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Developing and Validating Hiring Perception Metrics: Insights from a Pilot Study in the IT Industry

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Abstract

The IT industry, a leader in technological revolution, faces challenges in attracting and retaining skilled talent due to rapidly developing job roles, emerging technologies, and dynamic hiring practices. This pilot study aimed to refine and validate a questionnaire-based instrument designed to measure hiring perceptions among IT professionals. The study employed Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) to evaluate the reliability, validity, and factor structure of the instrument. The initial 66-item questionnaire was reduced to 39 items, demonstrating strong internal consistency (Cronbach's alpha = .896) and good model fit indices (GFI = .885, RMSEA = .067, CFI > .90). EFA revealed a five-factor model encompassing key aspects of hiring prediction, namely soft skills and behavioral traits, education and recruitment sources, emerging technologies and competencies, and time required to fill open positions. The results will assist HR professionals in optimizing recruitment efforts and aligning hiring procedures with industry expectations. For colleges, universities, and institutes, the study provides a validated measurement tool for further research on IT hiring trends and workforce management. This pilot study lays the groundwork for a larger-scale effort to create a reliable framework for investigating hiring effectiveness in the Indian IT industry.

Keywords: IT Hiring Trends, Predictive Hiring Models, Machine Learning, Technical Competencies, Industry 4.0.

Introduction

The IT Indian industry is one of the largest technology hubs in the world, which is significantly contributing to the GDP and employment. Though, forecasting hiring trends is a challenge because of continuous change in technology, growing job roles, and continuous change in demand of skills. Also, traditional recruitment process failed to forestall the dynamic nature of skill demands, creating a gap between industry needs and workforce availability [1]. IT organizations should forestall upcoming hiring requirements to endure competitive, yet few studies provide computable measures of these trends from the perspective of industry professionals and job seekers.

Current studies focuses on AI oriented hiring models which are highly adopted to improve efficiency, but concerns related to algorithmic bias, entrant matching, and unbiased recruitment persist [2]. Furthermore, HR analytics and predictive workforce planning have become vital tools in predicting talent demand, enhancing selection processes, and confirming diversity in hiring [3]. Organizations are leveraging data driven hiring techniques to line up hiring decisions with developing technical trends and global workforce shifts [4].

A review on hiring revolutions in the IT sector discloses that organizations are focusing toward skill based hiring, remote work models, and skill based recruitment strategies to appeal top talent [1].

This study reports this gap by conducting a pilot study to improve and authenticate a questionnaire measuring hiring perceptions, allowing organizations to predict workforce requirements effectively. By understanding developing skill demands and hiring practices, organizations can develop proactive hiring policies which aligns with industry trends.

Research Objectives: The objectives of this aim to design and authenticate a structured implementation which captures important perceptions of hiring practices in the IT sector. The objectives of this study are:

- Evaluating the reliability and validity of a questionnaire designed for evaluating hiring perceptions.
- Identifying significant hiring dimensions, including hiring strategies, competency requirements, educational qualifications, and recruitment efficiency.
- Filtering the survey through Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) to confirm measurement accuracy and clarity.
- Providing actionable understandings for IT recruiters, and HR professionals to optimize talent acquisition approaches.

By addressing these objectives, this study underwrites to both academic literature and industry practices, confirming a data-driven approach to IT.

Literature Review:

Evolution of recruitment in the IT sector has evolved significantly due to different technological advancements, automations, and changing expectations from the employees. Organizations are prioritizing a mix of technical expertise, and soft skills fit while recruitment of candidates [5]. Traditional recruitment procedures are gradually being replaced by AI driven assessments, skill based recruitment, and data driven decision making [6].

There are several factors which are influencing the IT Hiring Perceptions.

- Organizations are emphasizing on proficiency in AI, cybersecurity, cloud computing, and data analytics [7].
- Organizations are also focusing on Behavioral Qualities and Soft Skills such as Communication, problem solving abilities, and leadership skills which is significantly impacting hiring decisions [8].
- There are different recruitment tactics across different organizations, with various incorporating technical assessments, behavioral interviews, and problem solving in terms of coding challenges [9].
- Organizations are anticipating in increasing demand for AI specialists, data scientists, and different upcoming technologies [10].

Development of a strong tool requires careful and great attention to ensure accurate measurements. Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) are mostly used in research surveys to calculate factor structures, model fit, and reliability [11]. The improvement in survey items via expert reviews, statistical analysis, and qualitative feedback improves accuracy in measurement [12].

