To begin, the definition of AI is far from unanimous (Grosz et al., 2016), a fortiori in the field of human resources management (Strohmeier, 2022). However, this does not prevent authors from venturing formulations. For Meijerink et al. (2021), HR AI is defined as a category of software algorithms that enable an information system to perform HRM activities that would normally require a human being's knowledge and intervention.[4] According to Strohmeier (2022), an HR AI tool is any information system that, as part of an HR process, can not only imitate *natural intelligence* but can also evolve according to the data it is fed. Its objective is then either to completely replace performance of a task previously carried out by the HR function or to produce a result that can then be used to inform the HR function's choices. In this second mode of action, the tool is portrayed as a *decision-making aid*.

This study focuses on a very specific type of HR AI system: AI-based (pre-)selection tools (Hmoud, 2021; Schuetz and Venkatesh, 2020; Zu and Wang, 2019).[5] In broad terms, these tools consist of an AI system that studies the correspondence between CVs received and recruitment criteria using one or more suitable algorithms. If the system autonomously decides to accept or reject an application, it is an automated tool. However, if it simply makes a recommendation about a candidate's file, it is a decision support tool. In administering this study's questionnaire, we took care to capture these two modes of use.

Since no one has yet taken an interest in this subject, despite calls to do so (Venkatesh, 2022), this study's aim is to gain a better understanding of the determinants of the spread of this type of technical system in the staff recruitment processes of Swiss private and public organizations. Two general theoretical frameworks—presented in sections 2.2. and 2.3.—form the basis for the study; in section 2.4., where we present our complete research model and hypotheses, we unify these following the examples of Chong and Chan (2012) and Neumann et al. (2023).

2.2 TECHNOLOGY DIFFUSION/ASSIMILATION PROCESS

Technology adoption does not happen overnight, particularly for technologies marked by a certain complexity, as is the case with HR AI (Prikshat et al., 2023: 3). In fact, the scientific literature talks more about *diffusion* than *adoption*, in the sense that integrating a new technological tool is much more of a *process* than a *rupture*, where the latter is characterised by a *before* and *after* that are totally changed (Zhu et al., 2006). Few organizations can claim to have encountered no obstacles in searching for the best tool for their needs or in deploying and implementing a new tool (Prikshat et al., 2023: 5). This is because introducing a new technological tool into an organization is far from a smooth process, as it takes the form of an eminently contextual process. In this sense, a tool's introduction is always preceded by an *initiation* stage (Ibid.), sometimes called an *evaluation stage* (Chong and Chan, 2012). This can be understood as a preliminary phase in which the actors (actor) in position (s) to initiate acquiring such an object take(s) information and evaluate(s) the potential benefits of using it in their activities (Prikshat et al., 2023: 5). This step thus involves assessing an instrument's potential effectiveness in performing a task assigned to the HR function as compared to already established processes (Strohmeier and Piazza, 2015). Once a tool's potential effectiveness has been demonstrated, an organization can then decide to begin acquiring it. The second stage, *adoption*, then begins, during which the tool is deployed in the organization. This is followed by a series of adjustments—changes to work routines, speeding up operations, resistance, conflicts—which are used to assess the validity of the decision to adopt that tool (Hossain et al., 2016). Once this has been done, the tool will either be confirmed or eliminated (Bhattacherjee et al., 2008). In the first case, a phase of '*routinization*' begins, which indicates its use has become a commonplace component of the organization's operations (Hossain et al., 2016). The organization can then provide training and technical support to the people who will work with the tool (Ahearne et al., 2005). These two elements reduce the

[4] In its simplest sense, an algorithm is a set of instructions expressed in a particular computer language such as Java, Python, or C++ that is used to solve a well-defined problem (Casilli, 2019). Like a recipe, it is used to produce a result based on instructions. Depending on the data they are required to process, algorithms are divided into several fields that make up AI techniques such as natural language processing (NLP) or machine learning (ML) (Prikshat et al., 2023: 5; Strohmeier, 2022).

[5] This kind of tool is deliberately identified this way. In fact, some AI tools of this type pre-select, while others directly select candidates. We therefore used this term in our questionnaire to group these two methods together.

tool's opacity and consequently, stakeholders' aversion to it, as well as the potential dangers inherent in its use, such as data confidentiality or management problems (Prikshat et al., 2023: 7). Finally, in a fourth and final stage known as *confirmation* or *extension*, those who use the tool in question will use it to its full potential or even innovate.

Thus, that is the complete path, also known as *diffusion* or *assimilation*[6] (Prikshat et al., 2023: 2) of a technical object or innovation until it is fully embedded within an organization. The literature is relatively unanimous about this process, with a few variations (Basole and Nowak, 2018; Rogers, 1995; Zhu et al., 2006). Following Chong and Chan (2012) and Neumann et al. (2022), in this study, we base the conceptualisation of our dependent variables on the three phases of *evaluation*, *adoption,* and *routinization.* That said, what governs the transition from one stage to another is still not understood. What explains, for example, the fact that an organization positively evaluated our AI-based CV (pre-)selection tool and consequently decided to continue the process and adopt it? To develop this understanding, we largely base our study on the technology-organization-environment (TOE) framework (Tornatzky and Fleischer, 1990). However, we are extending its explanatory factors.

2.3 AN EXTENDED TO(E) FRAMEWORK

In the literature, the TOE model or framework is a theoretical framework commonly used to understand why organizations adopt technological innovations (Chen et al., 2021; Chong et al., 2010; Chong and Chan, 2012; Neumann et al., 2022; Tornatzky and Fleischer, 1990; Zhu et al., 2006). It has already been used to explain the spread of IT tools (Chong and Ooi, 2008) like medical devices (Chong and Chan, 2012) and human resources management information systems (HRMIS)[7] (Al-Dmour et al., 2017), in both the private and public sectors (Troshani et al., 2010). However, it has never been used to study the determinants of adopting a particular type of HR AI instrument, much less in the context of Swiss human resources. We do so in this study to examine the factors that influence the *evaluation*, *adoption,* and *routinization* phases of AI-based CV (pre)selection tools. This approach was also suggested by Venkatesh (2022) and Prikshat et al. (2023) in their proposal for a theoretical framework relatively similar to ours aimed at better understanding the determinants of diffusing AI-based tools in human resources.

The *TOE framework* predicts that diffusion of a new technology is influenced by three types of factors or dimensions: (1) technological, (2) organizational, and (3) environmental. Although the TOE framework is relevant in its entirety, for the purposes of this study, we focus solely on its technological and organizational dimensions, adding two explanatory factors.

2.3.1. TECHNOLOGICAL FACTORS

From the point of view of the players in our sample, five technological factors potentially influence the spread of our innovation within Swiss organizations: relative advantage, compatibility, complexity, cost reduction, and security.

A tool's **relative advantage** is defined as how it is perceived as being more effective or making it more possible to increase efficiency than the current process it will enhance or completely replace, particularly in terms of saving time or acquiring information that enables faster decision-making (Chong and Ooi, 2008; Warren, 2004). In the past, this dimension has also been referred to as '*perceived benefits*' (Chong and Chan, 2012: 8647). However, the literature more readily uses the term 'relative advantage' (Li et al., 2010; Neumann et al., 2023; Wang et al., 2010). As a hypothesis, then, the fact of perceiving that an instrument can enable obtaining a relative advantage is, in our view, positively associated with the three stages of its diffusion (Table 1. Hypotheses h1a, h1b, and h1c).

Compatibility is defined as the perceived ease with which a tool is likely to fit into an organization's pre-existing processes, operations, and infrastructures (Brown and Russell, 2007; Chong and Chan, 2012; Prikshat et al., 2023: 7). According to Strohmeier and Piazza (2015), such a perception leads to the belief

[6] In the remainder of this text, we use the terms *diffusion* and *assimilation* interchangeably for purely stylistic reasons, particularly to avoid repetition.
[7] '*HRIS constitute dynamic systems that are comprised of systematic procedures and functions for acquiring, storing, manipulating, retrieving, analysing, and disseminating pertinent information concerning an organization's human resources*' (Tannenbaum, 1990).

that a tool is useful or even more effective than current processes and operations. This perception could lead to its *adoption* and, further down the line, to its *routinization* by the very fact that HR function actors will have been able to derive essential added value from it or even innovate their ways of working from using it (Prikshat et al., 2023: 7). We therefore hypothesise that an instrument's perceived compatibility is positively associated with its three stages of dissemination (Table 1. Hypotheses h2a, h2b, and h2c).

Beyond compatibility with an organization, disseminating a technical object can also prove complicated if the organization and its stakeholders feel that the implementation involves too much effort to fit it into the IT infrastructure and/or existing processes. In the literature, this sub-dimension is referred to as **complexity** (Tsai et al., 2010). Our hypothesis is that the perceived complexity of our HR AI tool is negatively associated with the three stages of its diffusion (Table 1. Hypotheses h3a, h3b, and h3c).

The **cost** of technical objects, both to purchase and maintain, is often cited as the main barrier to their adoption (Lai et al., 2005; Mehrjerdi, 2010). When an organization considers acquiring a new tool, its expected cost is then weighed against the benefits expected from acquiring it, such as reducing time spent on recruitment, ultimately reducing its marginal cost (Azoulay et al., 2020; Mehrjerdi, 2010). Therefore, our hypothesis regarding this sub-dimension is as follows: the more actors perceive this HR AI tool as enabling them to reduce the costs inherent in the engagement process, the more inclined their organizations will be to acquire it. In other words, the *cost reduction* sub-dimension has a positive influence on the three diffusion stages considered in this study (Table 1. Hypotheses h4a, h4b, and h4c).

The **security** of the information gathered and processed by information systems is also a major concern for organizations wishing to implement them (Zafar, 2013), especially those in the public sector (Valcik et al., 2023a). For reasons of reputation or employer brand, organizations must be beyond reproach when it comes to protecting the data they collect and use (Denisova, 2023; Zafar et al., 2017). An organization whose stakeholders are convinced, for example, that candidates' profiles inserted into a CV or application processing software could be re-exploited by third parties or *leaked* (Wei et al., 2009), will, in our opinion, be less inclined to want to implement this type of tool. Our hypothesis, therefore, is that the security sub-dimension is positively associated with the three dissemination stages in this study (Table 1. Hypotheses h5a, h5b, and h5c).

We believe all these technological factors influence the three stages of disseminating a CV (pre-)selection type tool within the Swiss HR function. Given the relatively moderate level of use of this type of tool by the organizations surveyed, to which we return in Appendix 1, we nevertheless believe that the influence of these independent variables is strongest at the *evaluation* and *adoption* stages. Table 1 provides a systematic summary of the hypotheses formulated in this section regarding AI-based CV (pre)selection tools (hereinafter referred to as the *[tool]*) considered in this study.

