Understanding knowledge hiding under technological turbulence caused by artificial intelligence and robotics

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Abstract

Purpose

Artificial intelligence (AI) will be performing 52% of the tasks in companies by 2025. The increasing adoption of AI is generating technological turbulence in the business environment. Previous studies have also shown that employees are aware of the high risk of losing their jobs when being replaced by AI. The risk of employees engaging in opportunistic behaviors, such as knowledge hiding, is thus fairly high. Therefore, the aim of this paper is to analyze the mediating effect of employee's AI awareness on the relationship between technological turbulence generated by AI and the three types of knowledge hiding: evasive hiding, playing dumb and rationalized hiding.

Design/methodology/approach

Structural equations by the partial least squares method were used to test the proposed research model.

Findings

The most interesting finding is that employee's AI and robotics awareness fulfills almost all mediating functions in the relationship between technological turbulence generated by AI and the three types of knowledge hiding.

Originality/value

hide knowledge in all possible ways when perception that AI is a

threat to their job increases. In other words, technological turbulence generated by AI and employee's AI awareness are the two great new triggers of knowledge hiding in the digital age.

Keywords

Transaction cost theory
Knowledge hiding
Digital transformation
terproductive knowledge behavior
Intelligent process automation
oyee's artificial intelligence awareness

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Introduction

The World Economic Forum foresees that technologies grouped under the term Industry 4.0 will have radically changed the way of doing business in the short term. One of them, artificial intelligence (AI), will be performing 52% of the tasks in companies by 2025, relegating people to 48% (WEF, 2018). AI aims to design algorithms to provide computers with cognitive skills and competencies for sense-making and decision-making, and its various applications can be grouped into two major branches: data analytics and autonomy (Abbass, 2019). The also called "intelligent robots" most widely used in companies are chatbots, virtual assistants, recommendation agents to help customers in decision-making, stock trading bots, analytical models based on machine learning to segment or avoid customer leakage, among other purposes (Lu *et al.*, 2020; Papa *et al.*, 2020).

However, the arrival of AI is causing a lot of turbulence in the business environment due to the domino effect it generates in all sectors of the economy (Agrawal *et al.*, 2019), including high-tech and knowledge-intensive sectors (Dengler and Matthes, 2018). When companies in a certain sector decide to be pioneers in

replaced by intelligent robots (Lingmont and Alexiou, 2020;

Rampersad, 2020). Confronted with such a discouraging outlook, recent studies have found employees feel insecure, stressed, even undervalued and unappreciated at work (Li *et al.*, 2019).

This situation generates chaos and uncertainty in firms, as these negative feelings trigger employee depression, indifference, cynicism, intention to resign and significantly reduce organizational commitment and career satisfaction (Brougham and Haar, 2018). Some authors have coined the term AI and robotics awareness (Li 2019) to refer to this discomfort of employees in the digital hich specifically captures the extent to which employees view the likelihood of AI and robotics impacting negatively on their future prospects. The concept alludes to the fact that employees ive the intelligent robots implemented in firms to automate sses as a threat to their job/career (Lingmont and Alexiou, .

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tunately, the discussion around this new variable has been oped mainly at the individual level. On the one hand, research cused on the inventory of the previously mentioned negative gs and of the decisions that individuals can eventually make in a state of maximum concern in view of the imminent risk of being replaced by AI applications (Li *et al.*, 2019; Lingmont and Alexiou, 2020). On the other hand, other authors have dealt with identifying individual behaviors associated with a lesser sense of insecurity at work such as the personal use of certain technologies (Nam, 2019). Unfortunately, studies are lacking which analyze the various organizational implications of employee's AI and robotics awareness, especially as employees, despite facing the imminent risk of losing their jobs, continue to be key for their knowledge and experience in various organizational processes (Caputo *et al.*, 2019b; Dezi *et al.*, 2021; Orlando *et al.*, 2021), including the adoption of intelligent robots and process automation (Makarius *et al.*, 2020).

