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ORIGINAL ARTICLE

Performance in computer-mediated work: the moderating role of level of automation

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Abstract Organizations require good performance from individuals to achieve their objectives. In view of the growing presence of technology, it becomes necessary to understand performance in the context of information systems. Previous research shows that knowledge and perceived usefulness factors have direct effects on performance. However, the literature also recognizes that there may be different man–machine arrangements to carry out the tasks (level of automation). This study, using a multidisciplinary approach, evaluates empirically whether the level of intervention moderates the effects of knowledge and perceived usefulness on performance. A questionnaire was used to collect data from 201 users in different organizations and different functional areas. The structural equations model was used for analysis. The results show that the degree of automation moderates the direct relationships. Thus, in structured and proceduralized environments, at high levels of automation, the relevance of knowledge of the task may decrease, and at low levels of intervention, the relevance of perceived usefulness may fall.

Keywords Knowledge · Automation · Information system · Perceived usefulness of the system

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1 Introduction

For decades, human performance has been a topic of special interest in the literature due to its contribution to achieving the objectives of the organization (Zacher et al. 2010, p. 374). It is along this line that researchers have made progress in clarifying and broadening the concept of performance, as well as progressing in the specification of predictors and processes associated with this construct (Sonnentag and Frese 2005, p. 4). Traditionally, organizational literature holds that knowledge is a determinant factor in performance (McCloy et al. 1994), and there is ample empirical evidence to support this statement (Schmidt and Hunter 1998; Schmitt et al. 2003; Viswesvaran and Ones 2000).

However, various authors suggest that technology has changed the nature of work in different ways. Burke and Ng (2006, p. 89) mention the obsolescence of knowledge, the creation of the knowledge worker and distributed work. Kozlowski et al. (2001, p. 2) and Marler and Liang (2012) state that work is becoming more complex and requires greater cognitive skills. Burke and Cooper (2006, p. 83) state that new technologies also change the way in which employees are assessed, selected and trained.

This changing nature of work has challenged traditional schemes of understanding or explaining performance to the extent that information technology acquires an increasing role in carrying out tasks. Elias et al. (2012) recognise that technology has an increasingly important role in most tasks. Sonnentag and Frese (2005, p. 18) state that in many jobs the tasks are closely linked to technology. For example, it is impossible to imagine the work of a computer numerical control machine operator without reference to the machine. Ilgen and Pulakos (1999, p. 9) point out that in jobs with high levels of automation it is not clear what is the contribution of the individual and what the contribution of technology on performance. Finally, Hesketh and Neal (1999, p. 21) suggest that extensive use of technology in carrying out tasks threatens the traditional perspective in which performance is under exclusive control of the individual.

Some studies have responded to the challenge raised by the introduction of technology in the traditional explanation of performance. Hesketh and Neal (1999, p. 21) propose that performance is explained by the interaction of individual and technology components. This interactional model has not, however, been subject to empirical evaluation.

Parkes (2012), based on the model of individual-technology fit (Goodhue and Thompson 1995), suggests and evaluates an additive model where the fit in pairs of knowledge of the individual, complexity of the task and design of the technology, as well as perceived usefulness of the technology affect performance. Alternatively, Bravo et al. (2015), based on organizational literature (Bacharach and Bamberger 1995; Peterson and Arnn 2005) and information systems (Seddon 1997), suggest and evaluate an additive model where knowledge of the individual, perceived usefulness of the system and complexity of the task affect performance.

Although these latter models are valuable in understanding human performance in the context of information technologies, they do not distinguish between different man–machine arrangements that management may design to carry out the work. Frohm et al. (2008) state that the activities of the individual can be carried out along a continuum that goes from totally carried out by the person without the intervention of technology (totally manual) to totally carried out by technology without human participation (totally automated). Price (1985) states that organization allocates which activities are to be carried out by individuals and which by technology (the level of automation—LoA-).

In automation literature, there are studies about the relationship between LoA and performance. For example, Endsley and Kaber (1999) design an experiment where they subject individuals to different LoA in the supervision of tasks, similar to air traffic control. Likewise, Wei et al. (1998) subject individuals to different LoA in the supervision of activities that control flow and state of a system. Even more, Kaber et al. (1999), in their experiment with individuals who control a telerobot at different LoA, find that in normal operating conditions LoA was related to performance. However, these studies do not include the role of knowledge of the task or perceived usefulness in this phenomena.

Also, it is important to point out that automation literature does have research about the knowledge of the task and LoA, nevertheless, these studies do not explain or evaluate the relationship between these factors with performance. For example, Amalberti (1998) makes a theoretical review about the mismatches between human factor literature and its actual application in the aviation industry. Therefore, his focus is in the impact of human factors on the design of aviation infrastructure, more than the relationship between knowledge of the task and performance. Likewise, other authors have focused on the impact of automation on knowledge degradation but they do no link these factors with performance (e.g. Mascha and Smedley 2007; Parasuraman et al. 2000)".

In summary, the prior literature suggests that both individual factors (e.g. knowledge) and technological factors (e.g. perceived usefulness) appear to have an impact on performance. But it also shows that there can be a variety of man–machine arrangements depending on the degree of automation that the organization defines. However, in the literature reviewed, we have not found a study that shows empirically whether the relationship between individual and technological factors on performance vary depending on differing man–machine arrangements.

