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Research Article

Trapezoidal Fuzzy Approach to Prioritize Analytical Competencies of HR Professionals

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Abstract: An exploration of various human capital trends and skill requirements of human resource (HR) professionals strengthen the argument to build the talent pool that can utilize analytics for making the right HR decisions. In this context, the present study identified the analytical competencies required for HR professionals and prioritized them. Based on the literature in the area of HR analytics and analytical competencies, a 20-item survey instrument was developed and served to HR professionals. Responses from 390 HR professionals were collected, and data analysis was performed using descriptive and multivariate statistical techniques such as t-test and analysis of variance (ANOVA). The trapezoidal fuzzy approach, a Multi-Criteria Decision-Making method, has been used in the present study to prioritize and rank the analytical competencies. The results of the study indicate that there were no differences in analytical competencies by age and total work experience of HR professionals. HR professionals were having a reasonably good amount of understanding of several analytical competencies yet required further advancement to explore HR analytics fully. The present research contributes to analyzing various trends in changing skill requirements of HR professionals in light of the emergence of HR analytics, an area not widely studied from the viewpoint of HR professionals' readiness. Using the results, organizations can focus on the right skills in which professionals need training. Analytical competencies have been examined in the context of HR analytics for the first time using an multi-criteria decision-making (MCDM) approach. The research is novel in prioritizing analytical competencies using a trapezoidal fuzzy approach.

***Keywords*:** analytical competencies, HR analytics, HR competency, HR professionals, data analysis skills, fuzzy approach, MCDM

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Nomenclature

Term	Description
AC1	Performing basic statistical calculations-Averages (Mean, Median), Percentiles
AC2	Calculating statistically significant differences-Range, Variances, Standard deviation
AC3	Performing Correlation, Regression
AC4	Performing ANOVA, Factor Analysis
AC5	Using Advanced multivariate models (Structural equation models, Bivariate/multivariate choice models, Cross-level models)
AC6	Data identification, cleaning, and preparation for analysis
AC7	Identify causal paths
AC8	Six Sigma analysis
AC9	Formulate treatment vs. control groups
AC10	Selecting sample, designing survey items, verifying validity and reliability
AC11	Using interview techniques for data collection, interview coding, content analysis
AC12	Preparing statistical reports to make statistical results understandable
AC13	Presenting analysis and results through public speaking to different stakeholders
AC14	Knowledge about software packages-MS-Excel
AC15	Knowledge about software packages-SPSS
AC16	Knowledge about software packages-SAS
AC17	Knowledge about software packages-R
AC18	Knowledge about software packages-Python
AC19	Knowledge about software packages-Tableau
AC20	Knowledge about software packages-QlikView

1. Introduction

Technological advancement, particularly in the information arena, is changing the business landscape rapidly. Business organizations are constantly compelled to redefine their strategies and build the workforce that can align itself to the attainment of strategic goals. Organizations can gain competitive advantage strategically with effective human capital management [1]. Success of the organization is defined by the readiness of capabilities and competencies of the human resources [2]. Accordingly, professionals are expected to stay ahead with the changing technologies and acquire analytical skills [3]. In order to catch up with the dynamic global changes, HR professionals need to upgrade themselves and strive to integrate the HR function to contribute to the corporate strategy. To keep the competitive advantage with them, HR professionals need to equip themselves with analytical skills and be able to handle big data [4]. Human resource (HR) Analytics is a way to apply statistical and analytical techniques on employee data to explore the human capital strength and bring the right decision making backed by evidence. Though analytics has entered business functions long ago, its extensive application in the HR domain has not picked up the pace. In the Indian context, there are not enough industry level studies and literature to support the wide usage of HR analytics in Indian organizations [5]. If utilized at the best level, HR analytics can help organizations to tackle a lot of future HR issues as well as current HR challenges. In general, HR professionals lack analytical competencies to operate HR analytics [6]. There is a need to build the talent pool that can utilize analytics for making the right HR decisions.

Many studies on the topic of HR analytics have focused on the importance and conceptualization of HR analytics based on case studies [7]. However, the extent and type of analytical competencies required from the HR professionals to advance HR analytics is not studied well in the research parlance. The present study identifies the extent of analytical competencies and provides the base framework to study the competencies in HR analytics implementation. In the present study, an attempt is made to address the problem of identification and prioritization of analytical competencies among HR professionals. Use of Multi Criteria Decision Making technique to prioritize the competencies reduces the perceptual bias and offers better justified solution. The remainder of the study is presented in different sections. Continuation of subsections in the first part has focused on exploration of various human capital trends and skill requirements of HR professionals. The second section provides a comprehensive review of literature pertaining to competency frameworks and analytical competencies. The third section offers an overview of methods and measures use for development of the instrument, data collection, and analysis. Results of data analysis are presented in the fourth section. A discussion on the results and corresponding implications is carried out in the fifth section, while the sixth section presents the conclusions, the limitations of the present study and scope for future studies is discussed in seventh section.

1.1 *Changing human capital trends and skill requirements of HR professionals*

Change is a fact of life in every industry. Human capital is also subject to disruptions. This has been extensively researched. Global HR consultancy Deloitte has worked hard to generate excellent HR insights to assist the industry and update strategies to suit changing industry requirements globally. The annual Deloitte Global Human Capital Trends report has acquired popularity for its extensive coverage of human resource challenges. The following sections discuss changing trends in human capital, HR function, and HR analytics from the lenses of the shifts in global human capital trends and the corresponding shifts in the HR analytics and analytical competencies landscape.

1.2 *Shifts in global human capital trends-a comparison of top trends*

HR professionals and leaders across the world are involved in these studies. Deloitte reports the top 10 human capital trends based on the priority placed on the trend. These reports from the year 2014 to 2019 have been analyzed to understand the HR trends relevant to the present study.

In the year 2014, "leadership, retention and engagement, and reskilling the HR function" are rated as the top three priorities [8]. By 2015, culture and engagement have taken the top position, followed by leadership and learning and development [9]. In the year 2016, organizational design has topped the trends, while leadership remained the second most crucial priority followed by culture [10]. Eighty percent of organizations had positions requiring data analysis skills. Projections were made that another 2 percent of organizations were about to create such positions by 2016 [11]. A new form of 'organization of the future' has topped the 2017 trends, while careers and learning and talent acquisition occupied the second and third positions, respectively [12]. Nordic organizations have identified analytics and automation as the most relevant developments in the Nordics. 57 percent of firms indicate the trend is already relevant in their industry [13]. In 2018, 'the symphonic C-suite' was popular. 'From occupations to experiences' is the second most significant trend. In 2018, the groups were becoming social enterprises. Social enterprise transformation guarantees stakeholder support and respect while ensuring profitability [14]. In 2019, organizations continued to redefine themselves to be more human-centric. 2019 trends revealed several new topics, many of which are tied to HR technologies. While learning and human experience ranked first and second, HR cloud, which includes analytics, artificial intelligence, and digital HR, was sixth [15]. While the future seems bright for HR analytics and other developing technologies in the HR domain, the pace has been slower than predicted. Asia-Pacific organizations gave 86 percent emphasis to learning, human experience, and leadership trends. Asia-Pacific enterprises value the HR cloud trend, which includes HR analytics, artificial intelligence (AI), and diverse HR technology. People analytics controlling personnel strategies is a key trend for 2020 [16].

