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Research article

The effect of innovation performance on the adoption of human resources analytics in business organizations

Eithel F. Bonilla-Chaves[1], Pedro R. Palos-Sánchez[2,*], José A. Folgado-Fernández[3] and Jorge A. Marino-Romero[3]

[1] School of Business Administration, Technological Institute of Costa Rica, Cartago 30109, Costa Rica
[2] Department of Financial Economy and Operation Management, University of Sevilla, Sevilla 41018, Spain
[3] Department of Financial Economy and Accounting, Universidad de Extremadura, Cáceres 10071, Spain

* **Correspondence:** Email: ppalos@us.es.

Abstract: Our study objective is to examine the determinants that influence the adoption of human resource (HR) analytics, along with the influence of the external variable called Innovation Performance. The research model was developed by adapting the theoretical model of the unified theory of the acceptance and use of technology (UTAUT) by adding the external variable, Innovation Performance. The data was collected using a survey at Amazon Mechanical Turk (MTurk) in the USA. Initially, a total of 602 responses were obtained. Finally, a total of 554 questionnaires were obtained after using information quality filters for debugging. This study reveals that the main influence on the adoption of HR analytics is exerted by performance expectancy, social influence, facilitating conditions, and innovation performance on behavioral intention. Likewise, facilitating conditions, innovative performance, and behavior intention are the major influences for Use Behavior. This was found from an empirical analysis using the generalized structured component analysis (GSCA) software package that shows, with tabled data, the major relationships of the research model. This research into the use of HR Analytics investigated the standard determinants of UTAUT and the Innovation Performance external variable, that influence the adoption of HR analytics in business organization.

Keywords: business organization; companies; HR analytics; innovation performance; UTAUT; GSCA

1. Introduction

Harnessing the potential of digitization for strategic purposes is particularly relevant to the digital transformation of organizations with digital strategy being a decisive factor [1,2]. The formulation and execution of HR strategies along with HR practices are also relevant for human resource management (HRM) as they establish how digitization potential can be exploited to create value for organizations using the digital strategies presented by Strohmeier [3], and Marino-Romero et al. [4]. This is an example of the way HR analytics can systematically create value for an organization by basing all human resources decisions on evidence.

HR analytics is defined by Marler et al. [5] as an HR-enabled information technology practice that uses descriptive, visual, and statistical analysis of data related to HR processes, human capital, organizational performance, and external economic parameters to improve business impact and enable data-driven decision-making.

The COVID-19 pandemic has allowed some companies to recognize the relevance of HR analytics for crisis management [6–8]. However, the research by Dahlbom et al. [9] found that the low levels of expectation for the success of HR analytics in companies are due to an inability of managers to see the benefits of using it to manage people in the business when one of the most important points for the adoption of HR analytics is the support of management.

The adoption of HR analytics has become more relevant as Shet et al. [10] and Minbaeva [11] state that data quality, analytical skills, and strategic ability to act are critical elements for the effective and successful adoption of HR analytics in organizations.

Other studies of technology adoption [12,13] propose that an empirical examination can be used to find the practical application of the adoption and use of HR analytics for evidence-based decision-making for the organization and staff and can broaden understanding [14,15].

In addition, it is known by using effective strategic HR practices companies can increase their ability to introduce new products or services, as well as influence the staff to achieve better results and give a higher value to innovation. The adoption and use of HR analytics can play a critical role in this due to the influence of Innovation Performance. Vargas et al. [16] state that HR analytics should be considered a complex innovation as it integrates technological tools and data analysis.

The novelty of this study is the use of the generalized structured component analysis (GSCA) algorithm, which provides a global least squares optimization criterion with respect to PLS [17–19]. Moreover, GSCA can easily deal with both formative and reflective indicators and is also free from the problem of factor score indeterminacy [20].

The following research question has been formulated: What standard determinants, including Innovation Performance, can be identified as factors having a significant positive influence on the adoption of HR analytics? The main objective of this paper is to examine the determinants that influence the adoption of HR analytics with an empirical study and find the influence of the external variable, Innovation Performance.

This article is organized as follows: in the first part, the subject, the purpose, the objective, and the research question are presented. This section includes the literature review identifying and consulting the scientific articles about the adoption of HR analytics resulting in a proposal for the adaptation of the theoretical model of the UTAUT for the process of innovative technology adoption by including the Innovation Performance external variable to understand the model of HR analytics adoption. Then, it includes the eight hypotheses proposed for this study. The following section explains the methodology used in this study, which was a survey with a questionnaire. The questionnaire (Appendix A) was published on the Amazon MTurk crowdsourcing platform with a sample of (n = 602) users to understand their opinions of how HR can use analytics to manage people at work with a data-driven approach. The analysis of the results is then made using GSCA and this is followed by a discussion and conclusions with suggestions for possible future lines of research.

1.1. Adoption of HR analytics in business organizations

Fernandez et al. [21] identified the barriers to the adoption of HR analytics in organizations and grouped them into four categories Data and models, Software and technology, people and management, as shown in Figure 1.

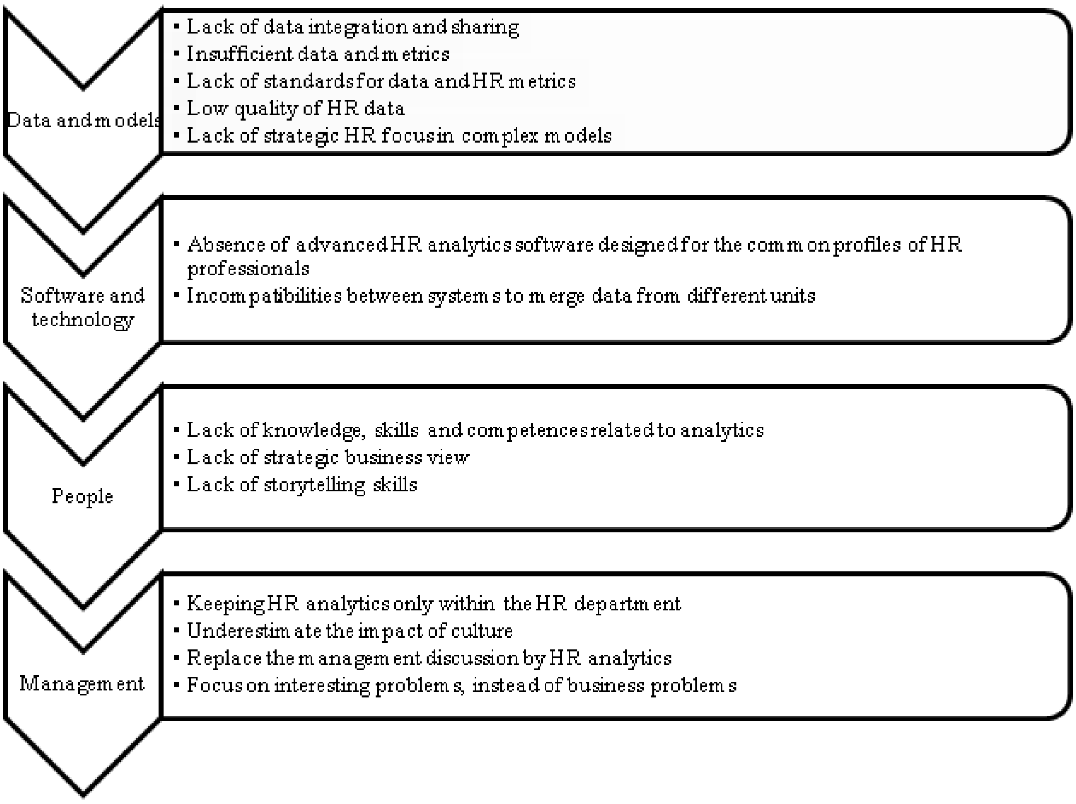

Figure 1. Barriers to the adoption of HR analytics. Adapted from Fernandez et al. [21].