Nevertheless, we suspect that one of the big organizational consequences of employee's AI and robotics awareness is knowledge hiding, understood as an intentional attempt by an individual to withhold or conceal knowledge that has been requested by a co-worker (Chatterjee *et al.*, 2021; Connelly *et al.*, 2012). Previous studies have shown that knowledge hiding in one of its three forms: evasive hiding, playing dumb and rationalized hiding (Ma *et al.*, 2020), is intensified when there is perceived career insecurity (Kumar Jha and Varkkey, 2018) and job insecurity (Feng and Wang, 2019), with the latter usually triggering mainly evasive hiding (Serenko and Bontis, 2016).

Unfortunately, studies on knowledge-hiding triggers have focused almost exclusively on individual aspects such as the dark side of personality (Banagou *et al.*, 2021; Pan *et al.*, 2018) or territoriality dealing with the analysis of factors exogenous to the organization that we believe can also become triggers for intra-organizational hiding; in this case, technological turbulence generated by AI.

Similarly, there is scarce research work addressing the three types of hiding in the context of the digital age. To date, the most representative previous finding indicates that in accordance with adaptive cost theory, knowledge hiding among big data analyst is the result of their lack of focus and motivation to attend to less nt tasks such as information request, given that processing ind generating insights are higher priority tasks for them (Ghasemaghaei and Turel, 2021). Thus, works analyzing knowledge ; related to other digital technologies such as AI are scarce. oove all, there is an evident need to find more appropriate etical lenses to explain this organizational behavior in relation uncertainty in the environment generated by this technology. ive cost theory and its assumption on task prioritization which een used to understand hiding in the digital age has serious tions and is insufficient to explain this phenomenon under ological turbulence generated by AI.

Therefore, the aim of this paper is to analyze the mediating effect of employee's AI and robotics awareness on the relationship between technological turbulence generated by AI and the three types of knowledge hiding: evasive hiding, playing dumb and rationalized hiding (Connelly *et al.*, 2012; Ma *et al.*, 2020). As such, we believe knowledge hiding in the digital age is first and foremost a strategy by employees to sabotage and induce failure in process automation, to reduce the risk of being replaced in the workplace by intelligent robots. In other words, technological turbulence generated by AI and employee's AI and robotics awareness are the two great new triggers of knowledge hiding in the digital age. Similarly, we consider that transaction cost theory is the most appropriate theoretical lens to explain this phenomenon, as its assumptions enable to theorize differently on hiding, particularly as an employees' opportunistic behavior for the protection of their personal interests.

Accordingly, our work contributes to the discussion on knowledge hiding in various ways. First, it considers the influence of an exogenous variable that acts as a trigger of hiding, namely, the technological turbulence generated by AI. Second, unlike previous studies, our study helps to understand knowledge hiding in a completely different context –the digital age. Finally, another major contribution of our work is concerned with redirecting the discussion on the repercussions of employee's AI and robotics awareness from the individual to the organizational level, where it plays a key role in the digital transformation of the company.

The article is structured as follows. First, the hypothesis regarding

the measurement model is assessed and the mediation is tested through structural equations by the partial least squares method. Finally, the results are discussed and the conclusions of the study are presented.

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Transaction cost theory, whose core assumption is opportunism, posits market players behave opportunistically, which is perceived …-interest seeking with guile (Williamson, 1975). Opportunism is strongly linked to environmental uncertainty, as it increases due to the unpredictability of an event, particularly market …opments, among other things (Williamson, 1996). Thus, …anies are forced to organize themselves in a way in which the … of opportunism can be controlled or reduced.

…action cost theory is hence the approach that has enabled to …fy the existence of different negative organizational behaviors … ow down the flow of knowledge in the company (King and …, 2008), including knowledge hiding – which is deep-rooted in opportunism and the protection of personal interests (Ghasemaghaei and Turel, 2021; Pan *et al.*, 2018). Consequently, transaction cost theory allows us to explain our mediation model, based upon the assumption that opportunistic behaviors are intensified by environmental uncertainty (Williamson, 1975, 1996). In our study, this uncertainty stems from the increasingly widespread use of intelligent robots in the business environment.

