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ADOPTION FACTORS IMPACTING HUMAN RESOURCE ANALYTICS AMONG HUMAN RESOURCE PROFESSIONALS IN KARACHI, PAKISTAN

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Abstract
Modern society adopts Big Data as well as analytics throughout all its sectors. Organizations leverage extensive online information for predicting customer buying patterns and detecting market trends along with consumer demand recognition. The requirement for HR professionals to serve as strategic business partners has forced them to enhance their usage of measurement and analytics to produce better organizational decisions. Organizations which implemented Human Resource Analytics reported outstanding achievements based on their adoption of this model. The author seeks to examine HR professionals' reluctance to use HRA and the variables that affect its implementation. Past studies enabled researchers to develop a model which defined critical elements that affect adoption. Partial Least Squares Path Modeling validated the model through assessment tests. Responses from 250 HR professionals demonstrated that the adoption of HRA depended heavily on social influence together with tool availability as well as effort expectancy and performance expectancy and quantitative self-efficacy. Data availability along with fear appeals and general self-efficacy were revealed to have no meaningful impact on the studied topic. According to the study HR professionals cannot determine HRA adoption by themselves because organizational support becomes a critical factor in this process. Organizations that want to use analytics for managing their HR operations must supply employees with appropriate tools alongside data access together with sufficient assets and organization-wide support. The findings from this study help expand the existing knowledge about how people accept new technologies within the field of HR. This research provides essential guidance to academics and industry leaders about necessary changes which will promote further implementation of HRA systems in work environments.

Keywords:
HR Analytics, Effort Expectancy, Performance Expectancy, UTAUT.

Introduction

Modern human resource management depends heavily on Human Resource Analytics (HRA) because this tool delivers critical information for organizational data-driven decision-making. HRA functions as an organizational tool through its data-enabled capability to produce better decisions. Traditionally, HR departments previously employed subjective evaluations together with instinct to handle their talent management and workforce planning operations. planning, and performance evaluation. However, the increasing availability of big data and advanced Through the availability of analytical instruments HR professionals now handle their responsibilities completely differently (Bassi, 2011; Fitzenz, 2010). 2010). The combination of statistical models with machine learning and business intelligence methods makes up HRA analysis. workforce-related data. Where HR professionals employ this method, they can forecast future trends alongside optimizing their hiring plans and enhancing employee connection and organizational performance results. Business performance at an organizational level improves simultaneously with employee engagement. By leveraging data analytics, Organizations can obtain more detailed understanding about staff conduct and evaluate the efficiency of HR programs through analytical tools. Workforce strategies drive toward business goals through the combination of interventions enabled by Cascio and Boudreau (2011) and Marler and Boudreau (2017). & Boudreau, 2017).Despite the potential advantages, the adoption of HRA remains inconsistent across industries. Many HR professionals struggle to integrate analytics into their daily operations due to a lack of technical expertise, resistance to change, and limited organizational support. Additionally, some HR leaders face challenges in demonstrating the tangible benefits of analytics to executives and decision-makers (Davenport, Harris, & Shapiro, 2010; Rafter, 2013).

The research investigates the elements which affect HRA adoption by HR workers while it assesses human resource performance constraints stemming from knowledge deficits and cultural interpretations and technological requirements. The research studies methods to increase HRA adoption and usage in order to establish HR as a strategic business partner. Organizations will achieve maximum benefits of HR analytics along with better workforce management and lasting competitive advantage when they resolve these issues (Sesil 2013; Sullivan 2013). Organizations striving to modernize their HR functions need to discover all factors that encourage or prevent HRA adoption. This research project adds valuable recommendations for HR analytics system implementation that enable professionals to effectively handle workforce analytics trends (Bersin 2013, Manyika et al. 2011).

Problem Statement

The central issue this study addresses is why more HR professionals are not utilizing HRA to enhance organizational performance and sustain competitive advantages. Given the proven benefits of HRA, its slow adoption raises important questions about the challenges HR professionals face when integrating analytics into their decision-making processes. Potential barriers may include a lack of familiarity with data analysis techniques, resistance to change, insufficient technological resources, or cultural resistance within organizations.

