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Untapped Potential and Country-of-Origin: Do Employee attitudes and HR Analytics Boost Career Growth with a COM-B model Application

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Abstract

Unexploited creative employees' potential and country of origin (COO) effects are vital for organizational performance. HR analytics has emerged as a critical tool in HRM, shifting the focus from intuition to data-driven decision-making based on the COO effect. This study examined the impact of determinants of employee attitudes towards HR Analytics (technological readiness, competitive pressure, organization preparedness) on organizational career growth and the level of HR analytics with COO effects in the service sector. This study investigates the mediational role of employee attitudes between antecedents, organizational career growth, and the level of HR analytics. A survey (n=344) targeting HR managers of Pakistan's tourism and services industries was collected via a self-administered questionnaire. We applied PLS-SEM 3 software to analyze the collected data. Findings show that organizational preparedness, technological readiness, and competitive pressures are all directly and positively linked with both levels of HR analytics and organizational career growth. Also, employee attitudes toward HR analytics significantly mediate the proposed paths. This research contributes to understanding how HR analytics determinants, mediated by employee attitudes, foster organizational career growth and the level of HR analytics adoption. The results offer valuable insights for HR managers and top management to consider COO effects and workers' potential, emphasizing the importance of fostering positive attitudes towards HR analytics to maximize its impact on employee career development and adopting HR analytics.

Keywords: Organizational Preparedness; Country of origin effect; Technological Readiness; Competitive Pressure; HR Analytics

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1 Introduction

Management considers local culture and country of origin (COO) effects to explore workers' untapped potential for better performance (Al-Sulaiti & Baker, 1998). Past studies have documented that COO effects are vital for data security, marketing, and HR managers in local business organizations to manage workers' behavior (Alhitmi et al., 2024; Li et al., 2024) in characteristic ways. Similarly, the COO effect is critical in the tourism, education, and health sectors (Jaffar et al., 2021; Tan et al., 2024). Managers take critical decisions for organizations and consider COO effect to hire parent country workers to recruit the required talent people (Al-Khulaifi et al., 2001; Majeed & Shahid, 2023). Scholars have debated on these factors and argued that country of origin or host country can better fit in responding to local culture and demands to satisfy consumers (Al-Sulaiti et al., 2023).

The field of HR analytics is undergoing a period of rapid advancements with the country of origin, fueled by a divergence of factors. The global market for HR analytics is projected to reach a staggering $ 9 bn by 2032, with a significant portion of organizations planning increased investment in technology-based HR solutions (Adroit Market Research, 2023). HR analytics (HRA) has emerged as a key innovation within the broader HRM domains (Bahuguna et al., 2024; Huselid, 2018). Its appeal lies in leveraging data to inform critical decisions across the employee's lifecycle, from recruitment and selection to performance management and talent development (Boudreau & Cascio, 2017; Bahuguna et al., 2024). Introducing disruptive technologies such as AI, machine learning, and the IoT has further accelerated the adoption of data-driven techniques in HRM (Dwivedi et al., 2021; Niu, 2024). These advancements pave the way for fresh applications such as sentiment analysis to measure worker morale and even data-driven candidate selection (Gelbard et al., 2018).

Through HR analytics, the business can transform data to inform HR decisions with COO effects; organizations can expect greater rigor, improved credibility of the HR function, and a strategic advantage stemming from a deeper understanding of their workforce (Huselid, 2018; McCartney & Fu, 2022; Starodub, 2015). However, despite its growing popularity, the academic field of HRA remains relatively nascent specifically. While research is growing, challenges persist in establishing a unified understanding of HRA practices, likely due to the ongoing evolution of the field (Margherita, 2022). The current state of HRA literature can be characterized by a lack of consistent frameworks, leading to a fragmented research landscape (Levenson & Fink, 2017).

The digital revolution has played a crucial role in enabling the growth of HR analytics. The increased use of IT has facilitated the collecting, storing, and analysis of large volumes of employee data (Marler & Boudreau, 2017; Niu, 2024). Modern HR information systems, cloud platforms, and mobile applications offer significant improvements over legacy systems in their capacity to manage and analyze data (Kim et al., 2021). Google's utilization of data analytics to inform recruitment decisions highlights the possible utilization of modern techniques (Hamilton & Sodeman, 2020; Xiao et al., 2023). According to van der Togt and Rasmussen (2017) are of view, Human resource analytics as an AI-driven tool to align employee performance with organizational objectives. According to the survey by Xiao et al. (2023) and SkyQuest (2022), only 63% of organizations are ready to opt for AI for Human resource analytics.

Researchers employ various terms: HR analytics, people analytics, and human capital analytics (Giermindl et al., 2022; Cavanagh et al., 2023; Minbaeva, 2021). These constructs converge on AI-powered methods for enhanced employee management and data-driven, objective HR decision-making (Margherita, 2022). Prior research indicates that HR analytics, powered by AI, can leverage progressive investigative and prognostic functionalities to improve employee performance. This generates substantial assistance for the entire organization. These benefits encompass superior financial performance (Aral et al., 2012; Qureshi et al., 2020). That increased return on investment (Gurusinghe et al., 2021; Harris et al., 2011). All these efforts improved business outcomes. Organizations achieve these advantages by deploying HR analytics to gather massive employee data of their workforce (Coco et al., 2011; Chatterjee et al., 2022).

This study had multifaceted contributions to existing literature. Firstly, it proposes and tests a theoretical framework based on the COM-B (Capability-Opportunity-Motivation-Behavior) model (Szinay et al., 2021) to understand HR manager's attitudes toward HR analytics. Secondly, drawing on Career Construction Theory (CCT), the framework assists us in understanding attitudes toward HR analytics by examining the antecedents behind HR analytics adoption.

Thirdly, the study identified the antecedents of employee attitude towards HR data analytics, how HR professionals' organizational preparedness, competitive pressure, and technology readiness influence individual attitudes toward HR analytics adoption. While prior research has extensively examined consumer TR, we address the gap in knowledge regarding employees' organizational preparedness, competitive pressure, and technology readiness (Bukhari et al., 2024). This study offers practical guidance by identifying these factors as crucial in enhancing the HR professionals' positive attitudes toward HR analytics for adoption, specifically in Pakistani service sectors.

Furthermore, the study is being conducted to answer how HR professionals enhance their technological skills and highlight the optimistic link between HR analytics implementation and career advancement, alongside the level of adoption itself. These findings underscore the importance of organizational preparedness. Organizations aiming to implement HR analytics must look for not only the technological readiness of employees but also organizational preparedness during HR professional recruitment and training processes.

2 Literature Review:

The decision to adopt HR analytics is influenced by internal and external factors based on local culture and COO effects. This section explores three key drivers: competitiveness pressure, organizational preparedness, and Technological readiness.

2.1 Competitive pressure and organization career growth

Business partners and competitors significantly impact an organization's technology adoption choices (Dastane, 2020; Musawa & Wahab, 2012). For instance, companies employing app-based interviews in FMCG) (Fast-Moving Consumer Goods) sector may gain an edge in mass recruitment (Musawa & Wahab, 2012). Effective people management is a cornerstone of organizational success. Competitors who leverage HRA to improve talent acquisition, development, and retention gain a strategic advantage, pressuring HR teams to follow suit (Etukudo, 2019; Huselid, 2018). HR managers must stay abreast of technological advancements and industry trends in HRA adoption to remain competitive.

2.2 Organizational Readiness and HRA Adoption

HRA implementation necessitates significant resources, including technology infrastructure and skilled personnel (Angrave et al., 2016). Both physical assets (tangible) and human expertise (intangible resources) are crucial for successful HRA adoption. A robust IT infrastructure and a competent analytics team are essential for data capture, transformation, analysis, and automation (Aral et al., 2012; Qureshi et al., 2020). Unfortunately, overlooking initial IT infrastructure development can create hurdles in the long run (Hsu et al., 2021). A positive association exists between strong IT capabilities (Maduku et al., 2016) and successful IT innovation adoption.