To bridge this gap, the objective of this article is to develop and empirically evaluate a model that reflects whether the degree of intervention of technology in tasks moderates the relationship between factors such as knowledge and perceived usefulness on performance.

This article contributes in two ways. Firstly, managers need to evaluate the performance of employees because it contributes to the objectives of the organization. This study will enable them to understand the dynamics of the factors that influence performance in contexts where technology is increasingly integrated with the individual in order to carry out tasks. This understanding may be useful, for example, to observe whether knowledge continues to be as relevant in explaining performance in designs that are more or less automated. Secondly, unlike previous works based on direct relationships, our study, by incorporating a moderating variable (level of automation), provides explanations into the reasons behind the relevance (or lack thereof) of each factor (knowledge or perceived usefulness).

In the next sections, we use interchangeably "level of intervention" and "level of automation (LoA).

The article is structured as follows: the conceptual model is developed, the methodology presented, results are shown and discussed, and finally conclusions are drawn.

2 Conceptual development

This section explains the direct effects on performance that have been put forward in the literature. The conceptual bases that will serve to set out the hypothesis of moderation will then be developed. Finally, arguments will be presented for the hypotheses of moderation.

2.1 Direct effects on performance

Briefly, we sum up research on the direct effects of knowledge and perceived usefulness.

Performance is defined as the degree of efficiency (obtaining results with the least amount of resources) and effectiveness (attaining the desired goals) in carrying out the individual's tasks (Alter 1999; Viswesvaran 2001).

One construct related to individual performance is knowledge. Reviewed literature has recognized that knowledge of individuals has direct effects on performance. In that way, organizational psychology distinguishes between declarative and procedural knowledge. Declarative knowledge is associated with knowing facts, principles or a particular discipline to carry out the tasks. On the other hand, procedural knowledge allows the transfer of that body of knowledge to the practical execution and relates to knowing how to carry out the tasks. For the purposes of this article, knowledge is related to the task which individuals have to perform and is defined as the degree of understanding of the requirements of the task (knowing what to do) and the processes to carry it out (know how) (Anderson 1989; Quinn et al. 1996).

Conceptually, if an individual knows what to do and how to carry out the tasks, he will have a greater possibility of achieving his objectives and minimizing errors or delays, which will affect performance (Schmidt and Hunter 1998; Schmitt et al. 2003). Several empirical studies in different settings have established a positive relationship between knowledge of the task and performance (Bravo et al. 2015; McCloy et al. 1994; Muhammed 2007).

This is the basis for the following hypothesis:

H1 The knowledge of the task has a direct and positive influence on individual performance.

Several authors have affirmed the direct effects of perceived usefulness on performance. Perceived usefulness is defined as the degree to which the individual assesses that the technology has improved his performance (Seddon 1997). Alternatively, perceived usefulness has been conceived as the measure in which technology helps the individual to carry out his/her work activities to be effective (Alter 1999).

Conceptually, a useful technology affects performance inasmuch as an information system facilitates the individual's work in achieving his/her purposes. Seddon (1997) holds that an information system is useful if it produces benefits, such as helping the user to do more or better work in the same time, or the same quality and quantity of work in less time. Empirically, Parkes (2012) and Bravo et al. (2015) found support for this relationship.

This is the basis for the following hypothesis:

H2 The perceived usefulness of the information system has a positive impact on individual performance.

2.2 Task allocation and level of intervention

The « level of intervention of the system » is defined as the degree to which technology participates in carrying out the tasks of the individual. It concerns the issue of task design. In that way, management must decide which agent, whether human or machine, or a combination of both, will carry out the tasks (DeWinter and Dodou 2011, p. 1; Fallon 2006, p. 581). Traditionally, the criterion for allocation has been performance (in terms of higher speed or precision). Therefore, activities are allocated according to the agent that contributes most to the performance (Fallon 2006, p. 584). A great extent of literature mentions several methods and positions with regard to allocation (e.g. Kaber and Draper 2004; Parasuraman et al. 2000).

Likewise, the level of intervention of technology is considered as a continuum, or as levels of automation. Therefore, machines, and computers in particular, are now able to carry out many functions that could once be carried out only by humans. In this line, a number of authors explain the existence of different levels of intervention of a technology. Kaber and Draper (2004) consider that intervention of technology has two dimensions. One is related to the quantity of tasks to be automated in relation to the total portfolio of tasks in the individual's remit. The second has to do with the level of automation to be applied for each task to be automated (or how many sub-tasks or activities are dealt with by technology). Parasuraman et al. (2000) propose a number of tasks, which can have a greater or lesser level of participation (e.g. acquisition of information, analysis of information, making the decision and putting it into practice). Similarly, Endsley and Kaber (1999) propose ten levels of intervention based on the combined allocation of four tasks (e.g. monitoring, generating alternatives, selecting alternatives and implementing the decision) to humans or technology. The greater the number of tasks assigned to technology, the greater its degree of intervention.

The foregoing suggests that the level of intervention is a continuum that goes from totally carried out by a human without the intervention of technology, to totally carried out by technology without the intervention of a human (Frohm et al. 2008).

In short, as shown in Fig. 1, a person can be assigned a portfolio of tasks (here, 1 through 4) and the organization can design the workload under different automation levels.