The literature highlights several shortcomings in HR professionals' use of HR analytics and KPI metrics (Rafter, 2013a). Many executives still perceive HR as primarily a function dealing with soft-skills rather than as a strategic business unit. This perception may stem from HR professionals' traditional focus on historical analysis rather than forward-looking predictive analytics, limiting their ability to contribute to business strategy and financial performance (Stuart, 2005).

Background and Justification

The literature review for this study includes empirical research from scholarly journals focusing on innovation, adoption of new technologies, and analytics in business contexts. Brown, Chui, and Manyika (2011) found that organizations leveraging business analytics for decision-making tend to experience higher productivity and increased returns on equity compared to those that do not.

Through professional certifications and specialized degrees HR professionals have gained recognition as strategic business partners. However, there remains a significant gap in the use of performance metrics. Traditionally, HR was largely administrative, concerned with compliance and employee relations. Over time, it has evolved toward a more strategic role, yet many HR professionals still adhere to traditional 20th-century management approaches (Sullivan, 2013). The shift toward data-driven HR requires HR professionals to develop new competencies in analytics and business intelligence (Lockwood, 2007).

This study is justified by the increasing emphasis on data analytics across industries and its growing importance in HR functions. Organizations that fail to integrate HRA risk falling behind in talent management, workforce planning, and employee performance optimization. The research aims to bridge the knowledge gap and provide actionable insights for HR professionals and organizations looking to embrace analytics.

Research Objectives

1. To identify and analyze the factors that act as barriers to the adoption of HRA among HR professionals.
2. To examine the role of technological, organizational, and individual factors in influencing the acceptance and utilization of HRA.
3. To evaluate the impact of HRA on organizational decision-making, workforce planning, and competitive advantage.

Research Questions

1. What factors serve as barriers to the adoption of HRA among HR professionals?
2. What are the reasons behind the disconnect between organizations' desire for data-driven HR practices and HR professionals' ability and willingness to implement HRA?

Delimitations

This study focuses exclusively adopting technological innovations through individual adoption by HR professionals. It does not examine organizational-level adoption of innovation, except as contextual background. The primary emphasis is on personal factors, such as knowledge, skills, attitudes, and perceived barriers, that influence HR professionals’ decision to adopt HRA.

The study does not extend to other business functions or general technological adoption within organizations. Instead, it is confined to the HR domain and its unique challenges regarding analytics integration. Additionally, the research is limited to HR professionals in organizations where HRA has been introduced but remains underutilized.

Assumptions

This study is based on several key assumptions. First, it assumes that HR professionals aspire to be viewed as strategic business partners and that their role is evolving to include data-driven decision-making. However, despite this aspiration, there remains a significant gap in financial literacy and analytical skills within the profession (Stuart, 2005).

HRA implementation often faces organizational obstacles because businesses acknowledge its advantages yet encounter obstacles from their employees' inability to adopt new techniques and insufficient technological resources and cultural challenges. Loss of competitive advantage and poor business results correlate closely with workforce analytics effectiveness (Bassi, 2011; Bersin, 2013d; Fitz-enz, 2010). The research projects that organizations will achieve better HR strategic outcomes after removing these barriers to improve effective utilization of HRA. This study maintains that willingness to adopt HRA depends mainly on the combination of staff self-efficacy alongside their social reception and obtainable training and resources. This study investigates different elements which either motivate or prevent HR professionals from implementing analytics practices within their work roles.

Literature Review

This chapter performs a thorough evaluation of scholarly work regarding business intelligence (BI) and business analytics (BA) and big data (BD) as well as human resources analytics (HRA). The discussion includes theoretical perspectives that clarify organizational HRA adoption and spread processes. Various aspects that affect HRA implementation are studied in this review starting with self-efficacy then going through organizational culture following management assistance and closing with technological platform requirements.

Human Resource Analytics (HRA) and Its Importance

HRA has gained increasing attention as organizations recognize the value of data-driven decision-making. By applying statistical models and machine learning techniques, HR professionals can better understand workforce trends, predict employee behaviors, and enhance overall HR strategies (Cascio & Boudreau, 2011). Research suggests that organizations leveraging HRA experience improved workforce planning, increased employee engagement, and enhanced retention rates (Bassi, 2012; Bersin, 2013).