Table 1. Hypotheses for technological factors

Relative advantage (R)	
H1a	R is positively associated with [the tool] evaluation stage.
H1b	R is positively associated with [the tool] adoption stage.
H1c	R is positively associated with the routinization stage of [the tool].
Compatibility (CO)	
H2a	CO is positively associated with [the tool] evaluation stage.
H2b	CO is positively associated with [the tool] adoption stage.
H2c	CO is positively associated with the routinization stage of [the tool].
Complexity (CX)	
H3a	CX is negatively associated with the evaluation stage of [the tool].
H3b	CX is negatively associated with the adoption stage of [the tool].
H3c	CX is negatively associated with the routinization stage of [the tool].
(Decrease) costs (D)	
H4a	D is positively associated with [the tool] evaluation stage.
H4b	D is positively associated with [the tool] adoption stage.
H4c	D is positively associated with the routinization stage of [the tool].
Security (S)	
H5a	S is positively associated with [the tool] evaluation stage.
H5b	S is positively associated with [the tool] adoption stage.
H5c	S is positively associated with the routinization stage of [the tool].

2.3.2. ORGANIZATIONAL FACTORS

Four organizational factors could potentially influence the spread of our innovation within Swiss organizations: top management support (TMS), the size of the organization or workforce, the financial resources specifically dedicated to it, and employees' technological expertise.

Organizational factors are certainly the most widely used to study IT innovation adoption and, more generally, information systems (Bondarouk et al., 2017; Gupta et al., 2020; Chong and Chan, 2012: 8648). In this respect, **support from the hierarchy** is depicted as one of the most influential factors in the 99 articles systematically reviewed by Jeyjaraj et al. (2006) and in more recent literature concerning complex information systems (Hmoud, 2021; Prikshat, 2023: 8; Shao et al., 2017). Integrating a new tool into an organization involves at least some minor, if not major, changes in how things are done, and tasks are accomplished. In this respect, TMS—in the sense of support for using the tool or the absence of negative sanctions for failure, at least initially—would be essential to ensure that any resistance to change is overcome (Brown and Russel, 2007; Liang et al., 2007; Shao et al., 2017). Prikshat et al. (2023: 8) state that '*Top management support can inspire, motivate, resolve conflict, rebalance power, and reward desirable behaviour at different phases of the technology assimilation lifecycle*'.[8] Our hypothesis for this sub-dimension is therefore as follows: TMS is positively associated with the three stages of diffusion considered in this study (Table 2. Hypotheses h6a, h6b, and h6c).

Workforce or **organization size** is also cited as an important factor in successfully assimilating technical objects. Intuitively, the larger the organization, the more resources it has to invest in correctly analysing its needs, acquiring exactly the tool it needs and, finally, successfully *routinising* a technical system (Brown and Russell, 2007; Wang et al., 2010). Although this is one of the technological diffusion factors most widely tested in the literature, the empirical results are not unanimous (Troshani et al., 2010: 4). The resources available due to an organization's size are sometimes counterbalanced by its inertia (Zhu and Kraemer, 2005). Several studies have also shown that small organizations are at least as, if not more, capable of adopting new technologies as large ones. Adopting a new technology requires collaboration and coordination between various players. These two elements are more easily achieved in small organizations (Hitt et al., 1990), which are more flexible, more agile in their decision-making, and less *path dependent*[9] on procedures and ways of working (Gobbs and Kraemer, 2004; Huang et al., 2008; Thong, 1999). The descriptive statistics on the workforces of the organizations in our sample show that they are indeed large in terms of the definition given by the State Secretariat for Economic Affairs,[10] which is incidentally based on that of the European Commission. That said, like Al-Dmour et al. (2017: 147), we believe that they are in a better position to possess or deploy the resources and skills needed to promote dissemination of our innovation than if they were medium-sized or small organizations. In this respect, our hypothesis is therefore that the *organization size* sub-dimension positively influences our three dependent variables (Table 2. Hypotheses h7a, h7b, and h7c).

The literature clearly shows that adopting technical objects is closely linked to the **financial resources** dedicated to them (Hossain et al., 2016; Wong et al., 2019; Prikshat et al., 2023). In our view, the presence of financial resources dedicated specifically to AI development is positively related to the different stages of diffusion of the HR AI instrument examined in this study (Table 2. Hypotheses h8a, h8b and h8c).

The **technological expertise** sub-dimension refers to an organization's level of technological sophistication, that is, whether they have enough skilled personnel to use a technical object. Here again, the literature shows that the presence of qualified personnel tends to positively influence a technology's

[8] For a more detailed overview of the role TMS plays in disseminating HRIS, and HRIS based on AI, see Teo et al. (2007), Chen et al. (2021), and Zerfass et al. (2020).

[9] Path dependency is a concept that originated in economics and then spread to political and management science. It is defined as continued use of a product or maintaining a practice for historical or usage reasons, that is, '*We've always done it this way. We're not going to change now*'. For scientific literature on this subject, particularly in management, see Rolland et al. (2021) or Scarbrough (1998).

[10] https://www.kmu.admin.ch/kmu/fr/home/savoir-pratique/politique-pme-faits-et-chiffres.html. Accessed on 31 January 2024.

diffusion stages (Chong and Chan, 2012: 8648; Prikshat et al., 2023: 8) as do our hypotheses on the assimilation of our CV (pre-)selection tools based on AI (Table 2. Hypotheses h9a, h9b and h9c).

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 (2022) 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 a new independent variable integrated into our TO(E) framework, 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 (Newman et al., 2020[11]), 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 2. Hypotheses h10a, h10b, and h10c).

Both private and public organizations are characterised by burdensome rules and procedures that constrain and regulate their activities and those of their employees (Pandey and Kingsley, 2000; Scott, 2002). In the literature, this phenomenon is known as **red tape**. Its most popular definition[12] is that of Bozeman (2000: 12): '*rules, regulations, and procedures that remain in force and entail a compliance burden, but do not advance the legitimate purposes the rules were intended to serve*'. The relationships between bureaucratisation (including formalisation, red tape, and organizational complexity) and innovation adoption have been extensively examined in the literature (Brown, 1981; Tornatzky and Fleischer, 1990; Bozeman et al., 1991; Bozeman and Crow, 1991). For example, Yu and Bretschneider (1998) discovered that higher levels of red tape are linked to lower IT innovativeness. Indeed, '*At low levels of red tape, organizations tend to initiate new programs and introduce innovative technological alternatives. The explanation for this is that organizations with low levels of red tape are less encumbered by administrative procedures, due to lower transaction costs associated with technological innovation. In other words, high levels of red tape delay and interrupt decisions to adopt new technology*' (Moon and Bretschneider, 2002: 277). Alternatively, it is reasonable to think that problems of red tape generate a demand within the organizations for effectiveness and efficiency and that, in turn, this stimulates demand for innovative solutions, in this case for human resources management AI systems. In this case, the perception of red tape is a facilitating rather than a constraining factor (Ibid.; Pandey and Bretschneider, 1997). Despite work on the influence of red tape on the adoption of e-HRM practices (Rana and Kaur, 2023; Sylvester et al., 2015), the scientific literature has not studied the link between red tape and the diffusion of HR AI systems. In this respect, we believe that red tape could positively influence the diffusion of HR AI tools in the hiring process (Table 2. Hypotheses h11a, h11b, and h11c).

Finally, Table 2 summarises our hypotheses for the organizational factor variables that influence the dissemination of AI-based CV (pre)selection tools.

Table 2. Hypotheses for organizational factors

Top management support (TMS)	
H6a	TMS is positively associated with the evaluation stage of [the tool].
H6b	TMS is positively associated with [the tool] adoption stage.
H6c	TMS is positively associated with the routinization stage of [the tool].
Size of the organization (E)	
H7a	E is positively associated with the evaluation stage of [the tool].
H7b	E is positively associated with the stage of adoption of [the tool].
H7c	E is positively associated with the routinization stage of [the tool].
Financial resources (F)	
H8a	F are positively associated with the evaluation stage of [the tool].
H8b	F are positively associated with [the tool] adoption stage.
H8c	F are positively associated with the routinization stage of [the tool].
Technological expertise (T)	
H9a	T is positively associated with [the tool] evaluation stage.
H9b	T is positively associated with [the tool] adoption stage.

[11] See also Bondarouk et al. (2017), Bos-Nehles and Veenendaal (2019), and Malik and Wilson (1995).

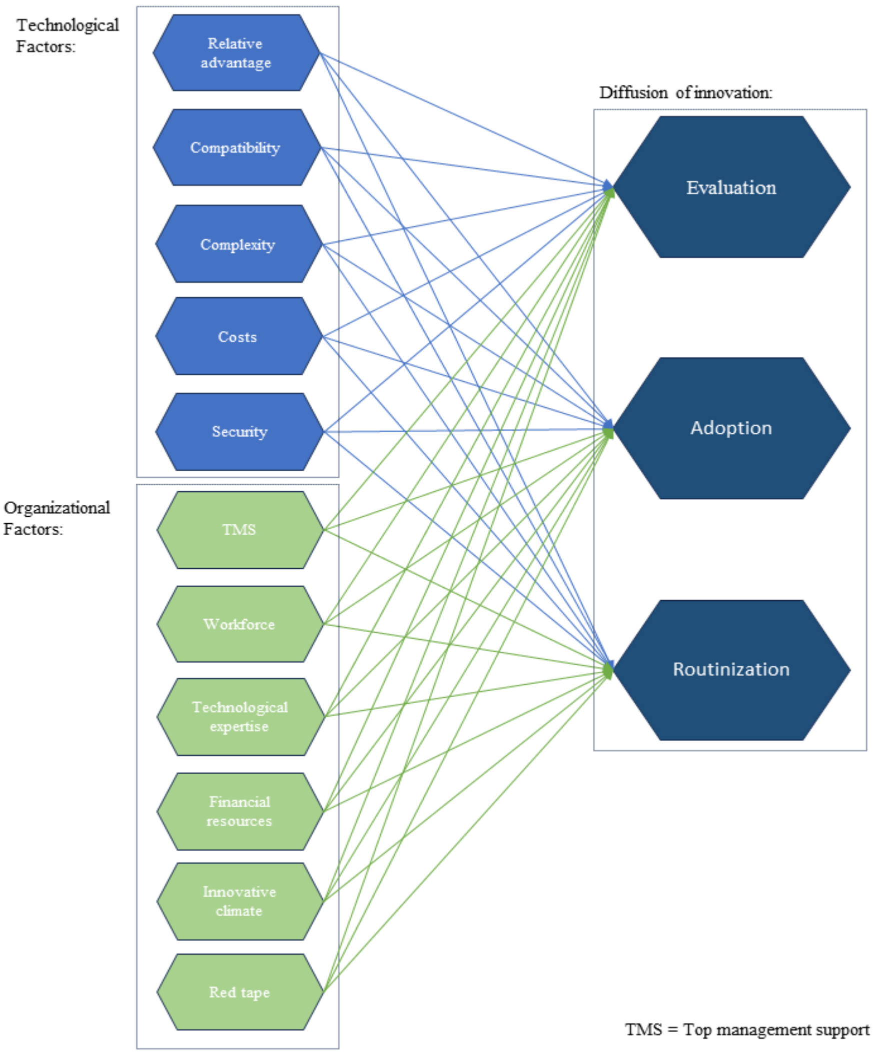
[12] It is cited, for example, in the work of Borry (2016: 2) and Giauque et al. (2013: 64).

H9c	T is positively associated with the routinization stage of [the tool].
Innovative climate (IC)	
H10a	IC is positively associated with [the tool] evaluation stage.
H10b	IC is positively associated with [the tool] adoption stage.
H10c	IC is positively associated with the routinization stage of [the tool].
Red tape (RT)	
H11a	RT is positively associated with [the tool] evaluation stage.
H11b	RT is positively associated with [the tool] adoption stage.
H11c	RT is positively associated with the routinization stage of [the tool].