Methodology

Research Design: Study follows a quantitative research approach to authenticate the Prediction of IT hiring questionnaire. The pilot study was conducted with 100 responses to assess its psychometric properties before complete implementation. The methodology is organized around data collected from the survey, EFA and CFA to confirm the dependability and authenticity of the measurement tool.

Questionnaire Development: The questionnaire's design centers on capturing insights into hiring trends across five distinct dimensions. These dimensions were not arbitrarily chosen, but rather emerged from a combination of thorough literature analysis and invaluable input provided by specialists within both the industry and academic sectors.

- Upcoming Technologies and Technical skills.
- Soft skills and Behavioral qualities
- Education and Hiring Sources
- Recruitment process and Time required to fill positions.
- Demand of workforce.

The refinement of the survey questions was informed by, and built upon, previously validated scales employed in workforce planning research [3]. Each question in the survey was designed to be answered using a 5-point Likert Scale, ranging from 'Strongly Disagree' at 1 to 'Strongly Agree' at 5. After setting up the scale, we took a structured approach to validating the questionnaire, which involved several distinct phases.

For validation of Questionnaire following steps were followed:

- Extensive Literature Review & Expert Review was done for aligning survey questions with industry trends.
- Pilot Testing & Feedback Collection was done for ensuring clarity and relevance.
- Exploratory Factor Analysis (EFA) was done for identifying underlying factor structures.
- Confirmatory Factor Analysis (CFA) was conducted for validating the measurement model.

Questionnaire Dimensions: To better understand what IT professionals and recent graduates think, we grouped their survey responses into the following categories within the IT Industry Hiring Practices Effectiveness Questionnaire:

Table 1 Questionnaire Dimensions

Dimension	Sub-Dimension
Organization Profile	1.1 Company Background
	1.2 Company Size and Revenue
Current Hiring Practices	2.1 Recruitment Volume and Roles
	2.2 Hiring Metrics and Budget
Competency Requirements	3.1 Technical Skills and Knowledge
	3.2 Soft Skills and Problem-Solving
Educational Requirements	4.1 Formal Qualifications
	4.2 Academic Performance
Selection Process	5.1 Screening and Assessment
	5.2 Process Efficiency
Future Hiring Projections	6.1 Hiring Outlook and Skill Demand
	6.2 Technological Impact and Challenges

Statement Construction:

The process of developing statements for the IT Industry Hiring Practices Effectiveness Scale involves a systematic approach to ensure clarity, relevance, and alignment with research objectives. Begin by reviewing the research objectives and key concepts related to hiring trends in the IT industry. This step involves a thorough literature review, examining existing research and publications on IT recruitment practices, emerging technologies, skill demands, and challenges faced by organizations (as highlighted in sources). We create original statements based on the insights gathered from the literature review, combined with practical knowledge gained from discussions with HR and IT professionals [1]. Sources validate the value of these discussions in identifying relevant variables and understanding real-world hiring practices. To confirm the quality and validity of the statements, consulted with subject-matter experts for validation. These experts reviewed the statements for clarity, relevance, and alignment with current industry standards. Also adapted the statements from existing validated research instruments to enhance the scale's reliability and comparability. This process ensures that the final statements accurately reflect the complexities of IT hiring practices and effectively measure the perceptions of IT industry professionals and recent IT graduates.

Table 2 Statement Construction

Dimension	Sub-Dimension	Questionnaire Items
Organization Profile	1.1 Company Background	Type of Company (Select one)
		Primary Business Domain
	1.2 Company Size and Revenue	Company Size
		Annual Revenue Range (in USD)
Current Hiring Practices	2.1 Recruitment Volume and Roles	Number of open positions currently
		Number of positions filled in the last year
		Specific job roles for which they are hiring
	2.2 Hiring Metrics and Budget	Experience level requirements
		Entry Level
		Mid Level
		Senior Level
		Executive Level
		Average cost per hire (in USD)
		Annual hiring budget allocation (% of revenue)
Competency Requirements	3.1 Technical Skills and Knowledge	Rate importance of technical competencies (1=Not Important, 5=Crucial) [Artificial Intelligence/ Machine Learning]
		Rate importance of technical competencies (1=Not Important, 5=Crucial) [Cloud Computing]
		Rate importance of technical competencies (1=Not Important, 5=Crucial) [Cybersecurity]
		Rate importance of technical competencies (1=Not Important, 5=Crucial) [Data Science/ Analytics]
		Rate importance of technical competencies (1=Not Important, 5=Crucial) [Software Development]
		Rate importance of technical competencies (1=Not Important, 5=Crucial) [Web Development]
		Rate importance of technical competencies (1=Not Important, 5=Crucial) [Mobile App Development]
		Rate importance of technical competencies (1=Not Important, 5=Crucial) [UI/UX Design]
		Rate importance of technical competencies (1=Not Important, 5=Crucial) [Blockchain]
		Rate importance of technical competencies (1=Not Important, 5=Crucial) [Project Management]
		Rate importance of technical competencies (1=Not Important, 5=Crucial) [Networking]
		Rate importance of technical competencies (1=Not Important, 5=Crucial) [System Design]
		Rate importance of technical competencies
		Rate importance of technical competencies
		Rate importance of technical competencies
		Rate importance of technical competencies
		Rate importance of technical competencies