Despite its potential, the adoption of HRA remains limited due to various barriers. Many HR professionals lack formal training in data analytics and struggle with interpreting and applying complex statistical data. Studies have found that HR professionals' self-efficacy in using quantitative methods plays a critical role in their willingness to adopt HRA (Bandura, 1982; Zimmerman, 2000). Ozgen (2013) highlights that mathematical and statistical literacy are essential competencies for HR professionals to effectively engage with analytics.

Theoretical Models Explaining HRA Adoption

The adoption of HRA is influenced by multiple theoretical frameworks. One of the most widely used models is Rogers' (1983) Diffusion of Innovation (DOI) Theory, which explains how new technologies spread within organizations. Rogers identified five crucial factors that influence HRA adoption: relative advantage, compatibility, complexity, trialability, and observability. HRA adoption is often hindered by complexity, as many HR professionals perceive analytics as difficult to learn and implement.

Another important theoretical framework is Davis' (1989) Technology Acceptance Model (TAM). TAM suggests that an individual's perception of an innovation's usefulness and ease of use determines whether they will adopt it. HR professionals are more likely to use HRA if they believe it will enhance their job performance and if they find the tools user-friendly (Davis, 1989). However, studies indicate that many HR analytics tools lack intuitive interfaces, making adoption challenging (Fitz-enz, 2010; Brown, Chui, & Manyika, 2011).

The Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh et al. (2003), builds on TAM and includes additional factors such as social influence and facilitating conditions. UTAUT suggests that management support, peer influence, and access to necessary resources significantly impact HRA adoption among HR professionals.

Key Variables Affecting HRA Adoption

Self-Efficacy

Self-efficacy states that it's an individual believe in his/her own abilities to achieve success. In the context of HRA adoption, HR professionals with higher self-efficacy in quantitative and data-related tasks are more likely to embrace analytics tools. Studies indicate that professionals with strong confidence in their analytical skills are more willing to adopt data-driven decision-making processes (Bandura, 1982; Zimmerman, 2000).

Organizational Culture

Organizational culture plays a crucial role in the adoption of HRA. Companies that foster a data-driven culture encourage HR professionals to integrate analytics into their decision-making processes. Resistance to change, traditional management styles, and lack of leadership support can hinder HRA adoption (Davenport, Harris, & Shapiro, 2010).

Management Support

Support from senior leadership is a critical factor in the successful adoption of HRA. When executives emphasize the importance of analytics, HR departments are more likely to secure the necessary resources, training, and tools to implement HRA effectively. Studies suggest that strong managerial advocacy for analytics can significantly accelerate adoption rates (Rafter, 2013).

Technological Infrastructure

The availability of advanced HR analytics tools and seamless integration with existing HR systems are key determinants of adoption. Organizations that invest in user-friendly and sophisticated analytics software enable HR professionals to efficiently utilize data for decision-making (Fitz-enz, 2010). Without proper technological support, HR professionals may struggle with data accessibility and analysis.

Social Influence

Social influence refers to the extent to which HR professionals are affected by their peers, industry trends, and professional networks. When HR professionals see others successfully using HRA, they are more likely to adopt it themselves (Venkatesh et al., 2003). Professional HR associations, conferences, and industry publications can play a crucial role in promoting HRA adoption.

Data Availability

The accessibility and quality of HR-related data significantly impact HRA adoption. Organizations that collect, store, and maintain high-quality workforce data provide HR professionals with the necessary resources to leverage analytics. Data silos, inconsistencies, and lack of centralized HR databases can hinder the effective use of HRA.

Effort Expectancy

Effort expectancy refers to the perceived ease of using HR analytics tools. If HR professionals find analytics software complicated and difficult to use, they are less likely to adopt it. Research suggests that tools with intuitive interfaces and comprehensive training programs increase adoption rates (Davis, 1989).

Performance Expectancy

Performance expectancy refers to the extent to which HR professionals believe that using HRA will improve their job performance. When professionals perceive analytics as a valuable tool for making informed decisions and enhancing HR outcomes, they are more likely to adopt it (Davis, 1989).