2.4. FINAL RESEARCH MODEL

Based on the above, Figure 1 summarises our conceptual or research model.

Fig 1. Final research model



3 METHOD

3.1 DATA COLLECTION AND SAMPLE CHARACTERISTICS

This study is based on a survey sent to private and public HR professionals in Switzerland between November 2022 and March 2023.

The associations HR Vaud (N=777)[13], HR Tessin (N=270)[14], and the *Zürcher Gesellschaft für Personalmanagement* (N≃600)[15] all agreed to distribute the questionnaire to their network and conduct at least one follow-up at a three-week interval following its first distribution. The HR Genève (N=720)[16] and HR Valais (N=330)[17] sections only agreed to distribute the questionnaire to their network one time.

Since 1848, the Swiss federal political system has consisted of three governance levels: the federal state, cantons, and municipalities. The principle of subsidiarity (Sciarini, 2023) gives each level a large degree of political autonomy and autonomy in how it organises its public administration, particularly in terms of infrastructure and information systems (Ladner et al., 2019). Consequently, contextual differences can be observed in this area, which is why we also surveyed the Federal Personnel Office (N=1), the 26 cantonal human resources departments, and 168 of the 2136 Swiss municipalities. We deliberately chose to restrict the municipalities to those with more than 10,000 inhabitants (OFS, 2021a). A municipality's size also generally determines whether it has an HR department (Ladner and Haus, 2021). This arbitrary threshold allows us to be certain that the respondents are confirmed members of the HR function. Each public authority was invited to take part in our questionnaire three times, at three-week intervals, by email and post. A total of 324 responses were received, for a return rate of 11.20%.[18] As Swiss HR professionals are quite busy, this rate is acceptable. Baldegger et al. (2020) obtained only 305 responses via the same umbrella organizations. Internationally, Chong and Chan (2012: 8649) obtained almost half as many responses as we did (N=183) for a barely higher response rate of 18.30%. To respect Switzerland's linguistic diversity, the questionnaire was translated into three of the four languages officially recognised by the Confederation—German, French, and Italian—as well as English.

The respondents' individual characteristics are shown in Table 3.

Table 3. Demographic description of the sample (N=324)

Variable	*Percentage*	*Variable*	*Percentage*
Gender		**Language area**	
Women	49.69	French Switzerland	44.44
Men	43.21	German Switzerland	42.90
Other	.00	Italian Switzerland	6.17
NA	7.10	NA	6.48
Hierarchical position		**Time with organization**[19]	
Employee	25.31	< 1	7.10
Proximity manager	4.32	1-3	15.43
Middle management	23.77	3-5	15.74
Executive management	39.51	5-10	22.22
NA	7.10	> 10	31.48
		NA	8.02
Age[20]		**Maximum activity level**[21]	
< 18	.00	International	30.86
18-25	.00	Federal	27.47
26-34	4.63	Cantonal	14.51
35-44	17.59	Communal	20.06
45-54	43.83	NA	7.10
55-64	25.93	**Private/Public**	
> 65	.00	Private	48.46
NA	8.02	Public	47.53
		NA	4.01

3.2 PREVENTING BIAIS

[13] According to https://hr-vaud.ch/vison-missions/. Official figures not provided. Page consulted on 26 June 2023.
[14] The figure was provided to us by the secretariat of HR Ticino.
[15] The approximate figure was provided by the ZGP secretariat.
[16] The figure was provided by the HR Geneva secretariat.
[17] According to https://www.hr-valais.ch. Official figures not provided. Page consulted on 26 June 2023.
[18] To calculate: 324*100/2892 = 11.203%, where 324 is the total number of responses out of the approximate potential of 2892 respondents.
[19] In years.
[20] In years.
[21] In other words: federalism.

Organizational behaviour research often faces methodological biases, particularly when researchers rely on self-administered questionnaires (Podsakoff et al., 2012). In some cases, this can threaten the validity of the relationships observed between variables and conclusions inferred from them (Pandey et al., 2008; Podsakoff et al., 2012). Good questionnaire design, a clear data collection strategy, and post-hoc data analysis are three ways to mitigate and verify that potential data measurement biases are neither present nor influential (Podsakoff et al., 2012). To this end, we guaranteed complete anonymity to all respondents (Pandey et al., 2008). The invitation to complete the questionnaire was accompanied by a description of the study aims and reminder of the essential rules of scientific ethics. Respondents were asked to answer freely and were informed that none of the information gathered would be passed on to anyone else. Although not absolutely necessary when using the PLS-SEM method (Hair et al., 2021: 11-12), as '*many scholars indicate that the absence of distributional assumptions is the main reason for choosing PLS-SEM'* (Hair et al., 2018: 11-12), post-hoc statistical tests of skewness and kurtosis were carried out to ensure the normality of our variables.[22] The measurement and structural models were also tested to ensure that our results met the guidelines for using the PLS-SEM method in human resources management (Ringle et al., 2020).

3.3 MEASUREMENTS

3.3.1 DEPENDENT VARIABLES

Our dependent variables, the *evaluation*, *adoption,* and *routinization* stages, are latent constructs (Williams and O'Boyle, 2008) whose items are measured on a four-point Likert scale with (1) indicating '*strongly disagree'* and (4) indicating '*strongly agree'*. Thus, each of these variables is a type of ordinal scale which, following the example of Blaikie (2003: 24) or Anderfuhren-Biget et al. (2010: 223), we assume to be continuous to apply the PLS-SEM method (Hair et al., 2021).

3.3.2 *INDEPENDENT VARIABLES*

Our independent variables are also measured using a four-point Likert scale with (1) representing '*strongly disagree*' and (4) representing '*strongly agree*'. Some of these are latent constructs, including relative advantage, compatibility, complexity, cost reduction, security, *TMS*, financial resources, and technological expertise. The workforce variable is the only *single construct* or single item in our model. Although Chong and Chan (2012) use a latent variable to measure how the size of an organization affects the stages of diffusing the technical object they study, we chose to base our analysis on the number of employees in the sample organizations. As they are formulated in the literature—item 1: '*my company's capital is high compared to that of the industry*; and item 2: '*my company's revenues are high compared to those of the industry*'—the underlying items focus exclusively on private organizations and are therefore not adaptable to public organizations, whose goals do not include profits. Because our sample also includes public organizations, we must do this to include them in our analyses. 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 (2019: 2571) and Malik and Wilson (1995). The same for the three-item red tape scale (TIRT) developed by (Borry, 2016).

3.4 ANALYSIS PROCEDURE

This section briefly summarises our analyses using the PLS-SEM method (Hair et al., 2021), which are transcribed in full in Appendix 2.

3.4.1 PRELIMINARY CONSIDERATIONS

[22] Note that the PLS-SEM method has the undeniable advantage of not requiring that variables be normally distributed, while producing particularly robust results when they are (Hair et al., 2022: 28).

Statistically, using PLS-SEM type structural equations is justified when a theoretical model includes many latent constructs and involves testing complex relationships between them that are proposed from a theoretical framework (Hair et al., 2021: 22). This is exactly the case in this study, which mobilises numerous latent constructs from the TOE framework (Tornatzky and Fleischer, 1990), DOI (Rogers, 1995) but also those of innovative climate (Newman et al., 2020) and red tape (Borry, 2016). However, our sample must meet two requirements for the PLS-SEM method to retain sufficient statistical power and for the results thus obtained to be generalisable (Hair et al., 2021: 15). These requirements are the 10-time rule (Hair et al., 2021: 16) and the inverse square root method (Hair et al., 2021: 17-18); our study complies with both. In addition, less than 300 iterations must be necessary for our model to converge (Hair et al., 2021: 82); as our model requires only 8 iterations, this condition is also met.

Having met all the preliminary considerations, we proceed with the analyses, starting with evaluating our measurement model.

3.4.2 EVALUATING THE MEASUREMENT MODEL

The evaluation of our measurement model depends, first, on the type of latent construct used. Our constructs are reflective latent constructs (Hanafiah, 2020) since they exist independently of the items used to measure them (Borsboom et al., 2004); moreover, perceptual, attitudinal, or personality trait measurement scales are typically reflective constructs (Coltman et al., 2008: 1252). Second, reflective constructs assume that causality runs from the concept to the indicators (Ibid.). They must also share a common theme and be interchangeable (Coltman et al., 2008: 1253), which is true for our constructs.

Empirically, evaluating a model made up of reflective constructs involves various tests for which we refer to the different commonly accepted thresholds (Cheung et al., 2023; Hair et al., 2021). These tests are divided into four stages. The first examines indicator reliability; the second assesses the internal consistency of the constructs; the third looks at the convergent validity of each conceptual measure; and the final stage examines construct discriminant validity, that is, the extent to which they differ from one another. The full details of these analyses are available in available in Appendix 2. All latent constructs except TMS meet all the evaluation criteria inherent in our measurement models. We therefore move on to evaluating our structural model.

3.4.3 EVALUATING THE STRUCTURAL MODEL

Hair et al. (2021: 116) propose the following systematic approach to assessing a structural model's quality: first, examine whether it contains collinearity problems; second, assess its significance and relevance; and third, assess its explanatory and predictive power. The full details of these analyses are available in Appendix 2. The results show that there is no reason to suspect that our structural model is unreliable regarding these criteria (Cheung et al., 2023; Hair et al., 2021). We therefore move on to present and interpret our results.

4 RESULTS

4.1 DESCRIPTION OF RESULTS

Table 4 provides a detailed summary of our results:

Table 4. Path coefficients, significance and R^2

	Evaluation (EV)	Adoption (AD)	Routinization (RO)
R^2	.386	.271	.078
R^2 adjusted	.364	.245	.045
Technological factors (T)			
R	.091*	.117*	.041
CO	.121**	.121**	.111*
CX	-.328***	-.201***	-.086
D	.200***	.174**	.035

S	.108*	.090	.081
Organizational factors (O)			
TMS	.069	.092	.104
E	.132**	.115**	.032
F	.090*	.075	.082
T	.126**	.095*	.111*
IC	.157***	.158**	.048
RT	.162***	.250***	.039

R: Relative advantage; CO: Compatibility; CX: Complexity; D: (Decrease) costs; S: Security; TMS: Top management support; F: Financial resources; T: Technological expertise; IC: Innovative climate; RT: Red tape; EV: Evaluation; AD: Adoption; RO: Routinization.

t Table for significance (two-tailed):

- Confidence interval 95%: t-value ≥ 1.960 (*)
- Confidence interval 99%: t-value ≥ 2.576 (**)
- Confidence interval 99.9%: t-value ≥ 3.291 (***)

The table results show that our model explains 36.4% of the variance in the dependent variable *evaluation*, compared with 24.5% for *adoption* and 4.5% for *routinization*.