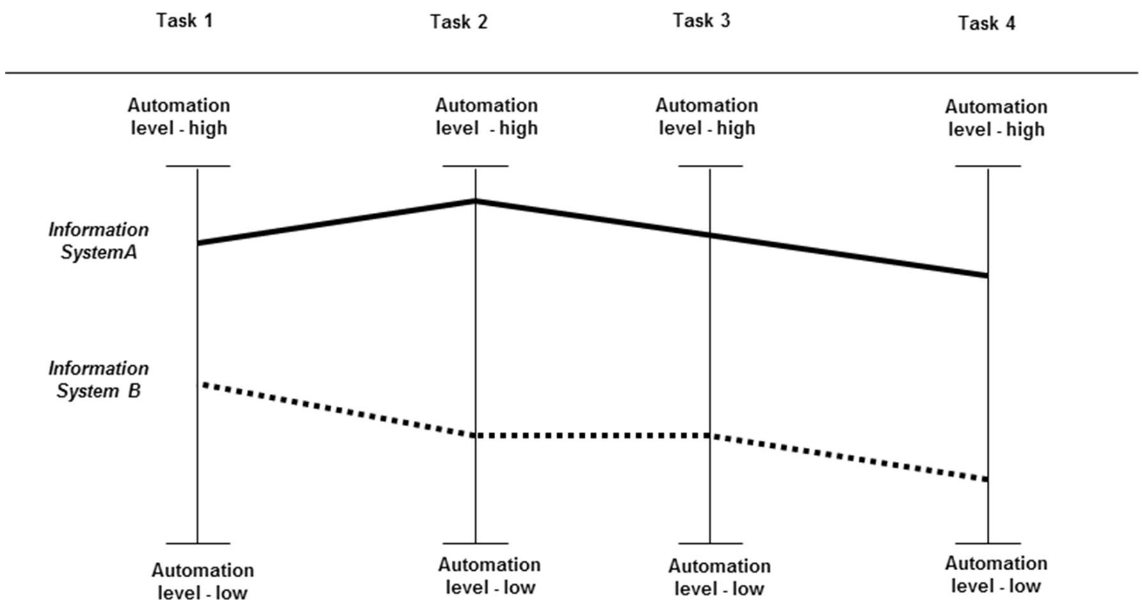

Fig. 1 Different automation levels of information systems—adapted from Parasuraman et al. (2000)

For information system "A", the average intervention level is higher than if information system "B" is chosen.

2.3 Theory of production

Production consists of the transformation of productive factors (i.e. inputs) into products (i.e. outputs, which can be goods or services). To produce optimally, that is, to maximize benefits and minimize costs, a firm faces two principal decisions: first, the choice of the level of production (quantities of output to produce) and second, the choice of the combination of productive factors (quantities of inputs to use).

As Varian (2010) asserts, when a firm makes choices, it faces many constraints that can be imposed by its consumers, by its competitors, and by nature. To simplify the explanation, we are going to focus only on the constraints imposed by nature. Nature imposes technological constraints on firms, ergo, only certain combinations of inputs are feasible ways to produce a given amount of output, and the firm must limit itself to technologically feasible production plans.

Hence, technology acts as the principal constraint for the firms and this is expressed mathematically in the production function: $y = f(x_1, x_2, \ldots)$, where y represents the level of production and $x_1, x_2, \ldots$ all the productive factors used in the production process.

The optimization problem for the rational firm is to determine the optimal combination of inputs to be used and to determine how much output it should attempt to produce in order to maximize the benefits. Nonetheless, firstly it is important to take into consideration the conditions the firm will face, that is, how much time it will have to adjust its inputs to their optimal level. The time period during which at least one factor of production is fixed is called the short run, and the time period long enough to vary all factors of production is called the long run (Schotter 2008).

Additionally, there is another period of time to consider: the very long run. This period is important to study because it is where technological progress occurs. When the firms learn new ways of working, the production function changes. This occurs, for example, as old machines are replaced by new ones that represent more advances techniques. Hence, a technological progress is defined as a displacement of the production function that generates a certain level of output with fewer inputs (Nicholson and Snyder 2011). A technological progress would manifest itself as a change in the production function. In the very long run, the production function would be: $y = f^i(x_1, x_2, \ldots)$, where y represents the level of production, $x_1, x_2, \ldots$ all the productive factors used in the production process and "i" the technology choice decision.

Usually in economics, two inputs are used to explain and simplify the production function: capital and labor. According to Hicks (1963), technological progress can be classified into three types: neutral, capital-intensive (or labor-saving) and labor-intensive (or capital-saving), depending on their effect on the ratio of the capital's marginal product to that of labor. An innovation is neutral when it raises the marginal productivities of labor and capital in the same proportion; it is 'capital-intensive' when it increases the marginal product of capital more than of labor; and it is 'labor-intensive' if it increases the marginal product of labor more than of capital.

Hence, if we use a simplified linear production function (at initial time) we will have: $Y = \propto * K + \beta * L$, where Y represents the production (output), K the capital and L the labor. We can see that β and α are the marginal productivities of capital and labor, respectively. After a technical progress (at a second time) we will have: $Y' = \propto' * K + \beta' * L$. As we can see, the marginal productivities have changed and production has increased. Hence, if we assume a capital-intensive technical progress, as explained before, the ratio of the marginal product of capital $(\partial Y / \partial K)$ respect the marginal product of labor $(\partial Y / \partial L)$ will increase; thus $\frac{\alpha}{\beta} < \frac{\alpha'}{\beta'}$. We find that the new ratio between the marginal productivities of the inputs is greater than before the technical progress. That is, following Hicks (1963), a capital-intensive technical innovation increases the marginal product of capital more than of labor. This would set a moderating effect of the technical progress from the economic perspective.