Challenges in Adopting HRA

Several studies have explored the challenges HR professionals face when adopting HRA. A key barrier is the lack of organizational support and leadership buy-in. Many executives still perceive HR as a function focused on administrative tasks rather than a strategic business partner (Davenport, Harris, & Shapiro, 2010). Without strong leadership support, HR departments may struggle to secure the necessary resources for implementing analytics-driven strategies.

Another challenge is data accessibility and integration. While organizations collect vast amounts of employee data, many HR professionals lack the tools and expertise to analyze it effectively. Research suggests that HR analytics tools must be seamlessly integrated into existing HR systems to encourage adoption (Fitz-enz, 2010. Additionally, many organizations operate in silos, making it difficult to aggregate and utilize workforce data across different departments

Resistance to change is another major barrier. HR professionals who have traditionally relied on intuition and experience may be hesitant to embrace a data-driven approach. Studies indicate that change management strategies, including training programs and leadership advocacy, are crucial for fostering a culture of analytics within HR departments (Rafter, 2013).

The literature review highlights the growing importance of HRA in modern organizations and the various factors influencing its adoption. While HRA offers significant benefits, challenges such as skill gaps, resistance to change, and data integration issues continue to hinder widespread adoption. Key variables such as self-efficacy, organizational culture, management support, technological infrastructure, and social influence play crucial roles in determining HRA adoption. Future research should focus on emerging technologies, ethical considerations, and the human impact of HR analytics to ensure that organizations can fully leverage data-driven HR strategies.

Research Framework

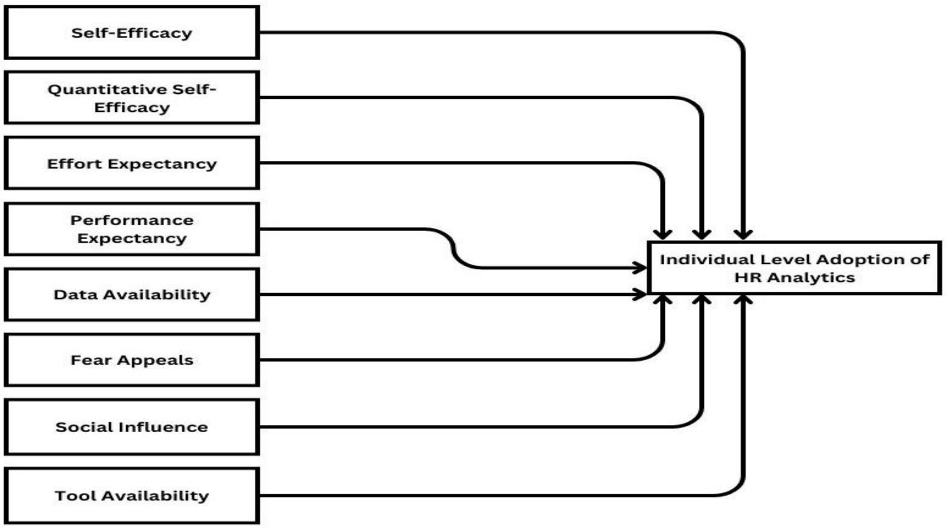

Figure 01: Research Framework (Vargas, 2015)

Research Methodology

Research Design

The study employs a quantitative research design to investigate the adoption of Human Resource Analytics (HRA) by HR professionals. This approach allows for the testing of hypotheses and the analysis of numerical data to identify the factors influencing HRA adoption. A structured methodology was followed, incorporating validated instruments from previous research to ensure reliability and validity in measurement (Vargas, 2015).

Research Approach

A quantitative approach was adopted, utilizing survey data to gather insights from HR professionals. The study focused on measuring specific constructs related to HRA adoption using structured questionnaires. This method ensures objectivity and enables statistical analysis to determine relationships between key variables (Vargas, 2015).

Population and Sample Size

The target population consisted of HR professionals currently employed in the field, irrespective of job title, industry, or years of experience. The final sample size for the full-scale study included 250 HR professionals (n = 250) who participated in the survey. This sample was deemed sufficient for conducting statistical analysis and hypothesis testing (Vargas, 2015).

