Vol 7, Issue 12, 2024 **Impact Factor: 5.355** DOI: https://doi.org/10.31426/ijamsr.2024.7.12.7958

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

Transformation of IT Recruitment During the COVID-19 Pandemic: Evaluating HR Strategies, Policy Shifts, and Digital Adaptation through SEM Analysis

Rupa Hazra [1]

[1] Research Scholar, Department of Management, Capital University, Koderma, Jharkhand, India.

Prof. Dr. Subodh Kumar Sinha [2]

[2] Supervisor, Department of Management, Capital University, Koderma, Jharkhand, India.

ABSTRACT

The COVID-19 pandemic significantly disrupted global business operations, profoundly impacting the Information Technology (IT) sector. One of the key areas affected was Human Resource (HR) management, particularly recruitment and selection processes. Traditionally reliant on in-person interactions, the IT sector rapidly transitioned to digital hiring practices in response to lockdowns and remote work requirements. This shift not only altered recruitment methods adopting video interviews and online assessments—but also redefined hiring criteria. Employers began valuing soft skills such as adaptability and collaboration alongside technical expertise, recognizing their importance in a remote and uncertain work environment. This transformation highlights how the pandemic catalyzed a lasting evolution in talent acquisition strategies within the IT industry.

Keywords : *Digital Recruitment, Human Resource Transformation, Soft Skills.*

1. INTRODUCTION

The COVID-19 pandemic has had a profound effect on the global economy and has led to significant changes in various industries. Among the sectors that faced immediate disruptions, the Information Technology (IT) sector has experienced both challenges and opportunities. One of the most critical functions within the IT sector that underwent substantial transformation during the pandemic was Human Resource (HR) management, particularly in the selection and recruitment of employees. Traditionally, the process of hiring in the IT industry relied heavily on face-to-face interactions, in-person interviews, and physical presence, as well as on-campus recruitment drives at colleges and universities. However, the global lockdowns, social distancing measures, and restrictions on travel forced HR professionals to rethink and adapt their recruitment processes. This adaptation was not just necessary for business continuity but also for ensuring that organizations could still attract top talent despite the social, economic, and technological challenges brought on by the pandemic. The primary objective of HR management, especially in recruitment and selection, is to identify, hire, and onboard employees who possess the right skill sets to align with the organization's strategic goals. Pre-COVID, this process was heavily reliant on in-person interviews, personal networks, and face-to-face job fairs. However, the onset of the pandemic made it impossible for HR professionals to continue conducting recruitment in the traditional manner. With offices shutting down and employees working remotely, HR professionals quickly adopted digital tools, including video conferencing platforms, online recruitment systems, and digital assessments, to continue hiring. These changes in the selection process were driven by the need for business continuity as well as the desire to ensure that the IT sector, which was among the few that were still operating, could maintain a strong talent pipeline during such uncertain times. The adaptation of HR in response to COVID-19 was not limited to just changing the method of selection; it also brought about a fundamental shift in the criteria used to evaluate potential employees. Pre-pandemic, employers in the IT sector typically prioritized technical skills, domain-specific expertise, and experience. However, the pandemic forced a rethinking of what skills were truly essential. Remote work, the increased reliance on digital communication, and the need for resilience in an uncertain environment shifted the focus to soft skills like adaptability, communication, collaboration, and problem-solving. As a result, the IT industry witnessed a redefinition of the employee selection process, with HR professionals placing a greater emphasis on identifying candidates who could thrive in a remote, digital-first workplace.