1.3 *Shifts in trends in HR analytics and the readiness with analytical competencies*

A look at the HR analytics trend across the years shows that "talent and HR analytics" was the sixth most popular topic in 2014. As trends changed, so did this tendency. In 2015, the trend "HR and people analytics" was ranked seventh, with "people data" everywhere' ranking tenth. Between 2016 and 2018, the "people analytics" trend ranked sixth. "People data" was the second trend in 2018, and it was recognized as a key trend in 2018.

In 2014, 14% of organizations reported analytic potential. However, over 60% of firms have a chaotic HR system that prevents significant data-driven decisions [8]. In 2015, 75% of organizations regarded people analytics as "important". But these groups lack the essential preparation. Only 8% rated themselves "strong" in people analytics, unchanged from 2014 [9].

In 2016, 77% of firms said people analytics was important. About 42% of respondents said they have enough data to support HR analytics projects. India ranks third on the list, giving the trend 83% importance [10]. Darien [11] reported that 54% of individual and middle management HR positions required data analysis.

People analytics saw a new trend in 2017 with organizational network analysis (ONA). Several companies also use "interaction analytics" to analyze employee responses [12]. While 80% of Nordic firms value HR analytics, only 37% are satisfied with how HR departments have used it [17].

In 2018, 84% of respondents valued people analytics. According to the 2018 survey, 69% of companies have integrated employee data analysis platforms [14].

As of 2019 and 2020, HR analytics trends have evolved into new forms that work with digital HR and the HR cloud. Internal mobility and performance management are viewed as major areas where analytics may help. People analytics must be used to assess workforce-related policies and procedures. This includes sophisticated analytics, artificial intelligence, and sentiment analysis. Increased acceptance of HR analytics is encouraging, but slow expansion is disappointing. A literature analysis was conducted to determine the causes for the slow expansion of HR analytics and the role of HR professionals' competencies in its adoption.

2. Literature review

HR analytics requires analytical skills. Thus, research on HR professionals' analytical skills is examined. Because HR analytics is a new field, prior research on HR professionals' analytical skills is sparse. Using research, an attempt is made to uncover themes in the domain of HR analytical competencies.

2.1 *Important role of analytical competencies in HR profession*

Previously, HR was not focused on transformational initiatives, but rather on low-value transactional tasks. Among other skills, HR practitioners must have technical HR skills. HR competencies in the area of analytics are critical for the adoption of HR analytics [18].

Rouse [19] attempted to categorize and rate the most critical HR competencies in their survey. In their study, analytical skills were mentioned 73 times out of 125, claiming 58% of importance. A study by [20] discussed how some companies discovered novel means of utilizing HR analytics to produce value.

Along with the uses of analytic data, Levenson [21] presented different models of applying people management in organizations. The study also attempted to define the analytical skills required for HR practitioners to apply HR analytics.

There is a disconnect between HR professionals' analytical talents and what organizations anticipate. Only a small percentage of HR professionals are skilled in analytics. Many firms rely on outside analysts to undertake basic statistical analysis and successfully explain the results. This situation makes it challenging to gain meaningful HR data insights. The fundamental skills and duties in data analytics are not clearly defined and are reliant on subjective perceptions [22].

Analytical competencies of HR professionals have proven to be of great benefit in furthering HR analytics and improving the efficiency and effectiveness of HR activities [23].

Using any new technology demands certain competencies. Insufficient analytical competencies of HR professionals have hindered the adoption of HR analytics [7, 24, 25], which is widely recognized by several studies and reports [25, 26].

A review of 39 articles published between the years 2004-2013 was carried out by [27] to describe the factors that moderate HR analytics. The review identified five primary ways to uncover moderating factors: identify issues, data infrastructure, IT, analytical skills, and enterprise approach. Six of the author's 11 most relevant publications for comparison underlined the moderating effect of HR professionals' analytical skills on HR analytics.

While implementing HR analytics takes a team of experts, HR professionals are regarded as key stakeholders in developing the proper insights [28]. Data and analysis functions have been avoided due to HR professionals' perceived mathematical and analytical weaknesses. Yet, HR professionals are also collecting and processing data. It takes a unique set of talents to work with HR analytics [29].

Progress and maturity of HR analytics is highly dependent on HR professionals' knowledge and skills in performing the analytic functions [30]. Aversion to HR analytics is due to the fact that predictive and prescriptive analytics software was designed for analytically skilled individuals [25]. No one outside of HR can perform HR analytics functions. If this is attempted, HR may lose its value in the organization.

2.2 *Composition of analytical competencies*

To leverage analytics advantage in HR, the right mix of skills to handle data, perform statistical operations, and understand business dynamics are essential [31].

Asper [32], analytical skills cover a range of data administration, analysis, and outcome management skills. The essential analytical skills are: "identifying data requirements, validation, quality; performing descriptive statistics, multi-dimensional modeling, regression, factor/cluster analysis, data presentation and reports; analytic conceptualization, interpretation of findings and limitations of statistical analysis". Besides having computer proficiency, analytic prowess, and professional skills, HR professionals need to possess interpretation skills for transforming the facts of the analytics into insights [33]. HR professionals must identify the core insights and how those insights can be used in their work.

Authors [34] attempted to describe and characterize analytical talent. They state that analytic specialists should be able to develop statistical models and employ optimization and simulation approaches. Popovska et al. [35] selected argument-based decision-making as one of nine competencies for HR professionals in their survey. Argument-based decision-making emphasizes data analytics to correctly analyze data and support business decisions. It identified research and data analytics skills as sub-competencies of argument-based decision-making.

HR workers need analytical skills to successfully manage talent and recruitment data. Gradually, organizations have started finding ways to apply predictive analytics in HR. Harris [36] opined that post-2016, HR professionals were required to enhance their quantitative skills by jointly working with IT experts, data scientists, and technology suppliers in order to make a big leap in promoting HR analytics and meeting the challenges.

To put HR analytics into action, specialists and teams from many fields are expected to collaborate. HR practitioners need to be more analytically literate. Analytics should not end at producing insights but should continue to deliver results. The focus should now be on developing HR professionals who understand and apply HR analytics.

2.3 *HR competency frameworks and analytical competencies*

The society for human resource management (SHRM) has been updating its HR competency models with substantial research backed by HR professionals worldwide and validated by subject matter experts. The SHRM's HR competency model outlines nine competencies [11]. The nine competencies are HR expertise, ethical practice, leadership and navigation, business acumen, consultation, critical evaluation, communication, global and cultural effectiveness, and relationship management.

Among these competencies, the critical evaluation competency is defined as "the ability to interpret information to make business decisions and recommendations". The sub-competencies of critical evaluation competency include measurement and assessment skills, research methodology, objectivity, decision-making, critical thinking, auditing skills, problem-solving, knowledge management, curiosity, and inquisitiveness.