To help companies overcome these barriers Fernandez et al. [21] also proposed a set of key factors, which are organized into four major categories, preparation, development, dissemination, and team, as seen in Figure 2.

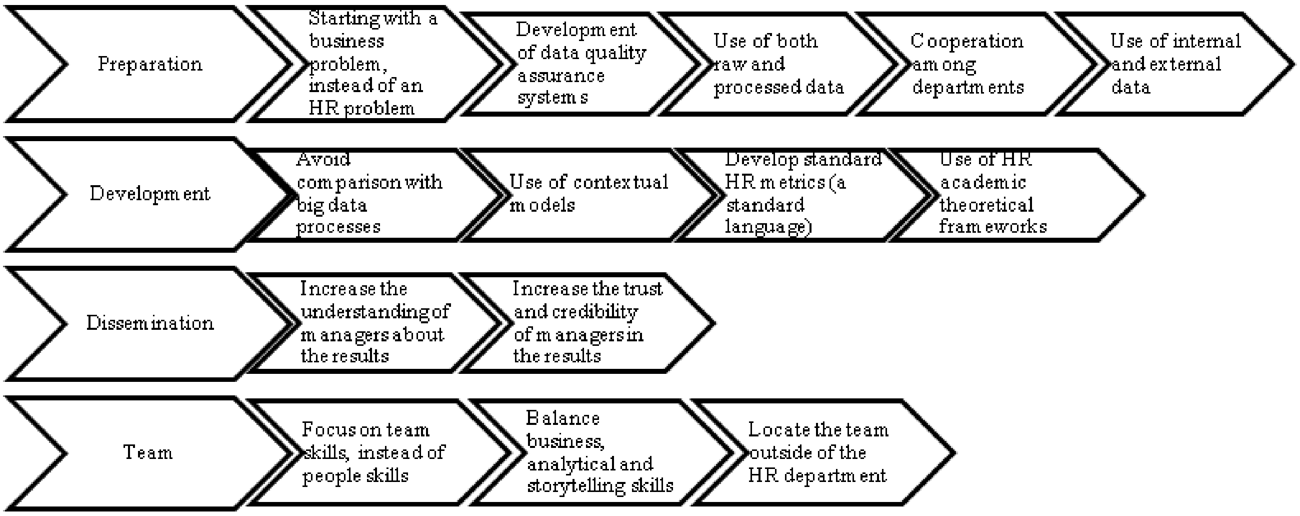

Figure 2. Key factors for HR analytics adoption. Adapted from Fernandez et al. [21].

Shet et al. [10] provide a framework for HR analytics adoption that identifies five factors that influence adoption. These are technological, environmental, data governance, and individual. The work by [22] complements such adoption by identifying three main areas of interest for HR analytics which are grouped as follows, (a) "HR analytics enablers", which are factors that enable or support HR analytics initiatives, include technological factors and organizational enablers, (b) "HR analytics applications", which refers to the different types of applications of HR analytics, from descriptive applications that are more traditional to predictive/prescriptive applications, and (c) "The value of HR analytics", which identifies the value generated by HR analytics, with a dual focus on employee-related value and organizational or business value. Concerning the "HR analytics applications", Figure 3 shows the stages of the evolution of HR analytics:

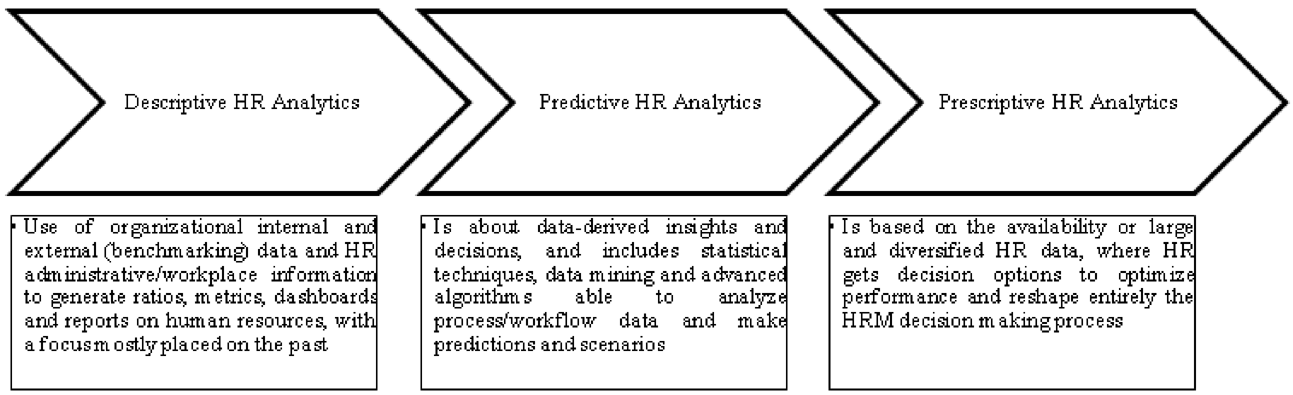

Figure 3. Stages of the evolution of HR analytics. Adapted from Margherita [22].

1.2. Previous studies on the adoption of HR analytics

Research by Ramzi et al. [23] explains that the research aimed to investigate the perception of

HR analytics by HR professionals and find the aspects that affect HR analytics adoption. The findings show that there is a negative relationship between the aspects of performance, effort expectation, and social influence in the adoption of HR analytics.

The study by Arora [24] evaluated the aspects that determine an individual's decision to adopt HR analytics. The results suggest that performance expectation influences the intention to adopt HR analytics. In contrast, effort expectation and social influence did not influence the behavioral intention to use it. In addition, the use behavior of HR analytics was determined by the behavioral intention to use it and the facilitating conditions.

In the research by Ekka et al. [25], the goal was to explore the behavioral intention to use HR analytics by HR professionals. The results revealed a significant positive influence of performance expectation, effort expectation, social influence, and facilitating conditions on behavioral intention to use HR analytics. Similarly, it was noted that behavioral intention has a significant positive influence on use behavior for HR analytics.