2. RESEARCH METHODOLOGY

This outlines the comprehensive methodology employed to investigate the impact of COVID-19 on HR performance in employee selection within the IT sector. Adopting a quantitative, cross-sectional research design, data were collected through a structured questionnaire targeting HR professionals. The study focused on key constructs such as pandemic-related disruptions, technological adoption, HR policy adaptations, candidate behavior, and regulatory changes. Data collection was conducted across metropolitan IT hubs, where digital transformation and virtual hiring practices were most prominent during the pandemic. The primary tool used was a structured, six-part questionnaire rated on a 5-point Likert scale. Purposive sampling ensured participation from HR practitioners directly involved in recruitment during COVID-19, resulting in 290 valid responses from organizations of varying sizes. Data analysis was performed using Structural Equation Modelling (SEM), allowing for measurement validation and path analysis. The dependent variable—HR Performance in Employee Selection (HRPES)—was assessed using four items, with a Cronbach's alpha of 0.844. Independent variables included COVID-19 effects (COV), Technology Adoption in Recruitment (TAR), Changes in HR Policies (CHR), Candidate Availability and Preferences (CAP), and Government and Industry Regulations (GIR), each measured with reliable, validated items. The study adhered to ethical standards, with data collection completed over a three-month period.

2.1 Description of Tools Used in the Present Study

The study utilized a detailed questionnaire, comprising 34 items across six sections, to measure the constructs of interest. Each item was designed to capture specific aspects of HR practices during the

IJAMSR

International Journal of Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

pandemic. The tool's reliability was established through Cronbach's alpha, with values ranging from 0.765 to 0.891, ensuring internal consistency. Data were processed and analysed using SEM software, which allowed for comprehensive model fit analysis, including chi-square tests and alternative fit indices.

2.2 Analysis and Interpretation of Data

Frequency and Reliability Analysis: The frequency distribution revealed noteworthy trends. For instance, in the Technology Adoption section, items like TAR1, TAR2, and TAR3 recorded a high level of disagreement (up to 89.7% negative responses for TAR1), suggesting that virtual recruitment tools were either underutilized or not perceived positively. Similar trends were observed across other constructs, with several items eliciting predominantly negative responses, indicating potential issues with item clarity or respondent experience.

Structural Equation Modelling (SEM): The SEM analysis was performed using a default model with 64 parameters estimated from 276 distinct sample moments, resulting in 212 degrees of freedom. The model achieved convergence with a chi-square value of 303.720 (df = 212, p = .000) and a chi-square/df ratio of 1.433, which is within acceptable limits. The regression weights indicated the following:

- **HRPES & CAP:** Estimate = 0.197, p = .029
- **HRPES & COV:** Estimate = 0.195, p = .002
- **HRPES & TAR:** Estimate = -0.102, p = .063 (not significant at the 5% level)
- **HRPES & CHR:** Estimate = 0.260, p < .001
- **HRPES & GIR:** Estimate = 0.375, p < .001

These results reveal that changes in HR policies (CHR) and government regulations (GIR) have the most substantial positive effects on HR performance in employee selection, while technology adoption (TAR) exhibits a slight negative influence.

Model Fit Summary: The model fit was further supported by a low chi-square/df ratio (1.433) compared to the independence model's ratio (12.594). Although the chi-square test was significant (p = .000), the overall fit indices suggest that the default model offers an adequate balance between parsimony and explanatory power. Additional fit indices (not detailed here) were also examined to ensure robust model evaluation.

Delimitation: The study is delimited to HR practices specifically in the IT sector during the COVID-19 pandemic. It focuses solely on employee selection processes and does not extend to other HR functions such as training or performance management. Moreover, the sample comprises HR professionals from urban IT hubs, which may limit the generalizability of findings to other industries or geographic areas. The reliance on self-reported data may also introduce response biases.

3. DATA ANALYSIS AND RESULT

Chapter presents the detailed interpretation and discussion of the research findings concerning the impact of COVID-19 on HR performance in the selection of employees within the IT sector.

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

Drawing on results from the descriptive statistics, reliability analysis, and structural equation modeling (SEM), this chapter provides a comprehensive evaluation of the various factors influencing HR practices, including pandemic effects, technology adoption, HR policies, candidate preferences, and governmental regulations. The chapter aims to offer a deeper understanding of how each factor has shaped recruitment practices during the pandemic and provides implications for future HR strategies in the IT sector.