Further, organization readiness, the availability of funds for investment, is a critical factor in HRA adoption. Scarcity of monetary funds can be obstacles for the acquisition of obligatory aptitude and information technology infrastructure. Human resource analytics is a rapidly growing arena demanding alliance across different skills that requires adequate financial support (Holbeche, 2022). Adoption costs include setup, training, and ongoing operational expenses, encompassing implementation and data security and privacy measures (Chau & Hui, 2001; Esteves & Curto, 2013; Ghobakhloo et al., 2012; Maroufkhani et al., 2019). Furthermore, realizing substantial results from HRA takes time, particularly in human resources; where measuring the influence of implemented commendations is a lengthy process. Furthermore, continuous employee training on new tools and technologies is key for adoption of HR analytics, pretense a significant challenge for organizations (Wamba et al., 2017; Cho et al., 2023). A seamless diffusion process can be achieved by providing on-the-job training (Nguyen et al., 2021; Radeva, 2019).

One important factor is the availability of suitable human resources. This comprises in-house resources, outside knowledge, or contracted experts (Provost & Fawcett, 2013). Employers need to make sure that their workforce have the data mining, aggregation, processing, and visualization capabilities that are necessary for implementation of HRA (Wang & Hajli, 2017).

The lack of dedicated HRA teams is a common challenge in many organizations, particularly those with limited in-house capabilities (Shet et al., 2021)

2.3 Employee Attitudes toward Analytics

Prior literature shows that employee attitudes significantly affect technology adoption, including HRA (Ekka & Singh, 2022). A positive and prompt attitude towards learning and adopting HRA is crucial for a smooth transition (Angrave et al., 2016; Shrivastava, 2024). However, HR professionals familiar to "soft skills" management may find data-driven analytics, especially when applied to human resources, unfamiliar and even uncomfortable. Training programs can help with this by giving HR professionals the know-how to comprehend analytics, recognize data sources, and incorporate data insights with more comprehensive organizational strategy. A successful HRA team requires a balance of analytical capability and strong HR and business acumen. Collaboration between HR and analytics teams fosters a deeper understanding of organizational challenges, enabling them to leverage data for actionable solutions (Nocker & Sena, 2019).

2.4 Technology Readiness and Individual Adoption

TR is a personality trait demonstrating an employee's openness to new technologies (Blut & Wang, 2020). The introduction of new technologies can induce feelings of insecurity and frustration (Son & Han, 2011). Therefore, an employee's willingness to embrace HRA results from a balance between positive motivators and negative inhibitors (Parasuraman, 2000). Generally speaking, technology readiness is seen as a two-dimensional term that includes both motivators and obstacles. (Blut & Wang, 2020). Few studies indicate that a strong correlation between TR and technology adoption (Blut & Wang, 2020; Son & Han, 2011). Positive TR motivators act as drivers, while negative inhibitors create resistance.

***H1:** Technology readiness motivators will be positively associated with attitudes toward HR analytics.*

2.5 Individual Adoption and Organizational Career Growth

OCG refers to an employee's perception of advancement opportunities within the current organization (Japor, 2021; Spagnoli, & Weng, 2019). It encompasses factors like career goal progress, professional development opportunities, promotion speed, and salary increases (Weng & Hu, 2009). With data analytics increasingly recognized as the future of HR (Chillakuri & Attili, 2021), HR professionals who develop proficiency in HRA are well-positioned for career advancement. The lack of analytical skills in HR departments often necessitates hiring external talent (Penpokai et al., 2023; Vargas et al., 2018). Conversely, HR professionals who embrace HRA gain a competitive edge and the opportunity to contribute strategically to organizational goals (Etukudo, 2019; Weng & Hu, 2009). Organizations that prioritize HRA are likely to value and reward employees who contribute to its successful implementation, further promoting career advancement for HR analytics managers. This aligns with the concept of adaptation in the COM-B model, where adapting a specific response precedes positive adaptation outcomes.

H2: *Individual attitude towards HR analytics will be positively linked with OCG.*

2.6 Individual Adoption as a Mediator

Organizational preparedness plays a critical role in fostering a positive environment for HR analytics adoption. When business invest in infrastructure, resources, and training programs related to HRA, create opportunities for employees to develop their capabilities (Duan et al., 2021). This supportive environment can translate into increased employee motivation and a willingness to embrace HRA (Girdwichai & Sriviboon, 2020; Moturi et al., 2022). Further, TR motivators encourage the adoption of new technologies, while inhibitors have the opposite effect. Moreover, HR managers' job chances are improved by implementing HRA skills (Vargas et al., 2018). Businesses are looking for HR personnel with experience in data analysis more and more (Batovrina et al., 2021). Therefore, the relationship between TR components and OCG is thought to be mediated by the individual use of HR analytics. According to Szinay et al. (2021), the COM-B model aligns the link between adaptability resources and adaptation outcomes through the mediation of adapting responses. Further, competitive pressure leads to a positive perception of HRA as a tool for improving the organization's competitiveness, employee attitudes will be more favorable. This increased motivation can translate into higher adoption rates and leads to OCG and level of HR analytics adoption (McCartney & Fu, 2022).
H3a: *Adoption of HR analytics mediates the relationship between technology readiness and a) OCG b) level of HR adoption.*
H3b: *Adoption of HR analytics mediates the relationship between organizational preparedness and a) OCG b) level of HR adoption.*
H3c: *Adoption of HR analytics mediates the relationship between competitive pressure and a) OCG b) level of HR adoption.*

2.7 Attitude towards Analytics

People develop opinions about the proposed innovation during the persuasive phase of the creativity-decision process (Rogers, 2003). Businesses using analytics anticipate that this information will foster favorable views among staff members for the novel strategy and innovation (Dehghan et al., 2024; Muhammad, 2023). However, it's critical that HR professionals are prepared for HR analytics. Their willingness, dedication to learning, and purpose to use this innovative approach to HR assessment are all included in their readiness (Vargas et al., 2018). According to Vargas et al. (2018), HR professionals and CEOs who have traditionally placed emphasis on "soft skills" may display unease with analytics, especially when it comes to issues pertaining to people (Al-Sulaiti, 2002).

HR personnel probably need training in the principles of analytics, which includes sources of data, comprehension, and synchronization with the company's overall strategy, in addition to internal measurements, in order to cultivate a more positive mindset (Han & Stieha, 2020). Positive attitudes lead to positive conduct and vice versa, according to Ajzen and Fishbein's (2000) theory of attitude prediction. They do, however, warn against drawing inconsistent conclusions from the use of general attitude indicators to forecast behavior in particular circumstances (such as HR). As a result, the specific environment and behavior (HR analytics adoption) require careful attention. The relationship between attitudes and adoption behavior has been investigated in a variety of innovation scenarios.

H4: *Attitude towards HR Analytics is positively related to the level of individual intention to a) adopt HR Analytics and b) OCG*

2.8 Capability-Opportunity-Motivation-Behavior (COM-B) Model- Theoretical Framework

This study leverages the COM-B model as a robust theoretical framework to investigate the intricate interplay between individual and organizational factors that shape HRA adoption and its subsequent impact on employee career growth and level of HR adoption (Kirkpatrick & Hoque, 2022). The COM-B model posits that specific behavioral outcomes, such as the adoption of a new technology, are driven by a confluence of psychological and contextual factors (Howlett et al., 2019). This study applies this framework to the context of HRA adoption, examining the following core components: Firstly, the capability refers to the individual's skill set and knowledge base necessary for effective HRA adoption and utilization (Shet et al., 2021). Technological readiness reflects an individual's openness to new technologies (Son & Han, 2011). Further, the opportunity component represents the organizational environment that either facilitates or hinders the adoption of a specific behavior.

Further, the psychological factors that drive or inhibit an individual's adoption of HRA. A central focus of this study is to understand employee attitudes toward HRA. Lastly, the behavior of an individual's adoption of HR Analytics (Vargas et al., 2018). The level of adoption can range from actively using and advocating for HRA to resisting its implementation. Through applying the COM-B model, this study aims to understand the complex interplay between these factors and their influence on HRA adoption within the Pakistani service sector.

While the COM-B model provides the core framework, we recognize the additional relevance of Career Construction Theory (CCT) (Savickas, 2013) in understanding employee attitudes. CCT emphasizes the role of individual career aspirations and the need to adapt to changing environments.