For the technological factors, relative advantage has a positive and significant relationship with the *evaluation* and *adoption* stages. However, it is not significantly associated with the *routinization* stage of the HR AI instrument considered here. Therefore, hypotheses *h1a* and *h1b* are supported by the empirical data, while hypothesis *h1c* is not. The compatibility subdimension has a positive relationship with all adoption stages of our HR AI instrument. This confirms our hypotheses *h2a, h2b,* and *h2c*. The perceived complexity of our instrument is significantly but negatively correlated with our first two diffusion stages, while it is not significantly associated with the *routinization* stage. Hence, hypotheses *h3a* and *h3b* are confirmed, while *h3c* is rejected. Costs, in this case, their perceived reduction when the object is evaluated, adopted, or routinised, are positively and significantly associated with the first two assimilation stages but not with the tool's *routinization*. Consequently, only hypotheses *h4a* and *h4b* are confirmed for this sub-dimension. Finally, the safety sub-dimension was only significant at the *evaluation* stage; therefore, only hypothesis *h5a* is confirmed. The technological factors are all significantly associated with the *evaluation* stage of our technical object. Four out of five are also associated with the *adoption* stage, but only one is associated with the *routinization stage*.

The results In Table 4 show that TMS is never significantly associated with our dependent variables. This is not surprising, as this latent construct violates several commonly accepted thresholds when the measurement model is evaluated. We can therefore only reject hypotheses *h6a*, *h6b,* and *h6c*. However, the number of staff in an organization is positively and significantly associated with the tool's *evaluation* and *adoption* but not with its *routinization*. Hypotheses *h7a* and *h7b* are therefore confirmed, while hypothesis *h7c* is invalidated. Financial resources were significantly correlated only with the *evaluation* stage, confirming only hypothesis *h8a*. Technological expertise is positively associated with all our dependent variables. Hypotheses *h9a*, *h9b* and *h9c* are therefore confirmed. The innovative climate is significantly associated with our first two diffusion stages. Hypotheses *h10a*, *h10b* are therefore confirmed, while *h10c* is invalidated. The last organizational sub-dimension, red tape, is also positively associated with the first two diffusion stages, confirming hypotheses *h11a* and *h11b*, while *h11c* is invalidated.

In general, all organizational factors except hierarchical support are associated with the *evaluation* stage Most of our organizational predictors also explain the adoption of our HR AI tool, except for TMS and financial resources. Finally, only technological expertise is linked to its *routinization*.

4.2 INTERPRETATION OF RESULTS AND DISCUSSION

This study examined the perceptions of Swiss HR function players regarding the technological and organizational factors that influence the three stages of disseminating AI-based CV (pre)selection tools within their organizations. The results show that this type of tool's perceived compatibility and technological expertise of employees are systematically and significantly associated with its complete assimilation within organizations. However, other factors are also linked to one or more of the stages in spreading this technology. This section describes these factors in detail and suggests possible interpretations based on our theoretical framework.

4.2.1 TECHNOLOGICAL FACTORS

The technological variables are all significantly associated with the tool's *evaluation* stage. In addition, all technological variables except security are significantly associated with the *adoption* stage for the type of tool considered in this study. Finally, only the compatibility variable is associated with the *routinization* stage.

Thus, according to the HR function, their perception that the tool enables them to obtain a **relative advantage** has a positive influence on the sample organizations when they assess the possibility of equipping themselves with this type of tool. Although no scientific study has yet conducted a quantitative evaluation comparable to ours,[23] several that specialise in disseminating information systems have reached similar conclusions regarding this variable's influence on the *evaluation* stage (Chen et al., 2021; Chong and Chan, 2012; Wang et al., 2010). One possible explanation for this association could be that, when evaluating the possibility of equipping themselves with this type of instrument, organizations try to ensure that the tool will enable them to improve the effectiveness and efficiency of the process in which it will be used. That said, relative advantage also has a stronger and more significant positive influence on the *adoption* stage of our HR AI tool than it does in the previous stage. This could be explained by the relative popularity of AI-based CV (pre)selection tools. In fact, since their reputation for effectiveness, efficiency and diversification of profiles recruited is well established (Azoulay et al., 2020; Volini et al., 2019), organizations' HR functions would be more inclined to adopt them to realise the relative advantages perceived during the previous stage. The fact that this result contradicts, for example, Chong and Chan (2012: 8650), who did not, however, study the same type of instrument, probably indicates that contingency factors, such as the Swiss context or type of tool studied, come into play. In any case, this variable does not influence the *routinization of* our tool. Chong and Chan (2012: 8651) state that this factor loses its explanatory power once organizations have decided to invest in and integrate a technical system. Once a tool has been integrated, its relative advantage no longer interests organizations; instead, the primary interest is its ability to perform its tasks, in other words, its performance in action, which is not a dimension operationalised in this study.

In our view, the same logic used for relative advantage applies to the **compatibility** factor, which is also positively associated with the *evaluation* stage. As far as HR function players are concerned, organizations are looking first and foremost to assess whether the tool they plan to use is compatible with both their IT infrastructure and processes. This is repeated during the *adoption* phase, at the end of which the tool is either definitively adopted or rejected, as well as during the *routinization* phase. Our empirical data therefore show that this type of tool's perceived compatibility with the IT infrastructure on the one hand and hiring process on the other, is essential at all three stages of their assimilation within the Swiss HR function. Chang and Chan (2012: 8651) show that this explanatory factor is only significant for the *routinization* stage. They suggest that this could be explained by the importance of this factor once a tool has been integrated into work routines. We thus show that Swiss organizations are not only concerned about the compatibility of this type of tool with their processes at the *routinization* stage but also at the two previous stages.

Unsurprisingly, HR function players indicate that Swiss organizations are looking for AI tools that they perceive as not being too complex or difficult to use, at least when it comes to AI-based CV (pre)selection tools. Of all the independent variables included in our model, **complexity** is one of the strongest in terms of coefficient and significance; the hypothesis of its association with the dependent variables *evaluation* and *adoption* is verified at a confidence interval of 99.9%. As explained in our theoretical section, this result makes perfect sense if we consider that adopting AI tools does not simply consist of equipping oneself with ready-to-use technologies. The changes, possible reluctance (Oliveira et al., 2014), and transformation of work processes brought about by acquiring this type of technical object all pose difficulties for organizations. Consequently, they are looking above all for simple tools that are not likely to increase the

[23] At the time of writing, no quantitative study exists of the factors that influence the spread of AI-based tools in human resources.

complexity of the HRM processes into which they will be incorporated. This result is consistent with the literature, which describes this latent construct as one of the main inhibitors to applying AI tools (Chen et al., 2021: 60). According to our empirical data, however, the *routinization* of AI-based CV (pre)selection tools is not associated with this sub-dimension. This result is not surprising, insofar as a tool's complexity is of concern to organizations only at the early stages of dissemination. By definition, a tool can only be *routinised* once the issues relating to its complexity have been overcome. If a tool is integrated into the HR function's day-to-day processes, then its complexity is no longer a barrier (Mehrjerdi, 2010).

Organizations are therefore likely to be attracted by the reduced **costs** of the engagement process this type of instrument promises (Jia et al., 2018: 109). Our results show that this is the second strongest predictor of the *evaluation* stage and is a highly significant predictor, since its relationship with this dependent variable is verified at a confidence interval of 99.9%. Its relationship is also verified with the *adoption* stage at a confidence interval of 99.0%. However, it is not linked to the tool's *routinization*. This result is consistent with the Swiss human resources literature, particularly that in the public sector. According to Emery and Gonin (2009: 400), Ball (2001), and Troshani et al. (2010: 1), HRIS are perceived not only as tools for improving the effectiveness of certain HRM processes, but also for promoting their efficiency, where efficiency is understood as using a minimum of human and financial resources[24] for a given result. Therefore, they function as a means of deploying more strategic human resources management, whose contribution to the organization's performance can be assessed and recognised. This result is in line with those of Mehrjerdi (2010), Chong and Chan (2012) and Scupola and Pollich (2019).

According to the HR function, this type of tool's perceived **security** is also a concern for organizations in the *evaluation* stage but not in the next two stages. This result is not surprising since the slightest data leak today can cause serious reputational damage (Makridis, 2021). Swiss organizations would therefore be particularly careful prior to adoption to assess whether this type of tool could cause breaches in data protection and storage. Once ascertained, this would no longer be an issue for them; in other words, it would no longer be a determining factor in disseminating this type of technical object. This result is also consistent with the information systems literature in both the private (Wei et al., 2009; Chong and Chan, 2012) and public (Troshani et al., 2010) sectors.

4.2.2 ORGANIZATIONAL FACTORS

Organizational variables are all significantly associated with the tool *evaluation* stage considered in this study, except for TMS, which failed the validity tests usually accepted in a PLS-SEM analysis (Hair et al., 2021). Four organizational variables – organization size, technological expertise, innovative climate and red tape – are significantly associated with the *adoption* dependent variable, while technological expertise is the only one significantly linked to the *routinization* stage.

Contrary to the existing literature on the diffusion of technical objects (Chen et al., 2021: 60; Chong and Chan, 2012; Hmoud, 2021), which depicts the **TMS** construct as a driver of information system adoption, TMS is not interpretable in this work due to its poor quality. However, our data show that the link between **organization size** and diffusion of the type of innovation considered here is significantly associated with the first two stages of our technical object's diffusion. In Switzerland, therefore, as an organization's size increases, it is more inclined to *evaluate* the possibility of equipping itself with an HR AI tool of the (pre) selection of applications type. Similarly, the larger an organization, the more likely it is to adopt this type of tool. These two results are consistent with the existing literature (Brown and Russell, 2007; Wang et al., 2010). According to Troshani et al. (2010: 8), the logic behind this association is as follows. The potential benefits of acquiring an HRIS are more perceptible when organizations anticipate that it will be spread over a broad user base. In other words, the more an organization perceives that a tool will serve, and serve well, numerous users within its organization, the more likely it will be to assess the possibility of acquiring and adopt it. The same authors put this into perspective, however, urging us not to generalise too hastily; the larger an organization, the more complex its operations. The existence of silos or internal power logics,

[24] In any case, the two go hand in hand based on the understanding that human resources can be quantified in terms of the costs represented by salaries; therefore, any activity carried out by them can also be given in terms of costs based on the time required to perform it.

to name just two factors likely to negatively influence the process of assimilating a technical object, could prevent it from being acquired and disseminated. In short, the complexity inherent in any organization acts as a contingency factor. Given this, although our results point to the workforce's positive influence on the first two stages of our technical object's diffusion, a certain amount of critical hindsight is required to avoid hastily generalising this conclusion. Even if our structural equation model is shown to have a great predictive power outside our sample (Appendix 2).

The perception of having sufficient **financial resources** dedicated to AI is only correlated with our first stage of dissemination. This makes perfect sense, since acquiring this type of tool requires a relatively substantial initial investment; therefore, it is only when organizations have the real means to do so that they gather information with a view to acquiring it. Although maintaining information systems is also costly for organizations (Valcik et al., 2023b), this does not influence the stages of *adoption* and *routinization* of the technical object considered here. In our view, the explanation could be as follows. Once the initial costs associated with acquiring an information system have been incurred, these costs—insofar as maintaining the system is justified by its effectiveness or efficiency, for example—are no longer included in the reasons for its *adoption* or *routinization*. Instead, other considerations take their place, for example, the instrument's perceived simplicity and the cost savings it brings.