The key findings from the data analysis, interpreting results in relation to the research objectives and literature review. The discussion highlights how COVID-19 has impacted HR performance in employee selection in the IT sector, with a focus on the roles of HR policy changes, government regulations, and technology adoption. Implications for theory and practice are examined alongside potential limitations. Future research directions are suggested to address unanswered questions and further explore emerging trends in HR practices. Overall, this chapter synthesizes empirical evidence and theoretical insights to provide a comprehensive understanding of the study's outcomes.

Reliability Analysis of each Factors

Factor	**Variables**	**Cronbach's Alpha**	**Number of Items**	**Valid Cases (N)**
TAR	TAR1, TAR2, TAR3	0.765	3	290
HRPES	HRPES1, HRPES2, HRPES3, HRPES4	0.844	4	290
COV	COV1, COV2, COV3, COV4	0.777	4	290
CAP	CAP1, CAP2, CAP3, CAP4	0.823	4	290
GIR	GIR1, GIR2, GIR3	0.787	3	290
CHR	CHR1, CHR2, CHR3, CHR4, CHR5, CHR6	0.891	6	290

I J A M S R

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

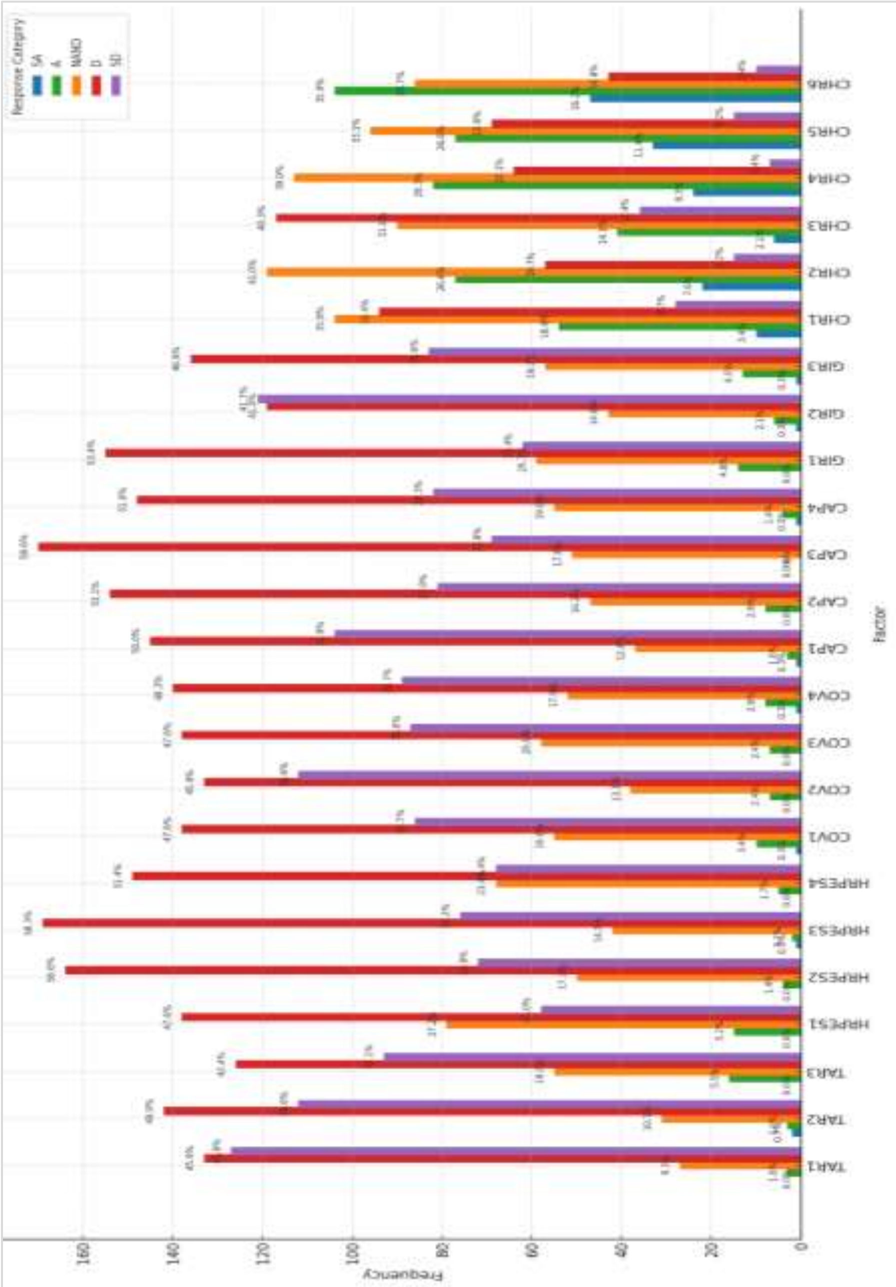

Fig: Frequency Response of Respondents

SEM Structure

Computation of Degrees of Freedom (Default Model)

Number of distinct sample moments:	276
Number of distinct parameters to be estimated:	64
Degrees of freedom (276 - 64):	212

International Journal of Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

In the default SEM model, degrees of freedom are computed by subtracting the number of estimated parameters from the number of distinct sample moments. Here, 276 distinct sample moments—derived from the covariance matrix and means—are available, while 64 parameters are estimated. Subtracting these values (276 - 64) yields 212 degrees of freedom. This measure reflects the model's overidentification and is critical for assessing overall model fit. A sufficient degree of freedom ensures that the model is not over-parameterized, enabling reliable application of statistical tests, such as the chi-square goodness-of-fit test. This ensures robust model evaluation.

Result (Default Model)

The chi-square value of 303.720, with 212 degrees of freedom and a probability level of 0.000, indicates a significant model fit issue. A chi-square test evaluates how well the model's predicted values align with the observed data, with lower chi-square values signifying better fit. A p-value of 0.000 (less than the typical threshold of 0.05) suggests that the model is not a perfect fit. This could indicate overfitting or that the model assumptions do not adequately represent the data. Further adjustments may be needed to improve the model's goodness-of-fit in subsequent iterations. In the default SEM model, the optimization algorithm successfully converged, as indicated by achieving the minimum. The overall model fit is assessed using the chi-square test, where a chi-square statistic of 303.720 was obtained with 212 degrees of freedom. This results in a probability level (p-value) of .000, indicating that the model's covariance structure significantly deviates from the observed data at conventional significance levels. Although a significant chi-square often suggests poor fit, large sample sizes can inflate chi-square statistics, so alternative fit indices should also be examined to comprehensively evaluate model adequacy. These additional indices provide a broader overall assessment.

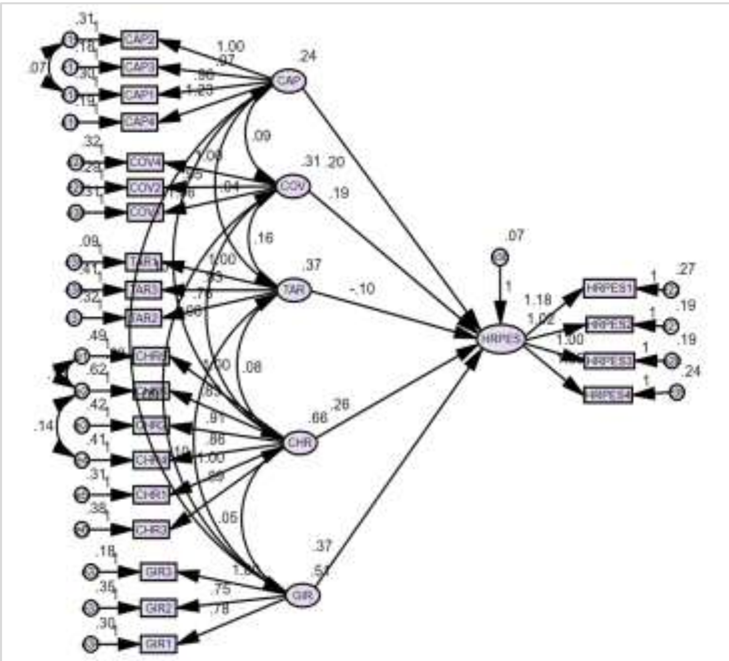

Fig: SEM Model (Propsoed Model)