Technological turbulence generated by artificial intelligence and employee's artificial intelligence and robotics awareness

Turbulence in the environment is basically generated by changes in customer preferences, intense competition or frequent technological changes (Bodlaj and Čater, 2019). Technological turbulence refers to the rate of technological advancement within an industry (Autry *et al.*, 2010). Currently, technological turbulence is mainly derived from the emergence and increasingly widespread use in companies of the various technologies grouped under the term Industry 4.0 (Oztemel and Gursev, 2020); of all of them, AI is having the most impact on the way of doing business (Butner and Ho, 2019; Ransbotham *et al.*, 2017). AI aims to design algorithms to provide computers with cognitive skills and competencies for sense-making and decision-making, which means that computational agents endowed with this type of algorithms are able to interpret data, assess opportunities and risks in contexts and situations, generate courses of action, perform tasks and learn, adapt and share knowledge to humans or other AI (Abbass, 2019).

making and decision-making and has the authority to execute its decisions (Loureiro *et al.*, 2020). In the business context, the main applications of AI are chatbots, virtual assistants, recommendation agents to help customers in decision-making, stock trading bots, analytical models based on machine learning to segment customers or avoid their leakage, among others (Caputo *et al.*, 2019a; Lu *et al.*, 2020).

On the other hand, employee's AI and robotics awareness captures the extent to which employees view the likelihood of AI and robotics ...ting negatively on their future career prospects (Brougham ...laar, 2018; Lingmont and Alexiou, 2020). The possibility of being replaced by intelligent robots and having their jobs and ...rs affected generates concerns in employees that trigger ...ve feelings such as fear, stress and even depression, which ...tely significantly affects their behavior in the organization ...hayakorn and Jermsittiparsert, 2019), particularly increasing ...rence and turnover intention and reducing organizational ...itment and career satisfaction (Li *et al.*, 2019).

...fore, the relationship between technological turbulence ...ated by AI and employee's AI and robotics awareness is fairly obvious. As the adoption of intelligent robots increases in the sector, for example, by the main competitors and suppliers, the company is forced to respond to these challenges in order not to see its competitive advantage eroded. This requires breaking the status quo of its processes and its current business model, and devising ways to also make inroads into the adoption of intelligent robots (Choi *et al.*, 2018). While this occurs in the environment, employees are increasingly aware of the arrival of AI and the implications it would have for their work and career, that is, they begin to notice the threat and growing risk of losing their jobs and being replaced by intelligent robots (Lingmont and Alexiou, 2020; Nam, 2019).

Technological turbulence generated by artificial intelligence, employee's artificial intelligence and robotics awareness and knowledge hiding

Knowledge hiding is understood as an intentional attempt by an individual to withhold or conceal knowledge that has been requested by a co-worker (Chatterjee *et al.*, 2021; Connelly *et al.*, 2012). There are three ways to withhold knowledge. First, playing dumb occurs when the hider deliberately pretends not to have mastery of the knowledge that has been requested when, in fact, they have deep knowledge (Anand and Hassan, 2019; Ghasemaghaei and Turel, 2021). Second, evasive hiding consists of the hider responding to the request by providing incorrect or incomplete information, or by making misleading promises to provide a complete answer in the future, when in fact they have no intention of doing so (Bari *et al.*, 2020; Ma *et al.*, 2020). Finally,

Jahanzeb *et al.*, 2021).

By playing dumb, the collaborator is somehow trying to display a certain degree of ignorance about the topic being discussed or the specific information they have been asked to provide (Ghasemaghaei and Turel, 2021; Pan *et al.*, 2018). In that sense, the increase in awareness of automation on the part of employees generates tensions with the organization. In addition to the feeling that their ability to contribute to the organization from their workplace is undervalued, for example, the worker perceives the introduction of these technologies as a violation of the ...ological contract composed of mutual expectations formed at ...eginning of the contract and expected to be fulfilled by the counterpart (Anand and Hassan, 2019; Jahanzeb *et al.*, 2021).

...fore, when employees work in an environment made more ...lt by the arrival of intelligent robots and the perception that ...epresent a threat to their work and their career increases, ...hoose to adopt defensive positions, including acting in a ...ent manner and hiding knowledge and information, ...nding not to be aware of the issues they have been asked to ...ss (Bari *et al.*, 2020; Feng and Wang, 2019). On the other ... while the collaborators experience these tensions and perceive a hostile environment, they will be careful and selective with the information they share; specifically, they will delay as much as possible the exchange of key knowledge so as to be somehow indispensable and irreplaceable in the company (Serenko and Bontis, 2016). Or they will build a false argument to justify the fact of not sharing knowledge (Kumar Jha and Varkkey, 2018; Ma *et al.*, 2020).