Peisl et al. [26] investigated the acceptance of technology and the use behavior of HR managers for the adoption of predictive HR analytics during hiring processes. However, the results of the study and the application of the hypotheses model are transferred to other researchers because they were developed or included by the authors.

2. Investigation model and research hypotheses

The research model and hypotheses are formulated to examine the determinants of HR analytics adoption and measure the effect of innovation performance. They were developed by adapting the theoretical model of UTAUT and the external variable, innovation performance. UTAUT has been widely used in research to investigate the adoption process for innovative technologies along with the behavioral intention to use them, as it has a predictive efficiency of 70% [27–29].

UTAUT was formulated after reviewing and comparing eight empirical models of information technology adoption and finding that four constructs act as direct determinants of acceptance by users and use behavior. These are performance expectancy, effort expectancy, social influence, and facilitating conditions [25]. The determinants of HR analytics adoption are presented below.

2.1.1. Performance expectancy

Performance expectancy is defined by Venkatesh [30] as the degree to which a person believes that using the system will help them improve work performance. Performance expectations have consistently proven to be one of the strongest predictors of behavioral intention to adopt and use information technology [31]. The study by Hmoud et al. [31] provides understanding and knowledge about the factors influencing the adoption of artificial intelligence (AI) in human resources information systems (HRIS) and the behavioral intention to use it by HR professionals. They found that Performance Expectation has an important influence on the behavioral intention to use AI by HR professionals in HRIS. The following hypothesis is thus proposed for this research:

Hypothesis 1 (H1). Performance expectation has a significant positive influence on the behavioral intention to use HR analytics.

2.1.2. Effort expectation

Effort Expectation is defined as how easy the user thinks the system will be to use. In the study by Ouirdi et al. [32], which focuses on the adoption of social networks in the recruitment and selection of employees, effort expectation had a positive influence on the behavioral intention to use social networks when hiring employees. Therefore, the following hypothesis was proposed:

Hypothesis 2 (H2). Effort expectation has a significant positive influence on the behavioral intent to use HR analytics.

2.1.3. Social influence

Social influence is defined by Venkatesh [30] as the degree to which an individual perceives that others believe it important to use the new system. Rahman et al. [33] identified the most important factors affecting HRIS adoption, and social influence was found to have a significant effect on behavioral intention to use the system in HRIS adoption. The following hypothesis was then proposed for this research:

Hypothesis 3 (H3). Social influence has a significant positive influence on the behavioral intention to use HR analytics.

2.1.4. Facilitating conditions

Facilitation conditions are defined by Venkatesh [30] as the extent to which a person believes that there is an organizational and technical infrastructure to support the use of the system. Hmoud et al. [31] found that facilitation conditions did not have a significant influence on the behavioral intention of HR professionals to use AI for HRIS. However, in the study by Ouirdi et al. [32] facilitation conditions had a positive impact on the use behavior for social media when hiring employees. The following hypotheses were proposed for this research:

Hypothesis 4 (H4). Facilitating conditions have a significant positive influence on the behavioral intention to use HR analytics.

Hypothesis 5 (H5). Facilitating conditions have a significant positive influence on the use behavior for HR analytics.

2.1.5. Behavioral intention to use and use behavior.

The behavioral intention to use refers to the intention to use a particular system or technology. In the study by Rahman et al. [28], it was also found that the behavioral intention to use has a significant effect on the use behavior in the adoption of HRIS. Similarly, in the study by Ouirdi et al. [32], the behavioral intention to use had a positive influence on the use behavior of social networks when hiring employees. The following hypothesis is therefore proposed for testing:

Hypothesis 6 (H6). Behavioral intention to use HR analytics has a significant positive influence on the use behavior of HR analytics.

2.1.6. Innovation performance

Innovation performance refers to the degree to which a company is successful in achieving its goals in terms of new products or services [34]. The study by Vargas et al. [16] used innovation theory to inspect the adoption of analytics applied to human resources. In the research by Shet et al. [10], the diffusion of innovation model (DOI) was used as the theoretical basis to understand and contextualize HR analytics as an innovation in HRM. The research of HR analytics at an organizational level by McCartney et al. [35] shows that interest in HR analytics can be linked to organizational outcomes, including innovation. In this research, the relationship between the adoption of HR analytics and the external variable, innovation performance will be studied using the following hypotheses:

Hypothesis 7 (H7). Innovation performance has a significant positive influence on the behavioral intention to use HR analytics.

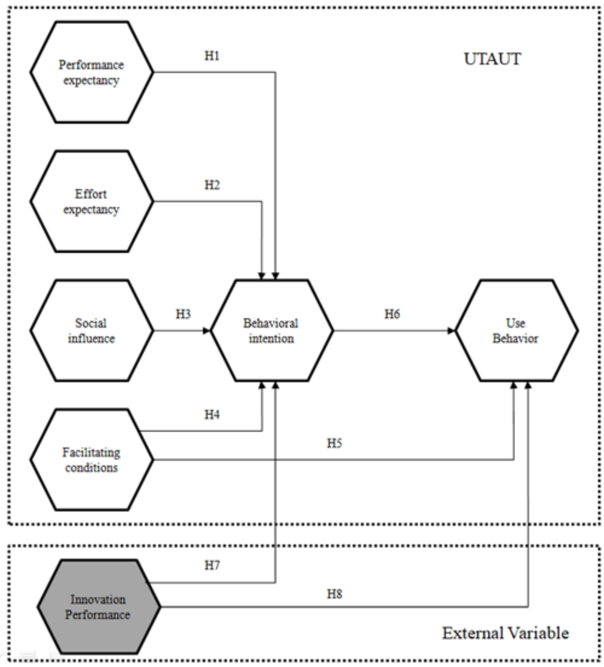

Figure 4. Suggested theoretical model. Source: Adapted from Venkatesh [30].

Hypothesis 8 (H8). Innovation performance has a significant positive influence on the use behavior for HR analytics.

The existing research explained above was used to create the research hypotheses and the suggested theoretical model shown in Figure 4. The constructs that influence HR analytics adoption are found by analyzing the constructs and their relationships. The hexagons in Figure 4 represent the constructs, which are also known as latent variables, connected by arrows numbered 1 to 8, showing the proposed hypotheses.

3. Materials and methods

The collection method and the measurement scale for the data of this study on the adoption of

HR analytics and innovation performance are presented in this section of the research work.

3.1. Data collection

The data for the suggested model was collected using a questionnaire. The questions were created after reviewing previous studies on technology adoption using the UTAUT technology acceptance model [30], and including the external variable of Innovation Performance to expand the model and find out if it is a determining factor for behavioral intention to use or use behavior for HR analytics.