IJAMSR
International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

In this path diagram, the structural equation model depicts five exogenous constructs—CAP, COV, TAR, CHR, and GIR—each measured by multiple observed variables. Factor loadings are shown along arrows from indicators to their latent factors, while residual terms reflect measurement error. The paths leading from these constructs to HRPES (HR Performance in Employee Selection) illustrate direct effects, with standardized estimates indicating their relative strengths (e.g., 0.66 from CHR to HRPES). Overall, the model suggests that Changes in HR Policies (CHR) exert the strongest influence on HRPES, followed by Government and Industry Regulations (GIR) and Technology Adoption (TAR).

Regression Weights: (Group Number 1 - Default Model)

			Estimate	S.E.	C.R.	P
HRPES	<---	CAP	.197	.090	2.186	.029
HRPES	<---	COV	.195	.064	3.028	.002
HRPES	<---	TAR	-.102	.055	-1.862	.063
HRPES	<---	CHR	.260	.037	7.062	***
HRPES	<---	GIR	.375	.063	5.944	***

In this structural equation model, Changes in HR Policies (CHR) and Government and Industry Regulations (GIR) show the strongest positive effects on HR Performance in Employee Selection (HRPES), with regression coefficients of 0.260 and 0.375, respectively, both highly significant ($p < .001$). Candidate Availability and Preferences (CAP) also exerts a positive, statistically significant influence ($p = .029$), while the COVID-19 Pandemic Effects (COV) variable is similarly significant ($p = .002$) with a positive coefficient of 0.195. By contrast, Technology Adoption in Recruitment (TAR) shows a small negative effect (-0.102) that is not significant at the 5% level ($p = .063$).

Model Fit Summary

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	64	303.720	212	.000	1.433
Saturated model	276	.000	0		
Independence model	23	3186.385	253	.000	12.594

In the model fit summary, the default model estimates 64 parameters and yields a chi-square (CMIN) of 303.720 with 212 degrees of freedom, leading to a highly significant p-value ($p = .000$). Despite significance, the chi-square/df ratio (CMIN/DF) is 1.433, which is below commonly accepted thresholds (e.g., 2 or 3), suggesting very acceptable fit. The saturated model, by definition, fits perfectly, whereas the independence model, which assumes no relationships among variables, demonstrates a poor fit with a chi-square of 3186.385 and a ratio of 12.594. Hence, the default model appears to provide an adequate balance between parsimony and overall fit.

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

4. CONCLUSION

This study examined the impact of the COVID-19 pandemic on HR performance in employee selection within the IT sector. Utilizing data from 290 HR professionals and analyzed through Structural Equation Modeling (SEM), the study revealed critical insights. The constructs demonstrated strong internal consistency, with Cronbach's alpha ranging from 0.765 (Technology Adoption in Recruitment) to 0.891 (Changes in HR Policies). Findings indicated significant dissatisfaction with technology adoption, as over 75% of respondents disagreed on effective use of virtual tools. HR performance in employee selection (HRPES) received mixed responses, especially regarding recruitment speed and efficiency.

SEM analysis showed that Changes in HR Policies (CHR) and Government and Industry Regulations (GIR) had the most substantial positive effects on HRPES, followed by Candidate Availability and Preferences (CAP) and COVID-19 Pandemic Effects (COV). Interestingly, Technology Adoption in Recruitment (TAR) had a weak negative and statistically insignificant impact, suggesting challenges in digital integration or user resistance. The study concludes that policy adaptability and regulatory compliance are key drivers of HR effectiveness during crises, while technology alone is insufficient without strategic alignment. It highlights the importance of understanding candidate preferences, such as remote work expectations, in refining recruitment strategies.

Based on the findings, the study recommends strengthening HR policy reforms, integrating supportive technology, and ensuring compliance with regulatory standards. Organizations should invest in comprehensive remote recruitment protocols, flexible work arrangements, and regular feedback mechanisms. Policymakers should provide clear regulatory frameworks to aid remote hiring. Furthermore, future research should extend to diverse industries, adopt longitudinal and mixed-method approaches, and explore other HR functions affected by the pandemic.