	3.2 Soft Skills and Problem-Solving	Communication
		Team Collaboration
		Problem Solving
		Time Management
		Leadership
		Rate importance of behavioral traits (1=Not Important, 5=Crucial) [Work Ethic]
		Rate importance of behavioral traits (1=Not Important, 5=Crucial) [Adaptability/ Flexibility]
		Rate importance of behavioral traits (1=Not Important, 5=Crucial) [Initiative]
		Rate importance of behavioral traits (1=Not Important, 5=Crucial) [Learning Agility]
Educational Requirements	4.1 Formal Qualifications	Preferred educational backgrounds (Rank 1-5, 1 being most preferred) [Computer Science]
		Preferred educational backgrounds (Rank 1-5, 1 being most preferred) [Information Technology]
		Preferred educational backgrounds (Rank 1-5, 1 being most preferred) [Electronics/Electrical Engineering]
		Preferred educational backgrounds (Rank 1-5, 1 being most preferred) [Mathematics/Statistics]
		Preferred educational backgrounds (Rank 1-5, 1 being most preferred) [Others]
	4.2 Academic Performance	Importance of academic performance (e.g., GPA, class rank)
Selection Process	5.1 Screening and Assessment	Number of interview rounds typically conducted
		Types of assessments used in the selection process (e.g., technical tests, coding challenges, behavioral interviews, group discussions, aptitude tests)
	5.2 Process Efficiency	Average duration of the selection process (from application to offer)
Future Hiring Projections	6.1 Hiring Outlook and Skill Demand	Estimated number of positions they plan to fill in the coming year
		Anticipated changes in the required skills and competencies for future roles
	6.2 Technological Impact and Challenges	Rate the importance of programming languages (1=Not Important, 5=Crucial) [Python]
		Rate the importance of programming languages (1=Not Important, 5=Crucial) [Java]
		Rate the importance of programming languages (1=Not Important, 5=Crucial) [JavaScript and its Versions]
		Rate the importance of programming languages (1=Not Important, 5=Crucial) [C++]
		Rate the importance of programming languages (1=Not Important, 5=Crucial) [C#]
		Challenges they foresee in meeting their future hiring needs (e.g., skill shortages, competition for talent, changing candidate expectations)
Recruitment Channels		Job portals
		Employee referrals
		LinkedIn/Social media
		Primary sources of successful hires (Rank 1-5, 1 being most successful) [Recruitment agencies]
Other		Would you like to receive the research findings?

Sample Selection: A directed sampling method was used to check representative data from IT professionals and college graduates. The target population includes HR professionals from IT sector, Mid-level and senior IT employees which are involved in hiring decisions [13]. 100 respondents registered their response for the survey. Preceding studies suggests that sample sizes of 100 to 200 responses are suitable for EFA and CFA based survey [14]. Participants with experience in IT hiring, and non-IT professionals were excluded for registering their response.

Data Gathering, Processing and Pre-Coding:

The data gathering was conducted to ensure high quality of response, representativeness, and inclusiveness for the study. The study used Google Forms for collecting the primary data, allowing for the efficient distribution and accessibility among the respondents. A purposive sampling approach was used to select participants who are involved in the IT recruitments. The pilot study aimed to gather information from two important groups. 1) IT professionals and recruiters wherein Individuals were responsible for hiring decisions in the organizations. 2) Recent IT graduates who are actively seeking for a job in the market.

Total respondents for the questionnaire were 100, ensuring an acceptable sample size for EFA and CFA [3]. The sample representativeness was maintained by considering mix of participants from different roles, organizations and experience level in the industry. All the respondents were made aware about the purpose of the study and voluntary participation and confidentiality of the data. This was done to ensure compliance with ethical research standards [15].

