MANAGEMENT
2025, Vol. 29, No. 2
www.management-poland.com
DOI: 10.58691/man/214273

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Role of Data Security Concerns in HR Analytics Applications Usage: Examining the Mediating and Moderating Mechanisms

Abstract

Research background and purpose: Digital technologies have transformed the business, including changes in Human Resources (HR) practices. As data-driven and evidence-based decision-making takes place, integrating HR analytics becomes essential for improving performance and strategic HR management. The dark side of HR analytics is yet to be explored. The dark side means the potential negative uses and ethical problematic consequences of analytics applications in HRM. This research aims to investigate the effect of data security concerns on Human Resource Analytics (HRA) applications usage through the theoretical lens of Privacy Calculus Theory (PCT). Furthermore, to investigate the mediating role of perceived risk between data security concerns and HRA. This research also aims to examine the moderating role of digital transparency clarity between perceived risk and HRA applications usage. The theoretical model of data security under the dark side of HR analytics that may impact HRA usage is grounded in the literature's suggestions for future research.
Design/methodology/approach: Using a purposive sampling technique, the data were gathered from 223 HR professionals working in Pakistan's Telecom industry. The SmartPLS V4 was used to analyze the gathered data.
Findings: The results indicated that data security concerns adversely impact HRA applications' usage, such as HRA usage decrease with higher security concerns. The findings of the study confirm that perceived risk is a significant negative factor that influences the usage of HRA. Findings also indicate that data security concerns positively impact perceived risk. The results reflected that perceived risk bridges the data security and HRA relationship. Furthermore, digital transparency clarity weakens the perceived risk-HRA applications usage relationship. Besides this, the direct impact of demographic factors appeared not to have influenced the HRA.
Value added and limitations: This study contributes to the body of knowledge by providing mediating and moderating mechanisms regarding HRA in HRM. Practically, it focuses on the requirements of vigorous data governance, ethical usage of HR analytics applications, and transparent policies that will lead to increased HRA usage. The organizations need to set up clear guidelines in the form of an ethical charter that outlines the "Dos" and "Don'ts" of data access in the HRA context. The limitations, future directions, and managerial implications of the study have also been discussed.

Keywords: *HR analytics applications, data security, perceived risk, digital transparency clarity, privacy calculus theory*

JEL Classification: M1

Received: 2025-07-26; **Revised:** 2025-10-03; **Accepted:** 2025-11-15

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1. Introduction

Advances and developments in information technology have changed the human resources (HR) functions in companies. Currently, the majority of companies are implementing HR analytics applications extensively to support core HR tasks & duties as well as increase the effectiveness of management, decision-making, and information sharing (Margherita, 2022). According to the Global Human Capital Trends survey, conducted back in 2018, 84% of participants said HR analytics was vital or very vital, making it the #2 top HR trend (Deloitte Insights, 2018). HR analytics is referred to as HR activities based on facts and data rather than intuition or personal experience (McAfee & Brynjolfsson, 2012). In the last decade, HR analytics has gained more attention in human resource management, and many believe it can answer all the challenges HR faces. With the help of data analytics, the purpose is to convert large complex data into information and thereby support the decision-making process in human resource management by helping to make more correct and evidence-based decisions and to predict the future, not just for illustrating past (Tomar & Gaur, 2022; Rasmussen & Ulrich, 2015).

Workplaces are increasingly digitized. Digital advancement and development are certainly a critical factor in achieving Sustainable Development Goal (SDG) 9, i.e., industrial innovation and infrastructure. All the things, ranging from employee communication to the progress of duties and work items, are saved and processed digitally. This empowers advanced HR analytics that process employee data to expedite the processes or aid with decision-making. However, unlike in the context of consumers, employees usually do not have any option about which tools to use in their workplace. In addition, data processing is impervious to the persons exposed to it. This lack of control and oversight by employees is a cause for concern (Teebken & Hess, 2021) and means that there are few options in the event of data, privacy, and security abuse. With rising automation and automated decision-making, the risks of data misuse, privacy, data quality, algorithmic biases, legal and regulatory risks and data security continue to grow (Giermindl et al., 2022; Lustig et al., 2016). Evidence-based insights can play a role in deciding whether a candidate should be called for a job interview, assigned to a project, or eligible for a career progression (Tursunbayeva et al., 2022). It is therefore vital that any misuse or data security concerns are disclosed and challenged (Rieke et al., 2018).

Ethical issues in HR analytics applications, particularly AI algorithm bias, data security concerns and HR management, require further investigation. Due to the growing importance of data security, HR analytics research must focus on data protection (Vadithe, & Bikrantkesare, 2024). Data security is of utmost importance because it lays the foundation for employees' trust. There can be regulatory fines and punishments in case of data breaches. There can be a question mark on organizational reputation if there are data security concerns. Big data brings its own set of ethical challenges, although not distinctive, that should be openly addressed in any organizational context; issues such as balancing privacy and the right to access, consent for information, professional ethics vs. organizational requirements, etc. (Calvard & Jeske, 2018). Future studies may look at the ethical side of big data in the human resource analysis context (Muhammad et al., 2024). Primary research is needed to understand how HRM methods change work in different types of organizations and their intended and unintended effects on employees (Tursunbayeva et al., 2022). To respond to these research gaps, the purpose of this research is to answer the questions: what challenges does the digital economy bring in the age of HR analytics in data security? How do data security concerns affect perceived risk and HR analytics applications usage? How does digital transparency clarity moderate the relationship between perceived risk and HR analytics applications usage?