2.9 Theoretical Framework

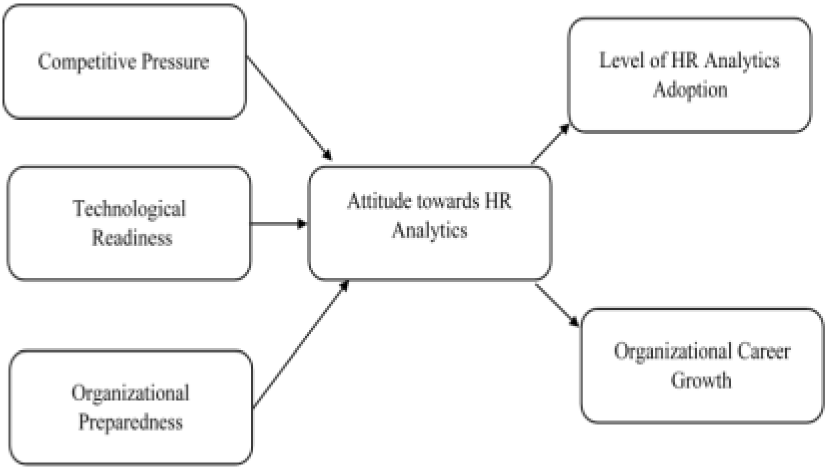

Figure 1: Theoretical Framework

3 Methodology

3.1 Sample:

A survey (n=344) targeting HR managers of the services sector (banking, insurance, hospitality Sector) was collected through self-administered questionnaires.

3.2 Measures

The structured questionnaire was self-administered and used a 5-point Likert scale, with 1 denoting strongly disagree and 5 denoting strongly agree. A three-item scale was used to quantify the competitive pressure (Trucharte et al., 2023). On the other hand, an instrument consisting of four items was utilized to assess organizational readiness (Chong et al., 2012; Pearson & Grandon, 2004). Five five-item measures recommended by Lumsden et al. (2013) and Liang et al. (2018) are used to test technology readiness. On the other hand, a 4-item scale was used to gauge respondents' attitudes on HR analytics (Johnston & Warkentin, 2010). Additionally, a 5-item Rogers (2003) adoption level scale was employed, and finally, a 15-item organizational career progression scale was employed (Tariq & Weng, 2018).

4 Data Analysis

The current study used the partial least squares-structural equation modeling (PLS-SEM) technique to analyses the collected data (Ringle et al., 2015). PLS-SEM-3 makes sense because it is a sophisticated and reliable second-generation analysis tool that uses a variance-based methodology (Hair et al., 2021). Additionally, it can simultaneously assess every interaction in the model studied (Hair et al., 2021; Kock & Hadaya, 2018). It is considered appropriate to use the PLS-SEM because the study's goal was to predict the endogenous variables (Hair et al., 2021). Even though the data distribution is not typically assumed as usual in PLS-SEM modeling, it is helpful to look at it. The researcher visually analyzed the data using histograms and normal probability plots created with SPSS 27 (Pallant, 2020). This analysis showed that the study's data were appropriately distributed.

The PLS-SEM approach was used because it can handle both reflective and formative constructs. In the current study, every construct was first-order and reflective. Hair et al. (2021) state that the measurement model must be evaluated before the structural model. Furthermore, the validity and reliability of each reflective construct used in this study must be assessed. First, each examined construct's outer loading was assessed for each item's reliability. The results showed that all items were retained since they fell within the acceptable range of 0.645 to 0.890, as shown in Table 1 (Duarte & Raposo, 2010; Hair et al., 2021). Figure II shows the measurement model. The internal consistency reliability was evaluated using composite reliability (CR) and Cronbach's alpha values, which were more significant than the 0.70 thresholds (Bagozzi & Yi, 1988; Hair et al., 2021).

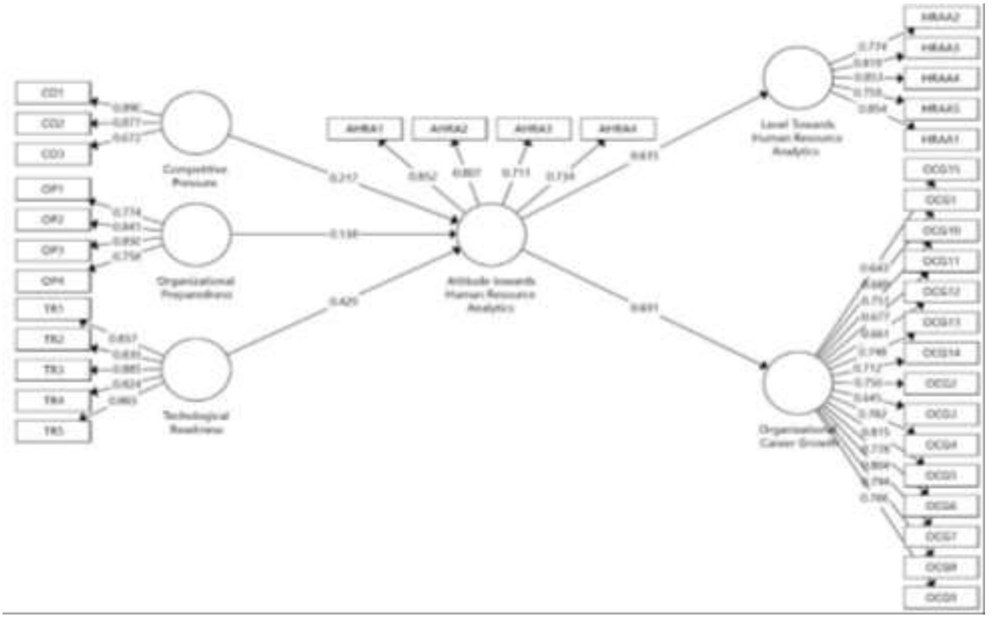

Figure 2: Measurement Model

Additionally, the convergent validity was evaluated using the average variance extracted (AVE) criterion, which was put out by Fornell and Larcker (1981). The AVE score exceeded the 0.5 impediment (Chin, 1998; Hair et al., 2021). Additionally, the heterotrait-monotrait (HTMT) ratio, cross-loadings, and the Fornell-Larcker test were used to assess discriminative validity (Fornell and Larcker, 1981; Hair et al., 2021; Henseler et al., 2015).

Table 1: Reliability and Validity Statistics

Construct	Items	Loading	α	Composite Reliability	AVE
Attitude towards Human Resource Analytics	AHRA1	0.852	0.790	0.859	0.605
	AHRA2	0.807			
	AHRA3	0.711			
	AHRA4	0.734			
Competitive Pressure	CO1	0.890	0.763	0.858	0.671
	CO2	0.877			
	CO3	0.672			
Level Towards Human Resource Analytics	HRAA1	0.854	0.872	0.907	0.661
	HRAA2	0.774			
	HRAA3	0.819			
	HRAA4	0.853			
	HRAA5	0.759			
Organizational Career Growth	OCG1	0.689	0.939	0.947	0.543
	OCG10	0.751			
	OCG11	0.677			
	OCG12	0.661			
	OCG13	0.748			
	OCG14	0.712			
	OCG15	0.643			
	OCG2	0.756			

	OCG3	0.645				
	OCG4	0.782				
	OCG5	0.815				
	OCG6	0.778				
	OCG7	0.804				
	OCG8	0.794				
	OCG9	0.766				
Organizational Preparedness	OP1	0.774	0.822	0.882		0.651
	OP2	0.841				
	OP3	0.850				
	OP4	0.758				
Technological Readiness	TR1	0.857	0.908	0.931		0.730
	TR2	0.839				
	TR3	0.885				
	TR4	0.824				
	TR5	0.865				

Discriminative validity was assessed using the Fornell-Larcker approach. This method requires that the square root of AVE be greater than the correlation between the constructs under study. Table II's data demonstrate that values exceeded the correlation among the latent constructs. The results in Table 3 indicate that HTMT loading was under the threshold value of 0.85, determined by Henseler et al. (2015) and Hair et al. (2021).