Continuing over three decades of research in redefining HR competencies, Ulrich et al. [37] have developed the '2016 HR competency model' with nine categories. Among the nine categories, three competencies, namely, strategic positioner, credible activist, and paradox navigator, are labeled as 'core drivers'. Another three competencies, Culture and Change Champion, Human Capital Curator, and Total Rewards Steward, are labeled under 'organizational enablers'. The remaining three competencies, Technology and Media Integrator, Analytics Designer and Interpreter, and Compliance Manager, are labeled under 'delivery enablers'.

As an analytics designer and interpreter, the HR professional should be capable of using analytics for better decision-making. Getting the right data and interpreting the business data are the sub-domains within analytics designer and interpreter. In addition, Ulrich et al. [37] also define some of the ways through which HR professionals display the analytics designer and interpreter competencies as "accurately interpreting statistics, excluding low-quality data from decision processes, understanding the limitations of data in ambiguous situations, incorporating rigorous data analysis when interpreting information, effective usage of HR analytics to create value for the organization, identifying organization's problems that can be solved with data, translating data into useful insights, and using data to influence decision-making in the organization.

The review of the literature offers the themes that HR professionals' technical competencies are among the critical competencies. There is a need to measure analytical competencies with decision-makers' understanding [19]. Analytical skills are among the essential skills required by HR professionals to perform their duties [20, 35].

HR professionals need computing, analytical, quantitative, qualitative, and interpretation skills [33, 34, 37]. HR professionals need expertise in using predictive analytics tools and skills in measurement, research methodology, and problem-solving [34, 11].

The fuzzy analytical hierarchical approach was applied by [38] in examining the role of competencies in employee selection. The fundamental concepts of competencies find similarity with the purposes of the fuzzy approach. Hence, many researchers found an association between the competencies of professionals and the fuzzy approach [39].

The unclear nature of evaluating competencies holds good as a case to apply the fuzzy logic approach as there is a lack of exact distinction among the analytical competencies [40]. The literature in this area provides several gaps to understand the state of analytical competencies of HR professionals as well as the prioritization of those competencies.

3. Methodology

The objective of the present study is to examine the levels of analytical competencies among HR professionals and prioritize the analytical competencies for HR professionals to handle the HR analytics function. Analytical competencies have not been previously examined in the research parlance to project any demographic associations. Hence, the present study hypothesizes the differences in analytical competencies among HR professionals by their gender, age, work experience, and educational qualifications. The trapezoidal fuzzy approach, a Multi-Criteria Decision-Making method, has been used in the present study to prioritize and rank the analytical competencies.

The study is aimed at testing the following hypotheses:

H1: Analytical Competencies are significantly different between the male and female categories of gender.

H2: Analytical Competencies are significantly different by respondents' age.

H3: Analytical Competencies are significantly different by respondents' total work experience.

H4: Analytical Competencies are significantly different by respondents' educational qualifications.

To achieve the objective of the study, a systematic approach is followed to collect and analyze the data of the analytical competencies of HR professionals. The methods followed are explained in this section.

3.1 *Study instrument and scales*

When a new research problem is undertaken, it is vital to comprehend the premises. It is essential to know which analytical skills are used by HR professionals. The real users of HR analytics who are already practicing can throw some light on this issue. By approaching actual practitioners of HR analytics, focus group discussions were conducted. Different views were presented by them on issues of analytical skills, technologies, and various issues related to HR analytics. The learnings from the exploration phase led to developing a customized survey instrument capturing essential analytical competencies for HR professionals. The survey items used in the study are adapted from preceding works carried out in similar domains. Expert professionals and researchers in the HR field are consulted to bring out the final shape of the questionnaire. Suggestions made by the experts are incorporated into the questionnaire to enhance the response rate and meet the desired research objectives. Finally, 20 items were organized in an orderly manner to develop the full instrument. Demographic characteristics of respondents such as age, gender, education, and total work experience of the respondent are also captured through the instrument. Further, the instrument is tested for validity. The final survey instrument consisted of 20 statements, other than the profile of respondents.

3.2 *Defining variables, measurement items, and formulation of hypotheses*

The operational definitions of variables under study and the measurement items are presented in Table 1. The formation of the construct analytical competencies, and the measurement items used in the study are as follows.

Table 1. Construct items for analytical competencies (AC)

Construct	Definition	Label	Measurement item
Analytical competencies	"A range of data administration, analysis, and outcome management skills" [31, 32]	AC1	Performing basic statistical calculations-averages (mean, median), percentiles
		AC2	Calculating statistically significant differences-range, variances, standard deviation
		AC3	Performing correlation, regression
		AC4	Performing ANOVA, factor analysis
		AC5	Using advanced multivariate models (structural equation models, bivariate/multivariate choice models, cross-level models)
		AC6	Data identification, cleaning, and preparation for analysis
		AC7	Identify causal paths
		AC8	Six Sigma analysis
		AC9	Formulate treatment vs. control groups
		AC10	Selecting sample, designing survey items, verifying validity and reliability
		AC11	Using interview techniques for data collection, interview coding, content analysis
		AC12	Preparing statistical reports to make statistical results understandable
		AC13	Presenting analysis and results through public speaking to different stakeholders
		AC14	Knowledge about software packages-MS-Excel
		AC15	Knowledge about software packages-SPSS
		AC16	Knowledge about software packages-SAS
		AC13	Knowledge about software packages-R
		AC18	Knowledge about software packages-Python
		AC19	Knowledge about software packages-Tableau
		AC20	Knowledge about software packages-QlikView

Competency depicts the readiness of an individual to take up a task and perform such a task. According to [41] a job competency is an underlying characteristic of an employee (i.e., a motive, trait, skill, aspect of one's self-image, social role, or a body of knowledge) which results in superior performance" [41].

A similar opinion to conceptualize competency is given by [42], "Competency refers to an individual's demonstrated knowledge, skills, or abilities". Another simpler way to define competencies is "work-related personal attributes; knowledge, skills, and values that individuals draw upon to do their work well" [43].

Nevertheless, competencies are not enough to bring results or to display performance. As in practice, capability (i.e., what someone actually does) is essential to fill the gap between competence and performance [44].

Focus on HR metrics and analytics is an essential competency among the core HR competencies. This new competency includes key measurement skills. Using these measurement skills or analytical skills, one should be able to identify problems and critical metrics and keep tabs on the essential growth parameters and strategies of the organization [45].

Analytical Competencies (AC): Competencies for any professional are vital to execute their tasks effectively. The round seven of the Human Resource Competency Study (HRCS) found that about 50 percent of the perceived performance of HR professionals comes from their competencies [46].

Analytics designer and interpreter is the one capable of applying analytics for the enhancement of decision-making outcomes [37]. The skillset required to leverage analytic advantage in HR is the right mix of data management skills, statistical/data processing prowess, and business acumen [31].

Data analysis skills are defined as the ability to gather, analyze, and draw practical conclusions from data, as well as communicate data findings to others [11]. The essential analytical skills, according to [32], are: identifying data requirements, validation, quality; performing descriptive statistics, multi-dimensional modeling, regression, factor/cluster analysis, data presentation and reports; analytic conceptualization, interpretation of findings, and limitations of statistical analysis.