The growing field of analytics has transformed the human resource management field, leading to enhanced data-driven decision making, rapidly raising significant apprehensions related to employee privacy and security of data (Fernández & Gallardo-Gallardo, 2020). Given the growing invasiveness of data collection, processing, and dissemination that transcends employees' work lives into their social and physiological spaces and frequently elicits resistance and negative reactions (Giermindl et al., 2021). This makes it necessary to examine how effective utilization of HR analytics is affected by perceived risks connected with data security in organizations.

There is a critical gap in understanding the mechanism between perceived risk, clarity of digital initiatives being transparent, and use of HR analytics, specifically related to recent developments in technological advancement and data privacy regulations (Giermindl et al., 2021). Specifically, the existing studies overlook the nuanced mediating effect of perceived risk towards HR analytics application, failing to fully address how concerns regarding data security lead to concrete hesitancy or adoption (Giermedl et al., 2021). Moreover, the moderating effect of digital transparency clarity on the connection between perceived risk and usage of HR analytics remained unexamined, particularly in an organizational context (Abdelhay et al., 2025). Furthermore, existing research has recognized the importance of data security and protection in HR analytics, while an inclusive understanding of the way these factors affect the willingness of HR professionals to use these applications is evolving (Nowicka et al., 2024; Zieglmeier et al., 2022). Despite substantial efforts to bridge the gap between research and practice in organizations, there exists a substantial gap in understanding the factors that affect retention of employees via predictive analytics and big data, specifically regarding the role of big data analytics in employee retention (Singh et al., 2022). Likewise, the ethical implications of adopting advanced analytical procedures to monitor and predict the behaviour of employees, though critical, have not been reliably integrated into models examining the adoption of HR analytics

(Giermindl et al., 2021). Hence, there is a need to empirically study mechanisms that investigate the mechanism through which data security concerns proliferate perceived risk, and lead to affect the extent to of HR analytics applications are leveraged and adopted for the strategic management of the workforce in the organization. These examinations are crucial for frameworks that address technology advancement and navigate psychological and ethical dimensions of data use in HR (Bagis & Yulianeu, 2024).

As per Huang et al. (2023), in order to fix uncertainties and risk factors associated with analytics applications, there is a need to develop a comprehensive framework. It may include boundary conditions under which the HR analytics applications usage can be increased. To mitigate data security issues, it is necessary to have digital transparency (Danner et al., 2023). If employees fully understand the aim of data gathering, data storage, and the security system, there are better chances for them to use more HR analytics applications.

This research is significant as it addresses the latest research gaps and provides an understanding of the multifaceted influence on HR analytics usage by offering a comprehensive framework that integrates data security, perceived risk associated with HR analytics usage, and clarity of digital transparency. This research provides practical insights for the firms looking to enhance the HR analytics investments, while increasing compliance and trust in data data-driven atmosphere (Álvarez-Gutiérrez et al., 2022). This model is crucial in the development of a socially responsible AI- empowered analytics model that leads to control ethical concerns and increase organizational sustainability (Chang & Ke, 2023). Moreover, this study will provide a deep exploration of the way organizations can effectively balance the benefits of data-driven HR institutions and the safety of employees' sensitive information (Venugopal et al., 2024; Ravesangar & Narayanan, 2024).

Researchers have used different theoretical lenses, such as the technology acceptance model (Davis, 1989), the resource view (Barney, 1991), the theory of planned behavior (Ajzen, 1991), and cloud computing theory (Wiley et al., 2015). The privacy calculus theory (Laufer & Wolfe, 1977) has not been widely used from the perspective of data-driven HRM. According to privacy calculus theory, individuals make decisions by weighing perceived benefits against perceived risks. In the HR analytics applications context, this theory could provide valuable insights into how employees might perceive and respond to data security issues and the usage of HR analytics applications. Privacy calculus theory is used to support the model due to its unique focus on the trade-off between risk and benefits. It provides a basic mechanism that is necessary for modelling of data-sensitive decisions, while the theory of planned behaviors and the technology acceptance model do not talk about trade-offs.

Employees can work from home, with a few organizations, especially telecom operators and software organizations, even adopting "all remote" configurations

(Choudhury et al., 2020). This may increase the employer's interest in employee surveillance using HR analytics. As there is a huge demand for software developers in the labor market, the innate power asymmetry between them and their employer is reduced. Data about these employees is saved in numerous systems and accessed through a large number of tools (Rao et al., 2019). In this situation, employees track their work in issue-tracking software and use Workplace Messenger. This means there is data about the specific technologies and problems they are working on, as well as who they are working with. Traditional detective enforcement makes it possible to use this data, for example, for managerial decision-making or coordination between peers. However, it provides scope for employee profiling and patronage based on data that may not represent the full picture or is insufficient for these uses. Employees can be discriminated against or fired because of misused or misinterpreted information, and have no remedy.

In summary, we present a comprehensive perspective and initial assessment of the dark side of HR analytics with a focus on data security issues in Pakistani telecom companies. The proposed research model is a novel attempt to detect the vulnerability of HR analytics applications and fix this issue using the lens of the privacy calculus theory.

2. Literature review

2.1. Data security concerns and HR analytics applications usage

HR analytics involves data collection and aggregating extensive user data, and at the same time, data leaks and constant privacy breaches create uncertainty among users and concerns regarding data privacy: is my information safe? What information is gathered for what purpose, and who can access it? Where are the files saved, and how long are they stored on the server? These questions regarding data security remain largely unaddressed. Lack of transparency is one of the main reasons behind it (Rantos et al., 2018). Concerns about data security should not be based solely on the information that such applications can collect about users, but most importantly on the conclusions regarding user behavior, preferences, and attitudes that can be determined by analyzing the algorithms of these applications (Zheng et al., 2018).