Each measurement item must have the highest loading at its constructs compared to other research constructs to further validate the discriminative validity of all latent constructs. Table IV contains cross-loading statistics. All in all, these findings supported the standard for validity and reliability of all the measurement models examined.

Table 2: Fornell-Larcker Test

	1	**2**	**3**	**4**	**5**	**6**
Attitude towards Human Resource Analytics	0.778					
Competitive Pressure	0.562	0.819				
Level Towards Human Resource Analytics	0.615	0.600	0.813			
Organizational Career Growth	0.691	0.625	0.702	0.737		
Organizational Preparedness	0.444	0.483	0.467	0.703	0.807	
Technological Readiness	0.635	0.650	0.548	0.656	0.469	0.854

Table 3: Heterotrait–Monotrait (HTMT) Ratio

	1	**2**	**3**	**4**	**5**	**6**
Attitude towards Human Resource Analytics						
Competitive Pressure	0.644					
Level Towards Human Resource Analytics	0.691	0.712				
Organizational Career Growth	0.756	0.720	0.766			
Organizational Preparedness	0.506	0.591	0.547	0.789		
Technological Readiness	0.720	0.760	0.610	0.708	0.530	

Table 4: Cross-Loading

	Attitude towards Human Resource Analytics	**Competitive Pressure**	**Level Towards Human Resource Analytics**	**Organizational Career Growth**	**Organizational Preparedness**	**Technological Readiness**

AHRA1	**0.852**	0.560	0.605	0.700	0.461	0.612
AHRA2	**0.807**	0.505	0.540	0.565	0.376	0.507
AHRA3	**0.711**	0.325	0.307	0.386	0.225	0.392
AHRA4	**0.734**	0.274	0.374	0.409	0.247	0.408
CO1	0.561	**0.890**	0.538	0.577	0.421	0.599
CO2	0.487	**0.877**	0.549	0.544	0.449	0.571
CO3	0.257	**0.672**	0.352	0.384	0.295	0.390
HRAA1	0.609	0.554	**0.854**	0.683	0.421	0.521
HRAA2	0.462	0.495	**0.774**	0.512	0.363	0.416
HRAA3	0.471	0.410	**0.819**	0.570	0.389	0.418
HRAA4	0.517	0.495	**0.853**	0.559	0.363	0.475
HRAA5	0.404	0.475	**0.759**	0.500	0.357	0.372
OCG1	0.425	0.521	0.511	**0.689**	0.450	0.464
OCG10	0.590	0.442	0.469	**0.751**	0.588	0.518
OCG11	0.469	0.368	0.421	**0.677**	0.589	0.396
OCG12	0.496	0.410	0.385	**0.661**	0.527	0.419
OCG13	0.514	0.444	0.467	**0.748**	0.617	0.450
OCG14	0.520	0.401	0.447	**0.712**	0.542	0.462
OCG15	0.559	0.530	0.663	**0.643**	0.395	0.509
OCG2	0.516	0.559	0.579	**0.756**	0.480	0.530
OCG3	0.365	0.431	0.472	**0.645**	0.374	0.421
OCG4	0.515	0.433	0.548	**0.782**	0.459	0.509
OCG5	0.510	0.449	0.585	**0.815**	0.522	0.479
OCG6	0.485	0.444	0.513	**0.778**	0.463	0.486
OCG7	0.495	0.456	0.536	**0.804**	0.495	0.490
OCG8	0.539	0.516	0.594	**0.794**	0.501	0.571
OCG9	0.559	0.490	0.532	**0.766**	0.708	0.502
OP1	0.268	0.335	0.343	0.480	**0.774**	0.277
OP2	0.410	0.358	0.370	0.587	**0.841**	0.395
OP3	0.394	0.472	0.441	0.604	**0.850**	0.453
OP4	0.332	0.383	0.344	0.584	**0.758**	0.359
TR1	0.589	0.547	0.450	0.562	0.412	**0.857**
TR2	0.503	0.543	0.468	0.550	0.399	**0.839**
TR3	0.563	0.592	0.498	0.573	0.440	**0.885**
TR4	0.489	0.571	0.478	0.542	0.343	**0.824**
TR5	0.557	0.526	0.450	0.573	0.403	**0.865**

Figure 3 shows that the next stage was bootstrapping to estimate a structural model. The variance inflation factor (VIF) was initially used to evaluate the collinearity problem (Hair et al., 2021). The results show no collinearity, with the VIF score being less than 5. The findings demonstrate the examined structural model's strong explanatory ability, with attitude towards HR Analytics R2=0.455. Furthermore, as Figure 2 illustrates, there is a substantial explanatory power for Level of HR analytics R2=0.378 and organizational career growth R2=0.478 (Hair et al., 2021). Furthermore, the Q2 test with blindfolding was utilized to assess the structural model's predictive relevance because the R2 criterion is insufficient for measuring the model's prudence, as shown in Fig IV. Hair et al. (2021) state that the study's structural models have predictive solid relevance for its endogenous variables if the Q2 value is not zero. According to the findings, the examined structural model (Q2 = 0.249) exhibits a robust predictive relevance for adopting artificial intelligence, whereas (Q2 = 0.227) and (Q2 = 0.237) demonstrate a tremendous predictive relevance for the level of HR analytics and organizational career growth.