Instrument Development

The primary instrument for data collection was an online survey, administered through Google Forms. The survey included demographic questions as well as specific items designed to measure theoretical constructs related to HRA adoption. A 5-point Likert scale was used to capture participant responses (Vargas, 2015)

Data Collection Methods

Data was collected through an online survey, distributed via multiple channels, including LinkedIn, email invitations, and social media platforms such as Facebook and WhatsApp, and Instagram. Additionally, the study employed a convenience sampling technique, encouraging participants to share the survey within their professional networks to enhance participation and reach a broader audience of HR professionals (Vargas, 2015).

Software Used

The collected data was analyzed using Partial Least Squares (PLS) structural modeling analysis, a statistical approach suited for testing relationships between multiple variables. This software ensured robust data analysis and accurate interpretation of results (Vargas, 2015).

Data Analysis

Descriptive Analysis

The demographic distribution of the respondents provides valuable insights into the composition of the survey participants. The sample consists of 112 male respondents (45%) and 138 female respondents (55%), indicating a relatively balanced gender representation, with a slightly higher proportion of female participants.

Regarding age distribution, the majority of respondents (59%) fall within the 31–50 years age group, suggesting that middle-aged individuals form the largest segment of the sample. Meanwhile, 15% of the respondents are 18–30 years old, and 26% belong to the 51–75 years category. This distribution implies that the study primarily reflects perspectives from working-age individuals, with a smaller representation of younger and older populations.

In terms of educational qualifications, nearly half of the respondents (49%) hold a Bachelor’s degree, followed by 37% with Graduate or Postgraduate degrees, while 14% have an Associate degree or lower. This indicates that the majority of the sample is well-educated, which may influence their financial knowledge and perspectives on fintech adoption.

Overall, the respondent profile suggests a sample with diverse demographic characteristics, with a slight female majority, a concentration in the 31–50 age group, and a relatively high level of education. These factors may have implications for the study's findings, particularly in assessing how demographic factors influence financial inclusion and stability within BRICS economies.

Table 01: Descriptive Analysis

Respondents' Characteristics	Frequency	Percentage (%)
Gender		
Male	112	45
Female	138	55
Age (Generation)		
18–30	38	15
31–50	148	59
51–75	64	26
Education		
Associate Degree or less	34	14
Bachelor Degree	123	49
Graduate and Postgraduate Degrees	93	37

Measurement Model

The table presents the outer loadings, Average Variance Extracted (AVE), and Composite Reliability (CR) for several constructs in the study, offering insights into the measurement model's validity and reliability. Constructs like General Self-Efficacy (GSE), Fear Appeals (FA), Effort Expectancy (EE), and Individual Social Influence (ISI) demonstrate strong measurement properties. The outer loadings for these constructs are high, with values ranging from 0.799 to 0.932. For instance, GSE's indicators (GSE1, GSE2, GSE3) show loadings between 0.814 and 0.887, which are well above the typical threshold of 0.7, indicating a strong relationship between the items and the construct. Furthermore, these constructs achieve high AVE values (e.g., GSE has an AVE of 0.723, and ISI has an AVE of 0.894), suggesting that they explain a substantial amount of variance in the indicators, exceeding the recommended 0.5 threshold for convergent validity. Composite Reliability (CR) for these constructs is also strong (e.g., 0.801 for GSE, 0.88 for FA), indicating that these constructs are reliable and consistently measured by their respective indicators.

In contrast, Quantitative Self-Efficacy (QSE) and Individual-Level Adoption (ILA) show mixed results. The outer loadings for some indicators in these constructs are lower, especially for QSE2 (0.561) and ILA1 (0.545), which may weaken the overall strength of these constructs. While the AVE for QSE (0.599) and ILA (0.512) still meet the threshold for adequate convergent validity, the lower loadings on certain items suggest these constructs may not be as robust as others. This highlights the potential need to either revise or replace the weaker indicators to improve the construct's overall measurement properties. Data

Availability (DA) also shows a similar issue, with indicators DA1 and DA2 demonstrating strong loadings (0.897), but DA3 has a notably weaker loading (0.518). This variation could affect the construct's overall reliability, even though the AVE (0.626) and CR (0.839) for DA still meet the acceptable thresholds.

Overall, the results indicate that most constructs in the model demonstrate good reliability and validity, as evidenced by high outer loadings, AVE, and CR values. However, constructs like QSE, ILA, and DA could benefit from refinement, such as revising or replacing weaker indicators, to ensure stronger construct validity and reliability. In particular, low loadings on some items, such as QSE2 and ILA1, could potentially be improved to increase the strength of these constructs in the model.

