Winter 12-1-2022

3T Framework for AI Adoption in Human Resource Management: A Strategic Assessment Tool of Talent, Trust, and Technology

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Abstract. Artificial intelligence (AI) is steadily entering and transforming the management, work, and organizational ecosystems. We observe AI-based applications assisting employees in daily tasks, project management, decision-making, and collaboration. AI applications are increasingly assisting also Human Resource Management (HRM) in undertaking time-critical tasks and managerial and administrative decision-making. However, more in-depth and comprehensive studies are needed to understand the specific factors affecting the full adoption of AI technology from a multi-level viewpoint and address the potential limitations of AI appropriation or its adverse outcomes in HRM.
The purpose of this study is to investigate the conditions in which human talent may take advantage of the unique opportunities offered by AI. However, whereas previous studies were conducted on the individual perception of AI and technology readiness or adoption, an integrated approach aiming to combine talent management-related dimensions and managerial-related dimensions is still not available. For this research gap, we build a strategic management assessment framework of the driving factors of Talent, Trust, and Technology (3T) in AI adoption in HRM.
We investigate the impact of these trends on the human-related and technology ecosystems and provide an integrated analysis of individual micro (talent management) organizational macro (trust and technology) adoption of AI technology. The paper advances the current definition and understanding of individual human facilitators and impediments behind the ability to speed up the adoption of AI-based technology. The practical contribution can facilitate the human-centered and trustworthy design and adoption of AI.

Keywords: Artificial Intelligence, Adoption, HRM, Talent Management, Trust, Technology, Framework, Strategic Assessment, Conceptual Paper.

1 Introduction

Artificial Intelligence (AI) is an increasingly fundamental aspect of modern life that has had a transformative impact on how we live and work [23].

AI represents refers to using human intelligence in machines through technological innovations [6]. AI is a key component of the fourth industrial revolution and transforms our previous understanding of human-technology relations [21]. AI is highly considered for its potential to improve various management, business, and organizational processes [13]. The success of AI was largely associated with the enormous amounts of data that became available around 2015 thanks to the diffusion of the Internet and social media, as well as the emergence of affordable and powerful graphics processing units that can power it [15].

Nevertheless, the introduction of AI, and other innovative technologies, into HRM is a complex phenomenon [13] (especially because of the complexity of human decision-making processes. In this regard, the individual and organization's readiness for the adoption of innovation is critical to the success of technological change [27]. Organizational readiness is a multi-level and multi-faceted construct [52]. It also incorporates the readiness for effective change [4]. Thus, beyond the technological challenges, the full success of AI adoption depends upon a set of various conditions and factors which remain insufficiently discussed. Whereas previous studies were conducted on the individual perception of AI and technology readiness or adoption, an integrated approach aiming to combine talent management-related dimensions and managerial-related dimensions is still not available. For this research gap, we build a strategic management assessment framework of the driving factors of Talent, Trust, and Technology (3T) in AI adoption. The study is aimed to highlight the importance of individual, managerial and organizational aspects which may assist in the successful adoption of AI applications in HRM. To do that we present a conceptual framework of AI adoption determinants – the strategic enabling factors of the talent, trust, and technology (3-T) that can advance existing understanding of the adoption of AI in HRM by providing unique insights into important characteristics or variations [30]. To do so we draw on three independent and so far fragmented streams of literature including Talent Management (TM), Trust in technology and more specifically in AI, and adoption of technology. We extract research highlights and gradually build a conceptual framework of key factors concerned with effectively implementing AI in the HRM domain. We focus specifically on HRM because AI applications in HRM have received relatively little scholarly attention compared to other areas with a strong focus on the use of AI and data analytics such as marketing [25].

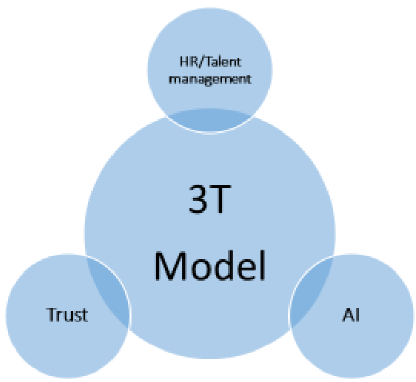
The paper advances the current definition and understanding of factors associated with AI adoption with a systematic analysis of cross-disciplinary elements. Such a framework can help future empirical studies suggest gaps to fill in existing understanding [30]. The paper has also a practitioner value since the framework represents a basis to guide managers and policymakers engaged to assess the individual to AI adoption and design effective AI adoption processes.