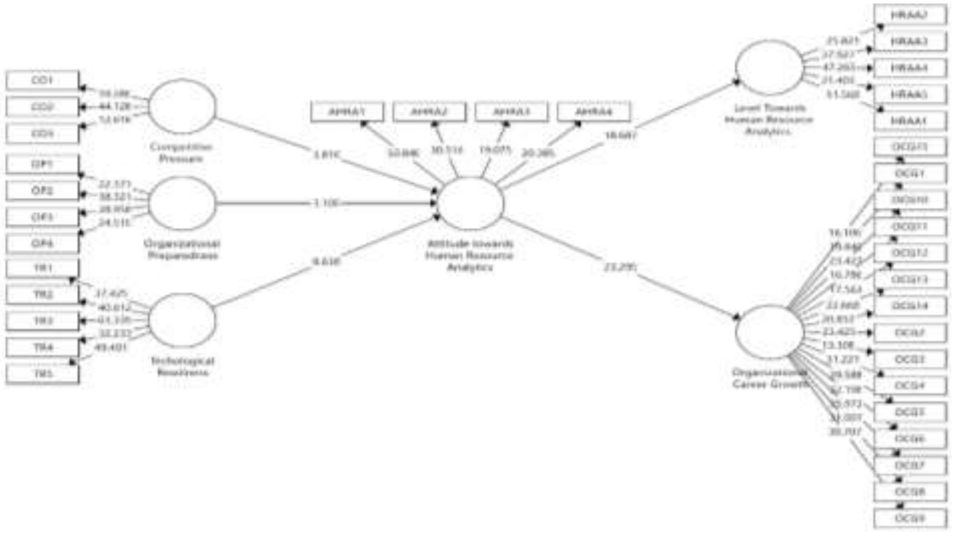

Figure 3: Structural Model

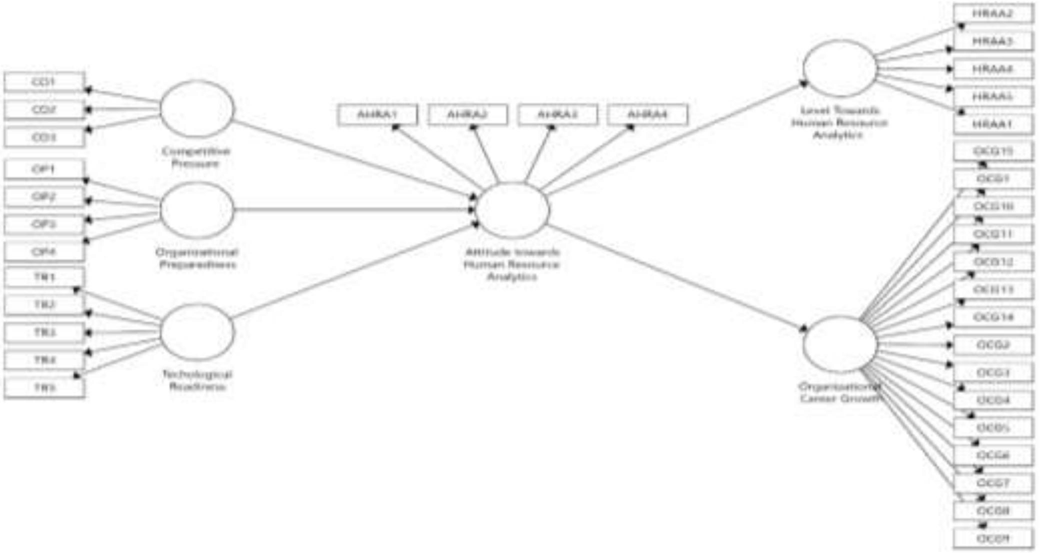

Figure 4: Blindfolding

Table 5: Hypothesis Testing

Hypotheses	β	S. error	t-value	p-value	Decisions	Confidence Interval 2.50%	97.50%
Attitude towards Human Resource Analytics → Level Towards Human Resource Analytics	0.615	0.032	19.233	0.000	Supported	0.545	0.671
Attitude towards Human Resource Analytics → Organizational Career Growth	0.691	0.030	22.923	0.000	Supported	0.622	0.742
Competitive Pressure → Attitude towards Human Resource Analytics	0.217	0.054	4.023	0.000	Supported	0.118	0.320
Competitive Pressure → Level Towards Human Resource Analytics	0.133	0.034	3.877	0.000	Supported	0.067	0.197
Competitive Pressure → Organizational Career Growth	0.150	0.038	3.936	0.000	Supported	0.078	0.225
Organizational Preparedness → Attitude towards Human Resource Analytics	0.138	0.045	3.069	0.002	Supported	0.047	0.221
Organizational Preparedness → Level Towards Human Resource Analytics	0.085	0.028	2.978	0.003	Supported	0.028	0.137
Organizational Preparedness → Organizational Career Growth	0.095	0.033	2.891	0.004	Supported	0.031	0.156
Technological Readiness → Attitude towards Human Resource Analytics	0.429	0.047	9.064	0.000	Supported	0.331	0.515
Technological Readiness → Level Towards Human Resource Analytics	0.264	0.033	8.054	0.000	Supported	0.198	0.329
Technological Readiness → Organizational Career Growth	0.296	0.037	8.033	0.000	Supported	0.225	0.366

Furthermore, the results in Table V demonstrate that a positive and significant relationship was found between attitude towards human resource analytics and level towards human resource Analytics ($\beta = 0.615$, $t = 19.233$, $p < 0.01$). Further, a positive and significant relationship was also found between attitude toward human resource analytics and organizational career growth ($\beta = 0.691$, $t = 22.923$, $p < 0.01$). A positive and significant relationship was found between Competitive

Pressure and Attitude towards Human Resource Analytics (β = 0.217, t = 4.023, p < 0.01). A positive and significant relationship was found between Organizational Preparedness and Attitude towards Human Resource Analytics (β = 0.138, t = 3.069, p < 0.01). A positive and significant relationship was also found between Organizational Preparedness and the Level of Human Resource Analytics (β = 0.085, t = 2.978, p < 0.01). A positive and significant relationship was found between Organizational Preparedness and Organizational Career Growth (β = 0.095, t = 2.891, p < 0.01). A positive and significant relationship was found between Technological Readiness and Attitude towards Human Resource Analytics (β = 0.429, t = 9.064, p < 0.01). A positive and significant relationship was found between Technological Readiness and the Level Towards Human Resource Analytics (β = 0.264, t = 8.054, p < 0.01). A positive and significant relationship was found between Technological Readiness and Organizational Career Growth (β = 0.296, t = 8.033, p < 0.01).

Table 6: Mediation Hypothesis Testing

Hypotheses	**β**	**S. error**	**t-value**	**p-value**	**Decisions**	**Confidence Interval 2.50%**	**97.50%**
Competitive Pressure → Attitude towards Human Resource Analytics → Level Towards Human Resource Analytics	0.133	0.034	3.877	0.000	Supported	0.067	0.197
Competitive Pressure → Attitude towards Human Resource Analytics → Organizational Career Growth	0.150	0.038	3.936	0.000	Supported	0.078	0.225
Organizational Preparedness → Attitude towards Human Resource Analytics → Level Towards Human Resource Analytics	0.085	0.028	2.978	0.003	Supported	0.028	0.137
Organizational Preparedness → Attitude towards Human Resource Analytics → Organizational Career Growth	0.095	0.033	2.891	0.004	Supported	0.031	0.156
Technological Readiness → Attitude towards Human Resource Analytics → Level Towards Human Resource Analytics	0.264	0.033	8.054	0.000	Supported	0.198	0.329
Technological Readiness → Attitude towards Human Resource Analytics → Organizational Career Growth	0.296	0.037	8.033	0.000	Supported	0.225	0.366

Table 6 shows that A significant indirect effect of competitive pressure on the level towards human resource analytics was found through attitude towards human resource analytics (β = 0.133, t = 3.877, p < 0.01). A significant indirect effect of organizational preparedness on the level of human resource analytics was found through attitude towards human resource analytics (β = 0.085, t = 2.978, p < 0.01). , Competitive Pressure has a significant indirect effect on Organizational Career Growth through Attitude toward Human Resource Analytics (β=0.150; t=3.936; p<0.01). Technological Readiness has a significant indirect effect on the Level Towards Human Resource Analytics through Attitude towards Human Resource Analytics (β=0.264; t=8.054; p<0.01). Technological Readiness has a significant indirect effect on Organizational Career Growth through

Attitude toward Human Resource Analytics (β=0.296; t=8.033; p<0.01). Which indicates that all indirect hypotheses are accepted.

However, whether mediation is partial or complete is still up for debate. Baron and Kenny (1986) introduced a methodical approach to evaluating mediation. On the other hand, several writers, like Zhao et al. (2010), challenged this obsolete method. Following Zhao et al.'s (2010) mediation model, we employed the bootstrapping method in the current investigation. As a result, we employed a systematic mediation analysis process in the current investigation (Hair et al., 2021). Table VI shows that this method approves complementary (partial) mediation since the direct and indirect channels are pertinent and positive.

5 Practical and Theoretical Implications

The study strengthens the COM-B model by demonstrating how individual capabilities (technological readiness), organizational opportunities (preparedness), and employee motivation (attitude towards HR analytics) interact to influence both adoption behaviors and organizational outcomes like career growth with country of origin effects. Critically, the research highlights the importance of employee attitudes as a mediator. Focusing solely on traditional factors like technology or resources might be insufficient. Fostering a positive attitude bridges the gap between capabilities, opportunities, and desired outcomes, aligning with Career Construction Theory (CCT). When employees feel motivated by competitive pressures and see HR analytics as valuable for career development, adoption is more likely.

Organizations can leverage these insights by investing in training programs that equip HR professionals with technical skills and address potential anxieties about using data for decision-making. This builds confidence and fosters a positive attitude towards HR analytics. Additionally, creating a supportive leadership environment that values data-driven decision-making and encourages exploration of HR analytics is crucial. Leaders who champion HR initiatives and communicate their value for employee career development can significantly impact adoption. Finally, fostering a culture of continuous learning where employees are encouraged to embrace new technologies like HR analytics is essential. This involves providing opportunities for experimentation, knowledge sharing, and celebrating successes. Results of this study are also consistent with strategic HR perspective, that combination of HR practices used by organization has a major role in encouraging the employees to perform more than their duties (Akhtar et al., 2016).

5.1 Limitations and Future Recommendations

The study's focus on HR managers in Pakistan's service sector limits the generalizability of the findings with country of origin effects. Future research could explore how these factors influence HR professionals across different industries, countries, and employee levels. The reliance on self-reported data from HR managers introduces potential bias. Future research could incorporate multi-source data, including objective measures of HR analytics adoption or employee performance. Further, the cross-sectional design hinders establishing causal relationships. Longitudinal studies tracking employee attitudes and HR adoption over time could provide a clearer cause-and-effect picture. Future research directions include exploring how national and organizational cultures influence employee attitudes toward HR analytics. This could involve comparative studies across countries or investigating the role of cultural dimensions within organizations.