This way of understanding knowledge hiding contrasts with the approach that has been adopted on hiding in the digital age, according to which hiding occurs due to employees' lack of focus and motivation to attend to less relevant tasks in their jobs such as information request (Ghasemaghaei and Turel, 2021). However, transaction cost theory enables to explain knowledge hiding in a novel manner, more consistent with the nature of this phenomenon, which is conditioned by uncertainty in the environment and the threat that the arrival of AI represents to employees. From this theoretical perspective, hiding is primarily an opportunistic behavior of employees to protect their personal interests against the imminent risk of losing their jobs when being replaced by intelligent robots.

Hence, in this context of digital transformation, the decisions made by the organization in terms of the adoption of intelligent robots are highly likely to be perceived by employees as unfair because they are contrary to their personal interests, and the intelligent automation of processes generates in them a permanent state of uncertainty and emotional exhaustion (Li *et al.*, 2019; Lingmont and Alexiou, 2020; Nam, 2019). Employees, in principle, will end up knowledge hiding in an opportunistic or "strategic" manner (Losada-Otálora *et al.*, 2020) to protect their personal interests (Feng and Wang, 2019).

In this regard, in the local context there are suspicions that employees are hiding knowledge for the purpose of sabotaging the company's digital transformation because they deliberately share partially or avoid revealing key and detailed information to the engineers responsible for automation, particularly the step-by-step organizational process or the task under their charge in the any. This prevents to carry out process automation successfully because the sabotage means that in the long run there gh risk that the intelligent robot will not add value and will ate bad experiences for internal and external customers. the organization will slow down the speed with which it is ing people with machines, a scenario employees are most sted in when there is awareness of AI and automation.

nmary, as the technological turbulence generated by AI rises the increasing adoption of intelligent robots in the company nment, a state of uncertainty encouraging knowledge hiding in the company emerges. However, this situation indeed reaches worrisome proportions when employees are aware of the inevitable negative consequences the arrival of intelligent robots has on their work and career; in other words, when there is employee's AI and robotics awareness. That is, the awareness of a real and growing risk of job loss when being replaced by intelligent robots is what really makes the technological turbulence generated by AI an actual trigger of the three types of knowledge hiding. Therefore, the following hypotheses are raised:

H1a. Technological turbulence caused by AI increases knowledges hiding, particularly playing dumb.

H1b. Technological turbulence caused by AI increases knowledges hiding, particularly evasive hiding.

H1c. Technological turbulence caused by AI increases knowledges hiding, particularly rationalized hiding.

H2a. Employee's AI and robotics awareness has a mediating effect on the relationship between technological turbulence generated by AI and playing dumb.

H2b. Employee's AI and robotics awareness has a mediating effect on the relationship between technological turbulence generated by AI and evasive hiding.

H2c. Employee's AI and robotics awareness has a mediating effect on the relationship between technological turbulence generated by AI and rationalized hiding.

Methodology

Sample and data collection

The proposed model (Figure 1) was tested on a sample of medium and low-technology manufacturing (Eurostat, 2009) and service companies (Table 1), from sectors where the adoption of intelligent s is increasing (Butner and Ho, 2019; Ransbotham *et al.*,). Fieldwork was carried out in the summer of 2019, through a questionnaire sent by e-mail and physically applied to the gement staff of a total of 200 companies that participated in ıg spaces on new technology management provided by a sity.

study, we used the minimum R-squared method to estimate mum sample size allowing to reach an acceptable level of ical power, 80%, to guarantee the statistical test performed ɔle to recognize a path coefficient as statistically significant (*P*) (Hair *et al.*, 2019; Kock and Hadaya, 2018). 136 valid responses were eventually obtained, a sample size guaranteeing a satisfactory statistical power above 80% (Hair *et al.*, 2017).

Measurement scales

To measure knowledge hiding, the scale developed by Connelly *et al.* (2012) was used, which has been adapted in multiple recent studies (Bari *et al.*, 2020; Ma *et al.*, 2020). For technological turbulence generated by AI, the scale used was that of by Choi *et al.* (2018), and for employee's AI and robotics awareness, the scale of Brougham and Haar (2018) was adapted (Table 2). In addition, a Likert scale was used, going from *totally disagree* (1) to *totally agree* (5).