The remainder of the paper is structured as follows. Section 2 illustrates the relevant background on AI adoption in HRM settings recognizing the efforts of previous scholars in TM, trust in AI, and AI adoption research streams. It also presents an integrative conceptual framework of the 3-T AI adoption and the relationship between these three dimensions. Section 3 discusses how the framework can be adopted, and its implications.

2 Theoretical Model and Literature Review

In building our theoretical model we are drawing on three important and independent literature streams comprising HR/Talent management, Technology adoption, and Human trust thus positioning the model at the intersection of these disciplines (see Figure 1).

Fig.1. Positioning of the theoretical model



2.1 Artificial Intelligence (AI)

AI is a multidisciplinary field of science. Thus, it has a wide variety of definitions. Some discuss it as complex technology that aims to stimulate human intelligence, while others as algorithms or digital and data science methods to harvest, analyze and visualize complex HRM-related information [48] though without specifically referring to such as to AI [34]. In our study, which aimed to be inclusive, we follow the definition of Bohr and Memarzadeh (2020) defining AI as the use of human intelligence in machines through technological innovations.

Back in 1995, AI could read zip codes off letters, in 1997 IBM's Deep Blue defeated the world chess champion, Gary Kasparov, while only 10 years after AI-written novel was a finalist in Japan's national literary prize competition [15]. AI is steadily entering and transforming various industries. It has taken care of repetitive, tedious (e.g. [46]), as well as knowledge-intensive tasks and has promised to assist with complex decisions that are often taken at work. Different industries are in various stages of AI adoption. For instance, public sector and small-medium enterprises are considered late adopters, while AI is gradually revolutionizing other industries [50] and organizational functions such as marketing [25]. Recent progress has been in the direction of digitized data acquisition, machine learning and computing infrastructure, resulting in AI applications that are steadily entering novel domains that were previously governed solely by human experts. As such, management and human resources specialists utilize AI tools as decision support systems [10, 40]. It is unsurprising, and to some extent encouraging, that HRM is keeping up with new technologies and seeking to improve their effectiveness and resilience through automation and better use of data [47]. However, such technologies, and especially AI can also reshape the number of jobs, and how people are managed thus exposing employees and organizations to new challenges, risks, and threats [48]. For employees, the emerging risks can include those for privacy, autonomy, career options, income and well-being, as well as raised concerns about mirrored or magnified bias [29], work-by-numbers, automated decision making, and the demise of choice, opportunity, ethics and fairness [48, 49]. For organizations, these are related to operational, reputation and legal aspects, especially with recent moves in several countries to regulate AI use [29]. "For these and other reasons the EU has named [AI in HR] a high-risk use of AI" [29]. Indeed, there are diverse examples of when HRM-focused AI innovations backfired, as in the case of Amazon's sexist hiring algorithm, which had been trained using skewed data primarily from male applicants [14], and as result had been discontinued. Despite all these, AI applications in relation to HRM have received relatively little scholarly attention, compared to other areas with a strong focus on the use of AI and data analytics such as education or marketing [8, 28, 34, 48]. Thus, few studies, outside of these domains consider the wider human resource and organizational-related factors relevant to AI adoption. Moreover, none provide a strategic management assessment tool of talent, trust and technology to speed up AI adoption, which is a strategic objective of many governments and individual companies [29]. This knowledge gap is the purpose of this study.

2.2 The Factors of AI Adoption in Organizational Settings

Previous studies discussed the driving factors and barriers to AI adoption and acceptance in specific domains. For example, Prikshat and colleagues (2021), focus on AI assimilation in the e-HRM domain concluding that the adoption and implementation of AI in the field of HRM is incomplete. They propose a model which includes technology, organization and people factors and utilizes the theory of innovation assimilation to explain various HRM outcomes. Another field in which AI implementation has been discussed is marketing [25]. Much of this research had discussed technical or economic attributes or factors of AI such as cost and time reduction, increased performance and customer satisfaction, or predictions and decision making [40]. Nevertheless, AI needs to be used by humans and embedded into individuals' job design and organizational processes, thus incorporating also social requirements/factors. Thus, in line with recent calls to focus more on AI-related exploration and research on the human, people, organizational and social aspects of AI technologies adoption, we conduct this research study to research factors associated with human-AI interactions, and to explore links with practice and new paradigms [10, 41].