Generally, many HRM concepts are measured using the five-point scale. Hence, respondents are habituated to answering. Also, a five-point scale prevents respondents' ambiguity in identifying differences within the scale levels that respondents may face while a seven-point scale is used [47]. Hence, a five-point scale is adopted throughout the study instrument. A five-point Likert-type scale with a range of "basic", "novice", "intermediate", "advanced", and "expert" [48] was used.

3.3 *Sample and data collection*

For obtaining the responses related to analytical competencies, primary data was collected from HR professionals working in India by serving the questionnaire online. To prevent any possible methodological bias, the respondents were given clear instructions about the purpose, context, anonymity, and confidentiality of the study. Also, care was taken to ensure accuracy and clarity in the wording of the questions.

After filling their basic details such as gender, age, organization, work experience, and educational qualifications, the respondents were requested to rate their level of analytical competencies (AC1 to AC20) on the scale of "basic", "novice", "intermediate", "advanced", and "expert". The respondents were advised to give their responses in 15-20 minutes. More than 700 HR professionals across the country were approached through various HR forums and professional networking platforms. A total of 450 responses were received from the respondents. However, some of the responses were not included as they were incomplete or rated with high leniency. Finally, a sample of 390 responses collected from HR professionals was considered, and further analysis was carried out.

The responses collected through the web form were transferred to spreadsheet software and imported into statistical analysis software. Data analysis was performed using descriptive statistical methods and multivariate statistical techniques such as the *t*-test and ANOVA. As several items correspond to the analytical competencies, to understand the critical analytical competencies among the identified ones, the trapezoidal fuzzy approach has been used in the present study.

To evaluate the analytical competencies, the five-level rating scale of the analytical competencies of HR professionals (from "basic" level to "expert" level) is converted into linguistic variables (Table 2) that satisfy trapezoidal properties.

While prioritizing the analytical competencies, the trapezoidal fuzzy numbers are defuzzified using the Center of Gravity (CoG) method, and the items are ranked (Table 3).

Table 2. Detailed composition of respondents by demographic variables

Demographic variable	Categories	Number of respondents	Percentage (%)
Industry type	IT	113	30
	Manufacturing	98	25
	Services	137	35
	Others	38	10
	Total	390	100
Organization size	Small	156	40
	Medium	137	35
	Large	97	25
	Total	390	100
Geographic region	North	78	20
	South	113	30
	East	98	25
	West	97	25
	Total	390	100
Role levels	Junior	136	45
	Mid-Level	137	35
	Senior	77	20
	Total	390	100

Table 3. Descriptive statistics and pairwise comparisons of analytical competencies by educational qualification

Educational qualification	Mean (M)	SD	n	Comparison	p-value	Significance ($\alpha = 0.05$)
Under graduation	3.66	0.53	137	Other certification/ higher qualification vs. under graduation	0.022	Significant
Post-graduation	3.64	0.68	209	Post-graduation vs. other certification/ higher qualification	0.012	Significant
Other certification/ higher qualification	3.94	0.50	44	-	-	-

3.4 *Sample characteristics*

The study utilized a sample of 390 HR professionals, which is considered adequate for statistical analysis. To provide a comprehensive understanding of the respondents, the following breakdown of the demographic variables is presented in Table 2. This includes information on industry type, organization size, geographic region, and role levels. The total sample size and percentages for each category are also highlighted to ensure transparency in the study's methodology.

The results in Table 2 show that the sample of 390 HR professionals was diverse in terms of demographic characteristics. The majority of respondents were from the services industry (35%), followed by IT (30%), manufacturing (25%), and others (10%).

Regarding organization size, small organizations were the most represented (40%), followed by medium organizations (35%) and large organizations (25%). Geographically, respondents were distributed across North (20%), South (30%), East (25%), and West (25%) regions of the country.

Regarding role levels, the largest group of respondents were junior-level professionals (45%), followed by mid-level (35%) and senior-level professionals (20%). This diverse composition ensures a balanced representation of HR professionals across various industries, organizational sizes, geographic regions, and professional levels, supporting the study's goal of examining analytical competencies comprehensively.

3.5 *Sampling technique*

The study employed a non-probability convenience sampling method to select respondents. The selection was primarily based on accessibility, leveraging professional networks to gather responses from HR professionals with relevant expertise in HR analytics. This approach was necessary due to practical constraints, such as time limitations and the challenges associated with accessing a broader population.

While this method facilitated efficient data collection, it is acknowledged that non-random sampling methods, such as convenience or purposive sampling, can introduce bias. This limitation may affect the generalizability of the results to the broader population of HR professionals. To address this, we have explicitly clarified the sampling approach in the Methodology section and acknowledged its potential limitations in the Limitations section. Future research could consider adopting probability sampling techniques, such as simple random sampling or stratified random sampling, to mitigate bias and improve the representativeness of findings.

3.6 *Survey instrument and pretesting*

The study utilized a customized survey instrument to assess analytical competencies (AC) among HR professionals. This approach was deemed appropriate given the evolving nature of HR analytics, where standardized instruments are limited. The survey was developed based on a comprehensive review of the literature and inputs from subject matter experts in HR analytics, ensuring that the instrument captured the constructs critical to this domain.

To establish the reliability and validity of the instrument, a pilot test was conducted with 30 HR professionals prior to the main survey. These participants were selected to represent the target population and provided feedback on the clarity, relevance, and comprehensiveness of the survey items. The pilot test results informed refinements to the survey, including rewording ambiguous items, enhancing the alignment of items with study objectives, and improving the overall structure of the instrument.

The reliability of the survey was assessed using Cronbach's alpha, which confirmed strong internal consistency for all constructs, with values exceeding 0.70. This ensures that the survey items consistently measure the intended dimensions of analytical competencies. Additionally, content validity was established through expert reviews, ensuring the instrument adequately reflects the theoretical underpinnings of HR analytics.

The finalized survey instrument, including the constructs and associated items, is presented in Table 1. This level of detail enhances the transparency and rigor of the study's methodology.

3.7 *Survey instrument or measurement scale*

The five-point Likert scale was chosen based on its widespread use and effectiveness in HR analytics research. [49] highlight its ability to balance simplicity and reliability in capturing analytical competencies, while [6] emphasizes its clarity in structured measurement. Additionally, [50, 51] note that five-point scales reduce cognitive burden and respondent fatigue, making them suitable for diverse professional populations.

Although this scale provides reliable data, the Limitations section acknowledges the potential for reduced precision and suggests exploring seven-point or ten-point scales in future studies.

3.8 *Methodology of trapezoidal fuzzy*

In order to identify the prioritized analytical competencies among the listed ones, a trapezoidal fuzzy number approach has been adopted. The Fuzzy theory was introduced by [52]. The fuzzy approach is popular among multi-criteria decision-making methods and can be used in solving several decision-making problems. The trapezoidal fuzzy number approach has a wide variety of applications. In the present work, a trapezoidal fuzzy approach is used with the responses of HR professionals on analytical competencies.

In this approach, first, the member function is defined. Then defuzzification is done, followed by the operations on the trapezoidal fuzzy numbers. Using the approach, computation of trapezoidal fuzzy numbers is carried out, and the corresponding rankings of analytical competencies are obtained based on the collected responses from HR professionals.