After the completion of the data collection phase, responses were stored in the structured format viz. CSV and SPSS. Upon storage, the missing values and inconsistencies were checked and made data ready for the statistical analysis including reverse coding for negatively worded questions. The data gathered was then subjected to reliability testing viz. Cronbach's Alpha, EFA and CFA for finding accuracy and to construct validity [16].

Data Analysis and Results

Reliability and Validity Testing:

To evaluate the internal uniformity of the survey, Cronbach's alpha was calculated. Cronbach's alpha is a degree of dependency which specifies how closely related a set of items are as a group. Generally the items in a scale whose Cronbach alpha value is more than .70 are considered to have same measuring underlying construct. The Cronbach's alpha for the 66 items in the questionnaire was .896, indicating good internal consistency [17].

The measurement model was carefully validated through a series of psychometric tests, before proceeding to test the structural relationships among the latent variables. This process confirmed that the observed questionnaire items are accurately and reliably measure the underlying constructs.

(EFA) Exploratory Factor Analysis:

An EFA was conducted using SPSS to observe the underlying factor structure of the questionnaire. Principal Component Analysis (PCA) with Varimax rotation was employed to maximize variance and produce a clearer factor structure [18]. The analysis proceeded systematically through multiple stages to ensure robust results.

The preliminary analysis revealed adequate sampling adequacy with a KMO value of .767 and a significant Bartlett's Test ($p < .000$), indicating suitability for factor analysis. The total variance explained was 75.875%, exceeding the recommended threshold of 60% [19].

Several items exhibited problematic cross-loadings requiring attention. The System Design item showed multiple significant loadings across Component 1 (.385), Component 2 (.347), and Component 4 (.556), necessitating removal due to insufficient loading differentiation. Similarly, the JavaScript and its Versions item displayed a complex loading pattern across Component 2 (.450), Component 8 (-.358), and Component 9 (.404), warranting elimination.

Item Reduction Process:

The following criteria guided the item reduction process:

- Primary loadings must exceed 0.5
- Secondary loadings should fall below 0.3
- A minimum difference of 0.2 between primary and secondary loadings
- Items loading significantly on three or more factors were removed

Table 3 Exploratory Factor Analysis – Component Loadings

Component	Factor	Factor Loading
Soft Skills & Basic Behavioral	Time Management	0.889
	Problem Solving	0.877
	Team Collaboration	0.867
	Communication	0.802
	Leadership	0.71
	Adaptability	0.549
Education & Recruitment Sources	Information Technology	0.922
	Computer Science	0.906
	Job portals	0.787
	Employee referrals	0.753
	LinkedIn/Social media	0.652
Emerging Technologies	Artificial Intelligence	0.844
	Machine Learning	0.838
	Generative AI	0.749
	Data Analytics	0.721
	Python	0.563
Time to Fill Positions	Senior Level	0.903
	Mid Level	0.89
	Executive Level	0.792
	Entry Level	0.751
Senior Experience Requirements	Experience level 4	0.916
	Experience level 3	0.888
	Experience level 2	0.604
Alternative Education	Mathematics/Statistics	0.885
	Others	0.859
	Electronics/Electrical Engineering	0.641
Behavioral Traits	Initiative	0.772
	Work Ethic	0.662
	Cultural Fit	0.619
Technical Competencies	Technical Others	0.793
	Programming Others	0.63
	DevOps	0.534
	Security	0.504
Junior Experience	Experience level 1	0.848
	Experience level 2	0.637
	Research findings	0.542
Traditional Technologies	Database Management	0.661
	Java	0.621
	Python (cross-loading)	0.513
Financial Metrics	Annual hiring budget	0.838
	Average cost per hire	0.745

Exclusion Criteria:
The analysis supports the exclusion of Components 8-11 due to their consistently weaker factor loadings (ranging from .504 to .838) and insufficient number of items per component. Additionally, items showing cross-loadings, such as Python with dual loadings of .563 and .513, were eliminated to maintain construct clarity. Single-item components were also removed to ensure measurement reliability.

Statistical Strength:
The five-component structure demonstrates superior statistical properties, with these components explaining the majority of variance in the data. The factor loadings are robust, ranging from .549 to .922, and the components exhibit clear, well-defined item groupings that support the underlying theoretical framework.

Theoretical Coherence:
The retained structure shows strong theoretical alignment by representing distinct constructs essential to IT hiring practices. These components effectively capture the key dimensions of soft skills, education requirements, emerging technologies, position timing, and experience levels, while maintaining clear conceptual boundaries between constructs [12].