Reliability and validity

The reliability and validity of the measurement model were examined with equations by the partial least squares method (Cepeda-Carrion *et al.*, 2018; Hair *et al.*, 2019). With respect to individual reliability, it was verified that all items had a loading equal to or greater than 0.7, or not less than 0.6 in the case of scales recently being used more recurrently in empirical work (Table 2). It was also verified that all constructs presented a Cronbach's alpha (CA), and composite reliability (CR) and Dijkstra-Henseler (pA) indices were higher than 0.7, and an average variance extracted (AVE) was higher than 0.5 (Hair *et al.*, 2020).

Discriminant validity

To establish discriminant validity, compliance with the Fornell–

0.85 (Hair *et al.*, 2020).

Mediating effect test

Regarding the hypotheses test, structural equations by the partial least squares method were used to obtain the confidence intervals at 95% and the *t* values of the coefficients of the different paths from the resampling of 5,000 subsamples (Cepeda-Carrion *et al.*, 2018; Hair *et al.*, 2019). As for the evaluation of the mediating effect of employee's AI and robotics awareness, the procedure by Zhao *et al.* (2010) was followed, which proposes the confirmation of the ical significance of the indirect effects (path *a* × paths *b*) as the criterion to account for the existence of a mediating effect (Figure 1). In case the effect exists, the next step is to establish ier the mediation is partial or total through the variance-nted-for (VAF) test, which allows to calculate the magnitude of direct effect with respect to the total effect (Hair *et al.*, 2017).

ılts

4 shows that in the direct model the direct effects of ological turbulence caused by AI on Evasive Hiding (β = 0.331), on Playing dumb (β = 0.313), and on Rationalized hiding (β = 0.294) are significant and with a positive sign. Therefore, hypotheses H1a, H1b and H1c are accepted. Additionally, the influence of control variables is not significant in the direct model nor in the mediated model. On the other hand, in the mediated model, the 3 paths of indirect effects are significant and with a positive sign: 1) Technological turbulence caused by AI → Employee's AI and robotics awareness → Evasive Hiding (β = 0.382). 2) Technological turbulence caused by AI → Employee's AI and robotics awareness → Playing dumb (β = 0.300). 3) Technological turbulence caused by AI → Employee's AI and robotics awareness → Rationalized hiding (β = 0.451). The above means the mentioned criterion defined in the procedure of Zhao *et al.* (2010) is met and leads to accepting hypotheses H2a, H2b and H2c.

In order to assess the significance of the mediating role of employee's AI and robotics awareness, the VAF test was conducted (Table 4), allowing to establish the magnitude of the indirect effect against the total one. In the case of playing dumb, 58% of its variance is explained by the indirect relationship via the mediator variable, while this percentage is 59% for both evasive hiding and rationalized hiding. This indicates that the mediation of employee's AI and robotics awareness is partial but close to the threshold of the total degree (Hair *et al.*, 2017).

Discussion

Our results confirm that technological turbulence generated by AI increases employee's AI and robotics awareness. These findings

resistance and possible acts of sabotage to automation processes cannot be underestimated. In many cases these are not even taken for granted because it is wrongly assumed that the adoption of intelligent robots is a strictly engineering process (Makarius *et al.*, 2020). Hence, the adoption of an intelligent robot in certain cases has led to value destruction and bad customer experiences (Canhoto and Clear, 2020).

However, the most interesting finding is that employee's AI and robotics awareness fulfills an almost total mediating function in the …onship between technological turbulence generated by AI and …ree types of knowledge hiding. Contrary to what previous studies have suggested, which have only verified the presence of …e hiding when there is job insecurity (Serenko and Bontis, … or of evasive hiding and playing dumb when there is distrust … *et al.*, 2020), our study shows that employees are willing to …nowledge in all possible ways when perception that intelligent …s are a threat to their work or career increases. The size of the …ting effects of employee's AI and robotics awareness and its … effect on the three types of hiding are quite similar, that is, …nanifest themselves simultaneously and in similar …rtions.