Following the examples of Chong and Chan (2012) and Garrison et al. (2015), the **technological expertise** of private or public employees is positively associated with all our dependent variables. Literally, this means that organizations with staff who are competent to use this type of tool place more value on the possibility of acquiring them, adopting them, and routinising them within their recruitment process. In practice, this again makes perfect sense: an organization that assesses the possibility of acquiring an information system must also consider that its employees can use it. Secondly, an organization that decides to adopt this type of tool would be concerned that its employees know how to use them. Finally, at the routinization stage, the daily use of a tool as part of the recruitment process necessarily requires a minimum of domain expertise, also to enable employees to innovate based on them, as Bos-Nehles et al. (2017) or Prikshat et al. (2023) point out.

Turning now to our first new predictor, **innovative climate**, this is very strongly linked to both the *evaluation* and *adoption* stages. Although this variable has never 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. That said, the idea that an atmosphere conducive to innovation favors, in its early stages, the diffusion of HR AI technologies is supported. For organizations, this result is good news insofar as it identifies a managerial lever on which to act to encourage the spread of emerging technologies like HR AI. Indeed, our results show that *evaluation* and *adoption* of this type of tool is generally done by organizations that are generally looking for new solutions, new ways of solving problems and where creativity is, among other things, encouraged. Putting these conditions in place could help organizations to function more effectively and efficiently, through the integration of HR AI tools.

Our results on **red tape** are particularly interesting too. Indeed, although some authors (Yu and Bretschneider, 1998), particularly in the IT field, show that this variable is negatively related to the diffusion of technical systems, our results show that the red tape is positively related to our first two stages of diffusion. In Swiss organizations, therefore, red tape may act more as an incentive for change, as described by Moon and Bretschneider (2002). Based on our results, there's every reason to believe that it encourages organizations to look for alternative technological solutions. In other words, that it acts as a facilitator to overcome administrative inertia through the acquisition of new technological solutions, rather than as a constraint. This result is not surprising, however, insofar as the Swiss HR function, increasingly focused on strategic human resources management (Emery and Gonin, 2009), could be particularly keen on the introduction of this type of tool, notably to accelerate its effectiveness and efficiency in recruitment (Schuetz and Venkatesh, 2020). In an increasingly competitive environment, optimizing the time spent on this process is essential to avoid discouraging candidates or 'losing' some of them through waiting, there is every reason to believe that this type of tool could be of great benefit to the Swiss HR function. At least, that's what this association link suggests.

5 LIMITS AND OUTLOOK

Our study has made it possible to identify the main technological and organizational factors that, according to the Swiss HR function, govern the *evaluation*, *adoption,* and *routinization* of AI-based CV (pre)selection tools within their organization. While all or almost all of them are involved in the intent to use this type of HR AI tool, and a large proportion of them also explain the decision to *adopt* this type of tool, only two are significantly associated with *routinization*. In our opinion, and this is the first limitation of this study, this could be because few organizations within our sample (Appendix 1) state that they *always* use this type of tool in their engagement process. Thus, the model's statistical power would be reduced for this dependent variable. The study should therefore be repeated in a few years when more organizations have adopted these information systems. We will then be able to observe whether our predictors influence this dependent variable or if they continue to be not significantly associated with it. As HR AI is still an emerging technology (Johnson et al., 2022; Strohmeier, 2022: 2; Young et al., 2021), we are nevertheless satisfied with the very low share of reasons that explain the *routinization* of these instruments, given the adjusted R^2 of .045.

In terms of replicating our study, it suffers from the weaknesses inherent in all cross-sectional studies (Connelly, 2016), where the main one is the impossibility of drawing causal inferences from the results. Our results are therefore limited to describing the relationships observed between the variables at a given moment in time. This makes it difficult to predict how the factors studied will in the future influence the *evaluation*, *adoption*, and *routinization* of AI-based CV (pre)selection tools, even though our model has strong predictive power, which suggests that its results can be generalized beyond the sample under consideration. We therefore invite researchers interested in related topics to replicate this work by also testing other explanatory factors such as trust in HRIS (Lippert and Swiercz, 2005), trust in technology (Choi, 2021; Hmoud and Várallyai, 2020), or algorithmic aversion (Dietvorst et al., 2015).

Another potential limitation is the presence of potential selection bias due to greater participation by organizations that already use AI in their HR processes. However, this bias is controlled insofar as around half of the organizations surveyed never use this type of information system as part of their recruitment process, as shown by the level of AI-based CV (pre)selection tools (Appendix 1).

These few limitations notwithstanding, this study has the advantage of laying the foundation for new avenues of research. Its main results show that almost all the independent variables included in our structural equation model are significantly associated with the fact that organizations *assess* the possibility of using them, more than half of the same predictors are associated with their *adoption*, and very few are linked to their *routinization*. This provides a better understanding of the factors that, according to the HR function players themselves, govern the spread of AI-based CV (pre)selection tools within Swiss organizations. Researchers could therefore consider investigating the subject in greater depth by studying, for example, the factors that influence the spread of other HR AI tools, such as chatbots, which are sometimes included in the recruitment process, or by including other independent variables – in addition to those we integrate into the TOE framework's usual organizational variables – in similar structural equation models. Another approach would be to conduct case studies of the reasons behind the spread of these AI tools within organizations, such as the influence of private players who actively promote this type of tool, sometimes solely for monetary reasons, despite any empirical evidence of their effectiveness or efficiency (Jemine and Guillaume, 2022). In short, this study establishes a basis from which researchers interested in the processes of diffusing AI in both private and public human resources will have ample opportunity to develop their own research questions.

REFERENCES

Ahearne, M., Jelinek, R., and Rapp, A. (2005). Moving beyond the direct effect of SFA adoption on salesperson performance: Training and support as key moderating factors. *Industrial Marketing Management*, *34*(4), 379-388.

Al-Dmour, R. H., Masa'deh, R. E., and Obeidat, B. Y. (2017). Factors influencing the adoption and implementation of HRIS applications: are they similar? *International Journal of Business Innovation and Research*, *14*(2), 139-167.

Anderfuhren-Biget, S., Varone, F., Giauque, D., and Ritz, A. (2010). Motivating employees of the public sector: does public service motivation matter? *International public management journal*, *13*(3), 213-246.

Azoulay, E., Lefebvre, P., and Marlin, R. (2020). Using artificial intelligence to diversify the recruitment process at L'Oréal. *Le journal de l'ecole de Paris du management*, *142*(2), 16-22.

Baldegger, R., Caon, M., and Sadiku, K. (2020). Correlation between entrepreneurial orientation and implementation of AI in human resources management (HRM). *Technology innovation management review*.

Ball, K. S. (2001). The use of human resource information systems: a survey. *Personnel review*, *30*(6), 677-693.

Baratelli, G., and Colleoni, E. (2022). Does Artificial Intelligence (AI) Enabled Recruitment Improve Employer Branding? *International Journal of Business and Management*, *17*(2).

Bhattacherjee, A., Perols, J., and Sanford, C. (2008). Information technology continuance: A theoretic extension and empirical test. *Journal of Computer Information Systems*, *49*(1), 17-26.

Blaikie, N. (2003). Analyzing Quantitative Data: From Description to Explanation. London: Sage.

Boltanski, L., and Chiapello, E. (1999). *Le nouvel esprit du capitalisme* (Vol. 10). Paris: Gallimard.

Bondarouk, T., Parry, E., and Furtmueller, E. (2017). Electronic HRM: four decades of research on adoption and consequences. *The International Journal of human resource management*, *28*(1), 98-131.

Borry, E. L. (2016). A new measure of red tape: Introducing the three-item red tape (TIRT) scale. *International Public Management Journal*, *19*(4), 573-593.

Borsboom, D., Mellenbergh, G. J., and Van Heerden, J. (2004). The concept of validity. *Psychological review*, *111*(4), 1061.

Bos-Nehles, A., Renkema, M., and Janssen, M. (2017). HRM and innovative work behaviour: A systematic literature review. *Personnel review*, *46*(7), 1228-1253.

Bos-Nehles, A. C., & Veenendaal, A. A. (2019). Perceptions of HR practices and innovative work behavior: the moderating effect of an innovative climate. *The International Journal of Human Resource Management*, *30*(18), 2661-2683.

Boukamel, O., and Emery, Y. (2018). Cultural brakes to innovation in public administration: Swiss specificities. *Gestion et management public*, *6*(2), 25-43.

Bozeman, B. (2000). *Bureaucracy and red tape* (Vol. 14, p. 210). Upper Saddle River, NJ: Prentice Hall.

Bozeman, B., & Crow, M. M. (1991). Red tape and technology transfer in US government laboratories. *The Journal of Technology Transfer*, *16*(2), 29-37.

Bozeman, B., Reed, P. N., & Scott, P. (1992). Red tape and task delays in public and private organizations. *Administration & Society*, *24*(3), 290-322.

Broderick, R., and Boudreau, J. W. (1992). Human resource management, information technology, and the competitive edge. *Academy of Management Perspectives*, *6*(2), 7-17.

Brown, L. A. (1981). Innovation Diffusion, New York: Methuen.

Brown, I., and Russell, J. (2007). Radio frequency identification technology: An exploratory study on adoption in the South African retail sector. *International journal of information management*, *27*(4), 250-265.

Casilli, A. A. (2019). *Waiting for the robots-Investigating the work of the click*. Media Diffusion.

Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., and Wang, L. C. (2023). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management*, 1-39.

Chen, H., Li, L., and Chen, Y. (2021). Explore success factors that impact artificial intelligence adoption on telecom industry in China. *Journal of Management Analytics*, *8*(1), 36-68.

Choi, Y. (2021). A study of employee acceptance of artificial intelligence technology. *European Journal of Management and Business Economics*, *30*(3), 318-330.

Chong, A. Y. L., and Chan, F. T. (2012). Structural equation modeling for multi-stage analysis on Radio Frequency Identification (RFID) diffusion in the health care industry. *Expert Systems with Applications*, *39*(10), 8645-8654.

Chong, A. Y. L., and Ooi, K. B. (2008). Adoption of interorganizational system standards in supply chains: an empirical analysis of RosettaNet standards. *Industrial Management* and *Data Systems*, *108*(4), 529-547.

Chong, A. YL., Ooi, K. B., Lin, B., and Raman, M. (2010). Factors affecting the adoption level of c-commerce: An empirical Study. Journal of Computer Information Systems, 50, 13-22.

Coltman, T., Devinney, T. M., Midgley, D. F., and Venaik, S. (2008). Formative versus reflective measurement models: Two applications of formative measurement. *Journal of Business Research*, *61*(12), 1250-1262.

Connelly, L. M. (2016). Cross-sectional survey research. *Medsurg nursing*, *25*(5), 369.

Denisova, A. (2023). The impact of negative media coverage, brand-hate, or consumer boycotts on the employer brand (in the example of Amazon).

Dietvorst, B. J., Simmons, J. P., and Massey, C. (2015). Algorithm aversion: people erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, *144*(1), 114.

Emery, Y., and Giauque, D. (2023). *Chapter 12: Human resource management.* In: Soguel, N., Bundi, P., Mettler, T., and Weerts, S. Modèle IDHEAP d'administration publique : vue d'ensemble.

Gerber, M., Krause, A., and Probst, J. (2023). HR Analytics in der Schweiz. *Personal Schweiz*, *2023*(2), 20-21.