2.4 A production approach to a performance model

The traditional model of performance can be seen as a production function where knowledge (KT) and perceived usefulness (SU) can be considered the factors; and performance, the result (PE). As mentioned before, the theory of production frequently uses two central factors: labor and capital. In the field of information systems, a number of authors have used production functions on this premise at macro (industrial sectors or countries) and micro level (the organization or an area within it) (e.g. Brynjolfsson and Hitt 1995; Dewan and Min 1997; Napoleon and Gaimon 2004; Sircar and Choi 2009; Wagner and Weitzel 2007).

Specifically, Napoleon and Gaimon (2004, p. 250) propose a production function where results (quantity and quality produced) depend on employees' level of knowledge, size of the workforce and availability of technology (in hours or equipment). These same authors state that this production function is established under a given technology and that each technological choice has a different impact on results (Napoleon and Gaimon 2004, p. 249). Further, they simulate their model under different technological options.

Although there has been scant use of economic models in the field of information systems at an individual level, there is some prior work. For example, Sun et al. (2013) use the economic theory of usefulness to reconceptualize and explain satisfaction with an information system. Dinev et al. (2015) use prospect theory to introduce bias in explaining privacy. Inspired by this research, we exploit the rich sources of theories in economics in order to explicitly lay out and discuss connections between economics and IS research.

Therefore, considering the aforementioned works at an individual level, the contribution of capital can be represented by the perceived usefulness of technology; the contribution of labor by individual knowledge; and the choice of technology by the level of intervention of the system.

2.5 Level of intervention and moderation of direct effects

With the background explained so far, the central proposal is that, although a production function can represent individual performance, the level of automation as a measure of technological progress may modify this production function.

The traditional performance model can be seen as an additive linear production function: PE = b_1 * SU + b_2 * KT (ratio factor = b_1/b_2). This equation assumes that technology is constant (i.e. b_1 and b_2 are constant for any value of SU or KT). However, if the technology progresses (a new level of intervention), the function of production changes: PE = b'_1 * SU + b'_2 * KT (and the new ratio = b'_1/b'_2) (Beattie et al. 1985).

Higher levels of automation may be considered capital-intensive in Hicks typology. For example, in a more advanced or automated technology, the same workforce (in quantity and knowledge) may lead to a greater result (Napoleon and Gaimon 2004, p. 252).

Thus, to that extent, a more intensive computer processing technology could increase the ratio of the factors, increasing the impact of the utility and reducing the impact of knowledge. This would set a moderating effect from the economic perspective.

But it is not only economy that can help us to establish the moderating nature of the level of automation. Hesketh and Neal (1999, p. 26) suggest that a working environment with a high level of automation can generate conditions where it is not possible to distinguish the contribution of individuals to performance. Conversely, a working environment with a low level of automation may offer great opportunity to detect such contribution.

In the context of information systems, on the one hand, the lower the level of intervention, the greater the number of tasks is assigned to humans. In this scenario, it is reasonable to expect that individual knowledge (declarative and procedural) will have a significant effect (regarding technology's perceived usefulness) on performance. Therefore, if there is no technology, and assuming other factors remain constant, performance could be determined by knowledge.

On the other hand, the higher the level of intervention, the greater the number of tasks assigned to technology. In this case, it is plausible to expect that technology's perceived usefulness will have a significant effect (as compared to human knowledge) on performance. Therefore, if tasks are fully automated without human intervention—and assuming other factors remain constant—performance would be determined based on the perceived usefulness of technology.

The effect of replacing human knowledge by technology to obtain similar performance levels has a two-pronged reason. First, the higher the level of intervention, the greater the amount of knowledge of the task that is transferred from the individual to technology. Zuboff (1985, p. 7) argues that, in the automation process, human skills are assumed by technology. Braverman (1998, p. 319) states that the greater the amount of science (i.e. knowledge) incorporated in technology, the smaller the amount of science the employee has. More recently, Axelsen (2012) explores the introduction and continued use of computerized decision-making aids for auditors and finds that they produce a reduction in the employee's knowledge.

Specifically, Markus and Tanis (2000, p. 189) state that many business procedures are embedded in information systems and these procedures code a number of rules, standards, data and formulas (Soh et al. 2003, p. 85). Such rules, data and formulas comprise knowledge that used to be held in individuals and is now embedded in technology. Kallinikos (2010, p. 4) points out that information systems incorporate rules that were previously the result of individual knowledge and experience in order to carry out tasks and process information. It is precisely these rules, data and formulas that are knowledge that previously resided in the individual and are now incorporated into the technology. It is possible that as the level of intervention increases, technology will appropriate knowledge. This will allow technology to carry out the task more efficiently and effectively (performance).