Another recommendation is to delve deeper into specific HR practices that foster a positive attitude toward HR analytics. This could involve investigating the effectiveness of different training programs or leadership styles. The study explores the relationship between HR analytics adoption and career growth, but its long-term impact remains unclear. Longitudinal studies tracking employees' careers could assess the long-term impact of HR analytics adoption on individual development and organizational performance. Finally, future research could examine how developing specific HR analytics capabilities (e.g., data visualization, storytelling with data) influences employee attitudes and adoption. This could inform the design of targeted training programs. Further, research could explore how cultural factors or specific HR practices influence employee attitudes toward HR analytics in different contexts. Additionally, longitudinal studies could track the long-term impact of HR analytics adoption on employee careers and organizational performance.

5.2 Conclusion

Management considers local culture and country of origin (COO) effects to tap into the untapped potential of employees and thus improve performance. Numerous studies have shown that COO effects are crucial for HR managers of local businesses to manage employee behavior characteristically. Similarly, COO effects are also crucial in tourism, education, and health sectors. Managers make critical decisions for their organizations and consider the COO effect in hiring home-country workers to recruit the required talent. Scholars debate these factors and argue that the country of origin or host country is better suited to respond to local culture and demands to meet consumer needs. This research sheds light on the complex interplay between individual and organizational factors influencing HR analytics adoption based on culture and country of origin effect in the service sector. The study demonstrates the critical mediating role of employee attitudes toward HR analytics by leveraging the COM-B model.

The findings offer valuable guidance for HR professionals and organizational leaders in considering the effects of culture and COOs. To maximize the benefits of HR analytics, fostering a positive employee attitude through targeted training, supportive leadership, and a culture of continuous learning is essential. This promotes individual career development and allows organizations to leverage data-driven insights for strategic decision-making and a competitive advantage.

References

Adroit Market Research. (2023). *HR analytics market growth analysis*. https://www.adroitmarketresearch.com/industry-reports/hr-analytics-market

Ajzen, I., & Fishbein, M. (2000). Attitudes and the attitude-behavior relation: Reasoned and automatic processes. *European Review of Social Psychology*, *11*(1), 1–33. https://doi.org/10.1080/14792779943000116

Akhtar, A., Nawaz, M. K., Mahmood, Z., & Shahid, M. S. (2016). Impact of high performance work practices on employees' performance in Pakistan: Mediating role of employee engagement. *Pakistan Journal of Commerce and Social Sciences*, *10*(3), 708–724.

Alhitmi, H. K., Mardiah, A., Al-Sulaiti, K. I., & Abbas, J. (2024). Data security and privacy concerns of AI-driven marketing in the context of economics and business field: an exploration into possible solutions. Cogent Business & Management, 11(1), 2393743. https://doi.org/10.1080/23311975.2024.2393743

Al-Khulaifi, A., Al-Sulaiti, K., & Metwally, M. (2001). Attitudes of Qatar Consumers towards Local Conventional Banks, Local Islamic Banks & Conventional Foreign Banks: A Multivariate Statistical Analysis. Journal of International Marketing and Marketing Research, 26(2), 77-90.

Al-Sulaiti, K. (2002). Marketing educational services in Qatar: A multivariate analysis. Journal of International Marketing and Marketing Research, 27(2), 87-98.

Al-Sulaiti, K. I., & Baker, M. J. (1998). Country of origin effects: a literature review. Marketing Intelligence & Planning, 16(3), 150-199. https://doi.org/10.1108/02634509810217309

Al-Sulaiti, K., Abbas, J., Al-Sulaiti, I., & Shah, S. A. R. (2023). Resetting the hospitality redux through country-of-origin effects: Role of tourism, culture, transportation and restaurants selection in Arab countries. Qatar University Press.

Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: Why HR is set to fail the big data challenge. *Human Resource Management Journal*, *26*(1), 1–11. https://doi.org/10.1111/1748-8583.12090

Aral, S., Brynjolfsson, E., & Wu, L. (2012). Three-way complementarities: Performance pay, human resource analytics, and information technology. *Management Science*, *58*(5), 913–931. https://doi.org/10.1287/mnsc.1110.1460

Bagozzi, R. P., Yi, Y., & Phillips, L. W. (1991). Assessing construct validity in organizational research. *Administrative Science Quarterly*, *36*(3), 421–458. https://doi.org/10.2307/2393203

Bahuguna, P. C., Srivastava, R., & Tiwari, S. (2024). Human resources analytics: Where do we go from here?. *Benchmarking: An International Journal*, *31*(2), 640–668. https://doi.org/10.1108/BIJ-06-2022-0401

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173–1182. https://psycnet.apa.org/doi/10.1037/0022-3514.51.6.1173

Batovrina, E. V., Oparina, N. N., & Cherniaeva, G. V. (2021, November). Modern HR analytics: Digital opportunities in assessing the effectiveness of personnel management. In P. V. Trifonov, & M. V. Charaeva (Eds.), *International Scientific and Practical Conference Operations and Project management: strategies and trends* (pp. 423-428). Cham: Springer International Publishing.

Blut, M., & Wang, C. (2020). Technology readiness: A meta-analysis of conceptualizations of the construct and its impact on technology usage. *Journal of the Academy of Marketing Science*, *48*, 649–669. https://doi.org/10.1007/s11747-019-00680-8

Boudreau, J., & Cascio, W. (2017). Human capital analytics: Why are we not there? *Journal of Organizational Effectiveness: People and Performance*, *4*(2), 119–126. https://doi.org/10.1108/JOEPP-03-2017-0021

Bukhari, M., Sattar, S., Nawaz, S., & Ijaz, S. (2024). Customers incivility, country-of-origin effects on the tourism sector, job satisfaction, and organizational citizenship behavior: testing a mediational model. Journal of Excellence in Management Science, 3(4), 01-19. https://doi.org/10.69565/jems.v3i4.342

Cavanagh, J., Bartram, T., Walker, M., Pariona-Cabrera, P., & Halvorsen, B. (2024). Health services in Australia and the impact of antiquated rostering practices on medical scientists: a case for HR analytics and evidenced-based human resource management. *Personnel Review*, *53*(1), 18-33. https://doi.org/10.1111/1744-7941.12392

Chatterjee, S., Chaudhuri, R., & Vrontis, D. (2022). Does remote work flexibility enhance organization performance? Moderating role of organization policy and top management support. *Journal of Business Research*, *139*, 1501–1512. https://doi.org/10.1016/j.jbusres.2021.10.069

Chau, P. Y., & Hui, K. L. (2001). Determinants of small business EDI adoption: An empirical investigation. *Journal of Organizational Computing and Electronic Commerce*, *11*(4), 229–252. https://doi.org/10.1207/S15327744JOCE1104_02

Chillakuri, B., & Attili, V. P. (2022). Role of blockchain in HR's response to new-normal. *International Journal of Organizational Analysis*, *30*(6), 1359–1378. https://doi.org/10.1108/IJOA-08-2020-2363

Cho, W., Choi, S., & Choi, H. (2023). Human resources analytics for public personnel management: Concepts, cases, and caveats. *Administrative Sciences*, *13*(2), Article e41. https://doi.org/10.3390/admsci13020041

Chong, A. Y. L., Chan, F. T., & Ooi, K. B. (2012). Predicting consumer decisions to adopt mobile commerce: Cross country empirical examination between China and Malaysia. *Decision Support Systems*, *53*(1), 34–43. https://doi.org/10.1016/j.dss.2011.12.001

Coco, C. T. (2011). Connecting people investments and business outcomes at Lowe's: using value linkage analytics to link employee engagement to business performance. *People and Strategy*, *34*(2), 28–33.