Giauque, D., Anderfuhren-Biget, S., & Varone, F. (2013). Stress perception in public organizations: Expanding the job demands–job resources model by including public service motivation. *Review of Public Personnel Administration*, *33*(1), 58-83.

Gross, F. (2022). HR machine learning on text data. In *Handbook of Research on Artificial Intelligence in Human Resource Management* (pp. 46-67). Edward Elgar Publishing.

Grosz, B. J., Altman, R., Horvitz, E., Mackworth, A., Mitchell, T., Mulligan, D., and Shoham, Y. (2016). Artificial intelligence and life in 2030: One hundred year study on artificial intelligence. *Stanford University*.

Gupta, S., Meissonier, R., Drave, V. A., and Roubaud, D. (2020). Examining the impact of Cloud ERP on sustainable performance: A dynamic capability view. *International Journal of Information Management*, *51*, 102028.

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., and Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook* (p. 197). Springer Nature.

Hair, J. F., Risher, J. J., and Ringle, C. M. (2018). When to use and how to report the results of PLS-SEM. 31 (1), 2-24.

Hair, J. F., and Sarstedt, M. (2021). Explanation plus prediction - The logical focus of project management research. *Project Management Journal*, *52*(4), 319-322.

Hanafiah, M. H. (2020). Formative vs. reflective measurement model: Guidelines for structural equation modeling research. *International Journal of Analysis and Applications*, *18*(5), 876-889.

Henseler, J., Ringle, C. M., and Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, *43*, 115-135.

Hitt, M. A., Hoskisson, R. E., and Ireland, R. D. (1990). Mergers and acquisitions and managerial commitment to innovation in M-form firms. *Strategic management journal*, 29-47.

Hmoud, B. (2021). The adoption of artificial intelligence in human resource management and the role of human resources. In *Forum Scientiae Oeconomia* (Vol. 9, No. 1, pp. 105-118). Wydawnictwo Naukowe Akademii WSB.

Hmoud, B. I., and Várallyai, L. (2020). Artificial intelligence in human resources information systems: Investigating its trust and adoption determinants. *International Journal of Engineering and Management Sciences*, *5*(1), 749-765.

Höddinghaus, M., Sondern, D., and Hertel, G. (2021). The automation of leadership functions: Would people trust decision algorithms? *Computers in Human Behavior*, *116*, 106635.

Hossain, M. A., Quaddus, M., and Islam, N. (2016). Developing and validating a model explaining the assimilation process of RFID: An empirical study. *Information Systems Frontiers*, *18*, 645-663.

Huang, Z., Janz, B. D., and Frolick, M. N. (2008). A comprehensive examination of Internet-EDI adoption. *Information Systems Management*, *25*(3), 273-286.

Jantan, H., Hamdan, A. R., and Othman, Z. A. (2010). Human talent prediction in HRM using C4. 5 classification algorithm. *International Journal on Computer Science and Engineering*, *2*(8), 2526-2534.

Jemine, G., and Guillaume, K. (2022). Lifting the veil on HRIS adoption: the role of vendors and consultants in the diffusion of HR innovations. *Information Technology* and *People*, *35*(7), 2418-2440.

Jia Q., Guo Y., Li R., Li Y.R., and Chen Y.W. (2018). A Jia, Guo, Li, Li and Chen conceptual artificial intelligence application framework in human resource management. In Proceedings of The 18th International Conference on Electronic Business (pp. 106-114). ICEB, Guilin, China, December 2-6.

Johnson, B. A., Coggburn, J. D., and Llorens, J. J. (2022). Artificial Intelligence and Public Human Resource Management: Questions for Research and Practice. *Public Personnel Management*, *51*(4), 538-562.

Kang, I. G., Croft, B., and Bichelmeyer, B. A. (2020). Predictors of turnover intention in U.S. federal government workforce: Machine learning evidence that perceived comprehen- sive HR practices predict turnover intention. *Public Personnel Management*.

Karami, A., Spinel, M. Y., White, C. N., Ford, K., and Swan, S. (2021). A systematic literature review of sexual harassment studies with text mining. *Sustainability*, *13*(12), 6589.

Ladner, A., Keuffer, N., Baldersheim, H., Hlepas, N., Swianiewicz, P., Steyvers, K., and Navarro, C. (2019). *Patterns of local autonomy in Europe* (pp. 229-230). London: Palgrave Macmillan.

Ladner, A., and Haus, A. (2021). *Aufgabenerbringung der Gemeinden in der Schweiz: Organization, Zuständigkeiten und Auswirkungen*. IDHEAP Institut de hautes études en administration publique.

Lai, F., Hutchinson, J., and Zhang, G. (2005). Radio frequency identification (RFID) in China: opportunities and challenges. *International Journal of Retail* and *Distribution Management*, *33*(12), 905-916.

Lawler, J. J., and Elliot, R. (1993). Artificial intelligence in HRM: an experimental study of an expert system. In *Proceedings of the 1993 conference on Computer personnel research* (pp. 473-480).

Li, J., Wang, Y. F., Zhang, Z. M., and Chu, C. H. (2010). Investigating acceptance of RFID in Chinese firms: The technology-organization-environment framework. In *2010 IEEE International Conference on RFID-Technology and Applications* (pp. 263-268). IEEE.

Liang, H., Saraf, N., Hu, Q., and Xue, Y. (2007). Assimilation of enterprise systems: the effect of institutional pressures and the mediating role of top management. *MIS quarterly*, 59-87.

Lippert, S. K., and Michael Swiercz, P. (2005). Human resource information systems (HRIS) and technology trust. *Journal of information science*, *31*(5), 340-353.

Makridis, C. A. (2021). Do data breaches damage reputation? Evidence from 45 companies between 2002 and 2018. *Journal of Cybersecurity*, *7*(1), tyab021.

Malik, A., Srikanth, N. R., and Budhwar, P. (2020). Digitisation, artificial intelligence (AI) and HRM. *Human resource management: Strategic and international perspectives*, *88*.

Malik, S. D., & Wilson, D. O. (1995). Factors influencing engineers' perceptions of organizational support for innovation. *Journal of Engineering and Technology Management*, *12*(3), 201-218.

Mehrjerdi, Z., Y. (2010). RFID-enabled healthcare systems: risk-benefit analysis. *International Journal of Pharmaceutical and Healthcare Marketing*, *4*(3), 282-300.

Meijerink, J., Boons, M., Keegan, A., and Marler, J. (2021). Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM. *The InTernaTIonal Journal of human resource managemenT*, *32*(12), 2545-2562.

Merhbene, G., Nath, S., Puttick, A. R., and Kurpicz-Briki, M. (2022). BurnoutEnsemble: augmented intelligence to detect indications for burnout in clinical psychology. *Frontiers in big Data*, *5*, 863100.

Mohamed, S. A., Mahmoud, M. A., Mahdi, M. N., and Mostafa, S. A. (2022). Improving efficiency and effectiveness of robotic process automation in human resource management. *Sustainability*, *14*(7), 3920.

Moon, M. J., & Bretschneiber, S. (2002). Does the perception of red tape constrain IT innovativeness in organizations? Unexpected results from a simultaneous equation model and implications. *Journal of Public Administration Research and Theory*, *12*(2), 273-292.

Neumann, O., Guirguis, K., and Steiner, R. (2023). Exploring artificial intelligence adoption in public organizations: a comparative case study. *Public Management Review*, 1-28.

Newman, A., Round, H., Wang, S., & Mount, M. (2020). Innovation climate: A systematic review of the literature and agenda for future research. *Journal of Occupational and Organizational Psychology*, *93*(1), 73-109.

OFS (2021a). Regional portraits and key figures for all communes. https://www.bfs.admin.ch/bfs/fr/home/statistiques/statistique-regions/portraits-regionaux-chiffres-cles/cantons/uri.html. Accessed 03.11.23.

Oliveira, T., and Martins, M. F. (2008). A comparison of web site adoption in small and large Portuguese firms. In *International Conference on E-business* (Vol. 2, pp. 370-377). SCITEPRESS.

Pandey, S. K., & Bretschneider, S. I. (1997). The impact of red tape's administrative delay on public organizations' interest in new information technologies. *Journal of Public Administration Research and Theory*, *7*(1), 113-130.

Pandey, S. K., & Kingsley, G. A. (2000). Examining red tape in public and private organizations: Alternative explanations from a social psychological model. *Journal of Public Administration Research and Theory*, *10*(4), 779-800.

Pandey, S. K., Wright, B. E., and Moynihan, D. P. (2008). Public service motivation and interpersonal citizenship behavior in public organizations: Testing a preliminary model. *International public management journal*, *11*(1), 89-108.

Podsakoff, P. M., MacKenzie, S. B., and Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual review of psychology*, *63*, 539-569.

Prikshat, V., Malik, A., and Budhwar, P. (2023). AI-augmented HRM: Antecedents, assimilation and multilevel consequences. *Human Resource Management Review*, *33*(1), 100860.

Rana, S., & Kaur, D. (2023). Exploring the challenges and facilitators in the adoption of e-HRM practices in Indian higher education institutions: a qualitative exploration. *International Journal of Organizational Analysis*.

Raithel, S., Sarstedt, M., Scharf, S., and Schwaiger, M. (2012). On the value relevance of customer satisfaction. Multiple drivers and multiple markets. *Journal of the academy of marketing science*, *40*, 509-525.

Ringle, C. M., Sarstedt, M., Mitchell, R., and Gudergan, S. P. (2020). Partial least squares structural equation modeling in HRM research. *The International Journal of Human Resource Management*, *31*(12), 1617-1643.

Ritz, A., Weißmüller, K. S., and Meynhardt, T. (2023). Public value at cross points: A comparative study on employer attractiveness of public, private, and nonprofit organizations. *Review of Public Personnel Administration*, *43*(3), 528-556.

Rodney, H., Valaskova, K., and Durana, P. (2019). The artificial intelligence recruitment process: How technological advancements have reshaped job application and selection practices. *Psychosociological Issues in Human Resource Management*, *7*(1), 42-47.

Rogers, E.M. (1995). *Diffusion of innovations*. New York: Free Press.

Rolland, K. H., and Hanseth, O. (2021). Managing path dependency in digital transformation processes: A longitudinal case study of an enterprise document management platform. *Procedia Computer Science*, *181*, 765-774.

Ruël, H., Bondarouk, T., and Looise, J. K. (2004). E-HRM: Innovation or irritation. An explorative empirical study in five large companies on web-based HRM. *Management revue*, 364-380.

Sarstedt, M., Ringle, C. M., and Hair, J. F. (2021). Partial least squares structural equation modeling. In *Handbook of market research* (pp. 587-632). Cham: Springer International Publishing.

Sarstedt, M., and Danks, N. P. (2022). Prediction in HRM research-a gap between rhetoric and reality. *Human Resource Management Journal*, *32*(2), 485-513.

Scarbrough, H. (1998). Path (ological) dependency? Core competencies from an organizational perspective. *British journal of management*, *9*(3), 219-232.

Sciarini, P. (2023). *Politique suisse: Institutions, acteurs, processus*. Presses polytechniques et universitaires romandes.

Scott, P. G. (2002). Examining red tape in public and private organizations: a further look at the role of individual perceptions and attributes. *The Social Science Journal*, *39*(3), 477-482.