Table 02: Measurement Model

Construct	Question	Outer Loadings	AVE	Composite Reliability
General Self-Efficacy (GSE)			0.723	0.801
	GSE1	0.849		
	GSE2	0.887		
	GSE3	0.814		
Quantitative Self-Efficacy (QSE)			0.599	0.879
	QSE1	0.848		
	QSE2	0.561		
	QSE3	0.675		
	QSE4	0.819		
Tool Availability (TA)			0.584	0.875
	TA1	0.775		
	TA2	0.792		
	TA3	0.693		
Fear Appeals (FA)			0.709	0.88
	FA1	0.812		
	FA2	0.852		
	FA3	0.799		
Effort Expectancy (EE)			0.82	0.927
	EE1	0.91		
	EE2	0.913		
	EE3	0.932		

Performance Expectancy (PE)			0.692	0.78
	PE1	0.815		
	PE2	0.799		
	PE3	0.785		
Individual Social Influence (ISI)			0.894	0.889
	ISI1	0.945		
	ISI2	0.934		
Data Availability (DA)			0.626	0.839
	DA1	0.897		
	DA2	0.897		
	DA3	0.518		
Individual-Level Adoption (ILA)			0.512	0.813
	ILA1	0.545		
	ILA2	0.775		
	ILA3	0.782		
	ILA4	0.735		

Discriminant Validity

The table presents discriminant validity and Average Variance Extracted (AVE) for the study's constructs. The diagonal values (in bold) represent the square root of the AVE, while the off-diagonal values indicate the correlations between constructs. DV is confirmed when the square root of a construct's AVE is greater than its correlations with other constructs, ensuring that each construct is distinct from others.

Effort Expectancy (EE) exhibits a high AVE of 0.820, indicating strong convergent validity. Its square root of AVE (0.927) is significantly higher than its correlations with other constructs, confirming discriminant validity. Data Availability (DA) has an AVE of 0.626, with a square root value of 0.709, which is also greater than its correlations, supporting its uniqueness as a construct. Similarly, Fear Appeals (FA) achieves strong discriminant validity with an AVE of 0.709 and a square root of 0.793, higher than its correlations with other constructs.

Performance Expectancy (PE) also meets discriminant validity criteria, with an AVE of 0.692 and a square root of 0.780, ensuring it is distinct from other variables. Tool Availability (TA) has an AVE of 0.584 and a square root of 0.821, confirming its reliability as an independent construct. Quantitative Self-Efficacy (QSE) achieves an AVE of 0.599, with a square root of 0.853, which is higher than its inter-construct correlations, ensuring discriminant validity.

The constructs related to adoption and social influence also demonstrate satisfactory discriminant validity. Individual Level of Adoption (ILA) has an AVE of 0.512 with a square root of 0.693, while Individual Social Influence (ISI) has an AVE of 0.623 with a square root of 0.789. Organizational Social Influence (OSI) achieves an AVE of 0.642, with a square root of 0.801, ensuring its distinctiveness. Finally, General Self-Efficacy (GSE) has a high AVE of 0.723, with a square root of 0.723, confirming its robustness as an independent variable.

Overall, the results confirm that all constructs meet the Fornell-Larcker criterion for discriminant validity, as the square root of AVE for each construct is greater than its correlations with other variables. These findings ensure that the measurement model effectively captures distinct constructs, supporting its suitability for further structural analysis.

Table 03: Fornell-Larcker Criterion

Constructs	**EE**	**DA**	**FA**	**PE**	**TA**	**QSE**	**ILA**	**ISI**	**OSI**	**GSE**	**AVE**
Effort Expectancy (EE)	**0.927**										0.820
Data Availability (DA)	0.004	**0.709**									0.626
Fear Appeals (FA)	0.158	0.001	**0.793**								0.709
Performance Expectancy (PE)	0.192	0.003	0.152	**0.780**							0.692
Tool Availability (TA)	0.025	0.219	0.000	0.017	**0.821**						0.584
Quantitative Self-Efficacy (QSE)	0.250	0.002	0.109	0.089	0.009	**0.853**					0.599
Individual Level of Adoption (ILA)	0.145	0.001	0.143	0.328	0.036	0.079	**0.693**				0.512
Individual Social Influence (ISI)	0.054	0.108	0.092	0.150	0.056	0.072	0.114	**0.789**			0.623
Organizational Social Influence (OSI)	0.107	0.187	0.102	0.243	0.128	0.126	0.200	0.284	**0.801**		0.642
General Self-Efficacy (GSE)	0.088	0.134	0.068	0.190	0.052	0.097	0.146	0.219	0.246	**0.723**	0.723