Conclusions

Theoretical and practical implications

As for academic contributions, the study helps with the discussion on knowledge-hiding triggers by calling the attention on an exogenous variable to the organization, namely, technological turbulence generated by AI. This study perspective contrasts with the research traditional that has almost exclusively considered triggers at the individual (Pan *et al.*, 2018; Singh, 2019), interpersonal (Xiong *et al.*, 2021; Yao *et al.*, 2020a) and organizational levels (Connelly *et al.*, 2019; Jahanzeb *et al.*, 2021). However, our results show that the rate of technological advancement within industries caused by intelligent robots does not pass unnoticed by employees. On the contrary, employees observe the environment and are increasingly aware of the implications of the advent of AI for their work and career, as well as find in hiding a defensive strategy to sabotage and induce failure in process automation, to reduce the risk of being replaced in the workplace by intelligent robots.

Hence, together with the study of Ghasemaghaei and Turel (2021), our work is one of the pioneering studies in the analysis of knowledge hiding in the digital age. This incipient study perspective is fairly novel because the most relevant works, even the most recent ones, continue to analyze knowledge hiding in relation to classic organizational phenomena occurring regularly in the context

phenomenon such as the advent of AI, which is currently radically changing the way business is conducted. In contrast, our results show that knowledge hiding has and will have a leading role in the digital age and tends to become more acute as the adoption of intelligent robots in companies deepens. In fact, our results indicate that hiding is already a recurrent behavior, given its potential to reduce the risks perceived by employees with the arrival of intelligent robots, and that its three forms, namely, evasive hiding, playing dumb and rationalized hiding, are manifested in the company in an intense, simultaneous and similar proportion.

er important contribution of our study is that it provides a way of understanding hiding and a new theoretical lens that asts with the approach that has been recently adopted on in the digital age. In accordance with the assumptions of ive cost theory, this phenomenon occurs due to people's lack us and motivation to attend to less relevant job tasks such as nation request (Ghasemaghaei and Turel, 2021). Conversely, sults indicate that hiding, viewed from the lens of transaction heory, is primarily an opportunistic behavior of employees to t their personal interests against the imminent risk of losing obs when being replaced by intelligent robots.

Hence, our results also suggest revaluating the theoretical lens that has been used so far to understand hiding in the digital age: adaptive cost theory, whose main assumption forces us to understand this type of organizational behavior in a simple and limited manner, specifically as a consequence of task prioritization at work (Ghasemaghaei and Turel, 2021). Conversely, transaction cost theory, particularly the assumption that the usual opportunism of market players' actions is intensified when there is uncertainty in the environment, is much more appropriate to explain phenomena such as knowledge hiding under technological turbulence caused by AI. In other words, transaction cost theory has a greater explanatory power than adaptive cost theory because its assumptions are more consistent with the nature and complexity of knowledge hiding in the digital age.

In that sense, our results partially contradict the findings of previous works that have minimized the importance of rationalized hiding because they usually only detect the presence of evasive hiding and playing dumb when the trigger is job insecurity (Feng and Wang, 2019; Serenko and Bontis, 2016) or when there is a climate of distrust (Yuan *et al.*, 2020). In other words, when these two situations appear close to the one represented by employee's AI and robotics awareness, only the most subtle and buried types of hiding are activated, such as evasive hiding and playing dumb, and there is no indication of rationalized hiding, which is more explicit, more shameless and more politically incorrect. However, our results indicate that employee's AI and robotics awareness detonates all three types of hiding simultaneously because, unlike the scope of

unabashedly resorting to all types of soft and hard hiding.

This work is also pioneering in analyzing the organizational repercussions of employee's AI and robotics awareness, contrasting with the theoretical perspective of previous studies that focus either on analyzing its direct incidence on variables that are on a strictly individual level such as turnover intention (Brougham and Haar, 2018; Li *et al.*, 2019), or on identifying individual behaviors associated with a lesser sense of job insecurity (Lingmont and Alexiou, 2020; Nam, 2019). In detail, our work offers a different study perspective that focuses on identifying the consequences that …oyee's AI and robotics awareness generates at the …izational level. In this case, there is a systematic hiding of knowledge that can completely inhibit digital transformation, given …eople, due to their experience and knowledge of the …sses, continue to be a success factor in the adoption of …gent robots and process automation (Makarius *et al.*, 2020).