The willingness and frequency to use HR analytics applications diminish with increased concerns regarding HR data security (Kalvakolanu et al., 2023). This happened due to increased awareness regarding potential breaches of data, non-compliance with privacy regulations, and misuse of data, and thus leads to enhanced risk associated with technologies (Shahzad et al., 2023; Sadeghi, 2024). Furthermore, these concerns exacerbate due to the heightened complexity of the data environment, associated with sophisticated cyber threats, which leads to limited or careful engagement with HR analytics platforms (Thakur et al., 2025). HR analytics benefits get hindered due to aversion to engagement, like reducing bias in HR processes, and improved efficiency (Sadeghi, 2024). Thus, according to privacy calculus theory, employees evaluate perceived benefits of revealing personal information with perceived risks, leading employees to restrict HR analytics use when risk increases from benefits (Giermindl et al., 2021). Hence, organizations need to manage the transparency and security of data to encourage the usage of HR analytics tools.

Previous research has shown that data security concerns have a direct impact on user behavior, such as negatively affecting the readiness to provide personal data (Dinev & Hart, 2006). Data security concerns are negatively linked with disclosure behavior and technology (Gerber et al., 2018). This phenomenon is called the privacy paradox. On the basis of the above-mentioned arguments, it is hypothesized that (Figure 1):

H_1. Data security concerns significantly and negatively impact HR analytics applications usage

2.2. Data security concerns and perceived risk towards HR analytics applications usage

Security is the ability to safeguard information against threats (Hua, 2009) or the ability to ensure that the system can resist attacks that may compromise information and system services (Schneider, 1999). Data security issues are important because employees and customers send personal and financial information in online transactions and systems, and these issues can be viewed as risky among participants (Akhter, 2014). Risk plays an important role in employee behavior and helps explain employee information-seeking behavior and the decision-making process. Previous studies have shown that there are perceived risks caused by uncertainty of employees, especially in online shopping (Bakos, 1997; Martin & Camarero, 2008), digital banking adoption (Iqbal et al., 2024), industry 4.0 (Humayun, 2021), and big data adoption (Tao et al., 2019). However, Youn (2009) mentioned that information security and privacy are associated with uncertainty about how organizations handle personal information and who has access to it. Rajasekharaiah et al. (2020) mentioned that perceived data security significantly impacts an individual's intention to use the latest technology, such as health informatics, big data, and analytics. Individuals do not show buying or usage behavior of such technologies if they do not have any confidence in such technologies.

HR data has a sensitive nature, leading to higher security concerns and risks associated with HR analytics. The increase in perceived risk originates from the chances of data breaches, noncompliance with privacy regulations, and misuse, which leads to an individual's choice to engage with such systems (Giermindl et al., 2021; Miltgen & Smith, 2018). This entails a strong understanding that the connection between data security and perceived risk is crucial for organizations' aims to increase adoption and effective use of HR analytics tools (Giermindl et al., 2021; Khan & Tang, 2016). Hence, considering how to control these risk perceptions, maybe through increased transparency and robust security procedures, is vital to foster broader acceptance and effective disposition of HR analytics (Al-Ma'aitah, 2024). In line with privacy calculus theory, employees make trade-offs among risks and benefits of data sharing, which sometimes leads to decreased engagement when risks exceed the benefits (Princi & Krämer, 2020; Zander & Zieglmeier, 2023). This leads to a dire need for in-depth scrutiny of the specific data security concerns leads to heightened risk among HR professionals, leading to effective decisions regarding adoption of HR analytics (Miltgen & Smith, 2018). Based upon the above arguments, it is hypothesized that (see Figure 1):

H_2. Data security concerns significantly and positively impact perceived risk towards HR analytics applications usage

2.3. Perceived risk and HR analytics applications usage

When it comes to the use of HR analytics applications, the importance of user data security must be considered. For example, the security of user data is inevitably compromised due to the sensitivity of the data required to track the entire functionality of a given data-driven human service. It manages applications and other data collected for machine learning purposes. Though, as the preceding statements show, HR analytics brings marvelous prospects, especially in the area of telecom (e.g., error reduction, efficiency and effectiveness, cost per hire, average time to fill position, succession planning, internal vs external hire rate, retention ratio, training penetration rate, recruitment channel breakdown, etc.). Therefore, the user needs to weigh the benefits he expects to get from using HR analytics applications against the risks associated with potential data breaches.

High perceived risk, like breaches in data or ethical concerns linked with the use of data, leads to fewer chances to adopt or use HR analytics, and is linked with the risk aversion principles (Bagis & Yulianeu, 2024; Giermindl et al., 2021). This aversion gets intensified due to uncertainty surrounding data governance and the chances for negative outcomes, leading towards a conservative approach of technology adoption (Bagis & Yulianeu, 2024; Vitari & Ologeanu-Taddeï, 2018). Hence, an increased observation of security risk, containing both security and privacy dimensions, leads to deterring the adoption and use of innovative technologies, containing HR analytics (Chopdar et al., 2018; Acosta-Enríquez et al., 2023; Youssef et al., 2021). This highlights the vital role of dealing with perceived risk to increase the diffusion and successful application of HR analytics in organizations (Shahzad et al., 2023; Bagis & Yulianeu, 2024).