Second, the higher the level of intervention, the greater the processing capacity that is transferred from the human processor to the computer processor. Several authors suggest that computer processing can be superior to human processing. Fitts' list, referenced by Hoffman et al. (2002), states the activities in which the human being can be surpassed by technology (e.g. execution of repetitive tasks, managing complex operations, deductive reasoning) and those in which the human being surpasses technology (e.g. improvisational skills, application of professional judgment and reasoning). Mukhopadhyay et al. (1997) establish that the effect of technology on performance arises when technology is used to change the speed and/or quality of information processing tasks. In that way, to the extent the level of intervention is higher, technology may replace the slower human processing; thus the task will be carried out with a higher level of performance.

On this basis, we can argue the following:

H3 The system's level of intervention negatively moderates the effect of the knowledge of the task on individual performance.

H4 The system's level of intervention positively moderates the effect of the perceived usefulness of the information system on the individual performance.

The following graph summarizes the research model (Fig. 2).

3 Method

In order to examine the proposed effects, a field study was carried out, using a questionnaire as a data-gathering technique and the structural equations model for analysis.

As is common in this type of research, we faced a decision of whether to test our model within a narrowly-controlled domain and generalize to a more global domain, or to test the model in a more generalized domain. A more narrowly-controlled domain would have removed extraneous influences, but made generalization more difficult. Similarly to Goodhue and Thompson (1995) and Torkzadeh et al. (2011), we decided to focus on a more generalized domain and to span multiple tasks, multiple types of users, and multiple organizational settings. Thus, we were testing to see whether a general measure would exhibit the relations suggested by our model. If it did, then we would have found support for our model at a very high level of generalization.

With a view to establishing the degree of generalization of the model, we consider three aspects of the domain in which the study will be carried out: (1) the information system will be an Enterprise Resource Planning System (ERP); (2) tasks are activities relating to the business processes that the individual carries out partially or totally by using an ERP; and (3) the individual is anyone who operates an ERP to carry out tasks independently of their level (operative or supervisory), functional area or industrial sector. The individual must also have used the information system for at least 6 months.

The questionnaire is based on previously used scales that are adapted to the context of the study. Performance was measured on the basis of a scale formulated by Muhammed et al. (2009). The items proposed by Muhammed et al. (2009) was used to measure knowledge of the task. The basis for measuring perceived usefulness is the scale developed by Seddon and Kiew (1997), with an additional item used by Stone et al. (2007). Measurement of the system's level of intervention was adapted from the scale developed by Muhammed (2007). Likert scales

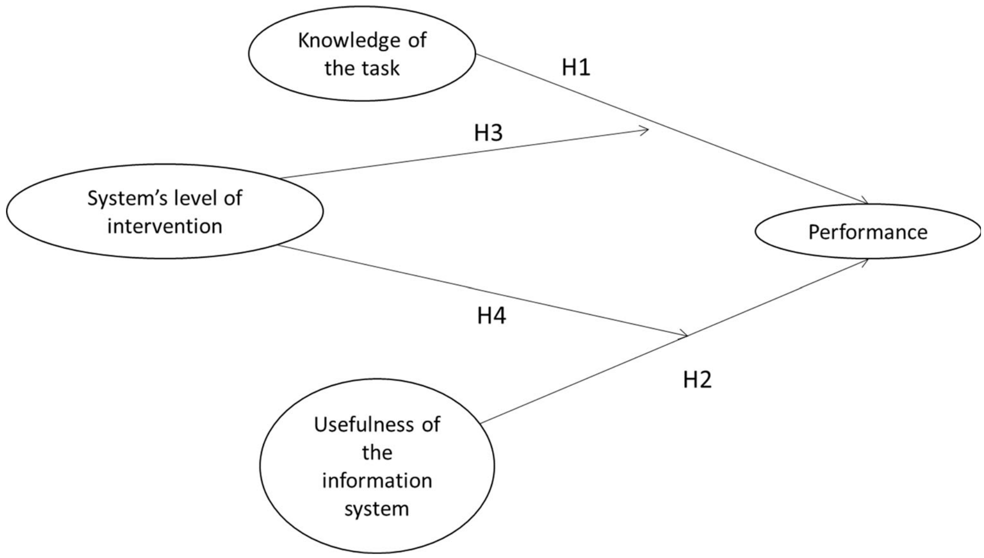

Fig. 2 Research model

(seven points ranging from totally disagree to totally agree) were used for questions. "Appendix 1" shows the items used in the definitive study.

In order to minimize biases, the questionnaire emphasized confidentiality, stated that there are no right or wrong answers, requested honest answers, and separated dependent and independent variables among other safeguards.

Considering that the population was Spanish speaking, and in order to ensure an equivalent translation, back-translation was used (Brislin and Freimanis 1995), a technique that has been used in a number of field studies (e.g. Sun et al. 2009).

In order to ensure validity and reliability, the scales were subject to a number of preparatory tasks. Thus, a pre-test was carried out by interviewing a group of users of an information system to detect potential comprehension problems. Then there was a pilot test under the same conditions and with the same type of participants as in the final questionnaire. The result of each of these activities led to minor improvements in the questionnaire.

In order to obtain the degree of generalization according to the previously specified domain, it was established that the data would be gathered from professionals who attended post-graduate programs in a well-known Latin American university. Those who attend these programs come from a range of industrial and service companies, have both operative and supervisory duties, and carry out their activities in the fields of finance, marketing, logistics and others—all features similar to the specified domain.