…ding the practical implications of the study, a first major …mendation is to strengthen the knowledge codification …gy in the company; that is, to intensify the mapping and …stive documentation of business processes or tasks that may …tomated and performed by an intelligent robot in the short and medium term. In our opinion, this strategy is the one that specifically helps to reduce the risk of automation failure resulting from hiding. Coding should even be accompanied by an aggressive financial incentives scheme that motivates individuals to support the documenting and, especially, the automating of the processes they have been in charge of for so long and which they know in great detail.

A second recommendation concerns the role of managers, who have a great responsibility leading change management to reduce employees' resistance and fears in the face of the arrival of intelligent robots and stopping them from losing confidence in the intentions of the individuals behind automation. Specifically, managers should emphasize the positive side and benefits of automation, stressing that the purpose of intelligent robots include supporting employees' operational tasks so that they can attend to other higher value tasks related to creativity and innovation. Managers could even frequently share business success stories and future scenarios showing what the real impact of automation would be on company jobs. In this way, they will change employees' perception of intelligent robots being an imminent threat, when substitution could in fact occur in the medium and long term and not in such a traumatic manner.

Nevertheless, other types of measures more consistent with the fact that many individuals will inevitably be replaced by automation are necessary to mitigate the adverse effect of employee's AI and robotics awareness and knowledge hiding. First, firms should implement new training programs aimed at helping employees to

employees who will be dismissed. This will help employees understand the changes caused by the arrival of AI in the labor market and be clear about the competencies they must develop to take advantage of new opportunities or, if necessary, make a complete career change and enter another sector or profession.

Limitations and future directions for research

One limitation of the present work lies in the fact that the results are limited to what occurs in the company when the environment is agitated by the arrival of AI. The study is not able to identify how ıs hiding can be when the adoption of intelligent robots has just started in the company, which is when the replacement of employees is imminent and concern for their work and their career s highest. At this point, there are some indications that the may move from knowledge hiding to a much more frontal, avellian and systematic sabotage of knowledge (Serenko, , or what is worse, lead people to sudden resignation gham and Haar, 2018; Li *et al.*, 2019), which would imply an rable loss of knowledge (Tung-Ching *et al.*, 2016). This could ınsuspected consequences and could significantly reduce the ɔility of building competitive advantages based on AI. That could be another reason why the adoption of an intelligent robot in certain cases has resulted in value destruction and bad customer experiences (Canhoto and Clear, 2020). Additionally, although the number of respondents (n = 136) is acceptable, sample size can also be considered as a limitation.

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Thus, future research should focus specifically on analyzing the effect of employee’s AI and robotics awareness on the three forms of knowledge hiding when the adoption of intelligent robots begins in the company; it should also evaluate the impact of hiding on the success of that implementation process. Our suspicion is that at that point, hiding would become acute to the extent of excessively prolonging or making process automation unfeasible. Therefore, the company would have no alternative but to rely solely on external knowledge sources such as consulting companies that offer automation services, undoubtedly the more expensive and riskier path. In addition, future studies should focus on the mechanisms helping companies minimize their knowledge loss in the transition to process automation, that is, on how to neutralize knowledge hiding and the possible acts of sabotage by people while deepening the implementation of AI applications.

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Table 1

Characteristics of the companies in the sample

Sector	Frequency	(%)
Wholesale and retail trade	22	16,18
Human health and social work activities	11	8,09
ncial and insurance activities	10	7,35
ufacture of food products	10	7,35
Office administrative, office support ' other business support activities	10	7,35
al manufacturing	9	6,62
cation	9	6,62

Table 2

urement scale items

Constructs	Items	Loadings
Evasive hiding (AVE = 0.929, CR = 0.932, pA = 0.950, CA = 0.825)		
Evas1	Our employees… agreed to help him/her but never really intended to	0.879*
Evas2	agreed to help him/her but instead gave him/her information different	0.920*

Table 3

Discriminant validity

	Fornell-Larcker					H
Constructs	1	2	3	4	5	1
1. Evasive hiding	*0.909*					
2. Rationalized hiding	0.712	*0.786*				0.
3. Employee's artificial	0.531	0.470	*0.941*			0.

Table 4

Models	Paths	β
Direct	*Direct effects*	
	Technological turbulence caused by Artificial intelligence (TTCAI) → Evasive Hiding ($R^2 = 0.11$)	0.331***
	TTCAI → Playing dumb ($R^2 = 0.12$)	0.313***

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Abstract

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