As it may not be possible for HR professionals to be well-versed with all the analytical competencies, they may focus more on gaining mastery over the analytical competencies that are given high ranks [53]. Hence, a fuzzy approach is useful in ranking the competencies.

Defining the member function of the trapezoidal fuzzy number: Let us assume the trapezoidal fuzzy number is $A = (a_1,\ a_2,\ a_3,\ a_4)$. The membership function of the trapezoidal fuzzy number A is $T_A(y)$, which is represented as follows (Figure 1) [54, 55].

$$T_A(y) = \begin{cases} 0, & y < a_1 \\ \dfrac{y - a_1}{a_2 - a_1}, & a_1 \le y \le a_2 \\ 1, & a_2 \le y \le a_3 \\ \dfrac{a_4 - y}{a_4 - a_3}, & a_3 \le y \le a_4 \\ 0, & y > a_4. \end{cases}$$

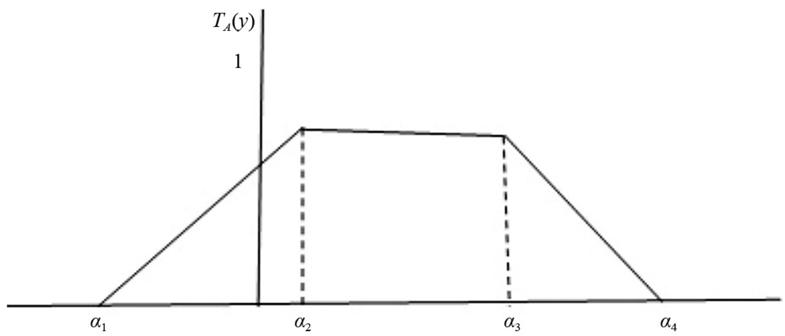

Figure 1. Trapezoidal number $A = (a_1,\ a_2,\ a_3,\ a_4)$

3.8.1 *Defuzzification*

The center of gravity (COG) method can be used for defuzzification of trapezoidal fuzzy numbers [56–58] and fuzzy ranking.

Let $\widetilde{B}$ be the trapezoidal fuzzy number $\widetilde{B} = (a_1,\ a_2,\ a_3,\ a_3)$. The simple center of gravity method (SCGM) for calculating the COG point $(\hat{x}_{\widetilde{B}},\ \hat{y}_{\widetilde{B}})$ of the trapezoidal fuzzy number $\widetilde{B}$ is shown as follows:

$$\hat{y}_{\widetilde{B}} = \begin{cases} \dfrac{a_3 - a_2 + 2}{a_4 - a_1 + 2}, & \text{if } a_1 \neq a_4 \\ \\ \dfrac{1}{2}, & \text{if } a_1 = a_4 \end{cases} \tag{1}$$

$$\hat{x}_{\widetilde{B}} = \frac{\hat{y}_{\widetilde{B}}(a_3 + a_2)(a + a)(1 - \hat{y}_{\widetilde{B}})}{2}. \tag{2}$$

Equation (1) measures the relative fuzziness within a trapezoidal fuzzy number by considering the relationship between its intermediate and boundary parameters, while Equation (2) computes a composite measure that integrates multiple attributes of the trapezoidal fuzzy number.

3.9 *Operations on trapezoidal fuzzy numbers*

Let the trapezoidal fuzzy numbers be $A = (a_1,\ a_2,\ a_3,\ a_3)$ and $B = (b_1,\ b_2,\ b_3,\ b_3)$, then:

• The addition and subtraction of two trapezoidal fuzzy numbers is also a trapezoidal fuzzy number.

• The multiplication, division, and inverse of two fuzzy numbers need not be a trapezoidal fuzzy number.

Addition:

$$A \oplus B = (a_1 + b_1,\ a_2 + b_2,\ a_3 + b_3,\ a_4 + b_4). \tag{3}$$

Subtraction:

$$A - B = (a_1 - b_1,\ a_2 - b_2,\ a_3 - b_3,\ a_4 - b_4). \tag{4}$$

Table 4. The fuzzy linguistic variables for analytical competencies rating scale

Linguistic variables	Trapezoidal fuzzy numbers
Basic	(1, 1, 3, 5)
Novice	(1, 3, 5, 7)
Intermediate	(3, 5, 7, 9)
Advanced	(5, 7, 9, 11)
Expert	(7, 9, 11, 11)

Table 4 presents a fuzzy linguistic rating scale for analytical competencies, using trapezoidal fuzzy numbers to represent each level of competency.

3.10 *Computations for collected data*

The following are the computational steps used to measure the scores.

1. Evolution of the Total Scores: Let us consider the fuzzy number B_j as the score of the jth respondent on the ith item, and TB_i as the total score of the ith item. The total score is computed as:

$$TB_i = \sum_{j=1}^{m} B_j, \quad i = 1, 2, 3, \ldots, n. \tag{5}$$

2. Evolution of Mean Scores: Let us consider the fuzzy number MB_i as the mean score of the ith item. The mean scores of each item are calculated using the following formula:

$$MB_i = \frac{TB_i}{m}, \quad i = 1, 2, 3, \ldots, n. \tag{6}$$

3. Defuzzification of the Mean Score: After calculating the mean score using step 3, we defuzzify the mean scores using the formulas (1) and (2).

4. Prioritization of the Items: Ranking the analytical competencies based on defuzzification scores from largest to smallest value.

3.11 *Trapezoidal fuzzy approach (TFA)*

The study employs the trapezoidal fuzzy approach (TFA) for analyzing subjective survey data. TFA was selected for its ability to handle the inherent uncertainty and vagueness present in human judgment, particularly in survey responses where linguistic variables are frequently used. Unlike traditional multi-criteria decision-making (MCDM) techniques such as analytical hierarchy process (AHP) or technique for order of preference by similarity to ideal solution (TOPSIS), TFA offers several advantages:

• **Handling Subjectivity:** AHP relies on pairwise comparisons, which may introduce inconsistency or bias, while TOPSIS requires strict normalization and distance measures. TFA, on the other hand, allows for flexible representation of subjective judgments through fuzzy numbers, making it more suitable for survey-based studies.

• **Simplification of Complexity:** By representing linguistic terms (e.g., “high”, “medium”, “low”) as trapezoidal fuzzy numbers, TFA simplifies the quantification of qualitative data, making the approach robust for subjective evaluations.

• **Applicability to Survey Data:** TFA is particularly effective in aggregating individual judgments into collective assessments, a feature critical for studies involving a large and diverse respondent base.

4. Results

The outcomes obtained by analyzing the data captured from the HR professionals on their analytical competencies are presented in this results section. Reliability was assessed using Cronbach’s alpha, following the guidelines of [59], with values exceeding the threshold of 0.70.

The reliability of the analytical competencies scale was first verified using Cronbach’s alpha value (Table 5), which stood at 0.714, whereas values above 0.6 are considered to have excellent reliability in the HR context.