Specific outcomes expected from HR analytics will lead to increased usage of HR applications and related products (Princi & Krämer, 2020; Kim et al., 2019; Karahoca et al., 2018). From a privacy perspective, the outcomes contradict the privacy and security risk defined as “the expectation of losses associated with the release of personal information” (Xu et al., 2011, p. 46). We further conclude that people will rather not utilize HR analytics when they perceive security risks (Figure 1):

H_3. Perceived risk significantly and negatively impacts HR analytics applications usage

2.4. Mediation of perceived risk between data security concerns and HR analytics applications usage

Security can be defined as the protection of hardware and software against damage, interference, misuse, malfunction, disoperation, or unauthorized use. Ostlund (1974) suggests that the negative consequences of information security lead to an important and deep-rooted concept in customer/employee behavior: perceived risk. Perceived risk is considered an important element of personal behavior and is often used to explain people’s risk-taking and reduction methods (Mitra et al., 1999; Shin, 2010). Many authors have studied the impact of risk on the adoption of mobile banking (Cunningham et al., 2005), big data adoption (Calvard & Jeske, 2018), artificial intelligence (Zhang et al., 2022), industry 4.0 (Pandey, Singh, & Gunasekaran, 2023), and health informatics (Yu et al., 2012). Jalali et al. (2019) concluded that the perceived risk was a major barrier to IoT adoption. Based upon the above arguments, it is hypothesized that (Figure 1):

H_4. Perceived risk mediates the relationship between data security concerns and HR analytics applications usage

2.5. Moderation of digital transparency clarity between perceived risk and HR analytics applications usage

Digital transparency refers to the “ability to look into digital operations and see how companies operate (Corradini et al., 2010, p. 303). According to Scholl and Luna-Reyes (2011), the higher the usefulness of applications will be if digital operations are transparent.

The linkage between perceived risk and HR analytics usage is grounded in such a way that, if employees’ perceived risks are higher, then there are fewer chances for the usage of HR analytics applications. However, the digital transparency clarity serves as a boundary condition; widespread visibility, availability, and transparency in data and analytics applications can weaken the said relationship in many ways, such as ensuring the accountable and ethical use of data (Matheus et al., 2023). It also reflects the analytical utility to social acceptability, reputational compliance, and protection. Accordingly, it is hypothesized that (Figure 1):

H_5. Digital transparency clarity moderates the relationship between perceived risk and HR analytics applications usage in such a way that the relationship gets weakened when digital transparency is high as compared to low

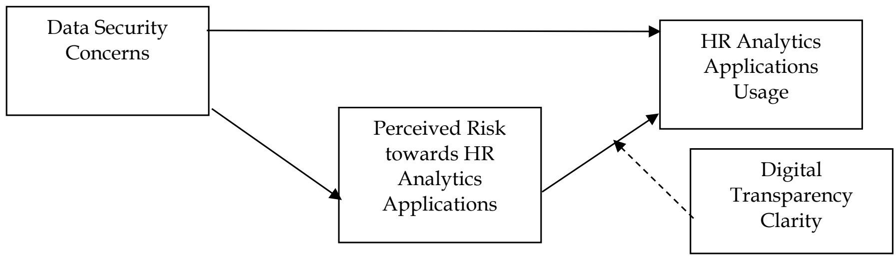

Figure 1. **Theoretical framework**

Source: own study

3. Methods

Quantitative research design was adopted for this study. Research design is based on a positivist philosophy of research, and a deductive approach is used. This enabled us to stay independent and objective throughout the study investigation. The reason for the quantitative methodological choice is to determine the effect size, quantify behavior, and determine the strength of the relationship among variables. This is a causal study where the purpose is to examine the impact of data security concerns on HR analytics applications through mediating and moderating mechanisms. This is a cross-sectional study; data were collected from human resource professionals of telecom operators in Pakistan.

First of all, the list of head offices of telecom operators was extracted. The offices/branches of telecom operators were contacted through personal approach and referral.

Then meeting with HR and branch heads was scheduled to brief them purpose of the research and seek their approval to ask HR representatives to fill out questionnaires. Once the consent and access to the participants were granted. Then, HR employees were approached physically in Rawalpindi and Islamabad in their pure working environment, as well as online using Google Forms to respond to the questionnaire. A well-structured, self-report survey was utilized to collect data on all variables that were filled out by the respondents themselves. The language of the survey was English (simple), the researchers tried to avoid any kind of ambiguity and double-barreled questions by making it clear and simple. The purposive sampling approach, under the non-probability sampling, was used. Only those HR professionals were approached who met our inclusion criteria, such as at least 01 year of working experience in HR departments, background knowledge of HRM and HR analytics, while the clerical staff and chief executive officers were excluded. According to Hoogland and Boomsma (1998), the "rule of five" was used to estimate the sample size, which is items × 05. Henceforth in our situation, there are a total of 24 items, so the minimum sample size should be 120 (24×5). It is recommended by various researchers to use the rule of five to estimate sample size (De Carvalho & Chima, 2014; Kline, 2005). The survey was sent to almost 275 HR employees of various telecom operators in Pakistan, and they were asked to fill out the survey and approach the researcher for any questions. A total of 229 responses were received, resulting in an 83% response rate. The data received from 223 respondents was complete and suitable in all these forms, so all the data was utilized, and the data gathering process was stopped after that. 82% of respondents were male while 18% were female; 76.2% were from the age group 26-40, 16.6% were from the 41-60 years old, and 7.2% from the age group 18-25. Out of 223 respondents, 51.6 % of the respondents were graduates, 44.4% were masters, 1.3% were PhD, and only 2.7% were intermediate. As far as position is concerned, only 1.8% of individuals were assistants, 55.6% were at the officer rank, and 42.6% were at the managerial level. The majority of the respondents (i.e. 75.8%) had 6-10 years' experience, 16.2% in between 0-5 years' experience, and 8% had 11-15 years' experience.