Scupola, A., and Pollich, Z. (2019). Adoption of human resource information systems in Danish SMEs. In *Conference Proceedings*.
Shao, Z., Feng, Y., and Hu, Q. (2017). Impact of top management leadership styles on ERP assimilation and the role of organizational learning. *Information* and *Management*, *54*(7), 902-919.
Schuetz, S., and Venkatesh, V. (2020). The rise of human machines: How cognitive computing systems challenge assumptions of user-system interaction. *Journal of the Association for Information Systems*, *21*(2), 460-482.
Strohmeier, S., and Kabst, R. (2009). Organizational adoption of e-HRM in Europe: An empirical exploration of major adoption factors. *Journal of Managerial Psychology*, *24*(6), 482-501.
Strohmeier, S., and Piazza, F. (2015). Artificial intelligence techniques in human resource management-a conceptual exploration. *Intelligent Techniques in Engineering Management: Theory and Applications*, 149-172.
Strohmeier, S. (Ed.). (2022). *Handbook of research on artificial intelligence in human resource management*. Edward Elgar Publishing.
Sylvester, E. O., Bamidele, A. D., & Oluyemi, O. S. (2015). Implementing e-HRM system in developing countries: Challenges and prospects. *International Journal of Applied Information Systems*, *9*(8), 38-41.
Tannenbaum, S. I. (1990). Human resource information systems: User group implications. *Journal of Systems management*, *41*(1), 27.
Teo, T. S., Lim, G. S., and Fedric, S. A. (2007). The adoption and diffusion of human resources information systems in Singapore. *Asia Pacific Journal of Human Resources*, *45*(1), 44-62.
Thong, J. Y. (1999). An integrated model of information systems adoption in small businesses. *Journal of management information systems*, *15*(4), 187-214.
Tornatzky, L., and Fleischer, M. (1990). *The process of technology innovation*. New York: Lexington Books.
Troshani, I., Jerram, C., and Gerrard, M. (2010). Exploring the organizational adoption of Human Resources Information Systems (HRIS) in the Australian public sector.
Tsai, M. C., Lee, W., and Wu, H. C. (2010). Determinants of RFID adoption intention: Evidence from Taiwanese retail chains. *Information* and *management*, *47*(5-6), 255-261.
Valcik, N. A., Sabharwal, M., and Benavides, T. J. (2023a). Existing research on HRIS in public organizations. In *Human Resources Information Systems: A guide for public administrators* (pp. 35-48). Cham: Springer International Publishing.
Valcik, N. A., Sabharwal, M., and Benavides, T. J. (2023b). The Costs of HRIS and Dangers of Migration of HRIS Data. In *Human Resources Information Systems: A Guide for Public Administrators* (pp. 153-161). Cham: Springer International Publishing.
Venkatesh, V. (2022). Adoption and use of AI tools: a research agenda grounded in UTAUT. *Annals of Operations Research*, 1-12.
Volini, E., Schwartz, J., Roy, I., Hauptmann, M., Durme, Y. V., Denny, B., and Bersin, J. (2019). Accessing talent: It's more than acquisition. *Retrieved September*, *20*, 2019.
Wang, G. (2016). Gunasekaran, A.-Ngai, EWT-Papadopoulos, T.: Big Data Analytics in Logistics and Supply Chain Management: Certain Investigations for Research and Applications. *International Journal of Production Economics*, *176*, 98-110.
Wang, Y. M., Wang, Y. S., and Yang, Y. F. (2010). Understanding the determinants of RFID adoption in the manufacturing industry. *Technological forecasting and social change*, *77*(5), 803-815.
Warren, M. (2004). Farmers online: drivers and impediments in adoption of Internet in UK agricultural businesses. *Journal of Small Business and Enterprise Development*, *11*(3), 371-381.
Wei, T. T., Marthandan, G., Chong, A. Y. L., Ooi, K. B., and Arumugam, S. (2009). What drives Malaysian m-commerce adoption? An empirical analysis. *Industrial management* and *data systems*, *109*(3), 370-388.
Williams, L. J., and O'Boyle Jr, E. H. (2008). Measurement models for linking latent variables and indicators: A review of human resource management research using parcels. *Human Resource Management Review*, *18*(4), 233-242.
Wong, S. H., Al-Hasani, H., Alam, Z., and Alam, A. (2019). Artificial intelligence in radiology: how will we be affected? *European radiology*, *29*, 141-143.

Young, M. M., Himmelreich, J., Bullock, J. B., and Kim, K.-C. (2021). Artificial intelligence and administrative evil. *Perspectives on Public Management and Governance*, *4*(3), 244-258.
Yu, P. J., & Bretschneider, S. (1998). Executive perceptions of innovativeness in information management. *Korean Review of Public Administration*, *3*(1), 179-213.
Zafar, H. (2013). Human resource information systems: Information security concerns for organizations. *Human Resource Management Review*, *23*(1), 105-113.
Zafar, H., Randolph, A. B., and Martin, N. (2017). Toward a more secure HRIS: The role of HCI and unconscious behavior. *AIS Transactions on Human-Computer Interaction*, *9*(1), 59-74.
Zerfass, A., Hagelstein, J., and Tench, R. (2020). Artificial intelligence in communication management: a cross-national study on adoption and knowledge, impact, challenges and risks. *Journal of Communication Management*, *24*(4), 377-389.
Zhu, K., and Kraemer, K. L. (2005). Post-adoption variations in usage and value of e-business by organizations: cross-country evidence from the retail industry. *Information systems research*, *16*(1), 61-84.
Zhu, K., Kraemer, K. L., and Xu, S. (2006). The process of innovation assimilation by firms in different countries: a technology diffusion perspective on e-business. *Management science*, *52*(10), 1557-1576.
Zu, S., and Wang, X. (2019). Resume information extraction with a novel text block segmentation algorithm. *Int J Nat Lang Comput*, *8*, 29-4.

Contact address:

Guillaume Revillod, Swiss Graduate School of Public Administration, University of Lausanne.
Rue de Mouline 28. Chavannes-près-Renens, CH-1022 Lausanne. Tel.: +41786192583, e-mail: guillaume.revillod@unil.ch

Declaration of AI and AI-assisted technologies in the writing process

The author(s) did not use any AI tools or services for content generation or analysis that would require disclosure in the preparation of this work. All content, analysis, and conclusions are the sole responsibility of the author(s).

APPENDIX 1: LEVEL OF USE OF CV (PRE)SELECTION AI TOOLS IN OUR SAMPLE

Table 1. AI-based CV (pre)selection tools in the sample

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

APPENDIX 2: FULL ANALYTICAL PROCEDURE

1. Assessing the measurement model

Empirically, evaluating a model made up of reflective constructs involves various tests for which we refer to the different commonly accepted thresholds, or rules of thumb (Cheung et al., 2023; Hair et al., 2021). These tests are divided into four steps.

1.1. Step 1 – Display 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 (Hair et al., 2021: 77). In the second stage, indicator reliability is examined. The commonly accepted threshold here is > .50 (Ibid.). 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. (2021) - is higher than .50 anyway.

Table 1. Indicator loadings - Dependent variables

	EV_CV	AD_CV	RO_CV
evaluation1_cv	.960		
evaluation2_cv	.928		
evaluation3_cv	.889		
adoption1_cv		.860	
adoption1_cv		.932	
adoption1_cv		.884	
routinization1_cv			.940
routinization2_cv			.953

Table 2. Indicator loadings - Independent variables

	R	CO	CX	D	S	TMS	F	T	IC	RT
ra1_cv	.947									
ra2_cv	.831									
ra3_cv	.789									
ra4_cv	.804									
cmpt1_cv		.939								
cmpt1_cv		.877								
cx1_cv			.950							
cx2_cv			.813							
costs1_cv				.929						
costs2_cv				.843						
costs3_cv				.746						
secu1_cv					.863					
secu2_cv					.909					
tms1_cv						.077				

tms2_cv						.951				
tms3_cv						.457				
rfin1_cv							.921			
rfin2_cv							.880			
tech1_cv								.877		
tech2_cv								.868		
tech3_cv								.765		
ic_1									.971	
ic_2									.842	
ic_3									.876	
ic_4									.847	
ic_5									.867	
rt_1										.928
rt_2										.842
rt_3										.787

R: Relative advantage; CO: Compatibility; CX: Complexity; D: (Decrease) costs; S: Security; TMS: Top management support; F: Financial resources; T: Technological expertise; IC: Innovative climate; RT: Red tape; EV: Evaluation; AD: Adoption; RO: Routinization.

Our measurements indicate that all items are reliable, except those reflecting the TMS construct.

1.2. Step 2 and 3 – 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 (Hair et al., 2021). 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 (Cheung et al., 2023). For a construct to be validated, the AVE must be > .50 (Ibid.). Table 3 shows these values for each of our constructs:

Table 3. Internal consistency reliability - α, rhoC, rhoA & Convergent validity- AVE

Latent constructs	Alpha (α)	RhoC	RhoA	AVE
Dependant variables				
Evaluation	.917	.947	.924	.857
Adoption	.873	.922	.880	.797
Routinization	.884	.945	.893	.896
Independent variables				
Relative advantage	.864	.908	.877	.714
Compatibility	.793	.904	.855	.825
Complexity	.742	.877	.947	.781
(Decrease) Costs	.799	.879	.884	.710
Security	.729	.880	.747	.786
TMS	.727	.539	-.910	.373
Financial resources	.770	.896	.790	.812
Technological expertise	.792	.876	.830	.703
Innovative climate	.928	.946	.938	.777
Red tape	.884	.945	.893	.730

As before, only the TMS construct poses a problem. The other constructs are all valid.

1.3. Step 4 - 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) (Henseler et al., 2015; Hair et al., 2021: 78). Henseler et al. (2015) propose two maximum thresholds: .90 and .85. The first is to be used for models in which the latent constructs are conceptually close and where they are more likely to capture the same part of reality. The second, more conservative, one is used for models in which the constructs are relatively distinct. In this study, the constructs used are conceptually distinct. The items used to measure the perceived *relative advantage* of our HR AI tool have little in common with those that measure the perceived *complexity* of the same tool. That said, we can afford to be stricter and adopt the second criterion. Table 4 shows the HTMT for each of our constructs.

Table 4. Heterotrait-monotrait ratio (HTMT)

	R	CO	CX	D	S	TMS	E	F	T	IC	RT	EV	AD
CO	.037												
CX	.029	.169											
D	.115	.172	.285										
S	.054	.046	.043	.088									
TMS	.067	.049	.128	.199	.057								
E	.079	.130	.018	.061	.018	.090							
F	.062	.113	.032	.120	.132	.047	.041						
T	.056	.078	.058	.118	.090	.049	.097	.082					
IC	.064	.029	.106	.077	.049	.034	.064	.081	.078				
RT	.041	.084	.071	.099	.063	.043	.055	.093	.042	.047			
EV	.124	.222	.481	.405	.176	.083	.123	.158	.213	.215	.221		
AD	.142	.185	.301	.319	.120	.100	.120	.108	.163	.196	.309	.788	
RO	.062	.146	.125	.129	.117	.082	.027	.112	.147	.072	.069	.438	.290

Noting that our HTMTs are systematically below the .85 threshold. In a complementary way, Henseler et al. (2015) suggest using bootstrap confidence intervals to determine whether HTMTs are significantly different from 1 and from our .85 threshold. We use the procedure described by Hair et al. (2021: 87). For the sake of brevity, however, the results of this procedure are not reported here. Nonetheless, the confidence intervals that emerge also confirm the discriminant validity of our various constructs. In sum, all latent constructs except TMS meet all the evaluation criteria for our measurement model.