The questionnaire was tested on 25 people with experience in the field of analytics or human resources who were not included in the study samples [2,3]. The respondents completed the questionnaire and provided information about the clarity or difficulty of the questions. The results confirmed the validity and reliability of the scales used in the final questionnaire [36].

Of the 602 questionnaires collected from the participants, 554 were valid, all "Mturkers" [37] from the Amazon MTurk platform in the United States of America (USA), characterized by the use of HR analytics to manage people at work with a data-driven approach. The questionnaire applied the good practices criteria for information collection on crowdsourcing platforms, selection of the MTurk worker, the validity of the survey, and quality filters for cleaning the information obtained [38–41]. The data was collected between November and December 2022. Before the questionnaire could be answered, a link in Qualtrics was prepared for the Mturk platform.

3.2. Measurements

A total of 6 questions were used to find general information about the respondent (industry sector, number of employees in the company, work experience, level of education, age group, and gender), and 2 questions were used as a quality control measure (What is 2 + 2? and When were you born?) and 27 questions were answered using a 5-point Likert scale where 1 = ("strongly agree") and 5 = ("strongly disagree"). The questions were grouped for the 7 constructs used in the research (performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral Intention, use behavior, and innovation performance).

3.3. Data analysis method

The GSCA approach [20,42] was used to test the hypothetical model presented in Figure 4 - All analyses were made using the GSCA software [43]. Although GSCA has been criticized [44], it has been used in a variety of domains and studies [45–48].

Afthanorhan et al. [49] have found that only a few studies are using GSCA. This algorithm is versatile enough to capture complex relationships between variables, including higher-order components and multi-group comparisons [20].

$$ZV = ZWA + E,$$

$$\Psi = \Gamma A + E, \tag{1}$$

Hwang et al. [20] explain $\Psi = ZV$, and $\Gamma = ZW$. In (1), Ψ is an N by T matrix of all endogenous observed and composite variables, Γ is an N by D matrix of all exogenous observed and composite variables, V is a J by T matrix of component weights associated with the endogenous variables, W is a J by D matrix of component weights for the exogenous variables, A is a D by T supermatrix consisting of a matrix of component loadings relating components to their observed variables, denoted by C, in addition to a matrix of path coefficients between components, denoted by B, that is, A = [C, B], and E is a matrix of residuals.

4. Results

A total of 554 valid questionnaires (92.02% of the 602 responses) were obtained for the following analysis stage of the research on HR analytics adoption. The results of the general information section have the descriptive statistics shown in Table 1.

Table 1. General information about the participants.

Variable	Range	Frequency
Gender	Female	193
	Male	360
	Other	1
Age group	18–29 years	246
	30–39 years	173
	4049 years	91
	50–59 years	28
	60 years and above	16
Level of education	High school	51
	Technical Specialty	19
	Undergraduate	377
	Postgraduate	107
Work experience	Less than 1 year	17
	1 to less than 3 years	168
	3 to less than 5 years	167
	5 years or more	202
Number of employees in the company	Less than 100 employees	158
	100 to 499 employees	273
	500 employees or more	123
Industry sector	Construction	18
	Energy and Utilities	7
	Finance and Insurance	65
	Health Care and Social Assistance	52
	IT and Telecom	255
	Logistics and Transport	8
	Manufacturing	76
	Public Sector and Education	10
	Wholesale and Retail	39
	Other	24

Table 2. Model FIT.

Measure	Values
FIT	0.55
AFIT	0.548
GFI	0.996
SRMR	0.031

Note: FIT = total variance of all variables; AFIT = Adjusted FIT; GFI = Goodness-of-fit Index; SRMR = Standardized root mean square residual.

Table 3. Estimates of loadings.

	Weights				Loadings			
Variable	Estimate	IS	95%CI		Estimate	IS	95%CI	
(ED1)	0.315	0.007	0.3	0.33	0.823	0.017	0.79	0.85
(ED2)	0.314	0.007	0.3	0.33	0.812	0.016	0.78	0.85
(ED3)	0.313	0.007	0.3	0.33	0.843	0.014	0.81	0.87
(ED4)	0.288	0.008	0.27	0.31	0.77	0.017	0.73	0.8
(EE1)	0.302	0.008	0.29	0.32	0.747	0.023	0.69	0.78
(EE2)	0.326	0.008	0.31	0.34	0.805	0.019	0.76	0.84
(EE3)	0.33	0.009	0.31	0.35	0.814	0.016	0.78	0.84
(EE4)	0.315	0.008	0.3	0.33	0.775	0.022	0.73	0.81
(IS1)	0.315	0.007	0.3	0.33	0.818	0.014	0.79	0.84
(IS2)	0.314	0.006	0.3	0.33	0.804	0.016	0.77	0.83
(IS3)	0.323	0.007	0.31	0.34	0.82	0.015	0.79	0.85
(IS4)	0.295	0.007	0.28	0.31	0.764	0.021	0.72	0.8
(CF1)	0.439	0.011	0.42	0.46	0.838	0.014	0.81	0.86
(CF2)	0.43	0.012	0.41	0.46	0.848	0.014	0.82	0.87
(CF4)	0.366	0.011	0.34	0.39	0.732	0.027	0.68	0.78
(DI1)	0.314	0.01	0.29	0.33	0.776	0.024	0.72	0.81
(DI2)	0.299	0.01	0.28	0.32	0.746	0.025	0.7	0.8
(DI3)	0.324	0.009	0.31	0.35	0.794	0.019	0.75	0.83
(DI4)	0.342	0.009	0.33	0.36	0.805	0.018	0.77	0.84
(IU1)	0.395	0.012	0.37	0.42	0.852	0.012	0.83	0.88
(IU2)	0.398	0.012	0.38	0.43	0.872	0.012	0.84	0.89
(IU3)	0.372	0.013	0.34	0.39	0.849	0.015	0.82	0.87
(AU1)	0.309	0.011	0.29	0.34	0.764	0.022	0.72	0.8
(AU2)	0.341	0.014	0.32	0.37	0.824	0.015	0.8	0.85
(AU3)	0.278	0.01	0.26	0.3	0.719	0.025	0.66	0.76
(AU4)	0.349	0.011	0.33	0.38	0.811	0.017	0.78	0.84

Note: SE = Standard Errors; CI = Confidence Intervals. ED = Performance expectancy; EE = Effort Expectancy; IS=Social Influence; CF = Facilitating conditions; DI = Innovation performance; IU = Behavior Intention; AU = Use behavior.

Table 4. Component correlations.

	ED	EE	IS	CF	DI	IU	AU
ED	1	0.734	0.841	0.762	0.747	0.817	0.813
EE	0.734	1	0.744	0.774	0.691	0.714	0.748
IS	0.841	0.744	1	0.751	0.786	0.801	0.79
CF	0.762	0.774	0.751	1	0.747	0.759	0.75
DI	0.747	0.691	0.786	0.747	1	0.756	0.755
IU	0.817	0.714	0.801	0.759	0.756	1	0.754
AU	0.813	0.748	0.79	0.75	0.755	0.754	1

Note: ED = Performance expectancy; EE = Effort Expectancy; IS = Social Influence; CF = Facilitating conditions; DI = Innovation performance; IU = Behavior Intention; AU = Use behavior

Table 5. Hypothesis testing.