3.1. Measures

The data were collected through self-administered questionnaires, which have been used in earlier studies. All rankings were made using a 5-point Likert scale where 1 shows strongly disagree, 2-disagree, 3-neutral, 4-agree, and 5 represents strongly agree. The questionnaire was in the original English language, because the participants were proficient in English to read and respond to the questions.

Data security concerns were assessed by using a 4-item scale developed by Libaque-Saenz et al., (2014). One sample item is "I am concerned about the safety of my personal information". A 5-item measure developed by Hui et al., (2007), and adapted by Chatterjee et al. (2022) was used to measure perceived risk towards HR analytics applications usage. One sample item is “I believe that there are risks associated with HR analytics applications”. A 9-item scale developed by Aral, Brynjolfsson, and Wu (2012) was used to measure HR analytics applications usage. One sample item is “I use HR analytics to standardize job descriptions and evaluations by making them available online”. To measure the digital transparency clarity, a 6-item scale is used, developed by Portes, N’goala, and Cases (2020). One of the sample items is “There is precise information on the use of personal data.”

3.2. Reliability and validity

The data analysis was conducted using the partial least squares (PLS) method to test the research hypothesis. In this research Smart PLS (partial least squares equation modelling) technique was used to test the hypothesis of the study (Hair et al., 2016). This method has been widely used in prior research studies to examine survey-based data due to its strong predictive validity and robustness (Iqbal et al., 2023; Jaleel & Sarmad, 2024; Shahzad et al., 2023). PLS-SEM is used when the aim of the researcher is to identify key drivers like in the case, data security concerns, as the main driver of HR analytics applications usage. It can be used in small and medium sample sizes, whereas covariance-based SEM requires a larger sample size. Statistical power of PLS-SEM is also high. PLS-SEM is used when researchers want to verify the theory rather than development of the theory. It has no normal data distribution assumptions. Furthermore, PLS-SEM proved to be effective in using resampling methods during significant research analysis (Hair et al., 2014). It consists of a two-stage process of evaluation for the research model (Anderson & Gerbing, 1988) that depicts the measuring model primarily assessed with the use of reliability and validity estimates, linked with analysis of the structural model.

The measurement model involves discriminant and convergent validity to determine consistency, reliability, and validity, whereas the structural model indicates path coefficients (Islam et al., 2020). Confirmatory factor analysis (CFA) was performed to evaluate the consistency of the scales utilizing SmartPLS. The composite reliability was checked to examine the reliability, and data validity was determined using discriminant and convergent validity tests. Fornell and Larcker is applied in research to assess the discriminant validity, which ensures that latent constructs in the model are different from each other, and measure distinct phenomena (Al-Doghan & Abdulhaeva, 2025; Hamid et al., 2017; Zhu et al., 2022). This establishes a researchers that the constructs of their model are unique, ensure an exact explanation of relationships, and prevent multicollinearity issues (Al-Doghan & Abdulhaeva, 2025; Hamid et al., 2017; Hilkenmeier et al., 2020). The findings of CFA are presented in Figure 2. As per Fornell and Larcker (1981) criterion, the minimum threshold for a factor item loading is 0.6, composite reliability (CR) is equal to or more than .60, average variance extracted (AVE) is greater than 0.50, construct reliability > 0.70 and Cronbach's alpha is > 0.6. The results indicate that all items have factor loadings higher than 0.5.

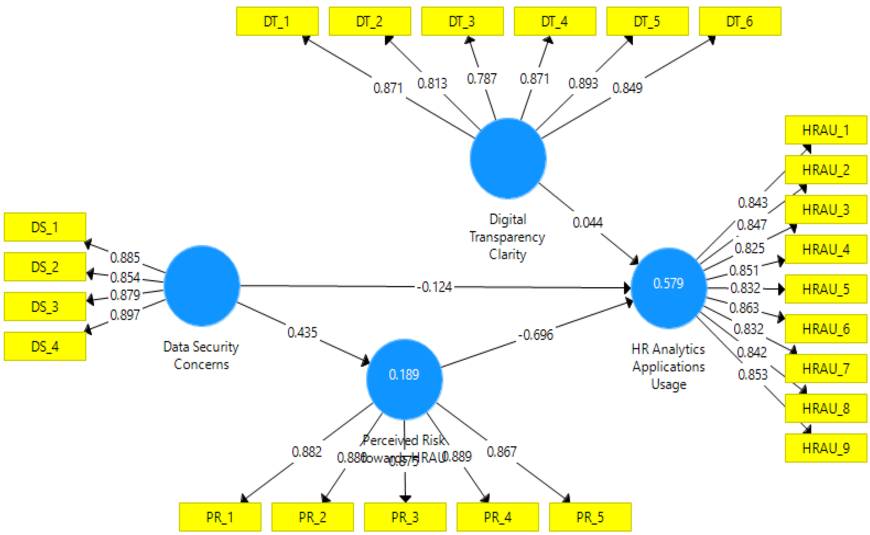

Figure 2. **Confirmatory Factor Analysis**

Source: own study

Table 1. **Factor loadings and convergent validity**

VARIABLE	ITEMS	LOADING	CRONBACH ALPHA	COMPOSITE RELIABILITY (CR)	AVERAGE VARIANCE EXTRACTED (AVE)
DATA SECURITY CONCERNS	DSC1	0.885	0.902	0.931	0.772
	DSC2	0.854			
	DSC3	0.879			
	DSC4	0.897			