The questionnaires were distributed in person and participants were told completion was voluntary. Once the questionnaires that were blank, incomplete or outside the specified domain had been discarded, there were 201 usable questionnaires. A number of field studies have gathered data on university premises and sorted according to previously defined criteria (e.g. Gefen et al. 2003).

The individuals worked primarily in the areas of finance (36%), logistics (35%), and marketing (5%). Participants used the information system an average of 23 h a week. On average, they had been using the system for 35 months. The systems mostly used are SAP (31%), Oracle (16%) and Microsoft (5%) business systems. The tasks reported by the individuals correspond to typical activities in business processes for their respective areas (e.g. warehouse management, purchase management, invoicing).

4 Results

Table 1 shows the average and the standard deviation for the constructs. These were calculated by previously averaging out the responses on the items for each scale.

To study the properties of the instruments, confirmatory factor analysis is carried out. The measurement model was estimated with the maximum likelihood method and the covariance matrix. The software used is IBM SPSS AMOS version 22. Table 2 presents the correlations, variance extracted and reliability, all calculated based on the data and AMOS estimations.

Table 1 Descriptive statistics

Construct	Mean	Standard deviation
Performance (PE)	5.2	1.08
Knowledge of the task (KT)	5.7	1.00
System's perceived usefulness (SU)	5.1	1.14

Table 2 Correlations, reliability and average variance extracted (AVE)

Construct	Correlations and square root of AVE (*)			Cronbach's α	AVE
	PE	KT	SU		
PE	0.89			0.94	0.80
KT	0.61	0.93		0.95	0.86
SU	0.62	0.54	0.91	0.93	0.83

(*): Diagonal numbers are the square root of AVE for each construct and off-diagonal numbers are the correlations between constructs

Reliability as evaluated with Cronbach-α shows acceptable values, above 0.7. Convergent validity is verified given that all the standardized factorial loadings are significant and greater than or equal to 0.7. Discriminant validity is verified given that correlation between a pair of latent variables is less than the square root of the extracted variance of the variable (Table 2). Fit indices indicate adequate model-data fit, χ^2 ratio = 2.02, CFI = 0.978, TLI = 0.973, and RMSEA = 0.071. Acceptable values recommended in the literature are χ^2 ratio < 3, CFI > 0.90, TLI > 0.90 and RMSEA < 0.08 (Gefen et al. 2000; Hair et al. 2006).

In order to evaluate the moderating effects, we followed the method proposed by Deng et al. (2005). Firstly, we examined model-data fit and parameter estimates for the entire sample ($n = 201$). The structural model had a Chi square (χ^2) of 147.6 with 73 degrees of freedom (d.f.). Fit indices indicate adequate model-data fit, RMSEA = 0.07, TLI = 0.97, and CFI = 0.98. The results indicated that the structural model was appropriately specified, a proper solution was obtained, and the solution fit the entire sample adequately. Table 3 shows the standardized regression weights for the entire sample. These results support hypotheses H1 and H2.

Secondly, in order to establish the invariance degree of the structural model with regard to different groups of the sample, we conducted a multi-group analysis. Thus, we separated the sample between on the one hand, those participants with high level of intervention ($n = 104$), and on the other hand, participants with low level of intervention ($n = 97$).

We then conducted an analysis of invariance of the item-factor loadings. The invariance of the item-factor loadings is critical since a failure to prove the invariance of the measurement model across the subgroups of interest pragmatically invalidates any further examination of model parameters (Deng et al. 2005, p. 752). To that end, we established Model 1: "Equal pattern baseline model", whose parameters are free. The results show that the data fits model 1 (RMSEA = 0.059, TLI = 0.957, CFI = 0.966) and generates a $\chi^2 = 246.97$ with 146 d.f. Afterwards, we established Model 2: "Factor loadings invariant", which considers that all the factorial loadings are equal among groups. The results show that the data fits model 2 (RMSEA = 0.058, TLI = 0.958, CFI = 0.964) and generates a $\chi^2 = 262.72$ with 157 d.f. The evaluation between Model 1 and Model 2 shows the invariance of the factorial loadings between these groups ($\Delta\chi^2 = 15.75$, Δd.f. = 11, p value = 0.151).

Since the measurement model appeared to be invariant across subgroups, we could continue by testing the hypothesis concerning the structural weights. We therefore established Model 3, in which we fixed the parameters that correspond to the paths between KT- > PE and SU- > PE of our model. The results show that the data fits the model 3 (RMSEA = 0.06, TLI = 0.956, CFI = 0.962) and generates a $\chi^2 = 271.65$ with 159 d.f. The comparison between Model 2 and Model 3 shows the variance of parameters between groups ($\Delta\chi^2 = 8.93$, Δd.f. = 2, p value = 0.011).

The structural weights are shown in Table 4 for the two groups. These structural weights were estimated with the item-factor loadings held equal across groups. Thus, they are the best estimates of the true structural weights. They were not affected by differences in item factor loadings across groups (Deng et al. 2005, p. 754).

There were substantial differences in these structural weights among groups. For the group with a high level of intervention, the structural weight for KT was non-significant, suggesting that KT was not an important factor affecting PE for this group. In contrast, for the group with a low level of intervention, the structural weight for SU was non-significant, suggesting that SU was not an important factor affecting PE for this group.