Measurement Quality:
Each component demonstrates strong measurement properties with 4-6 reliable indicators per construct. The structure shows high internal consistency and clear operational definitions, providing a compact foundation for measurement. The various pointers per construct confirm reliable measurement of individual theoretical dimension [17].

Model Validation:
The five-component model attains an ideal balance between statistical rigor and theoretical relevance. This distinguished structure delivers a compact foundation for subsequent confirmatory analyses while maintaining operational definitions for each construct, supporting both statistical and theoretical validity of the measurement model [20].

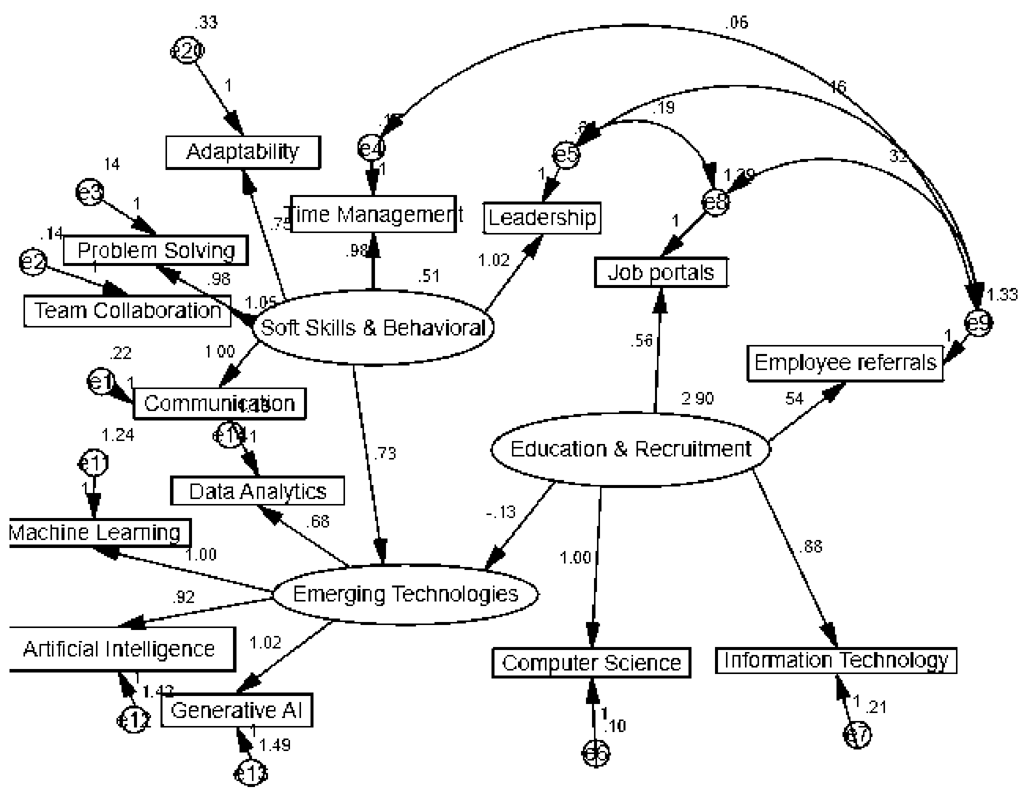

Figure 1 Confirmatory Factor Analysis

Final Structure of EFA:
The refined factor construction showed considerable improvements across various dimensions. Primary loadings occurred with clear distinction and strong magnitudes, representing good relationships between items and their respective factors. Cross-loadings were successfully minimized through the systematic removal of problematic items, resulting in a cleaner and more interpretable factor structure. The improved construct validity was evidenced by the logical grouping of items within their theoretical constructs, while the overall model fit characteristics showed marked improvement. The streamlined factor solution presents a explanation of constructs, making it particularly suitable for the planned Confirmatory Factor Analysis in AMOS.

Confirmatory Factor Analysis (CFA):
CFA (Confirmatory Factor Analysis) was conducted in AMOS to evaluate the measurement model. Based on the EFA (Exploratory Factor Analysis) and the subsequent component analysis, a five-factor model was verified. This model was planned to capture the main aspects of the questionnaire: (1) Soft Skills & Basic Behavioral Traits, (2) Education & Recruitment Sources, (3) Emerging Technologies, (4) Time to Fill Positions, and (5) Senior Experience Requirements. The model was verified based on factor loadings from EFA and theoretical validity. This analysis meticulously tested the relationships between the observed variables and their corresponding constructs [21].