Hypotheses	Path	Estimate	IS	95%CI	
H1	ED→IU	0.342*	0.057	0.225	0.455
H2	EE→IU	0.06	0.052	-0.035	0.143
H3	IS→IU	0.21*	0.068	0.104	0.333
H4	CF→IU	0.169*	0.051	0.098	0.286
H7	DI→IU	0.168*	0.047	0.068	0.255
H5	CF→AU	0.29*	0.06	0.18	0.4
H8	DI→AU	0.314*	0.054	0.193	0.415
H6	IU→AU	0.297*	0.062	0.166	0.411

Note: *Statistically significant at 0.05 level. SE = Standard Errors; CI = Confidence Intervals. ED = Performance expectancy; EE = Effort Expectancy; IS = Social Influence; CF = Facilitating conditions; DI = Innovation performance; IU = Behavior Intention; AU = Use Behavior

The largest group was men, with the largest age group between 18 to 29, and the smallest age group 60 and over. Most of the participants had university degrees, followed by postgraduate studies. The largest group had 5 years or more of work experience. Most of the participants worked for companies with between 100 and 499 employees and most companies were in the IT and Telecom industry.

The FIT of the model in Table 2 was tested and found to be acceptable at 0.55 which in this study represents 55% of the total variance of all variables, according to the criterion suggested by Hwang et al. [50], so the research model showed a good FIT for the data.

After removing one load that did not exceed the threshold (CF3), the remaining loads in Table 3 were greater than 0.70, indicating that the instrument had good reliability. The model estimate is also statistically significant because 95% of the confidence intervals have an estimate of 0.05 if the confidence interval does not include 0. The correlation between components is shown in Table 4.

The next stage of the analysis is the verification of the hypotheses using the information collected. This is done by estimating the path coefficients, standard errors, and the 95% confidence intervals of the hypotheses. The research model shown in Figure 4 above shows the theoretical framework for this study. The aim is to analyze the relationships between the variables for the use and adoption of HR analytics. This allows us to confirm the theoretical proposition of the variables used in the research.

The results are shown in Table 5 and indicate that the influence was statistically significant and positive for Performance expectancy in H1, Social Influence in H3, Facilitating conditions in H4, and Innovation performance on behavior intention in H7. There is also a statistically significant, positive influence of Facilitating conditions in H5, Behavior Intention in H6, and innovative performance on Use Behavior in H8. The hypotheses are assessed by the value of the Path estimation coefficients which are significant with $\alpha = 0.05$.

However, Effort expectancy in the H2 hypothesis was not supported due to the values of zero in the confidence intervals.

5. Discussion

This research was done to broaden the knowledge and understanding of the practical applications of adopting and using HR analytics for evidence-based decision-making. We used the UTAUT model with the incorporation of an external variable called innovation performance.

The determinants and the relationships between the variables that influence the adoption of HR analytics were analyzed along with the influence of the external innovation performance variable. The results validated the significant positive influence of most of the proposed relationships between the research variables for the adoption of HR analytics.

The results above answer the research question "What are the determinants that can be identified as factors with a significant positive influence on the adoption of HR analytics?

The only exception to the proposed determinants was the Effort Expectancy variable, which was found to not have any influence on the Behavioral Intention to use HR analytics. This determinant identifies how easy using the system is expected to be and it can be assumed that there may be difficulties using HR analytics, but these will have to be investigated further in other studies.

H1: Performance expectation has a significant positive influence on behavioral intention to use HR analytics. The results of the analysis in this study show that the value of the Estimate = 0.342 with 95% IQ (0.225–0.455)], indicating that hypothesis H1 is accepted, and performance expectation does have a significant positive influence on the behavioral intention to use HR analytics. This means that people believe that using HR analytics to manage people at work with a data-driven approach will help improve performance at work.

H2: Effort expectancy has a significant positive influence on behavioral intention to use HR analytics. The results of the analysis show that the value of the Estimate=0.06 with 95% CI (-0.035-0.143)], indicating that hypothesis H2 is not accepted, meaning that effort expectancy does not have a significant positive influence on behavioral intention to use HR analytics. This shows that this factor does not affect people's decisions to use HR analytics to manage people at work with a data-based approach.

H3: Social influence has a significant positive influence on the behavioral intention to use HR analytics. The findings of this research show that the value of the Estimate = 0.21 with 95% IQ (0.104–0.333), indicating that hypothesis H3 is accepted and that social influence has a significant positive influence on the behavioral intention to use HR analytics. This finding means that when people see that others believe HR analytics is useful for managing people at work with a data-driven approach, they will also want to use it.

H4: Facilitating conditions have a significant positive influence on behavioral intention to use HR analytics. The findings of the analysis show that the value of Estimate = 0.169 with 95% IQ (0.098–0.286), indicating that hypothesis H4 is accepted and facilitating conditions have a significant positive influence on the behavioral intention to use HR analytics. This result means people believe that if there is an organizational and technical infrastructure to support the use of HR analytics, people will use it to manage people at work with a data-driven approach.

H5: Facilitating conditions have a significant positive influence on the use behavior of HR analytics. The findings of the analysis show that the Estimate = 0.29 with 95% IQ (0.18–0.4)], indicating that hypothesis H5 is accepted and that facilitating conditions do have a significant positive influence on the use behavior of HR analytics. This means people believe that when there is an organizational and technical infrastructure to support the use of HR analytics, people will use it to manage people at work with a data-driven approach.

H6: The behavioral intent to use HR analytics has a significant positive influence on the use behavior of HR analytics. The findings of the analysis show that the value of the Estimate = 0.297 with 95% CI (0.166–0.411), indicating that hypothesis H6 is accepted and that the behavioral intention to use the system has a significant positive influence on the use behavior of HR analytics. This means that when people have a behavioral intention to use the system, they will use it to manage people at work with a data-driven approach.

H7: Innovation performance has a significant positive influence on behavioral intention to use HR analytics. The findings of the research show that the value of the Estimate = 0.168 with 95% IQ (0.068–0.255), indicating that hypothesis H7 is accepted, with innovation performance having a significant positive influence on the behavioral intention to use HR analytics. This shows that people believe that using HR analytics to manage people at work with a data-driven approach will help the company achieve its goals for new products or services.

H8: Innovation performance has a significant positive influence on the use behavior of HR analytics. The findings of the analysis show that Estimate = 0.314 with 95% IQ (0.193–0.415), indicating that hypothesis H8 is accepted, so innovation performance has a significant positive influence on use behavior for HR analytics. This means people think that using HR analytics to manage people at work with a data-driven approach will enable the company to achieve its objectives for new products or services.