PERCEIVED RISK TOWARDS HR ANALYTICS APPLICATIONS USAGE	PR1	0.882	0.927	0.939	0.720
	PR2	0.886			
	PR3	0.875			
	PR4	0.889			
	PR5	0.867			
HR ANALYTICS APPLICATION USAGE	HRU1	0.843	0.949	0.957	0.711
	HRU2	0.847			
	HRU3	0.825			
	HRU4	0.851			
	HRU5	0.832			
	HRU6	0.863			
	HRU7	0.832			
	HRU8	0.842			
	HRU9	0.853			
DIGITAL TRANSPARENCY CLARITY	DTC1	0.871			
	DTC2	0.813			
	DTC3	0.787	0.926	0.944	0.772
	DTC4	0.871			
	DTC5	0.893			
	DTC6	0.849			

Abbreviations: DSC-Data Security Concerns; PR-Perceived Risk; HRU- HR Analytics Applications Usage; DTC-Digital Transparency Clarity

Source: own study

Table 1 represents the factor loadings for each item of the variables and convergent validity. None of the items possessed factor loadings less than 0.5, so all items were retained as per Fornell and Larcker's (1981) recommendation. Table 1 shows the results for alpha reliability, construct and composite reliability, and AVE. All the values meet the threshold.

3.3. Discriminant validity

To know exactly whether items are distinct from each other or not, a discriminant validity test was performed. Fornell & Lacker's criteria and the HTMT ratio, both these methods were used in this research to determine discriminant validity. In Table 2, as per Fornell & Lacker's criteria, all non-diagonal values are smaller than the diagonal values, which confirms the discriminant validity of variables. According to Henseler et al. (2015), the new HTMT measure was also checked. The findings of the HTMT ratio (Table 3) show that all variable values are less than the predefined minimum threshold value of 0.85. Moreover, the findings of the HTMT ratio study demonstrate that the variables were distinct from one another. The results are presented in Table 3. The HTMT ratio validates the discriminant validity test.

Table 2. **Fornell and Lacker's criterion**

Variables	01	02	03	04
DS	0.879			
DTC	0.009	0.848		
HRU	-0.427	0.060	0.843	
PR	0.435	-0.025	-0.725	0.879

Abbreviations: DSC-Data Security Concerns; PR-Perceived Risk; HRU- HR Analytics Applications Usage; DTC-Digital Transparency Clarity

Source: own study

Table 3. **HTMT ratio**

Variables	01	02	03	04
DS				
DTC	0.045			
HRU	0.460	0.062		
PR	0.475	0.043	0.800	

Abbreviations: DSC-Data Security Concerns; PR-Perceived Risk; HRU- HR Analytics Applications Usage; DTC-Digital Transparency Clarity

Source: own study

3.4. Model fit indices

To check the model fit indices, there are recommended thresholds for SRMR and NFI i.e., (SRMR < 0.08; NFI > 0.90) (Ringle et al., 2024). The results indicated that both the values are met (SRMR 0.040; NFI 0.918).

4. Results

This study employed two analysis methods: the first is quantitative, and the second is statistical analysis. Initially, the missing values and outliers were checked, as none of the missing values and outliers were reported, so further analysis began. In quantitative analysis, a demographic data set of variables was utilized, which involved the use of One-way ANOVA. On the other hand, statistical analysis is done through correlation and regression analysis to examine the association among variables and test hypotheses. Two different software tools were used to calculate results; the first one was SPSS for quantitative analysis, which involved one-way ANOVA and correlation analysis. SmartPLS 4 is used for SEM, CFA, and regression analysis. To prevent the common method bias, Harman's single-factor test was employed. The findings indicated a 38.03% variation, which is below than the threshold, i.e., 50%. So, there was no common-method bias issue in data.

4.1. Control variables

To examine the impact of demographics on the outcome variable, i.e., HR analytics applications usage, a one-way ANOVA test was performed through SPSS. The results indicate that gender ($F= 1.482$, $p > .05$), age ($F= 1.105$, $p > .05$), education ($F= 1.777$, $p > .05$), and designation ($F= .425$, $p > .05$) don't have the potential to bring change in the dependent variable. The demographics don't bring any variation in the outcome variable except experience. The experience ($F= 2.996$, $p < .05$), has the potential to significantly impact on dependent variable. Furthermore, regression analysis was performed to check the actual impact of experience on HRA applications usage. The results indicated that there is no significant impact of experience on HRA applications usage ($\beta = .108$, $p > .05$). The results of one-way ANOVA are presented in Table 4.

Table 4. **One-way ANOVA**

Demographics	F Statistics	p Value
Gender	1.482	.225
Age	1.105	.333
Education	1.777	.152
Designation	0.425	.654
Experience	2.996	.032

Source: own study

4.2. Hypothesis testing

Smart PLS software was used to perform multiple regression analysis to examine the effects or impact of the comprehensive study model, by considering both direct and indirect paths. The regression analysis was performed to examine the direct as well as the mediation and moderation regression path analysis. Structural Equation Model (SEM) has been examined by algorithmic as well as boot-strapping analysis. The values of beta and R-squared were determined by algorithmic analysis. On the other hand, the significance was determined using the p-value obtained through bootstrapping.