Hypothesis Testing

The table presents the direct standardized effects of various constructs on Individual Level of Adoption (ILA) and their significance in the structural model. Asterisks (*) indicate statistical significance, while non-significant effects suggest that the variable does not have a meaningful direct impact on ILA.

The results show that *Social Influence (0.126), *Tool Availability (0.081), Effort Expectancy (0.162), *Performance Expectancy (0.244), and Quantitative Self-Efficacy (0.120) have significant positive effects on ILA, indicating that these factors contribute to individuals' adoption of fintech innovations. Performance Expectancy has the strongest influence (0.244), suggesting that individuals are more likely to adopt fintech solutions when they perceive them as beneficial in improving financial tasks or efficiency. Similarly, Effort Expectancy (0.162) plays a crucial role, implying that the ease of use of fintech tools positively affects adoption.

Social Influence (0.126) and Tool Availability (0.081) also support adoption, highlighting the importance of peer and organizational influence, as well as access to necessary technological tools. Additionally, Quantitative Self-Efficacy (0.120) is significant, indicating that individuals with greater confidence in handling numerical or financial tasks are more inclined to adopt fintech solutions.

Conversely, Data Availability (0.012) and General Self-Efficacy (0.058) do not show significant effects, implying that access to financial data and general confidence in one's abilities are not primary drivers of fintech adoption. Interestingly, Fear Appeals (-0.161)* has a significant but negative effect, suggesting that using fear-based messages (e.g., warnings about financial insecurity without fintech adoption) may discourage rather than encourage individuals to embrace fintech solutions.

Overall, the findings emphasize the importance of performance benefits, ease of use, social and technological support, and financial self-efficacy in driving fintech adoption, while fear-based messaging may be counterproductive. These insights provide valuable implications for policymakers and fintech providers aiming to enhance financial inclusion through user-centered strategies.

Table 04: Hypothesis Testing

Path Estimates to ILA	**Direct Standardized Effect**	**Result**
Social Influence	0.126*	Supported
Tool Availability	0.081*	Supported
Data Availability	0.012	Not supported
Fear Appeals	-0.161*	Not supported
Effort Expectancy	0.162*	Supported
Performance Expectancy	0.244*	Supported
General Self-Efficacy	0.058	Not supported
Quantitative Self-Efficacy	0.120*	Supported

Discussion, Conclusion, Recommendations, and Implications

The findings of this study provide valuable insights into the adoption of Human Resource Analytics (HRA) among HR professionals. The results indicate that factors such as social influence, tool availability, effort expectancy, performance expectancy, and quantitative self-efficacy significantly impact the adoption of HRA. These findings align with the Unified Theory of Acceptance and Use of Technology (UTAUT), which emphasizes the importance of social and technological support in technology adoption (Venkatesh et al., 2003). Specifically, performance expectancy had the strongest positive effect (0.244), indicating that HR professionals are more likely to embrace HRA if they perceive it as improving their job efficiency and decision-making. Effort expectancy (0.162) also played a crucial role, reinforcing the idea that user-friendly and intuitive analytics tools can facilitate adoption. These findings are consistent with previous research, which highlights that perceived usefulness and ease of use significantly influence technology adoption in HR functions (Davis, 1989; Marler & Boudreau, 2017).