Table 3 Regression weights (entire sample; $n = 201$)

Path	Unstandardized regression weights	Standardized regression weights	p value
KT- > PE	0.408	0.383	0.001
SU- > PE	0.410	0.415	0.001

Table 4 Regression weights—model 2- “factor loadings invariant”

Path	High level of intervention			Low level of intervention		
	Unstandardized regression weights	Standardized regression weights	*p* value	Unstandardized regression weights	Standardized regression weights	*p* value
KT- > PE	0.146	0.122	0.181	0.544	0.555	0.001
SU- > PE	0.517	0.565	0.001	0.211	0.185	0.058

The difference in Chi square between Model 3 and Model 2, 8.93 with 2 d.f., was non-significant at *p* value = 0.01, indicating that hypotheses H3 and H4 (i.e. the structural weights of KT- > PE and SU- > PE were variant across groups) were supported. This would set a moderating effect.

5 Post-hoc analysis

Since analysis of covariance is a common method used to test for differences in regression coefficients among population subgroups, we were interested in comparing results obtained via multi-group analysis of structural invariance with those obtained via analysis of covariance (ANCOVA). Table 5 shows results of ANCOVA analysis.

The test of the invariance of the structural weights across the two groups yielded results that are roughly comparable to those obtained by using analysis of covariance to test for differences in the regression coefficients. The “High level of intervention” group had by far the highest structural weight for SU and the lowest structural weight for KT in both analyses. The “Low level of intervention” group had the lowest structural weight for SU and the highest structural weight for KT in both analyses.

If researchers use ANCOVA in latent variable models to test differences in regression coefficients across groups, they should be cautious in interpreting results. They should be aware that scale differences across groups might confound their analysis. Regardless of whether significant differences are found, the findings may be due to measurement differences (e.g. item-factor true scores) among groups rather than real differences in regression coefficients (Deng et al. 2005, p. 756).

Since this study dealt with latent variables and the sample size was adequate, our discussion of the practical implications of the results was based on the multi-group analysis of structural invariance.

6 Discussion

The study shows that knowledge of the task and perceived usefulness are relevant in explaining performance. Moreover, on an empirical basis, system level of intervention moderates these direct effects.

Specifically, the results reflect that knowledge of the task explains performance (H1). This suggests that, if the individual has a command of the work requirements, routines and procedures, this person may probably focus on accomplishing key goals, increase production and minimize faults. These results are coherent with prior studies carried out in organizational psychology (Borman et al. 1991; McCloy et al. 1994; Muhammed et al. 2009).

Our study also shows that the perceived usefulness of the system has an impact on performance (H2). This suggests that a system, even though it is a support tool, enables individuals to carry out their activities faster and with higher quality levels, which ultimately have an impact on performance. These results are aligned with prior empirical studies carried out in the field of information systems (Bravo et al. 2015; Parkes 2012).

In addition, the results showed that the system’s level of intervention may have a negative impact on the relationship between knowledge and performance (H4) and may have a positive effect on the relationship between perceived usefulness and performance (H5). This suggests that if the system has a more significant intervention in carrying

Table 5 Unstandardized regression weights—ANCOVA

Path	Group: high level of intervention		Group: low level of intervention	
	Unstandardized regression weights	*p* value	Unstandardized regression weights	*p* value
KT- > PE	0.262	0.003	0.522	0.001
SU- > PE	0.484	0.001	0.166	0.066

Level represents high or low level of intervention out tasks, simultaneously, the individual (based on his/her knowledge) may decrease his/her level of contribution to performance while technology (based on its perceived usefulness) may strengthen its contribution to performance, thus resulting in the moderating effect. Previous theoretical models in the field of economy and management suggest this moderating effect. Our study empirically supports this proposal.

Although results show that the system's level of intervention affects performance through perceived usefulness and knowledge of the task in an IS context, specifically in ERP, it seems that system's level of intervention produce a substitution effect from human to machine. This should lead to a revision of design strategies to consider. For example, the principles of human–machine cooperation, which point out that, instead of addition-subtraction designs, cooperative designs are possible. This paradigm could enhance the interaction between humans and technology (Hoc and Lemoine 1998; Pacaux-Lemoine et al. 2016; Zieba et al. 2010).

Contributions to the literature are mentioned. Firstly, previous performance models consider only the contribution of the individual (knowledge) and of technology (perceived usefulness of the system) to performance. Our study suggests that the task, and specifically the design of the task (level of intervention), is also relevant in explaining performance.

Secondly, this model, unlike a model based on direct relationships, provides insights into the reasons behind the relevance of each factor (or lack thereof). In structured and proceduralized environments and extreme situations the results show that one of the two factors may decrease its relevance. However, we should keep in mind that other demands emerge in this type of context. For example, automation could create the necessity for new knowledge and attentional requirements related to the understanding of complex systems and the interaction with them (Sarter et al. 1997).

Thirdly, the study draws together literature from various fields (information systems. organizational, automation and economy) to explain the contribution of the individual and of technology to performance at differing levels of automation. This is in the line suggested by Cacciabue et al. (2014), who demand the use of automation literature in other fields. Recent studies use concepts from both streams to propose explanations that are more comprehensive (e.g. Ghazizadeh et al. 2012).