Dastane, D. O. (2020). The impact of technology adoption on organizational productivity. *Journal of Industrial Distribution & Business*, *11*(4), 7–18. http://doi.org/10.13106/jidb.2020.vol11.no4.7

Dehghan, M., Maazallahi, M., Jabarpour, M., & Abbas, J. (2024). The Impact of Covid-19 outbreaks on adherence to hand hygiene in a medical teaching hospital: A case of iran. Mosul Journal of Nursing, 12(1), 29-36. https://doi.org/https://www.iasj.net/iasj/article/299504

Duan, J., Peluso, A. M., Yu, L., & Pilati, M. (2021). How employment relationship types influence employee work outcomes: The role of need for status and vigor. *Journal of Business Research*, *128*, 211–221. https://doi.org/10.1016/j.jbusres.2021.01.051

Duarte, P. A. O., & Raposo, M. L. B. (2010). A PLS model to study brand preference: An application to the mobile phone market. In V. E. Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of partial least squares: Concepts, methods and applications*. Springer.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, Article e101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Ekka, S., & Singh, P. (2022). Predicting HR professionals' adoption of HR analytics: An extension of Utaut Model. *Organizacija*, *55*(1), 77–93. https://doi.org/10.2478/orga-2022-0006

Esteves, J., & Curto, J. (2013, October 24–25). *A risk and benefits behavioral model to assess intentions to adopt big data* [Paper presentation]. In Proceedings of the 10th international conference on intellectual capital, knowledge management and organisational learning. Washington, DC, USA.

Etukudo, R. (2019). *Strategies for using analytics to improve Human Resource Management* (Publication No. 13814090) [Doctoral dissertation, Walden University].

ProQuest Dissertations & Theses.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Gelbard, R., Ramon-Gonen, R., Carmeli, A., Bittmann, R. M., & Talyansky, R. (2018). Sentiment analysis in organizational work: Towards an ontology of people analytics. *Expert Systems*, *35*(5), Article e12289. https://doi.org/10.1111/exsy.12289

Ghobakhloo, M., Hong, T. S., Sabouri, M. S., & Zulkifli, N. (2012). Strategies for successful information technology adoption in small and medium-sized enterprises. *Information*, *3*(1), 36–67. https://doi.org/10.3390/info3010036

Giermindl, L. M., Strich, F., Christ, O., Leicht-Deobald, U., & Redzepi, A. (2022). The dark sides of people analytics: reviewing the perils for organisations and employees. *European Journal of Information Systems*, *31*(3), 410–435. https://doi.org/10.1080/0960085X.2021.1927213

Girdwichai, L., & Sriviboon, C. (2020). Employee motivation and performance: Do the work environment and the training matter?. *Journal of Security & Sustainability Issues*, *9*, 42–54. https://doi.org/10.9770/jssi.2020.9.J(4)

Gurusinghe, R. N., Arachchige, B. J., & Dayarathna, D. (2021). Predictive HR analytics and talent management: A conceptual framework. *Journal of Management Analytics*, *8*(2), 195–221. https://doi.org/10.1080/23270012.2021.1899857

Hair Jr, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review*, *26*(2), 106–121. https://doi.org/10.1108/EBR-10-2013-0128

Hair, J. F. Jr, Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications

Hamilton, R. H., & Sodeman, W. A. (2020). The questions we ask: Opportunities and challenges for using big data analytics to strategically manage human capital resources. *Business Horizons*, *63*(1), 85–95.

Han, S. J., & Stieha, V. (2020). Growth mindset for human resource development: A scoping review of the literature with recommended interventions. *Human Resource Development Review*, *19*(3), 309–331. https://doi.org/10.1177/1534484320939739

Harris, J. G., Craig, E., & Light, D. A. (2011). Talent and analytics: new approaches, higher ROI. *Journal of Business Strategy*, *32*(6), 4–13. https://doi.org/10.1108/02756661111180087

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*, 115–135. https://doi.org/10.1007/s11747-014-0403-8

Holbeche, L. (2022). *Aligning human resources and business strategy*. Routledge.

Howlett, N., Schulz, J., Trivedi, D., Troop, N., & Chater, A. (2019). A prospective study exploring the construct and predictive validity of the COM-B model for physical activity. *Journal of Health Psychology*, *24*(10), 1378–1391. https://doi.org/10.1177/1359105317739098

Hsu, C. H., Lin, H. H., Jhang, S. W., & Lin, T. Y. (2021). Does environmental engineering help rural industry development? Discussion on the impact of Taiwan's "special act for forwardlooking infrastructure" on rural industry development. *Environmental Science and Pollution Research*, *28*, 40137–40150. https://doi.org/10.1007/s11356-020-11059-6

Huselid, M. A. (2018). The science and practice of workforce analytics: Introduction to the HRM special issue. *Human Resource Management*, *57*(3), 679–684. https://doi.org/10.1002/hrm.21916

Jaffar, A., Mubeen, R., Iorember, P. T., Raza, S., & Mamirkulova, G. (2021). Exploring the impact of COVID-19 on tourism: transformational potential and implications for a sustainable recovery of the travel and leisure industry. Current Research in Behavioral Sciences, 2, 100033. https://doi.org/10.1016/j.crbeha.2021.100033

Japor, J. E. (2021). Organizational career growth: Literature review and future agenda. *Japor, JE (2021). Organizational career growth: Literature review and future agenda. International Journal of Business and Administrative Studies*, *7*(1), 12–24. https://doi.org/10.20469/ijbas.7.10002-1

Johnston, A. C., & Warkentin, M. (2010). The influence of perceived source credibility on end user attitudes and intentions to comply with recommended IT actions. *Journal of Organizational and End User Computing*, *22*(3), 1–21. https://doi.org/10.4018/joeuc.2010070101

Kim, J., Dibrell, C., Kraft, E., & Marshall, D. (2021). Data analytics and performance: The moderating role of intuition-based HR management in major league baseball. *Journal of Business Research*, *122*, 204–216. https://doi.org/10.1016/j.jbusres.2020.08.057

Kirkpatrick, I., & Hoque, K. (2022). Human resource professionals and the adoption and effectiveness of high-performance work practices. *Human Resource Management Journal*, *32*(2), 261–282. https://doi.org/10.1111/1748-8583.12403

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal*, *28*(1), 227–261. https://doi.org/10.1111/isj.12131

Levenson, A., & Fink, A. (2017). Human capital analytics: too much data and analysis, not enough models and business insights. *Journal of Organizational Effectiveness: People and Performance*, *4*(2), 145–156. https://doi.org/10.1108/JOEPP-03-2017-0029

Li, L., Schotter, A. P. J., & Beamish, P. W. (2024, 2024/06/01/). The origin and nationality of general manager successors in local-market-seeking MNE subsidiaries. International Business Review, 33(3), 102272. https://doi.org/10.1016/j.ibusrev.2024.102272

Liang, L. H., Brown, D. J., Ferris, D. L., Hanig, S., Lian, H., & Keeping, L. M. (2018). The dimensions and mechanisms of mindfulness in regulating aggressive behaviors. *Journal of Applied Psychology*, *103*(3), Article e281. https://doi.org/10.5465/amj.2014.0651

Lumsden, J. R., & Gutierrez, A. (2013, October 17–18). *Understanding the determinants of cloud computing adoption within the UK* [Paper presentation]. Proceedings of European, Mediterranean & Middle Eastern Conference on Information Systems. Windsor, United Kingdom.

Maduku, D. K., Mpinganjira, M., & Duh, H. (2016). Understanding mobile marketing adoption intention by South African SMEs: A multi-perspective framework. *International Journal of Information Management*, *36*(5), 711–723. https://doi.org/10.1016/j.ijinfomgt.2016.04.018

Majeed, H., & Shahid, M. (2023). Emotional Exhaustion, Organizational Commitment, and Job

Hopping in the Banking Sector: A Mediation Analysis Approach. Journal of Excellence in Management Science, 2(2), 44-60. https://doi.org/https://journals.smarcons.com/index.php/jems/article/view/110

Margherita, A. (2022). Human resources analytics: A systematization of research topics and directions for future research. *Human Resource Management Review*, *32*(2), Article e100795. https://doi.org/10.1016/j.hrmr.2020.100795

Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR Analytics. *The International Journal of Human Resource Management*, *28*(1), 3–26. https://doi.org/10.1080/09585192.2016.1244699

Maroufkhani, P., Wagner, R., Wan Ismail, W. K., Baroto, M. B., & Nourani, M. (2019). Big data analytics and firm performance: A systematic review. *Information*, *10*(7), Article e226. https://doi.org/10.3390/info10070226

McCartney, S., & Fu, N. (2022). Bridging the gap: why, how and when HR analytics can impact organizational performance. *Management Decision*, *60*(13), 25–47. https://doi.org/10.1108/MD-12-2020-1581

Minbaeva, D. (2021). Disrupted HR?. *Human Resource Management Review*, *31*(4), Article e100820. https://doi.org/10.1016/j.hrmr.2020.100820

Moturi, D. G., Wekesa, S., & Juma, D. (2022). Effect of performance expectancy on employee acceptance rate of human resource analytics in licensed microfinance institutions in Nairobi, Kenya. *African Journal of Emerging Issues*, *4*(11), 18–39.