Table 5. Reliability statistics for analytical competencies scale

S. No.	Construct	No. of items	Cronbach’s alpha
1	Analytical competencies	20 items	0.714

4.1 *Distribution of analytical competencies*

Analytical competencies of respondents were assessed at five levels viz., basic, novice, intermediate, advanced, and expert. Summary statistics were calculated for the responses of different analytical competencies AC1 to AC20. Summary statistics of the analytical competencies of respondents are presented in Table 6. The data indicates that a higher proportion of respondents reported being at the intermediate level in terms of several analytical competencies such as using advanced multivariate models (38%), identifying causal paths (36%), six sigma analysis (37%), formulating treatment vs. control groups (43%), selecting the sample, designing survey items, verifying validity and reliability (42%), preparing statistical reports to make statistical results understandable (37%), presenting analysis and results through public speaking to different stakeholders (38%), knowledge about software packages-R (33%), knowledge about software packages-Python (36%), knowledge about software packages-Tableau (39%), and knowledge about software packages-QlikView (48%).

For the competency calculating statistically significant differences-range, variances, standard deviation-the respondents were equally represented (42% each) at both the intermediate and advanced levels. A higher proportion of respondents reported being at the advanced level of expertise for analytical competencies such as performing basic statistical calculations-averages (mean, median), percentiles (65%), performing correlation, regression (46%), performing ANOVA, factor analysis (37%), data identification, cleaning, and preparation for analysis (36%), using interview techniques for data collection, interview coding, content analysis (35%), knowledge about software packages-SPSS (37%), and knowledge about software packages-SAS (35%).

For the analytical competency knowledge about software packages-MS-Excel (36%), only a higher proportion of respondents rated themselves at the expert level.

Table 6. Distribution of analytical competencies among respondents ($n = 390$)

Items	Basic		Novice		Intermediate		Advanced		Expert	
	n	%	n	%	n	%	n	%	n	%
AC1	16	4.1	13	3.3	79	20.3	252	64.6	30	7.7
AC2	20	5.1	21	5.4	163	41.8	163	41.8	23	5.9
AC3	31	7.9	32	8.2	105	26.9	181	46.4	41	10.5
AC4	42	10.8	43	11	137	35.1	145	37.2	23	5.9
AC5	39	10	36	9.2	148	37.9	136	34.9	31	7.9
AC6	35	9	40	10.3	131	33.6	142	36.4	42	10.8
AC7	37	9.5	54	13.8	139	35.6	138	35.4	22	5.6
AC8	46	11.8	42	10.8	145	37.2	124	31.8	33	8.5
AC9	44	11.3	43	11	168	43.1	111	28.5	24	6.2
AC10	28	7.2	54	13.8	163	41.8	114	29.2	31	7.9
AC11	30	7.7	55	14.1	133	34.1	137	35.1	35	9
AC12	32	8.2	58	14.9	146	37.4	114	29.2	40	10.3
AC13	46	11.8	39	10	149	38.2	121	31	35	9
AC14	9	2.3	31	7.9	94	24.1	115	29.5	141	36.2
AC15	36	9.2	46	11.8	127	32.6	143	36.7	38	9.7
AC16	60	15.4	60	15.4	108	27.7	137	35.1	25	6.4
AC13	53	13.6	51	13.1	130	33.3	127	32.6	29	7.4
AC18	73	18.7	52	13.3	141	36.2	102	26.2	22	5.6
AC19	62	15.9	55	14.1	153	39.2	102	26.2	18	4.6
AC20	58	14.9	36	9.2	188	48.2	93	23.8	15	3.8

4.2 *Differences in analytical competencies by gender*

An attempt is made to check whether the male and female respondents differ in their analytical competencies. To this extent, a two-tailed independent samples *t*-test was carried out to assess the differences in means of analytical competencies by gender. The results of the *t*-test are presented in Table 7.

It is identified that the results of the *t*-test were significant, $t(159.23) = 2.43,\ p = 0.016$. The results show that the mean of analytical competencies significantly differed between the male and female respondents. Also, the mean of analytical competencies in the male respondents ($M = 3.73$) was significantly higher than the mean of analytical competencies in the female respondents ($M = 3.55$).

Table 7. Difference in analytical competencies by gender

Variable	Male		Female		*t*	*p*	*d*
	M	*SD*	*M*	*SD*			
Analytical competencies	3.73	0.55	3.55	0.74	2.43	0.016	0.29

The small effect size (Cohen's $d = 0.29$) suggests that while gender-based differences in analytical competencies are statistically significant, the practical implications may be limited. This finding indicates that observed competency differences might reflect broader systemic trends rather than substantial skill gaps between men and women.

Accordingly, organizations are encouraged to focus on equitable access to analytics training and development opportunities, supporting skill growth across all genders. Such initiatives could mitigate potential disparities and promote a more balanced competency landscape within HR analytics.

4.3 *Differences in analytical competencies by age, work experience, and educational qualifications*

The ANOVA test was carried out to ascertain differences in analytical competencies by age, total work experience, and educational qualification. The ANOVA results are shown in Table 8. To ensure the validity of the ANOVA results, the assumptions of normality and homogeneity of variance were tested.

The Shapiro-Wilk test was conducted to assess normality for each group, and the results indicated that the assumption of normality was satisfied (all p-values > 0.05). Additionally, Levene's test was performed to evaluate the homogeneity of variances, yielding non-significant results ($p > 0.05$), confirming that the variances across groups were homogeneous.

Overall, ANOVA results for age and total work experience did not indicate any significance ($F(8,\ 381) = 1.53,\ p = 0.145$). Age ($F(4,\ 381) = 1.34,\ p = 0.253$) and total work experience ($F(4,\ 381) = 1.51,\ p = 0.200$) did not show significant differences in analytical competencies.

However, analytical competencies differed significantly (at 95% confidence level, $F(2,\ 387) = 4.34,\ p = 0.014,\ \eta_p^2 = 0.02$) by educational qualification. The eta squared value of 0.02 indicates that educational qualification explains approximately 2% of the variance in analytical competencies. The results of the means and standard deviations for analytical competencies in association with the educational qualification of HR professionals are shown in Table 7.

4.3.1 *Age-related influences on analytical competencies*

The ANOVA results indicate no statistically significant differences in analytical competencies across age groups (refer to Table 8). This finding is intriguing, as one might expect younger professionals to possess more technical skills, given their increased exposure to digital tools and technologies, and older professionals to demonstrate enhanced decision-making abilities refined through experience. The non-significance of age differences suggests that age alone may not be a decisive factor in determining analytical competencies among HR professionals.

The lack of significant variation in competencies by age may suggest that analytical competency is more a function of structured training and professional development rather than innate age-based characteristics. This aligns with research on digital competence, which points to the importance of continuous learning and upskilling opportunities as key drivers of analytical capability across age demographics [3]. Such findings underscore the need for organizations to focus on lifelong learning initiatives that cultivate analytical skills in HR professionals of all ages.

Future research could delve deeper into the role of age-related digital competence and lifelong learning trends in shaping analytical competencies. A targeted investigation into the impact of training interventions across age cohorts could provide further insight into how organizations might more effectively foster analytical skills uniformly across age groups, thereby enhancing their HR analytics capabilities.

4.3.2 *Work experience and analytical competencies*

The ANOVA results indicate no statistically significant differences in analytical competencies based on total work experience (refer to Table 8). This suggests that analytical competencies may not develop automatically through years of experience alone. Unlike traditional competencies that improve with tenure, analytical skills often require targeted training and specific educational interventions. This finding implies that organizations cannot rely solely on job experience to build strong analytical capabilities among HR professionals.