Table 5 describes that there is a negative and significant impact of data security concerns on HRA applications usage ($\beta = -.124$, $p < .05$), thereby supporting H1. Data security concerns had a positive and a direct effect on the perceived risk towards HR analytics applications usage ($\beta = .435$, $p < .05$), thereby supporting H2. Perceived risk significantly and negatively impacts HR analytics applications usage ($\beta = -.705$, $p < .05$), thereby supporting H3.

Table 5. **Direct paths**

Paths	Original Sample	Standard Deviation	T Statistics	p Value
Data Security Concerns HR Analytics Applications Usage	-0.124	0.048	2.603	0.010
Data Security Concerns Perceived Risk towards HR Analytics Applications Usage	0.435	0.050	8.699	0.000

Perceived Risk Towards HRUA HR Analytics Applications Usage	-0.705	0.043	16.586	0.000

Source: own study

Moreover, Table 6 results from the analysis show that the data security concerns negatively impact HR analytics applications usage through perceived risk (β = -.307, p <.05), thus supporting H4. Results indicate that the assumptions of Privacy calculus theory, as it validates the significance of the benefit component and cost component. Moreover, the relative magnitude of benefits and risk coefficients indicates equilibrium of the calculus. PC theory provides contextual evidence of the way trade-off is balanced in practice.

Table 6. **Indirect paths**

Paths	Original Sample	Standard Deviation	T Statistics	p Value
Data Security Concerns Perceived Risk Towards HR Analytics Applications Usage HR Analytics Applications Usage	-0.307	0.041	7.493	0.000

Source: own study

Moreover, Table 7 results from the analysis show that the digital transparency clarity moderates the relationship perceived risk towards HRA applications usage and HR analytics applications usage in such a way that the relationship gets weakened when digital transparency clarity is high as compared to low and vice versa, (β = -.180, p <.05), thus supporting H5. The moderation slope/graph is as below (Figure 3)

Table 7. **Moderation path**

Paths	Original Sample	Standard Deviation	T Statistics	p Value
Perceived Risk Towards HR Analytics Applications Usage HR Analytics Applications Usage-DTC	-0.180	0.057	3.161	0.002

Source: own study

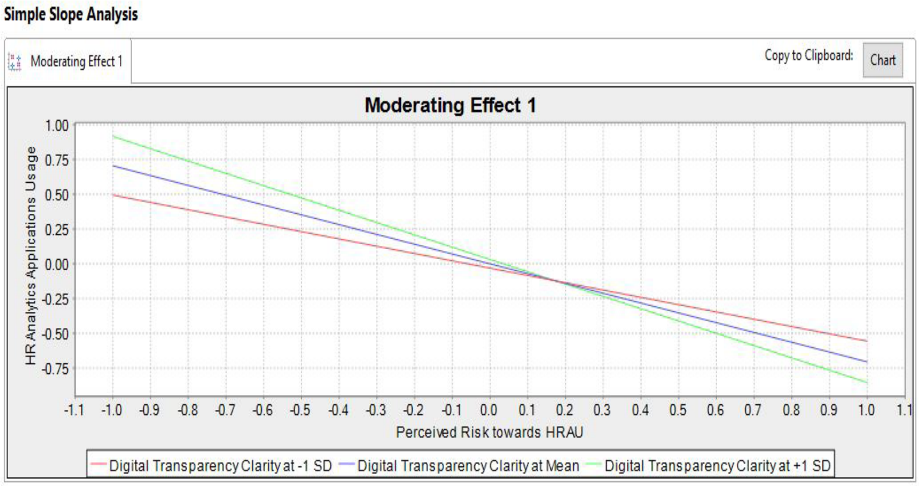

Figure 3. **Moderation graph**

Source: own study

5. Discussion

This study challenges many scholars' and experts' arguments about HR/ people analytics. These views range from the view that modern technological advancements in HR analytics are generally more objective and amenable to human decision-making (e.g., Kryscynski et al., 2018; Martin-Rios et al., 2017), that people analytics can increase transparency and reduce biases (Jabagi et al., 2020), that future behaviour can be precisely extrapolated based on past or current behaviour, etc. (e.g., Chamorro-Premuzic et al., 2017). This study identified the dark side of HR analytics applications, i.e., data security concerns.

This study also shows that there is a dark side of HR analytics, i.e., data security concerns adversely affect HRA applications usage (H1). Data security positively impacts perceived risk (H2). These findings are in line with the findings of previous research (Cui et al., 2018; Koo & Fallon, 2017; McKnight et al., 2011). The study shows that perceived risk negatively impacts the HR analytics applications usage (H3), which is consistent with the idea of privacy calculus theory (Laufer & Wolfe, 1977).

This study found the mediating role of perceived risk between data security and applications of HR analytics. Thus supporting (H4). The findings of the study are aligned with the results of earlier studies that data security triggers perceived risk and risk ultimately leads to the decline in the usage of HR analytics applications (Tiwari et al.2024).

The results of H5 are aligned with the findings of Scholl and Luna-Reyes (2011) and Matheus, Faber, and Janssen (2023). The digital transparency depends upon the beholder's eyes and what he/she is looking for. The release of data from analytics applications, digital operations is required to create transparency to win individuals' trust and confidence in HR analytics applications.