Muhammad, A. (2023). Innovation, self-efficacy and creativity-oriented HRM: What helps to enhance the innovativeness of organization employees? Journal of Personnel Management, 1(1), 54-67. https://doi.org/https://journals.smarcons.com/index.php/jpm/article/view/198

Musawa, M. S., & Wahab, E. (2012). The adoption of electronic data interchange (EDI) technology by Nigerian SMEs: A conceptual framework. *Journal of Business Management and Economics*, *3*(2), 55–68.

Nguyen, T. Q., Nguyen, A. T., Tran, A. L., Le, H. T., Le, H. H. T., & Vu, L. P. (2021). Do workers benefit from on-the-job training? New evidence from matched employer-employee data. *Finance Research Letters*, *40*, Article e101664. https://doi.org/10.1016/j.frl.2020.101664

Niu, X. (2024). Exploration on human resource management and prediction model of data-driven information security in Internet of Things. *Heliyon*, *10*(9), Article e29582.

Nocker, M., & Sena, V. (2019). Big data and human resources management: The rise of talent analytics. *Social Sciences*, *8*(10), Article e273. https://doi.org/10.3390/socsci8100273

Pallant, J. (2020). *SPSS survival manual: A step by step guide to data analysis using IBM SPSS*. Routledge.

Parasuraman, A. (2000). Technology Readiness Index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research*, *2*(4), 307–320. https://doi.org/10.1177/109467050024001

Pearson, J. M., & Grandon, E. E. (2005). An empirical study of factors that influence e-commerce adoption/non-adoption in small and medium sized businesses. *Journal of Internet Commerce*, *4*(4), 1–21. https://doi.org/10.1300/J179v04n04_01

Penpokai, S., Vuthisopon, S., & Saengnoree, A. (2023). The relationships between technology adoption, HR competencies, and HR analytics of large-size enterprises. *International Journal of Professional Business Review*, *8*(3), Article e0971. https://doi.org/10.26668/businessreview/2023.v8i3.971

Provost, F., & Fawcett, T. (2013). Data science and its relationship to big data and data-driven decision making. *Big Data*, *1*(1), 51–59. https://doi.org/10.1089/big.2013.1508

Qureshi, M. A., Thebo, J. A., ur Rehman, S., Shahbaz, M. S., & Sohu, S. (2020). The role hr analytics, performance pay and HR involvement in influencing job satisfaction and firm performance. *International Journal of Advanced Science and Technology*, *29*, 382–392.

Radeva, S. (2019). On-the-job training as a model for adapting to the working environment. *KNOWLEDGE-International Journal*, *31*(5), 1609–1614.

Ringle, C., Da Silva, D., & Bido, D. (2015). Structural equation modeling with the SmartPLS. *Brazilian Journal of Marketing*, *13*(2), 56–73. https://doi.org/10.5585/remark.v13i2.2717

Rogers, E. M. (2003). *Diffusion of innovations* (Fifth ed.). Free Press

Savickas, M. L. (2020). Career construction theory and counseling model. In S. Brown, & R. Lent (Eds.), *Career development and counseling: Putting theory and research to work*. Wiley Online Library.

Shet, S. V., Poddar, T., Samuel, F. W., & Dwivedi, Y. K. (2021). Examining the determinants of successful adoption of data analytics in human resource management–a framework for implications. *Journal of Business Research*, *131*, 311–326. https://doi.org/10.1016/j.jbusres.2021.03.054

Shrivastava, N. (2024). Adopting HR Analytics: Factors influencing Human Resource Professionals. *International Journal of Research and Analytical Reviews (IJRAR)*, *11*(1), 1–11.

SkyQuest. (2022). *Human resource technology market to touch $35.68 billion by 2028 63% business are willing to make use of AI for HR analytics*. https://www.globenewswire.com/news-release/2022/09/08/2512740/0/en/Human-Resource-Technology-Market-to-Touch-35-68-Billion-by-2028-63-Business-are-willing-to-Make-Use-of-AI-for-HR-Analytics.html

Son, M., & Han, K. (2011). Beyond the technology adoption: Technology readiness effects on post-adoption behavior. *Journal of Business Research*, *64*(11), 1178–1182. https://doi.org/10.1016/j.jbusres.2011.06.019

Spagnoli, P., & Weng, Q. (2019). Factorial validity, cross-cultural equivalence, and latent means examination of the organizational career growth scale in Italy and China. *The International Journal of Human Resource Management*, *30*(21), 2951–2970. https://doi.org/10.1080/09585192.2017.1340325

Starodub, K. (2015). *HR and people analytics: Stuck in neutral*. SAP Insider. https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Technology/gx-cons-tech-sap-hr-and-people-analytics-2015.pdf

Szinay, D., Perski, O., Jones, A., Chadborn, T., Brown, J., & Naughton, F. (2021). Perceptions of factors influencing engagement with health and wellbeing apps: A qualitative study using the COM-B model and theoretical domains framework as an analytical framework. *JMIR mHealth and uHealth*, 9(12), Article e29098. https://doi.org/10.2196/29098

Tan, X., Pilař, L., & Shah, S. A. R. (2024). The Role of Digital Management and Smart

Technologies for Sports Education in a Dynamic Environment: Employment, Green Growth, and Tourism. Journal of Urban Technology, 30, 1-32. https://doi.org/10.1080/10630732.2024.2327269

Tariq, H., & Weng, Q. (2018). Accountability breeds response-ability: Instrumental contemplation of abusive supervision. *Personnel Review*, *47*(5), 1019–1042. https://doi.org/10.1108/PR-05-2017-0149

Trucharte, A., Calderón, L., Cerezo, E., Contreras, A., Peinado, V., & Valiente, C. (2023). Three-item loneliness scale: psychometric properties and normative data of the Spanish version. *Current Psychology*, *42*(9), 7466–7474. https://doi.org/10.1007/s12144-021-02110-x

van der Togt, J., & Rasmussen, T. H. (2017). Toward evidence-based HR. *Journal of Organizational Effectiveness: People and Performance*, *4*(2), 127–132. https://doi.org/10.1108/JOEPP-02-2017-0013

Vargas, R., Yurova, Y. V., Ruppel, C. P., Tworoger, L. C., & Greenwood, R. (2018). Individual adoption of HR analytics: a fine grained view of the early stages leading to adoption. *The International Journal of Human Resource Management*, *29*(22), 3046–3067. https://doi.org/10.1080/09585192.2018.1446181

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J. F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, *70*, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

Wang, Y., & Hajli, N. (2017). Exploring the path to big data analytics success in healthcare. *Journal of Business Research*, *70*, 287–299. https://doi.org/10.1016/j.jbusres.2016.08.002

Weng, Q., & Hu, B. (2009). The structure of career growth and its impact on employees' turnover intentions. *Industrial Engineering and Management*, (1), 97–104.

Xiao, Q., Yan, J., & Bamber, G. J. (2023). How does AI-enabled HR analytics influence employee resilience: job crafting as a mediator and HRM system strength as a moderator. *Personnel Review*. [Preprint]. https://doi.org/10.1108/PR-03-2023-0198

Zhao, L., Zhao, S., Zeng, H., & Bai, J. (2021). To share or not to share? A moderated mediation model of the relationship between perceived overqualification and knowledge sharing. *Baltic Journal of Management*, *16*(5), 681–698. https://doi.org/10.1108/BJM-01-2021-0006