Overall, the barriers to AI adoption include economic and technical aspects, related to the adoption costs and maintenance, the need for support in infrastructure, lack of useable data, non-reusability of models, and limited applicability for some types of problems. Equally important are social and human barriers. For example, increased dependence on machines, job security fears, lack of knowledge and understanding of potential benefits, safety issues, lack of trust, and difficulty in obtaining multiple stakeholder perspectives. Furthermore, these social barriers such as knowledge or trust are frequently described as lacking. Some scholars articulated that state-of-the-art management may remedy these challenges and may assist in overcoming some technological challenges [1].

In this study, we thus focus our analysis on an important perspective of social-systems analysis in the form of the influencing factors (e.g., facilitators and barriers) that may impact the adoption or use of AI technologies that have been previously overlooked.

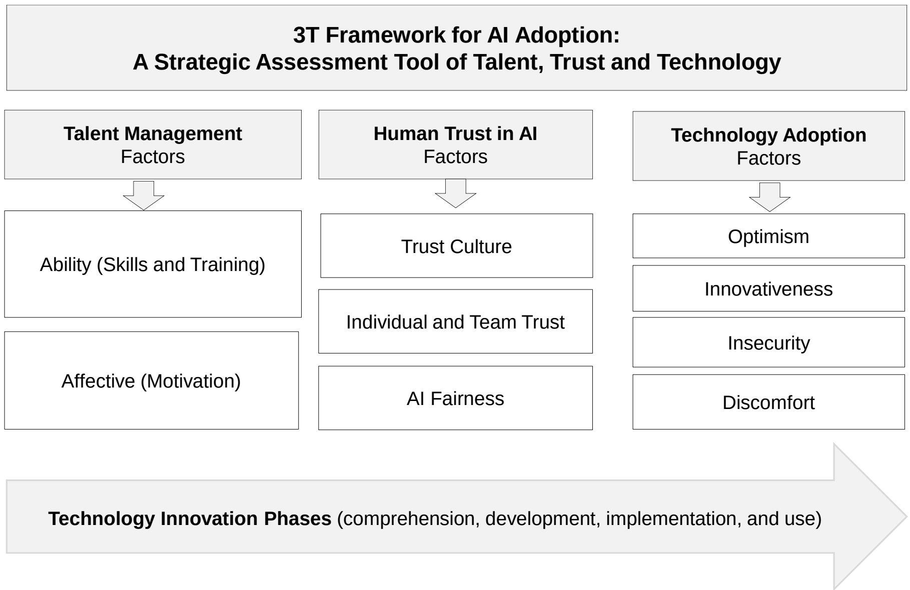


Fig.2. 3T Framework

To achieve our research aim, and with the goal to provide a strategic assessment tool of AI adoption challenges, we draw on the knowledge accumulated in three fragmented so far literature streams including TM, Human Trust in AI, and Technology innovation adoption, and build the 3T framework providing a theoretical illustration of three identified categories of factors that can impact AI adoption in management and organizational settings. Below we briefly describe each dimension of the 3-T framework and acknowledge the work of others in this area.

2.2.1 Talent Management Factors

TM has been extensively discussed in HRM literature motivated by the "war for talent" term introduced by McKinsey [35]. Since then, the interest in TM has only increased as evident by the increasing number of relevant articles and books.

TM is a complex and multi-dimensional concept with numerous definitions, which can vary between industry or occupational fields [19]. Thus, suffering from conceptual confusion.