The research of Ramzi et al. [23] found that performance expectation, effort expectation, and social influence did not have a positive influence on the adoption of HR analytics. In the research by Arora et al., performance expectation had a positive influence on the intention to use HR analytics in some cases, and the behavioral intention to use and the facilitating conditions had a positive influence on the use behavior for HR analytics. However, the hypotheses for effort expectation and social influence were not supported and did not have a positive relationship with behavioral intention to use.

In the work by Ekka et al. [25], the findings display that all the hypotheses were supported and performance expectation, effort expectation, social influence, and facilitating conditions all have a significant, positive influence on behavioral intention to use HR analytics. Likewise, behavioral intention to use has a significant positive influence on the use behavior of HR analytics.

Ekka et al. [25] highlight the strength of the relationship between social influence on the adoption of innovation, and the study by Vargas et al. [16] identifies that social influence plays an essential role for organizations when adopting HR analytics.

The results of this work expand the knowledge of the adoption and use of HR analytics because the external variable, performance innovation is incorporated into the study. Most of the research hypotheses in the suggested model were supported after quantitative measuring and testing, except for effort expectation which does not have a significant positive influence on the behavioral intention to use HR analytics. These results provide rigorous and consistent results for the data gathered in the questionnaire.

The limitation of this empirical study is that information was only collected on the Amazon

MTurk platform. This study is limited to this source of data for the information gathered with the questionnaires. Another limitation is that the questionnaire was only used in one country, the USA.

Among the practical limitations of this empirical research on the adoption and use of HR analytics is that it shows difficulties with the use of HR analytics due to the Effort Expectancy variable not having any influence on the behavioral intention to use HR analytics, which could be related to the digital transformation processes that companies may or may not have [6,9].

6. Conclusions

This empirical analysis has allowed us to find the factors that influence the adoption of HR analytics, along with the influence of the external variable, performance innovation. The data was analyzed using the generalized structured component analysis (GSCA) software package.

The results show that the theoretical model of the UTAUT is valid and applicable for the analysis of the adoption of HR analytics. The suggested research model, adapting the theoretical UTAUT model is new for research into the use and adoption of HR analytics. The innovation performance factor used as an external variable in this model could also be researched further. This factor has been seen in other studies in the literature review along with the proposal for further research of this variable by Bonilla-Chaves et al. [15].

Previous studies analyze the adoption of HR analytics by HR professionals in a single context and in a controlled way.

We go further and consider the users' perceptions of the adoption and use of HR analytics the analysis and empirical evidence of the results verify that there is an increase in the use of HR analytics for managing people at work with a data-driven approach. However, there are difficulties using HR analytics that will need to be investigated to expose the gaps and opportunities for improvement that HR professionals and business managers need to know about.

In addition, it is valuable to mention that this work increases the information available about HR analytics adoption and use since the results include information about the innovation performance external variable. It was shown that people think that using HR analytics to manage people at work with a data-driven approach will enable the company to achieve its objectives for new products or services. This research found that this relationship with innovation is positive and that innovation influences the adoption of HR analytics, confirming the claims of previous authors [5,16].

Additional research is required to increase the amount of information about the use of HR analytics. This work shows that the Effort Expectancy variable can be investigated more since it was not seen to have any influence on the behavioral intention to use HR analytics, and for this reason, it is assumed that there may be difficulties for people using HR analytics. HR professionals and managers of companies could eliminate these barriers by identifying them with research using the key factors proposed by Fernandez et al. [21].

The adoption and use of HR analytics in large, medium, and small companies should be investigated more. Companies with less than 500 employees could provide a wider scope for the research topic, as well as other sectors where the use of HR analytics and data analysis are innovative ways to develop. The IT and Telecom sectors are the most advanced in this area at the moment. Researchers and data scientists in these organizations can look for new improvements as a result of adopting and using HR analytics.

Other future lines of research could be investigating the adoption of HR analytics in other countries [14], longitudinal studies using the UTAUT model including other variables of interest, and the increase in the use of HR analytics in HRM [51]. The adoption and use of HR analytics means the digital transformation of the HR practices of a company by using technology in HR strategies and basing all HR decisions on evidence [3]. For future research work, it will be necessary to compare the results of the GSCA model with the PLS-SEM model for the adoption of HR analytics.

Other, future research could consider the major causes for the increase in the adoption of HR, which are mentioned by Shrivastava [52]. These include more interest by the top management and the board of directors of organizations to measure and quantify decisions about the staff in their companies, the growing belief that HR should be more quantitative, and that HR professionals should consider a business view and find a connection between decision using data analysis and employee performance [53,54].

From the analysis of the outcomes of the adoption and use of HR analytics and the effect on innovation performance, there are opportunities for filling the gaps in the knowledge about HR analytics adoption by continuing to study this subject. This research can be interesting for researchers and HR professionals who wish to increase their knowledge of this scientific field.

Use of AI tools declaration

The authors declare that they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare that there are no conflict of interest.

References

1. J. A. Marino-Romero, P. R. Palos-Sánchez, F. Velicia-Martín, Evolution of digital transformation in SMEs management through a bibliometric analysis, *Technol. Forecast. Soc. Change,* **199** (2024), 123014. https://doi.org/10.1016/j.techfore.2023.123014
2. P. Brazo, F. Velicia-Martín, P. R. Palos-Sanchez, R. G. Rodrigues, The effect of coercive digitization on organizational performance: How information resource management consulting can play a supporting role, *J. Global Inf. Manage.*, **31** (2023), 1–23. https://doi.org/10.4018/JGIM.326282
3. S. Strohmeier, Digital human resource management: A conceptual clarification, *Ger. J. Hum. Resour. Manage.*, **34** (2020), 345–365. https://doi.org/10.1177/2397002220921131
4. J. A. Marino-Romero, P. R. Palos-Sanchez, F. A. Velicia-Martin, R. G. Rodrigues, A study of the factors which influence digital transformation in Kibs companies, *Front Psychol.*, **13** (2022), 993972. https://doi.org/10.3389/fpsyg.2022.993972