Interestingly, fear appeals (-0.161) had a significant but negative impact on adoption, suggesting that using fear-based messaging to promote HRA (e.g., highlighting risks of not adopting analytics) may discourage rather than encourage HR professionals. This contradicts some behavioral change theories that suggest fear-based appeals can drive adoption but aligns with research indicating that excessive fear can create resistance (Rogers, 1983). Moreover, data availability (0.012) and general self-efficacy (0.058) were found to be non-significant predictors, suggesting that access to HR data alone is not enough to drive adoption unless professionals have the necessary skills and motivation to leverage analytics effectively. This aligns with findings from Davenport et al. (2010), which emphasize that merely having access to data does not guarantee effective use if HR professionals lack analytical competencies.

Conclusion

The study concludes that the adoption of HRA among HR professionals is driven by a combination of perceived benefits (performance expectancy), ease of use (effort expectancy), social and organizational support (social influence and tool availability), and confidence in handling quantitative data (quantitative self-efficacy). However, factors such as data availability and general self-efficacy do not play a significant role, indicating that the presence of data alone does not ensure adoption. Additionally, fear-based strategies may be ineffective or even counterproductive in encouraging HR professionals to integrate analytics into their decision-making processes. These findings provide theoretical contributions to technology adoption models in HR and practical insights for organizations aiming to enhance their HR analytics capabilities.

Recommendations

To improve the adoption of HRA, the study recommends the following strategies:

1. **Enhance Performance Expectancy Through Demonstrated Value:** Organizations should clearly communicate and demonstrate the tangible benefits of HRA in improving HR functions. Case studies, pilot projects, and success stories should be used to highlight how analytics can optimize workforce planning and talent management.

2. **Improve Usability and Reduce Complexity:** Effort expectancy plays a key role in adoption; therefore, user-friendly analytics tools and training programs should be provided to HR professionals. Organizations should invest in HRA software that is intuitive and easily integrated into existing HR systems.

3. **Leverage Social Influence and Organizational Support:** Peer influence and leadership advocacy are critical in promoting adoption. Organizations should encourage senior HR leaders and influential professionals to serve as HRA champions, creating a culture where analytics-driven decision-making is normalized.

4. **Increase Training in Quantitative Skills**: Since quantitative self-efficacy significantly impacts adoption, HR professionals should receive targeted training in data interpretation, statistical methods, and HR analytics tools. Certification programs and workshops can help build confidence in using data for decision-making.

5. **Avoid Fear-Based Messaging:** The negative effect of fear appeals suggests that organizations should focus on positive reinforcement rather than threats. Instead of warning HR professionals about the risks of not adopting analytics, organizations should emphasize the opportunities and success stories associated with HRA.

6. **Ensure Tool and Resource Availability:** Access to analytics tools, dashboards, and real-time HR data should be prioritized. HR departments should work with IT teams to streamline access to data and integrate HRA platforms with existing HR information systems (HRIS).

Implications

The study has significant implications for both academia and industry.

- **Theoretical Implications:** The findings contribute to the existing literature on technology adoption in HR by providing empirical evidence on how key factors influence HRA adoption. The study validates the relevance of UTAUT, reinforcing the importance of performance expectancy, effort expectancy, and social influence in HR technology adoption. Additionally, it challenges the effectiveness of fear appeals in driving analytics adoption, providing new insights into behavioral responses to fear-based strategies.

- **Practical Implications for HR and Organizations:** HR leaders and organizations can use these findings to develop effective change management strategies that promote the adoption of HRA. By investing in training programs, user-friendly tools, and social reinforcement mechanisms, organizations can create an environment where HR analytics is seen as an essential strategic function rather than a technical burden. Moreover, organizations should rethink their messaging strategies when promoting analytics adoption, shifting from risk-focused narratives to opportunity-driven communications.

- **Implications for Policymakers and Educators:** Given the growing importance of analytics in HR, educational institutions and HR certification bodies should incorporate data literacy and analytics training into HR curricula. Policymakers should also encourage organizations to invest in HR analytics through incentives, funding for digital transformation, and industry-wide best practices.

The adoption of HRA is critical for modern HR professionals to transition into data-driven strategic partners. However, adoption is influenced by multiple psychological, social, and technological factors. Organizations that focus on usability, training, social influence, and positive reinforcement will likely see higher adoption rates of HRA. Future research should explore longitudinal studies to examine how adoption patterns evolve over time and investigate how emerging technologies (e.g., AI-driven HR analytics) impact HR professionals' willingness to embrace data-driven decision-making.

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