2. Evaluating the structural model

2.1. Step 1 - Examining collinearity issues

Potential collinearity problems are examined using variance inflation factors (VIF). Ideally VIF values should be below 3 (Hair et al., 2021: 117). As our VIF values are systematically below 3, there is no reason to suspect any collinearity problems in our structural model.

2.2. Step 2 - Assessing the structural model's significance and relevance

The second step in evaluating our structural model is examining the significance of the path coefficients and their relevance. Hair et al. (2021: 125) recommend inspecting the bootstrapped paths and setting the number of bootstraps at 10,000. The structural model's significance is then assessed using two indicators: inspecting t-values and the confidence intervals of the path coefficients (Hair et al., 2021: 117). For a 95% confidence interval, which is common in social and management sciences, the t-value of each path coefficient must exceed 1.960 (Hair et al., 2021: 126). Alternatively, a confidence interval, as indicated for each path coefficient by the values provided in the boxes '*2.5% CI*' and '*97.5% CI*, that would pass through 0 is problematic. In general, when the t-value is above 1.960, the confidence interval never passes through 0 (Ibid.). For relevance, we examine the path coefficient estimates, which are given in the Original Est. column of Table 5. Path coefficient estimates are generally between -1 and +1. A negative value close to -1 indicates a strong negative relationship between exogenous and endogenous variables, while a positive value close to +1 indicates a strong positive relationship between two variables. The interpretation of a path coefficient of, for example, .505, is that when the value of the predictor increases by 1, the dependent variable value increases by .505.

Table 5. Bootstrapped paths, nboot = 10,000, confidence interval 95%

	Estimates	T Stat.	2.5% CI	97.5% CI
R → Evaluation	.090	1.961*	.003	.186
R → Adoption	.108	2.175*	.013	.207
R → Routinization	.039	.669	-.079	.150
CO → Evaluation	.120	2.686**	.033	.209
CO → Adoption	.113	2.525**	.025	.202
CO → Routinization	.110	2.048*	.006	.217
CX → Evaluation	-.328	-7.474***	-.412	-.240
CX → Adoption	-.171	-3.326***	-.272	-.069
CX → Routinization	-.081	-1.104	-.221	.063
D → Evaluation	.199	4.217**	.107	.292
D → Adoption	.148	2.844**	.049	.253
D → Routinization	.030	.439	-.105	.163
S → Evaluation	.108	2.207*	.010	.202
S → Adoption	.070	1.420	-.028	.166
S → Routinization	.077	1.332	-.038	.188
TMS → Evaluation	.068	.791	-.154	.155
TMS → Adoption	.099	.882	-.193	.199
TMS → Routinization	.106	1.063	-.160	.206
E → Evaluation	.132	2.968**	.042	.215
E → Adoption	.140	2.960**	.043	.227
E → Routinization	.036	.675	-.071	.140
F → Evaluation	.090	2.008*	.002	.178
F → Adoption	.057	1.127	-.043	.157
F → Routinization	.078	1.374	-.037	.187
T → Evaluation	.126	2.822**	.040	.215
T → Adoption	.100	2.219*	.012	.191
T → Routinization	.111	2.067*	.006	.218
IC → Evaluation	.157	3.691***	.075	.241
IC→ Adoption	.158	3.185**	.060	.255
IC → Routinization	.048	.859	-.059	.157
RT → Evaluation	.162	4.104***	.083	.238
RT → Adoption	.250	4.623***	.141	.353
RT → Routinization	.038	.677	-.073	.151

2.3. Step 3 - Assessing the model's explanatory power

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

2.4. Step 4 - Assessing the model's predictive power

Many researchers interpret the R^2 statistic as a measure of their models' predictive power of their models (Sarstedt et al., 2022). This approach is not completely accurate because R^2 only indicates the explanatory power of the model for the sample under consideration (Hair et al., 2021: 119) and says nothing about its predictive power within the population (Hair and Sarstedt, 2021). To assess the predictive power of PLS-SEM models, researchers can use several indicators to quantify prediction errors, such as the root-mean-square error (RMSE) or mean absolute error (MAE) (Hair et al., 2021: 120). In general, when the prediction error distribution is highly asymmetric, that is, characterised by a long tail to the left or right in the prediction error distribution, then MAE is a more appropriate metric than RMSE (Hair et al., 2021: 129). Our visuals indicate relatively symmetric prediction error distributions for our first six items and highly asymmetric ones for the last two:

Figure 1. Distribution of predictive error for evaluation items

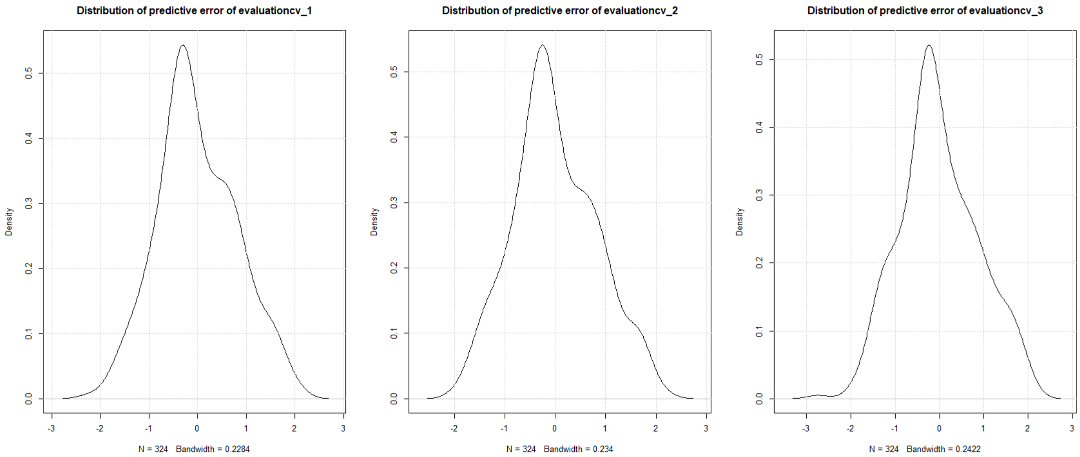


Figure 2. Distribution of predictive error for adoption items

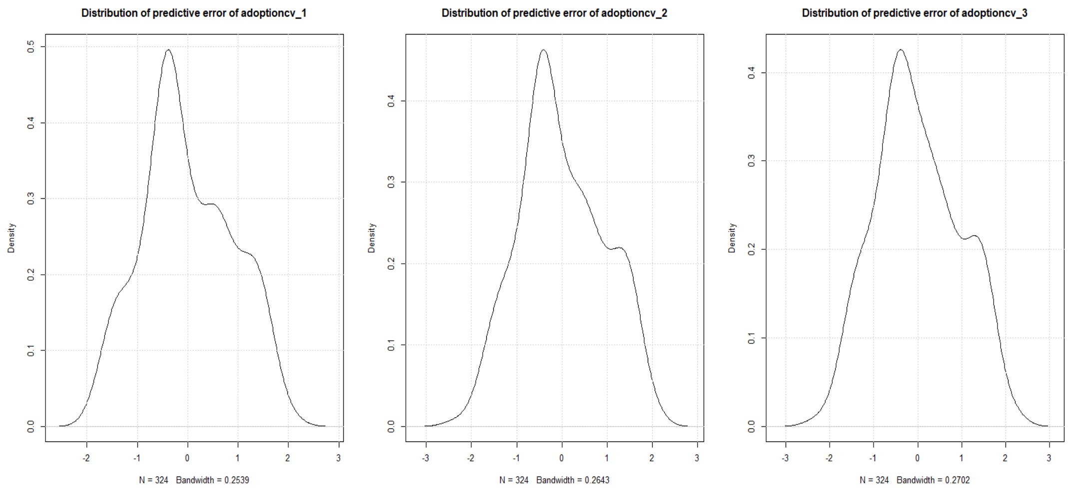
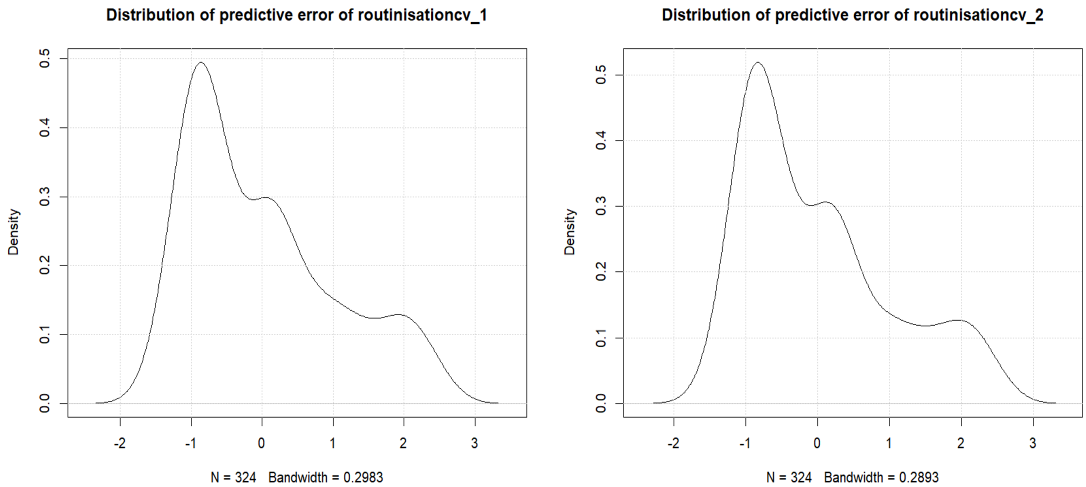


Figure 3. Distribution of predictive error for routinization items



Therefore, we use RMSE for the first six and MAE for the last two. Their interpretation then depends on their comparison with another indicator, the linear regression model (LM) benchmark. Hair et al. (2021: 121) formulate the following rules of interpretation:

Table 6. PLS VS LM benchmark - General rules of interpretation

Configuration	General rule
1	If all the indicators of the dependent variables 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, we must first generate predictions using the *predict_pls( )* function. We perform this procedure with *k* = *10* folds and ten repetitions and set *noFolds* = *10* and *reps* = *10*. We also use the *predict_DA* approach (Hair et al., 2021: 129). The predictions thus generated place us in the first configuration where all our PLS indicators has a value less than or equal to the corresponding LM values (Table 7). Consequently, our model has a high predictive power which makes it possible to generalize its conclusions beyond the sample under consideration.

Table 7. 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:	.761	.775	.829	.841	.861	.879	1.014	.994
MAE:	.607	.617	.653	.687	.695	.708	.843	.823
	LM out-of-sample metrics:							
	ecv_1	ecv_2	ecv_3	acv_1	acv_2	acv_3	rcv_1	rcv_2
RMSE:	.798	.810	.858	.867	.894	.906	1.061	1.041
MAE:	.640	.650	.681	.711	.722	.730	.882	.859

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