5. J. H. Marler, J. W. Boudreau, An evidence-based review of HR Analytics, *Int. J. Human Resour. Manage*., **28** (2017), 3–26. https://doi.org/10.1080/09585192.2016.1244699
6. D. Minbaeva, Disrupted HR?, *Hum. Resour. Manage. Review.*, **31** (2021), 100820. https://doi.org/10.1016/j.hrmr.2020.100820
7. P. Ficapal-Cusí, J. Torrent-Sellens, P. Palos-Sanchez, I. González-González, The telework performance dilemma: Exploring the role of trust, social isolation and fatigue, *Int. J. Manpower*, preprint. https://doi.org/10.1108/IJM-08-2022-0363
8. P. Palos-Sánchez, P. Baena-Luna, M. García-Ordaz, F. J. Martínez-López, Digital transformation and local government response to the COVID-19 pandemic: An assessment of its impact on the sustainable development goals, *SAGE Open*, **13** (2023). https://doi.org/10.1177/21582440231167343
9. P. Dahlbom, N. Siikanen, P. Sajasalo, M. Jarvenpää, Big data and HR analytics in the digital era, *Baltic J. Manage.*, **15** (2020), 120–138. https://doi.org/10.1108/BJM-11-2018-0393
10. V. Shet Sateesh, T. Poddar, F. Wamba Samuel, Y. K. Dwivedi, Examining the determinants of successful adoption of data analytics in human resource management–A framework for implications, *J. Bus. Res.*, **131** (2021), 311–326. https://doi.org/10.1016/j.jbusres.2021.03.054
11. D. Minbaeva, Building credible human capital analytics for organizational competitive advantage, *Hum. Resour. Manage.*, **57** (2018), 701–713. https://doi.org/10.1002/hrm.21848
12. P. Palos-Sanchez, J. R.Saura, The effect of internet searches on afforestation: The case of a green search engine, *Forests*, **9** (2018), 51. https://doi.org/10.3390/f9020051
13. M. R. Sánchez, P. Palos-Sánchez, F. Velicia-Martin, Eco-friendly performance as a determining factor of the adoption of virtual reality applications in national parks, *Sci. Total Environ.*, **798** (2021) ,148990. https://doi.org/10.1016/j.scitotenv.2021.148990
14. E. F. Bonilla-Chaves, P. Palos-Sánchez, Exploring the evolution of human resource analytics: A bibliometric study, *Behav. Sci.*, **13** (2023), 244. https://doi.org/10.3390/bs13030244
15. E. F. Bonilla-Chaves, P. Palos-Sánchez, Strategic HRM Practices, innovation performance and its relationship on export performance: An exploratory study of SMEs in an emerging economy, in *Perspectives and Trends in Education and Technology*, Springer, (2022), 607–620.
16. R. Vargas, Y. V. Yurova, C. P. Ruppel, Leslie C. Tworoger, R. Greenwood, Individual adoption of HR analytics: A fine grained view of the early stages leading to adoption, *Int. J. Hum. Res. Manage*., **29** (2018), 3046–3067. https://doi.org/10.1080/09585192.2018.1446181
17. Z. Yuan, X. Deng, T. Ding, J. Liu, Q. Tan, Factors influencing secondary school teachers' usage behavior of dynamic mathematics software: A partial least squares structural equation modeling (PLS-SEM) method, *Electron. Res. Arch.*, **31**(2023), 5649–5684. https://doi.org/10.3934/era.2023287
18. X. Tang, Z. Yuan, X. Deng, L. Xiang, Predicting secondary school mathematics teachers' digital teaching behavior using partial least squares structural equation modeling, *Electron. Res. Arch.*, **31** (2023), 6274–6302. https://doi.org/10.3934/era.2023318
19. F. Gimeno-Arias, J. M. Santos-Jaén, M. del C. V. Martínez, M. Sánchez-Pérez, From trust and dependence commitment to B2B engagement: An empirical analysis of inter-organizational cooperation in FMCG, *Electron. Res. Arch.*, **31** (2023), 7511–7543. https://doi.org/10.3934/era.2023379
20. H. Hwang, Y. Takane, Generalized structured component analysis, *Psychometrika*, **69** (2004), 81–99. https://doi.org/10.1007/BF02295841

21. V. Fernandez, E. Gallardo-Gallardo, Tackling the HR digitalization challenge: Key factors and barriers to HR analytics adoption, *Competitiveness Rev. Int. Bus. J.*, **31** (2020), 162–187. https://doi.org/10.1108/CR-12-2019-0163
22. A. Margherita, Human resources analytics: A systematization of research topics and directions for future research, *Hum. Res. Manage. Rev.*, **32** (2022), 100795. https://doi.org/10.1016/j.hrmr.2020.100795
23. B. Ramzi, M. Elrayah, The reasons that affect the implementation of HR analytics among HR professionals, *Can. J. Bus. Inf. Stud.*, **3** (2021), 29–37. https://doi.org/10.34104/cjbis.021.029037
24. M. Arora, A. Prakash, A. Mittal, S. Singh, Moderating role of resistance to change in the actual adoption of HR analytics in the Indian banking and financial services industry, *Evid. Based HRM*, **11** (2022), 253–270. https://doi.org/10.1108/EBHRM-12-2021-0249
25. S. Ekka, P. Singh, Predicting HR Professionals' Adoption of HR Analytics: An extension of UTAUT model, *Organizacija*, **55** (2022), 77–93. https://doi.org/10.2478/orga-2022-0006
26. T. Peisl, R. Edlmann, Exploring technology acceptance and planned behaviour by the adoption of predictive hr analytics during recruitment, in *Systems, Software and Services Process Improvement*, (Eds. Yilmaz M, Niemann J, Clarke P, et al.,), Springer International Publishing, (2020), 177–190. https://doi.org/10.1007/978-3-030-56441-4_13
27. N. D. Oye, N. A. Iahad, N. A. Rahim, The history of UTAUT model and its impact on ICT acceptance and usage by academicians, *Educ. Inf. Technol.*, **19** (2014), 251–270. https://doi.org/10.1007/s10639-012-9189-9
28. Y. K. Dwivedi, N. P. Rana, A. Jeyaraj, M. Clement, M. D. Williams , Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model, *Inf. Syst. Front.*, **21** (2019). 719–734. https://doi.org/10.1007/s10796-017-9774-y
29. E. Garcia-Rio, P. Palos-Sanchez, P. Baena-Luna, M. Clement, M. D. Williams, Different approaches to analyzing e-government adoption during the Covid-19 pandemic, *Gov. Inf. Q.*, **40** (2023), 101866. https://doi.org/10.1016/j.giq.2023.101866
30. V. Venkatesh, M. G. Morris, G. B. Davis, F. D. Davis , User acceptance of information technology: Toward a unified view, *MIS Q.*, **27** (2003), 425–478. https://doi.org/10.2307/30036540
31. B. I. Hmoud, L. Várallyai, Artificial intelligence in human resources information systems: Investigating its trust and adoption determinants, *Int. J. Eng. Manage. Sci.*, **5** (2020), 749–765. https://doi.org/10.21791/IJEMS.2020.1.65
32. M. E. Ouirdi, A. E. Ouirdi, J. Segers, I. Pais, Technology adoption in employee recruitment: The case of social media in Central and Eastern Europe, *Comput. Hum. Behav.*, **57** (2016), 240–249. https://doi.org/10.1016/j.chb.2015.12.043
33. M. A. Rahman, X. Qi, M. S. Jinnah, Factors affecting the adoption of HRIS by the Bangladeshi banking and financial sector, *Cogent Bus. Manage.*, **3** (2016), 1262107. https://doi.org/10.1080/23311975.2016.1262107
34. C. C. J. Cheng, E. K. R. E. Huizingh, When is open innovation beneficial? The role of strategic orientation, *J. Prod. Innovation Manage.*, **31** (2014), 1235–1253. https://doi.org/10.1111/jpim.12148
35. S. McCartney, N. Fu, Promise versus reality: A systematic review of the ongoing debates in people analytics, *J. Organ. Effect. People Perform.*, **9** (2022), 281–311. https://doi.org/10.1108/JOEPP-01-2021-0013
36. H. Aguinis, I. Villamor, R. S. Ramani, MTurk research: Review and recommendations, *J. Manage.*, **47** (2021), 823–837. https://doi.org/10.1177/0149206320969787