Overall, the term talent is everywhere: newspapers, journals, magazines, and even TV (e.g., Italia's Got Talent show). In organizational settings, talent is often used as a term to describe both an approach to expressing the characteristics of people, or their natural abilities [19]. One of the well-rounded recent definitions described talent as "systematically developed innate abilities of individuals that are deployed in activities they like, find important, and in which they want to invest energy. It enables individuals to perform excellently in one or more domains of human functioning, operationalized as performing better than other individuals of the same age or experience, or as performing consistently at their personal best" [19]. This definition operationalizes TM as both ability and affective components that function as necessary preconditions for achieving excellence in some specific field. This definition has been adopted in this research as it considers these two main dimensions of talent that have been echoed in many following frameworks and studies [19]. Moreover, we considered these dimensions as we believe these are a valuable starting point to analyze why some individuals are more open to AI than others, and why some HRM processes are more successful in their AI projects than other. Below, we discuss the ability and affective components of the TM and describe specific factors relevant to these dimensions that can potentially affect AI adoption by talents.

Ability component

Discussions on the ability component have originated in the giftedness literature in the field of education [7]. Some refer to talent as to a native ability [19]. Later scholars have revisited this definition suggesting talent is a "systematically developed innate abilities that drive excellent performance in one or more domains of human functioning". Gagne (2004), for example, distinguished four ability domains such as intellectual, creative, socio-affective and sensorimotor that can lead to extraordinary performance in different domains of human functioning including business and technology. Different scholars connected the discussion on employees' ability to their competencies that play an important role in performing organizational tasks [31]. What is competency? One definition is "the sum of knowledge and behaviors an individual possesses" [31]. Competencies are also viewed as the skills and behaviors that lead an individual to be successful on the job (e.g., problem-solving). Compared to competencies, skills are specific learned abilities to perform well on a given task or job (e.g., coding, handling accounts; AI screening) [20, 44]. Skills and competencies often serve as the building blocks for understanding and measuring individual contributions. Competencies assist in various managerial processes, which are AI-enabled. For example, recruitment, job and talent profiling, and more broadly TM [20]. Some scholars [31] acknowledge that competency also involves behaviors. Thus, it is the ability to meet complex demands by drawing on and mobilizing resources to perform complex tasks. Literature has revealed that individuals require a wide range of skills and competencies to overcome the complex challenges of modern HRM. Thus, firms explore options to enhance both individual and group-based skills and competencies in agreement with the exploration of various work models, therefore they are considered the building blocks of organizational human capital. With regards to AI work-related skills, researchers have pointed to various directions. For example, a "skills fit" in a digital era [11], hard and soft skills analysis [2, 21] and sustainable skills required the digital work domain [44]. Skills are micro-level and task-specific, making them important for AI project execution [20] and more broadly for the digital transformation of HRM [45]. Thus, some even proposed that there should be a person-skills fit, that is, skills level and relevancy associated with jobs in future HRM or future of work more broadly, which is "a growing adoption of AI in the workplace, and the expansion of the workforce to include both on-and off-balance-sheet talent" [10]. Contextualizing the discussion on person-skills fit also to our discussion of AI, it can be intended that there should be also a fit between talent skills available and AI (to be) adopted in the organization.

Although many people believe that genius is created purely through genetics (e.g., Amadeus Myth), [17] claimed that such gifts must be nurtured into talents to deliver excellent performance. Thus, extended and deliberate practice is a necessary condition for the manifestation of talent into excellence. This can be achieved through (systematic) learning activities inside or outside of the workplace [19]. The latter is primarily concerned with organizational activity aimed at improving the performance of individuals and groups in the organization [10]. For example, skills development is even perceived as a strategic management tool to cope with the current business environment, primarily because the market landscape has changed from one of mass production to one of customization where price, quality and speed of delivery are stressed, and industries need to face challenges of digital transformation and industry 4.0 [45]. With regards to AI both technical and softer (e.g., ethical or social AI issues) approach is crucial to their successful adoption in HRM. However, overall, it is worthwhile to acknowledge that the return on investment on organizational training and development activities, and especially of those related to AI is not easy to estimate, while it is very important [10]. Based on all the above we build the following proposition:

Proposition 1: *Effective organizational TM could provide talent with the abilities and skills to embrace AI (in HRM)*

Affective component

The latter affective component - discussed mostly in giftedness literature, the positive psychology literature, and vocational psychology literature - intends that the factors ultimately accounting for achievement are likely to be unique personal and behavioral dispositions that the individual brings to the actual performance. Thus, while the definition of the ability component of talent focuses primarily on diverse intellectual abilities, the affective component considers non-intellectual motivational attributes and how these could affect the performance of individuals [19]. This factor, although important seems to be mostly overlooked so far in the literature on AI besides some rare exceptions confirming that motivation is important in AI use and that it can vary between intrinsic motivation, extrinsic motivation, or force choice motivation [12]. From this perspective on motivation and its role in AI adoption, we propose the following:

Proposition 2: *Talent motivation may impact talent-AI fit, and thus may also impact AI adoption in HRM.*

2.2.2 Human Trust in AI (HTAI) factors

Trust Defined

The literature defines trust as the willingness to rely on a partner for whom one has confidence and regard [42]. Mayer and colleagues (1995) defined trust as "the willingness of one party to be vulnerable to the actions of another party, based on the expectation that the other party will perform particular actions important to the trustor, irrespective of the first party's ability to monitor or control that other party" (p. 710).

The literature has discussed two dimensions of trust: organizational trust and interpersonal trust. The dichotomy of cognitive and affective trust is often used to indicate two divergent forms of trust [16]. The cognitive and affective forms of trust can be seen as two dimensions that describe trust between two parties, and most relationships contain elements of both. Mishra and Mishra (1994) demonstrated through their fieldwork in organizational downsizing that in specific organizational circumstances, mutual trust can enhance organizational performance.

Trust is a dyadic reciprocal construct associated with social exchange theory, making it meaningful in traditional work. Scholars suggested that people are eager to explore relationship quality, which is built on trust and reciprocity between two sides. They described trust and reciprocity as features of relationship quality, along with optimism and satisfaction. These features also affect power relationships, communication, and goal compatibility [53]. The question of interest within the scope of this study is whether we can draw reciprocal lines between human trust and AI adoption.

Human Trust in AI

Our 3T Framework implies that human trust in AI plays a significant role in AI adoption. Human trust in AI has long been a multi-faceted subject in which the emotional complexity of users toward AI and technology acceptance has been complex [53].

Recently, it has been accepted by scholars that the role of trust in AI adoption is important for the successful execution of key goals. For example, Lockey and colleagues (2021), introduce key AI challenges and respective vulnerabilities each challenge creates for stakeholders. They propose a "concept matrix" of five key AI trust challenges developed by including: 1) Transparency and explainability 2) Accuracy and reliability 3) Automation versus augmentation 4) Anthropomorphism and embodiment and 5) Mass Data Extraction. Furthermore, Zhang and colleagues (2021) focus on user motivations and social emotion and discuss a gap that exists regarding the path taken from emotion to AI acceptance. They show that functionality and social emotions both have a significant effect on trust, whereas perceived humanity does not. Additionally, they demonstrate the mediating effect of trust.

Glikson and her colleagues (2020) claim that integrating AI into HRM critically depends on workers' trust in AI technology. They determine the human trust in AI and identify three forms of AI representation (robot, virtual, and embedded) and propose a framework that addresses the elements that shape users' cognitive and emotional trust per representation. The authors identify four behavioral factors - tangibility, transparency, reliability, and immediacy - in developing cognitive trust, and the role of AI's anthropomorphism specifically for emotional trust. Furthermore, Araujo and colleagues (2020) demonstrated the various risks, fairness and usefulness of AI-based decision-making at the societal level and showed that attitudes towards AI are influenced by individual characteristics.

Because trust has been found to improve the performance of working teams [5], we take a multi-level perspective and analyze human trust in AI from both the individual and team levels. We believe that understanding human trust in the technology is key in assessing organizational resources for successful AI adoption.

Multilevel Perspective

Partially in order to fill this gap and given the profound theoretical and practical needs to better understand trust in AI from a multilevel perspective, we propose a contextual individual approach to exploring human trust in AI and its role in technology adoption. It has long been acknowledged that context is important in understanding various phenomena, attending to the nuances of a given context [26] – individual trust, team trust and fairness in AI - can provide new insights for theory development and provide more practical relevance [1]. Since the field has now accumulated a large body of research on trust, we believe it is time to make the differentiation across levels to see when and how human trust in AI differs, potentially influencing technology adoption [16].