Data security is a major challenge since technology brings risks to people as well. Firms need to be responsible, accountable, and capable of protecting employees' sensitive information (Kakkar & Kaushik, 2019). HR employees need to consider data security when gathering data about employees, particularly when obtaining information from external sources. Additionally, considering the rapid generation of data due to digital technologies such as HR analytics applications and online information sharing, it is essential to evaluate whether companies possess the authority and right to gather employee data.

This study contributes to the body of knowledge by examining how perceived risk mediates between data security concerns and HR applications usage. It also provides a theoretical contribution by providing a moderating mechanism (digital transparency) through which data security concerns lead towards HR analytics usage.

HR practitioners better understand and trust the way data is being utilized, when digital transparency clarity is high, HR professionals are better able to understand and trust how their data is being used, thus decreasing the effect of perceived risks on the willingness of employees to use HR analytics (Chen et al., 2024). Conversely, a dearth of digital transparency clarity can increase the negative effect of perceived risks, making HR professionals more reluctant to engage with HR analytics implementation despite strong security measures (Zieglmeier & Pretschner, 2023). This is specifically relevant in the setting of emerging AI-enabled HR analytics, where data processing and transparency regarding algorithmic decision making, effect user acceptance and control perceived risk (Shahzad et al., 2023; Bagis & Yulianeu, 2024).

5.1. Implications

This study contributes to the theoretical body of HR analytics by showing how data security concerns and perceived risks can lower the usage of HR analytics applications. This study contributes towards theory on HR analytics adoption as it is one of the first frameworks to mitigate data security issues through digital transparency clarity among HR professionals, the telecom sector of Pakistan, which is often overlooked in empirical research. The research framework is built upon privacy calculus theory, and digital transparency clarity has been added in this model to improve HR analytics applications usage. This study makes a significant contribution to evidence-based HRM literature by highlighting the process (i.e., the mediation of perceived risks) through which data security concerns influence HR analytics applications usage. The available literature is sparse in research investigating the data security concerns, perceived risk, and digital transparency clarity (Vadithe & Bikrantkesari, 2024; Huang et al., 2023).

The telecom sector and other organizations need to set up comprehensive and clear guidelines in the form of an ethical charter that outlines the “Dos” and “Don’ts” of data access in the HRA context. It is recommended that HR professionals understand the approach to data access, data storage, and analysis, which ways are permitted in their jurisdiction; who their stakeholders are and their rights to access; and who owns the data on devices such as personal computers, laptops, servers, and mobile phones. Keeping aside the legal requirements, organizations are advised to inform employees about their right to withdraw data gathering process and offer them an opportunity to do so. Employees are the key stakeholders in HR analytics applications projects and must not feel afraid to raise their concerns (Leong, 2017*). Giving attention to employees’ concerns and viewpoints can elucidate questionable practices that management has potentially overlooked. The companies must emphasize effectiveness by displaying a higher transparency level in digital operations and analytics applications by releasing the data and insights.

5.2. Limitations and future directions

While the findings listed above have noteworthy and significant implications for human resource management professionals, it is equally vital to note a few limitations of this research. The data gathered was quantitative in nature. The quantitative data has the benefit of offering a standardized format that enables researchers to give a snapshot of employees’ views of HR analytics. Though the findings extracted from the quantitative data did not include too many details and considerations about how respondents chose certain answers, and the lack of personalization to further discuss the questions also risks not capturing the bigger picture of the variables. So, future researchers can conduct qualitative research on the risk factors of HR analytics applications to get a more in-depth understanding of issues in HR analytics applications. A small sample (HR professionals of telecom operators) was used in the study. Data was collected only from telecom companies located in Rawalpindi and Islamabad, affecting the generalizability of the study. It is also important to note that the effect of the country and the sector should be interpreted with caution, as the survey only focused on the telecom sector of Pakistan. This could therefore be improved by considering more Asian/ developing countries and industries and conducting additional analysis to ensure that the results are accurate and consistent. Future research can investigate the privacy aspects of big data in the HRA context. The study provides an avenue for exploring the moderating effects of cybersecurity and digital leadership between perceived risk and HRA. The moderating role of ethical climate and ethical leadership can also be tested in said relationship.

6. Conclusion

This study shows the dark side of the emerging technology, i.e., HR analytics applications usage in the Pakistan telecom sector. This research study aims to present empirical findings for a theoretical framework that relates data security concerns to the usage of HRA among HR professionals in a developing country, i.e., Pakistan. Furthermore, the mediating mechanism of perceived risk and the moderating role of digital transparency clarity between data security and HRA were tested. The framework was tested on a sample of HR professionals working in the telecom sector of Pakistan, and the results were obtained using structural equation modeling, partial least squares. The key findings from the study summarize that data security positively impacts perceived risk; data security concerns and perceived risk have been found with a negative impact on the usage of HRA among professionals in Pakistan's telecom industry. The perceived risk acts as a mediator between data security and HRA linkage. Moreover, the role of digital transparency clarity in weakening the perceived risk-HRA applications usage relationship was also tested and validated. HR and Top professionals can improve the usage of HR analytics through transparent digital operations. Consequently, all of these five hypotheses were accepted.

Authors' contribution

M.Q.S.: article conception, research methods applied, conducting the research, analysis and interpretation of results, draft manuscript preparation. **M.P.:** theoretical content of the article, data collection. **R.A.A.K.:** theoretical content of the article, data collection, draft manuscript preparation.

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

While preparing this work, the authors did not use any tool/service.

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