The non-significant relationship between work experience and analytical competency underscores the need for structured upskilling initiatives. Literature suggests that specialized training programs, certifications, and formal education in analytics are critical for HR professionals to develop the data skills necessary in today's data-driven HR landscape [6]. Organizations should thus consider providing regular, skill-specific training programs across all levels of tenure to ensure a consistently high level of analytical competence among their workforces.

Future research could examine the specific types of training and educational interventions that are most effective for developing analytical competencies among HR professionals. Additionally, studying the role of external education (e.g., certifications in data analysis, workshops) versus experiential learning within the organization could provide insights into best practices for competency development. Such research could guide organizations in tailoring their training programs to build analytical skills effectively across all experience levels.

Table 8. Analytical competencies by age, total work experience, and educational qualification using ANOVA

Variable	SS	df	F	p	η_p^2
Age	2.03	4	1.34	0.253	0.01
Total work experience	2.27	4	1.51	0.200	0.02
Educational qualification	3.26	2	4.34	0.014	0.02

Post-hoc Analysis: Tukey pairwise comparisons were made for the hypothesis that yielded significance based on an alpha of 0.05. The means of analytical competencies were compared by the levels of educational qualification using a *t*-test.

When the effect of educational qualification was tested, the mean of analytical competencies for post-graduation ($M = 3.64$, $SD = 0.68$) was significantly smaller than for other certification/higher qualification ($M = 3.94$, $SD = 0.50$), $p = 0.012$. Also, the mean of analytical competencies for other certification/higher qualification ($M = 3.94$, $SD = 0.50$) was significantly larger than for under graduation ($M = 3.66$, $SD = 0.53$), $p = 0.022$.

The ANOVA results demonstrate significant differences in analytical competencies among respondents with varying educational qualifications (see Table 3). Specifically, higher levels of education, such as postgraduate degrees or certifications, are associated with greater analytical competencies. This finding aligns with prior research emphasizing the role of advanced academic training in building foundational analytical skills. Educational programs, particularly those focused on analytics, statistics, and human resource metrics, appear to equip HR professionals with the critical tools necessary to excel in analytics-driven roles.

While the results highlight the importance of formal education in enhancing analytical competencies, it is essential to recognize its limitations. Formal education alone does not guarantee sustained competency, especially in rapidly evolving fields like HR analytics. Continuous professional development (CPD) plays a crucial role in ensuring that professionals remain proficient in the latest tools, methodologies, and practices. Without ongoing learning and skill enhancement, the competencies acquired through formal education may become obsolete. This underscores the need for organizations to complement academic qualifications with structured training programs that prioritize up-to-date analytics skills.

To build on these findings, future research could explore the combined impact of formal education and CPD initiatives on analytical competencies. Investigating how these two factors interact could provide organizations with actionable insights on fostering sustainable competency development. Additionally, examining the specific types of certifications or training programs that most effectively enhance analytical skills across educational levels could guide the design of targeted upskilling initiatives.

The hypothesis testing results are summarized in Table 9. The results provide insights into the relationship between analytical competencies and various demographic factors.

Table 9. Summary of hypotheses testing results

Hypothesis (Expected sign)	Variables compared to test differences	Sig.	Hypothesis validation	d or η_p^2 Value	Effect size
H1 (+)	Analytical competencies by gender	$p < 0.05$	Supported	$d = 0.29$	Small
H2 (+)	Analytical competencies by age	$p > 0.05$	Not Supported	-	-
H3 (+)	Analytical competencies by work experience	$p > 0.05$	Not Supported	-	-
H4 (+)	Analytical competencies by educational qualification	$p < 0.05$	Supported	$\eta_p^2 = 0.02$	Small

4.4 *Prioritization of analytical competencies*

The analytical competencies are prioritized and ranked accordingly using the trapezoidal fuzzy approach as per the procedure explained in the methodology section. From Table 9, it is observed that AC14 has been ranked first; this means that among the analytical competencies, 'Knowledge about software packages-MS-Excel' is of high priority.

The second-ranked item is 'Performing basic statistical calculations-Averages (Mean, Median), Percentiles' (AC1), followed by the third item 'Performing Correlation, Regression' (AC3), the fourth item 'Calculating statistically significant differences-Range, Variances, Standard deviation' (AC2), and the fifth item 'Data identification, cleaning, and preparation for analysis' (AC6).

The five analytical competencies that received the least importance are 'Formulate treatment vs. control groups' (AC9), 'Knowledge about software packages-SAS' (AC16), 'QlikView' (AC20), 'Tableau' (AC19), and finally 'Python' (AC18).

Table 10. Prioritization of analytical competencies

Item	Trapezoidal fuzzy number	Y	X = Defuzzified number	Rank
AC1	(4.4564, 6.3795, 8.3795, 10.2256)	0.3911	7.3561	2
AC2	(3.8615, 5.759, 7.759, 9.641)	0.391	6.7543	4
AC3	(4.0256, 5.8667, 7.8667, 9.6564)	0.3925	6.8511	3
AC4	(3.5436, 5.3282, 7.3282, 9.2103)	0.3922	6.3578	9
AC5	(3.6308, 5.4308, 7.4308, 9.2718)	0.3924	6.4432	8
AC6	(3.7744, 5.5949, 7.5949, 9.3795)	0.3928	6.584	5
AC7	(3.4667, 5.2769, 7.2769, 9.1641)	0.3918	6.3003	14
AC8	(3.5231, 5.2872, 7.2872, 9.1139)	0.3929	6.3074	13
AC9	(3.3692, 5.1436, 7.1436, 9.0205)	0.3923	6.1348	16
AC10	(3.4821, 5.3385, 7.3385, 9.1395)	0.3918	6.3338	11
AC11	(3.6256, 5.4718, 7.4718, 9.2923)	0.3922	6.464	7
AC12	(3.5333, 5.3692, 7.3692, 9.1641)	0.3925	6.3568	10
AC13	(3.5436, 5.3077, 7.3077, 9.1282)	0.393	6.3248	12
AC14	(4.8308, 6.7846, 8.7846, 10.0615)	0.3971	7.5805	1
AC15	(3.7026, 5.5139, 7.5139, 9.3231)	0.3926	6.5148	6
AC16	(3.3436, 5.0359, 7.0359, 8.9077)	0.3932	6.0904	13
AC13	(3.4154, 5.1436, 7.1436, 8.9949)	0.3931	6.1809	15
AC18	(3.1077, 4.7333, 6.7333, 8.6205)	0.3938	5.8126	20
AC19	(3.1077, 4.7897, 6.7897, 8.6974)	0.393	5.8582	19
AC20	(3.1487, 4.8513, 6.8513, 8.7744)	0.3926	5.9183	18

4.5 *Summary of results*

The results of the study indicate that there were differences in analytical competencies by gender and educational qualification but not by age and total work experience. For the analytical competency knowledge about software packages-MS-Excel alone, a higher proportion of respondents rated at the expert level. No other analytical competencies received expert level ratings from a higher proportion of HR professionals. A higher proportion of respondents reported to be at the advanced level of expertise for analytical competencies such as performing basic statistical calculations-averages (mean, median), percentiles, performing correlation, regression, ANOVA, factor analysis. A higher proportion of respondents were also at the advanced level of expertise in data identification, cleaning, and preparation for analysis, using interview techniques for data collection, interview coding, content analysis, and knowledge about software packages- such as SPSS and SAS. The analytical competencies were prioritized with the highest priority placed on Knowledge about MS-Excel, followed by Performing basic statistical calculations-Averages (Mean, Median), Percentiles. Performing Correlation and Regression, Calculating statistically significant differences-Range, Variances, Standard deviation, and Data identification, cleaning, and preparation for analysis as the top five analytical competencies for HR professionals.