37. G. Paolacci, J. Chandler, Inside the Turk: Understanding mechanical turk as a participant pool, *Curr. Dir. Psychol. Sci.*, **23** (2014), 184–188. https://doi.org/10.1177/0963721414531598
38. C. Cobanoglu, M. Cavusoglu, G. Turktarhan, A beginner's guide and best practices for using crowdsourcing platforms for survey research: The case of Amazon Mechanical Turk (MTurk), *J. Glob. Bus. Insights.*, **6** (2021), 92–97. https://doi.org/10.5038/2640-6489.6.1.1177
39. R. Kennedy, C. Scott, T. Burleigh, P. D. Waggoner, R. Jewell, N. J. G. Winter, The shape of and solutions to the MTurk quality crisis, *Political Sci. Res. Methods*, **8** (2020), 614–629. https://doi.org/10.1017/psrm.2020.6
40. M. G. Keith, L. Tay, P. D. Harms, Systems perspective of Amazon mechanical Turk for organizational research: Review and recommendations, *Front. Psychol.*, **8** (2017). https://doi.org/10.3389/fpsyg.2017.01359
41. W. Mason, S. Suri, Conducting behavioral research on Amazon's Mechanical Turk, *Behav. Res.*, **44** (2012), 1–23. https://doi.org/10.3758/s13428-011-0124-6
42. I. E. Allen, C. A. Seaman, Likert scales and data analyses, *Qual. Prog.*, **40** (2007), 64–65.
43. H. Hwang, Visual GSCA 1.0–A graphical user interface software program for generalized structured component analysis, *New Trends Psychometrics*, (2008), 111–120.
44. J. Henseler, Why generalized structured component analysis is not universally preferable to structural equation modeling, *J. Acad. Mark. Sci.*, **40** (2012), 402–413.
45. V. T. Nguyen, The perceptions of social media users of digital detox apps considering personality traits, *Educ. Inf. Technol.*, **27** (2022), 9293–9316. https://doi.org/10.1007/s10639-022-11022-7
46. A. B. Saka, D. W. M. Chan, A. M. Mahamadu, Rethinking the digital divide of BIM adoption in the AEC industry, *J. Manage. Eng.*, **38** (2022), 04021092. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000999
47. L. C. Nawangsari, A. H. Sutawidjaya, Talent management in mediating competencies and motivation to improve employee's engagement, *Int. J. Econ. Bus. Adm.*, **7** (2019), 140–152. https://doi.org/10.35808/ijeba/201
48. T. Doleck, P. Bazelais, D. J. Lemay, Social networking and academic performance: A generalized structured component approach, *J. Educ. Comput. Res.*, **56** (2018), 1129–1148. https://doi.org/10.1177/0735633117738281
49. A. Afthanorhan, Z. Awang, M. Mamat, A comparative study between GSCA-SEM and PLS-SEM, *MJ J. Stat. Probab.*, **1** (2016), 63–72.
50. H. Hwang, G. Cho, H. Choo, *GSCA Pro User's Manual*, (2021).
51. S. A. Khan, J. Tang, The paradox of human resource analytics: Being mindful of employees, *J. General Manage.*, **42** (2016), 57–66. https://doi.org/10.1177/030630701704200205
52. S. Shrivastava, K. Nagdev, A. Rajesh, Redefining HR using people analytics: The case of Google, *Hum. Res. Manage. Int. Dig.*, **26** (2018), 3–6. https://doi.org/10.1108/HRMID-06-2017-0112
53. J. A. Folgado-Fernández, M. Rojas-Sánchez, P. Palos-Sánchez, A. G. Casablanca-Peña, Can virtual reality become an instrument in favor of territory economy and sustainability?, *J. Tourism Serv.*, **14** (2023), 92–117. https://doi.org/10.29036/jots.v14i26.470
54. J. F. Arenas-Escaso, J. A. Folgado-Fernández, P. Palos-Sánchez, Internet interventions and therapies for addressing the negative impact of digital overuse: A focus on digital free tourism and economic sustainability, *BMC Public Health*, **24** (2024), 176. https://doi.org/10.1186/s12889-023-17584-6

Appendix A

Table A1. Questionnaire and constructs.

Items	Description
Performance expectancy. Adapted from Venkatesh et al. [30]	
(ED1)	I would find HR analytics useful in my work.
(ED2)	Using HR analytics allows me to perform tasks more quickly.
(ED3)	Using HR analytics increases my work performance.
(ED4)	If I use HR analytics, I will increase my chances of getting a raise.
Effort Expectancy. Adapted from Venkatesh et al. [30]	
(EE1)	If I used HR analytics, I would find this clear and understandable.
(EE2)	It would be easy for me to become proficient in using HR analytics.
(EE3)	I would find HR analytics easy to use.
(EE4)	Learning how to use HR analytics is easy for me.
Social Influence. Adapted from Venkatesh et al. [30]	
(IS1)	The people who influence my behavior think I should use HR analytics.
(IS2)	The people who are important to me think I should use HR analytics.
(IS3)	The senior management of the company has been helpful in supporting the use of HR analytics.
(IS4)	In general, the organization has supported the use of HR analytics.
Facilitating conditions. Adapted from Venkatesh et al. [30]	
(CF1)	I have the resources required to use HR analytics.
(CF2)	I have the knowledge required to use HR analytics.
(CF3)	HR analytics is not compatible with other systems I use.
(CF4)	A person (or group) is available to help with any difficulties I have using HR analytics.
Innovative performance. Adapted from [53–55]	
(DI1)	The company's new products and services are often perceived as very novel by customers.
(DI2)	New products and services in the company often pit us against new competitors.
(DI3)	The company has introduced more innovative products and services than its competitors over the past 5 years.
(DI4)	The company is faster in bringing new products or services into the market than its competitors.
Behavior Intention. Adapted from Venkatesh et al. [30]	
(IU1)	I intend to use HR analytics in the coming months.
(IU2)	I can predict I will use HR analytics in the coming months.
(IU3)	I plan to use HR analytics in the coming months.
Use behavior. Adapted from Venkatesh et al. [30]	
(AU1)	Using HR analytics is a good idea.
(AU2)	HR analytics makes work more interesting.
(AU3)	Working with HR analytics is fun.
(AU4)	I like working with HR analytics.