Our proposed multilevel framework is also embedded in the trust culture. Empirical evidence supports the importance of a trust culture. For example, Von Krogh and colleagues (2012) highlight that a trust culture enhances the speed of communication by empowering employees to willingly share personal concerns, thus may assist in technology adoption. Similarly, Cohen and Prusak (2002) suggest that high levels of trust lower transaction costs and improve sharing of expertise. Other scholars highlight that the absence of trust is one of the main barriers to knowledge transfer and sharing [16, 53]. Indeed, a trust culture can be improved and supported amongst teams in order to speed up AI adoption. Despite these exhortations on the importance of a trust culture, it remains to be analyzed how the trust culture influences individual and team trust in AI for more smooth technological transits [1]. From this perspective on trust and its role in AI adoption, we provide the following propositions:

Proposition 3: *Human trust in AI can impact AI adoption in HRM.*

Proposition 3a: *A trust culture can impact multilevel (individual/team) trust in AI, thus affecting AI adoption in HRM.*

AI fairness

To the extent that trust is a flexible phenomenon, several scholars have proposed that trust is primarily a characteristic of an ongoing process [53]. Following this line of research, we believe and propose in our framework that the perception of fairness in AI is an important aspect that should be assessed in order to grasp the fuller picture of human trust in AI.

An increasing number of decisions are being controlled by AI algorithms, with the increased adoption of automated decision-making systems in business and managerial settings [39]. AI is expected to perform better than human beings for several reasons. First, AI can integrate a huge amount of data. Second, AI can perform complex computations much faster than human beings. Third, human decisions can be subjective, and they often include biases. Hence, it is a common belief that using AI makes decisions more objective or fair. However, some scholars noted that AI is not as objective as we would expect [39], which influences human trust in AI. Many AI-based automated decisions can significantly impact individuals' lives. For example, job placement, loan rendering, and healthcare, among others. Thus, to increase trust levels, it is important to assess and improve the ethics of the decisions made by these automated systems.

Following this, recent research is increasingly interested in algorithmic fairness. As a result, increasing attempts to define, evaluate and improve fairness in AI algorithms [42]. It is important to note, however, that the task of improving the fairness of AI algorithms is not trivial since there exists an inherent trade-off between accuracy and fairness. This has important implications for user-based trust. We thus propose the following:

Proposition 4: *Perceived AI Fairness can impact AI adoption in HRM.*

2.2.3 Technology Adoption factors (TA)

The human impact of technology transformation and the changing dynamics of the digital ecosystems is evident in terms of the number of new issues within the organization and management and the changing required skill set. The critical relevance of human resource adoption in rapidly changing socio-technical environments requires adopting advanced tools to effectively address these challenges [3, 40].

The basic assumptions underlying technology user acceptance models comprise individual reactions to using information technology that can lead to their intentions, and later to the actual use of technology. The technology adoption research stream has extensively investigated a number of potential factors that can lead to specific technology adoptions in HRM such as performance or effort expectancy, social influence, or facilitating conditions [43, 45] among many others.

Following on key adoption ideas proposed by Kadosh and Chalutz-Ben Gal's analysis (2021) that build on the work of Lin and colleagues (2007) we also believe that the factors that can influence the adoption of AI comprise optimism, innovativeness, insecurity, and discomfort (Technology Readiness and Acceptance Model (TRAM) model). We focus on these four factors because we believe that they provide a broad perspective and capture the complexity of the new technology acceptance process [51]. Furthermore, the four perspectives enable us to explore a holistic approach to AI technology adoption in HRM, considering important elements associated with potential users [51].

Optimism, innovativeness, insecurity, and discomfort and their role in AI-adoption

Optimistic people generally expect that "good rather than bad things will happen to them" [43]. The way in which they approach the world has an impact on their attitudes toward risk perception and acceptance in relation to technology, where optimism relates to a positive view towards technology and trust that it will offer people more efficiency, flexibility, and control [38].

It was stated that "innovativeness" is used to assess the "newness" of innovation, with innovative products being labeled as having a high degree of newness. Parasuraman introduced the technological dimension and referred to "a propensity of being a technology pioneer and influencer" [38, p. 311]. Thus, we believe that innovativeness has a positive influence on AI adoption in HRM.

Discomfort attributes have been defined as "a perceived lack of control regarding technology and the sense of being overwhelmed by it" [38, p. 311]. It was argued that the high-complexity features of technology products have a negative impact on product evaluation because of the user's learning cost [37].