5. Discussion

HR professionals nowadays require analytical competencies in order to implement HR analytics. The study aimed to evaluate the analytical competencies of HR professionals. All the identified analytical competencies have received considerably high mean scores, indicating the existence of such analytical competencies at a fairly good level among HR professionals. The analytical competencies that are identified and rated are consistent with the propositions made by [34], [35], SHRM Competency Model [11, 37].

The major findings relating to the distribution of analytical competencies are the following. Almost all respondents have reported that they are quite familiar with the usage of MS-Excel and are applying it for performing analytical functions. Fink [60] has conveyed a similar opinion that useful analyses can be performed by HR professionals using Excel or spreadsheets. A very small proportion of the respondents have an advanced level of analytical competencies. They are using correlation and regression techniques, ANOVA, factor analysis, and other advanced techniques, demonstrating proficiency in SPSS and SAS.

The findings align with previous research, which reported that companies were using reasonably good analytical tools like regression. Most of the respondents rated themselves at the intermediate level in terms of many analytical competencies. Though they are familiar with and use basic analytical tools, they have yet to learn and apply advanced statistical techniques in the HR domain. The present study also observed very few instances of organizations using advanced methods like SEM or discrete choice analysis, which aligns with the observations of [21] that a gap exists between the analytical skills HR professionals possess and those expected by organizations. Through substantial training, these competencies can be acquired, irrespective of an individual's age and work experience.

Although HR professionals are familiar with and using basic analytical tools, they still need to learn and apply advanced statistical techniques in the HR domain. This can be attributed to the focus on developing general concepts for work practices taking precedence over implementing HR analytics (HRA), as noted by [61]. Expert-level knowledge of MS-Excel has been given the highest priority. Furthermore, performing basic statistical calculations, statistically significant differences, and performing correlation and regression are considered higher priority areas among analytical competencies.

While prescribing job competencies for HR professionals, recruiting managers ought to place greater importance on verifying candidates' readiness with these competencies for handling current and future tasks of data analysis in HR. Any planned training activities should also be based on prioritized analytical competencies. The research by [62] also suggested considering HR business partners' competencies to align with software solutions being adopted. Any planned training activity should also be based on prioritized analytical competencies.

6. Implications

The results indicate a significant role of those analytical competencies in directing HR professionals towards HR analytics. The findings of the present research offer several implications that corporate managers can use to improve the conditions prevailing for HR analytics in their respective organizations. Specific competencies are essential to apply technologies, particularly the ones like HR analytics. The study has highlighted that HR professionals require analytical competencies to use HR analytics effectively. Like any other technological area, training HR professionals is the most important element to encourage the usage of HR analytics. Though several HR professionals are familiar with the use of MS-Excel package, they are not able to fully explore that for testing sophisticated statistical procedures. Organizations must take steps to fill the skill gap in this emerging area. The present study supports that HR professionals do possess a fairly good number of analytical competencies. Hence, it is expected by the organizations to provide broader awareness on how HR analytics can enhance the job roles performed by HR professionals, which in tune will make the HR professionals apply and use HR analytics extensively. Organizations can take the initiative to arrange special workshops and training programs to create more awareness among HR professionals. HR professionals have to approach external agencies and institutes offering programs on HR analytics to gain better understanding and certifications. External experts and certification bodies are to be involved in training HR professionals. The present research theoretically contributes to the assessment of analytical competencies. Also, the study identified the relative importance of certain competencies over the others using ranking. The results indicate a significant role of analytical competencies in enabling HR professionals to effectively utilize HR analytics. Organizations must prioritize bridging the skills gap in advanced analytics tools like Python and Tableau. While many professionals demonstrate proficiency with MS-Excel and basic statistical techniques, the limited prioritization of advanced tools suggests a need for targeted training programs. Organizations aiming to leverage advanced analytics should initiate structured workshops and certification programs in tools such as Python and Tableau, thereby equipping HR professionals with the competencies required for data-driven decision-making.

Furthermore, the findings emphasize that analytical competency is not inherently developed through age or work experience but rather through targeted education and continuous learning opportunities. This highlights the importance of fostering a culture of lifelong learning within organizations, ensuring skill enhancement for professionals across all demographics.

Finally, the study identifies that while formal education enhances analytical competencies, it is not sufficient by itself. Continuous professional development (CPD) is crucial for maintaining relevance in the rapidly evolving field of HR analytics. To complement formal education, organizations should provide ongoing learning opportunities, certifications, and practical exposure to advanced tools, bridging the gap between basic and advanced analytics.

7. Conclusions

HR professionals' analytical competencies vary based on their gender and educational qualification, but not their age or work experience. To address this, it's crucial to design targeted training programs to bridge competency gaps, especially focusing on gender-neutral and inclusive skill development. Therefore, HR training and development initiatives should cater to professionals of all experience levels, recognizing that competence can be achieved at any stage of their career. MS-Excel has become the only competency with a higher proportion of expert level ratings. To enhance HR professionals' effectiveness, organizations should prioritize advanced training in Excel, including data analysis, visualization, and automation to streamline HR processes. Advanced level expertise is reported in performing basic statistical calculations, data identification and preparation for analysis, interview techniques for data collection, interview coding, content analysis, and knowledge about software packages such as SPSS and SAS. It is important to encourage HR professionals to leverage these skills to make data-driven decisions in recruitment, performance management, and other HR functions. The top five analytical competencies prioritized by HR professionals were knowledge about MS-Excel, performing basic statistical calculations like averages and percentiles, performing correlation and regression, calculating statistically significant differences such as range, variances, standard deviation, and data identification, cleaning, and preparation for analysis. Training programs should align with these priorities to address HR professionals' needs effectively.

8. Limitations and scope for further research

The present study is focused on evaluating analytical competencies, which is an area yet emerging and not extensively studied in the context of HR analytics. Hence, the items considered are largely taken from the available reports and expert opinions, which may pose a limitation requiring wider research and repeated validation. As a trend associated with technology, competencies in general, and the gamut of analytical competencies for HR professionals may not remain the same for long periods. Continuous monitoring of the changing trends and adaptation of the new competency requirements is an area having scope for extensive research. The study has limitations of time and resources.

Future studies may be taken up to extend the identification of competencies of HR professionals from time to time. As a variation, different fuzzy approaches can also be used to prioritize the competencies. Not limited to HR profession, studies can also be carried out in niche areas where new job profiles are emerging. Research can be extended in prioritizing the competencies by using ranking methods or combination of multi-criteria decision-making methods.

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Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this research.

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