Contributions to management are also mentioned. Firstly, the study suggests that the decision on the design of the task in terms of how much to automate is not trivial but rather presents challenges with regard to human management in organizations as they have traditionally run. For example, evaluation of performance has emphasized aspects of the individual such as his or her knowledge, commitment and so on. However, the results of the article show that in jobs with a high level of automation these evaluation schemes may prove insufficient. Further, an employee may perceive that his evaluation does not depend on himself but to a large extent on aspects that are out of his control, such as the design of the task. Similarly, incentive systems (both monetary and non-monetary) frequently focus on the individual. One of the challenges for management is how to incentive an employee whose performance does not depend primarily on him or herself but on the level of intervention of technology.

Second, this study reminds management that higher levels of automation may result in knowledge impairment. In cases where the higher the intervention levels, a portion of the individual's knowledge may be transferred to technology and no longer used and finally forgotten. Degradation of cognitive skills may be particularly important following the failure of an information system (Parasuraman et al. 2000, p. 291). Therefore, the question what we should automate remains open (Dekker and Woods 2002). The human center design could be an alternative to respond this question (Lintern 2012).

Third, management should take in mind that high levels of automation may reduce individual's situation awareness (Parasuraman et al. 2000). Situation awareness implies the understanding what's going on and it is product of mental mechanisms such as perception and information processing and leads to decision making and action execution (Endsley 1995; Millot and Pacaux-Lemoine 2013). In IS context, if tasks are executed by the technology, the individual may not be able to sustain a good "picture" of his/her work because he/she is not actively engaged in its configuration or execution. This lack of awareness could lead to errors in the execution of tasks (Sarter 2008)."

Some limitations of this study must be acknowledged. First, data was collected through a sectional survey, which does not provide conclusive evidence on causal relationships. Although the hypotheses are derived from theoretical grounds, longitudinal studies are required to establish causality through the constructs' precedence. Second, all the measures are perceptual, so future studies could include contrasts with objective measures. Third, LoA scales (Endsley and Kaber 1999; Inagaki and Sheridan 2012; Parasuraman et al. 2000) consider that tasks to be automated can be structured, for example, in the following activities: acquisition, information analysis, decision and implementation. Nevertheless, our study considers LoA in a general view as a perception of the degree of technology's intervention in the individual's activities. Therefore, we do not assume a pre-defined structure because users of an ERP-system carry out varied and operative tasks (financial tasks, logistical tasks, etc.). However, we consider that a more comprehensive approach using pre-defined activities could be useful in IS arena, especially in decision support systems. Fourth, our study considers human–system interaction at operational level, however, a more comprehensive approach could be useful to evaluate human–system interaction at different levels (strategic, tactic or operative) such automation literature suggest (Pacaux-Lemoine et al. 2016).

7 Conclusions

In relation to the above, two main conclusions emerge from this research. First, individual performance is not only linked to individual's factors, as has traditionally been studied; nor to technology factors, as recent research has done. Moreover, individual performance is also related to the management's design of the task (i.e. level of intervention of technology).

Second, the way in which the level of intervention is related to the other variables is through a moderating effect. In that way, this research extends the typical models of direct relationships for the explanation of performance and conceptualize it as a production function (based on the economy literature) in order to explain the moderating effect of the system's level of intervention. Thus, this type of theoretical consideration provides a broader picture of the relationship between the individual's knowledge of the task, the perceived usefulness of a system and its performance in an IS context.

Therefore, the results suggest that depending the level of automation, the contribution of knowledge and perceived usefulness on performance change in intensity. In well-structured and extreme conditions of automation, they could even reduce significantly their impact on performance.

Also, the study shows that the literature on automation (e.g. aviation, automated manufacturing systems) can provide concepts (e.g. LoA) and models (e.g. Human Machine Cooperation) that can be useful in the field of information systems. We encourage future studies in this field to take advantage of the valuable advancement in the automation literature.

Accordingly, the study as a whole also poses challenges to the management of human talent in contexts with of high levels of intervention of a technology, where performance does not depend primarily on the individual. Traditional methods of evaluating performance assume that good or poor execution of tasks is under the responsibility of the individual. But at high levels of automation, the results may depend largely on the technology. Thus, new methods to evaluate performance are necessary.

Finally, the study raises the need for business process management to evaluate carefully on the task allocation and its positive and negative implications. The introduction of systems that automate tasks has been successful in terms of efficiency. However, a considerable number of unexpected problems have also been observed. For example, it increases mental load, causes situation awareness problem, triggers skills degradation or demands new knowledge. Maybe human-centered designs could help managers to have a better perspective about task allocation.

Appendix 1

See Table 6.

Table 6 Scales of measurement

Measurement items
Perceived usefulness of the information system
The information system:
Is useful to me in carrying out my tasks
Allows me to carry out my tasks more quickly
Improves the results of my tasks
Improves the quality of my tasks
Knowledge of the tasks
On average, I have full knowledge of:
How to carry out my tasks
How to implement the routines of my tasks
The actions I need to take to carry out my tasks
The procedures to carry out my tasks
The requirements of my tasks
Systems's level of intervention
To a great extent:
My tasks are carried out through the information system
My tasks are mostly mediated by computers
The information system supports most of the activities of my tasks
My tasks are embedded in the information system
The execution of my tasks depends on the information system
Performance
Over the last 3 months:
The performance of my tasks exceeds what my company expects
I carry out my tasks with greater efficiency than expected by my company
I carry out my tasks with greater speed than expected by my company
The quality of my tasks is greater than expected by my company
The results obtained from my tasks are greater than expected by my company

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