To evaluate the CFA model, it is essential to make sure its identification. Model identification refers to whether there is enough information in the data to evaluate the model parameters exclusively. The model was carefully specified to meet the essential conditions for identification, including observed variables than predicated parameters and confirming proper scaling of latent variables. The maximum probability estimation method was used to predict the model parameters. This process is majorly used in CFA and is considered to be the suitable method for data which meet the assumptions of multivariate normality. Different model fit indices are usually used to check the adequacy of CFA models, providing a quantitative assessment of how well the proposed model reproduces the observed data. These indices offer understandings into the model's ability to represent the underlying relationships among the variables. The selection of specific fit indices depends on the research question, sample size, and complexity of the model. Though there are no globally agreed-upon criteria, certain thresholds are often used as guidelines for interpreting model fit. Complete fit indices evaluate the overall goodness of fit of the model to the data [22]. Examples include:

- **CMIN/DF:** The chi-square statistic (CMIN) divided by its degrees of freedom (DF). Values below 3 are generally considered indicative of a good fit. A CMIN/DF value of 1.444 suggests excellent fit for the "Soft Skills & Behavioral" factor. However, a value of 4.374 for the "Education & Recruitment" factor suggests poor fit.
- **GFI:** Values closer to 1 indicate a better fit. A GFI of 0.885 is considered marginally acceptable, suggesting that the model is reasonably consistent with the data.
- **RMSEA:** Values below 0.08 suggest a good fit. An RMSEA of 0.067 indicates a good fit. Incremental fit indices compare the fit of the proposed model to the fit of a baseline model, often a "null" model that assumes no relationships among the variables. Examples include:
- **CFI:** Values above 0.90 indicate a good fit.
- **TLI:** Values above 0.90 indicate a good fit. Other indices focus on the residuals, which represent the difference between the observed and estimated covariance matrices. For example:
- **SRMR:** Values below 0.08 suggest a good fit.

Item Analysis: To evaluate the quality of the questionnaire items, an item analysis was conducted, focusing on item discrimination. While item difficulty is a relevant metric, it was not calculated for this pilot study. Item discrimination was assessed using independent samples t-tests, comparing the mean scores of the upper and lower 27% groups of respondents based on their total questionnaire scores [23]. This analysis aimed to identify items that effectively differentiate between high and low-scoring participants, under the assumption that items with a high t-statistic and a significant p-value are strong indicators of the overall construct. For each t-test, the independent variable was group membership (upper 27% vs. lower

27%), and the dependent variable was the score for each individual item [24]. With degrees of freedom (df) of 52 and an alpha level (α) of 0.05 for a two-tailed test, the critical t-value was ±2.007. Therefore, the null hypothesis of equal means was rejected when the absolute t-value exceeded 2.007.

Discussion

The findings of this pilot study contribute valuable insights to the field of IT recruitment by validating a reliable and valid instrument for measuring hiring perceptions. The initial 66 item questionnaire is scaled down to a refined 39 item scale, based on EFA and CFA, which has demonstrated the importance of psychometric testing in the development of the survey. The five-factor model—which includes soft skills, education and recruitment sources, emerging technologies, time to fill positions, and senior experience requirements; provided a comprehensive framework for understanding the important dimensions of IT hiring practices.

The high internal reliability, which was specified by a Cronbach's alpha of .896, and the strong model fit indices suggest that the questionnaire is a robust tool for assessing hiring predictions. Additionally, the study underlines the necessity for educational institutions to work together meticulously with industry for bridging the gap. The authenticated questionnaire can serve as a important tool for universities and colleges to conduct further research on hiring trends and adapt their programs to meet the evolving needs of the IT sector.

Conclusion and Future Research

This study effectively established and authenticated a questionnaire-based instrument for measuring hiring predictions in the IT industry. The distinguished 39-item scale, derived from a rigorous psychometric evaluation, suggests a reliable and valid framework for evaluating the important dimensions of IT hiring. The study's results have substantial implications for HR professionals, academic institutions, and policymakers, providing a data-driven approach to talent acquisition and workforce development.

The limitations of the study are, First, the sample size of 100 may considered as small for generalizing the predictions to the IT industry. Future work can aim to duplicate the same study with a higher number and more diverse sample to enhance the results. Second, the cross-sectional design of the study is limited to the ability to draw casual inferences. Longitudinal studies may provide in depth understanding of the dynamic nature of IT hiring trends and impact on organizational goal.

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