Insecurity "implicates a distrust of technology and the disbelief about its ability to work properly" [38, p. 311]. Although the TRAM Model suggests that insecurity has a negative impact on the perceived ease of use and perceived usefulness of technology adoption.

Moreover, following Bunduchi and her colleagues (2019) we also consider that AI adoption factors can vary depending on the technology innovation stage (see Figure 1). For example, Bunduchi and colleagues (2019) in their study of a national HR information system roll-out found out that changes in the nature of the task actors focus on at different stages during the technology innovation project means that the same institutional logics may direct actors' attention onto different aspects of the organizing vision at different times. Thus, this research also draws upon a four-stage model of IS innovation which has been widely deployed in institutional IS research [36] to examine the introduction of IT in HRM. The model charts comprehension or intention to adopt (preparing strategies and information), development (developing the procedures necessary to enable the program), adoption (introducing the system into the organization) and use or assimilation (the system is fully embedded). Following this approach, also in our research while analyzing TM, trust and technology adoption factors that can influence AI adoption in HRM, we consider that such factors can vary between different stages of technology innovation in HRM. Thus, our proposition is as follows:

Proposition 5: TM and human trust in AI can vary across the different phases of technology adoption.

3 Discussion and Conclusions

In this study, we drew on three so far mostly interdependent literature streams including TM, trust in AI, and AI adoption to create a well-rounded framework on AI adoption for/in HRM.

The discussion of our study and research outcomes, and the deriving implications at the theoretical and practical levels, may be articulated along with two main reflecting questions. First, what are the key drivers to AI adoption in organizational settings, which factors and specific elements influence the adoption of AI in HRM, and whether and how these are subject to temporal fluctuations? Second, what framework can serve as a strategic assessment tool for managers when evaluating AI adoption in initiatives within their firms?

To answer these questions, in this research we investigate key elements to promote AI adoption within the technology ecosystem. We do this by offering a multi-dimensional framework of TM, trust and technology and providing integrated analysis of micro and macro factors concerning the adoption of AI technology within the general industry.
Our proposed 3T framework for AI adoption offers key supporting scopes. Thus, our research contributes with an investigation of the interrelated TM, trust, and technology factors, which influence the adoption of AI in firms. The research effort also contributes to the interdisciplinary scholarly debate on the potential benefits, challenges, limitations and requirements of AI adoption in organizational settings and addresses complex challenges.

The proposed integrative framework is in line with previous AI adoption frameworks which explore the AI-based technology acceptance process in various organizational settings focused on man-technology interactions [2, 21, 27, 33, 41, 53]. Moreover, our study complements and advances previous contributions such as the TRAM model, Technology Readiness and Acceptance Model [22, 32], and the approaches defined to facilitate the introduction and AI, also addressing the explainability of AI-based decisions [24].

Our study also advances the extant academic knowledge by gathering factors related to strategic components of talent, trust and technology, which play, and are expected to continue to do so, a central role in the adoption of AI across industries, HRM, and work teams. We provide a potential strategic and important managerial assessment tool for AI adoption for the benefit of management and HRM alike.

We constrained our analysis to three main factors that can influence the adoption of AI in HRM. It is worthwhile to acknowledge that in reality many more factors can come into play in this complex process. Moreover, this paper does not report on empirical data. We address this shortage, and to test the applicability of our conceptual framework developed in this paper, we currently are conducting a scoping literature review on AI adoption in HRM, as more empirical research is also needed in the field of AI adoption. The description of the methodology and results of this literature review are out of the scope of this paper. Finally, we refer to AI in a broader sense without relying on some specific classification of AI (e.g., machine learning or robots). Future scholars might like to test empirically the applicability of our framework and consider how the dimensions of our framework could be affected by different types of AI.

Despite these limitations, we believe that our paper still has important scholarly and practical implications. For the former, it addresses the need for more conceptual and qualitative studies and makes a conceptual contribution to HRM and AI literature by providing a new framework that advances [30] the current definition and understanding of individual human facilitators behind the ability to speed up the adoption of AI-based technology. The practical contribution can facilitate the assessment of human-centered and trustworthy design toward an effective adoption of AI in HRM. Thus, we believe, the findings of this research would be of interest to broad categories of actors and build an agenda for future interdisciplinary research.

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