REFERENCES

1. Shiferaw, T. (2022). Impact of Human Resource Management Practices on Employee Performance: The Case of Bule Hora University, Ethiopia, Africa. *Organization and Human Capital Development*, *1*(1), 53-61.
2. Kakarougkas, C., & Papageorgakis, E. (2023). Evaluating the Effectiveness of Training Methods on the Performance of Human Resources in Greek Hotel Businesses. *Journal of Advances in Humanities Research*, *2*(1), 62-82.
3. Madhani, P. M. (2023). Human resources analytics: leveraging human resources for enhancing business performance. *Compensation & Benefits Review*, *55*(1), 31-45.
4. Arokiasamy, L., Fujikawa, T., Piaralal, S. K., & Arumugam, T. (2023). A systematic review of literature on Human capital investment and its significance for human resource development. *International Journal of System Assurance Engineering and Management*, *14*(5), 1810-1826.
5. Abuhantash, A. (2023). The Impact of Human Resource Information Systems on Organizational Performance: A Systematic Literature Review. *European Journal of Business and Management Research*, *8*(3), 239-245.

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

6. Papademetriou, C., Anastasiadou, S., & Papalexandris, S. (2023). The effect of sustainable human resource management practices on customer satisfaction, service quality, and institutional performance in hotel businesses. *Sustainability*, *15*(10), 8251.
7. Awan, F. H., Dunnan, L., Jamil, K., & Gul, R. F. (2023). Stimulating environmental performance via green human resource management, green transformational leadership, and green innovation: a mediation-moderation model. *Environmental Science and Pollution Research*, *30*(2), 2958-2976.
8. Zebua, S., & Chakim, M. H. R. (2023). Effect of Human Resources Quality, Performance Evaluation, and Incentives on Employee Productivity at Raharja High School. *APTISI Transactions on Management*, *7*(1), 1-8.
9. Budiarto, B. W., Karyadi, S., Judijanto, L., & Febrian, W. D. (2024). Analysis Of The Influence Of Spiritual Capital, Motivation And Work Competencies On Performance Of Human Resource In Smes Sector. *JEMSI (Jurnal Ekonomi, Manajemen, Dan Akuntansi)*, *10*(1), 240-246.
10. Chali, B. D., & Lakatos, V. (2024). The Impact of Human Resource Management on Financial Performance: A Systematic Review in Cooperative Enterprises. *Journal of Risk and Financial Management*, *17*(10), 439.
11. Rony, Z. T., Wijaya, I. M. S., Nababan, D., Julyanthry, J., Silalahi, M., Ganiem, L. M., ... & Saputra, N. (2024). Analyzing the Impact of Human Resources Competence and Work Motivation on Employee Performance: A Statistical Perspective. *Journal of Statistics Applications & Probability*, *13*(2), 787-793.
12. Raman, R., Venugopalan, M., & Kamal, A. (2024). Evaluating human resources management literacy: A performance analysis of ChatGPT and bard. *Heliyon*, *10*(5).
13. Peretz, H. (2024). Sustainable human resource management and employees' performance: The impact of national culture. *Sustainability*, *16*(17), 7281.
14. Esan, O., Ajayi, F. A., & Olawale, O. (2024). Managing global supply chain teams: human resource strategies for effective collaboration and performance. *GSC Advanced Research and Reviews*, *19*(2), 013-031.
15. Salman, M., Anwar, I., Ganie, S. A., & Saleem, I. (2024). Impact of Human Resource Management Practices on Organizational Performance: Evidence from the Indian Banking Industry. *Management and Labour Studies*, *49*(1), 97-118.

Questionnaire

Section 1: Technology Adoption in Recruitment (TAR)

Please rate your agreement with the following statements on a scale of 1 (Strongly Disagree) to 5 (Strongly Agree):

TAR1: Our organization adopted virtual interview platforms during the COVID-19 pandemic.
TAR2: The use of AI-driven recruitment tools increased during the pandemic.
TAR3: Online skill assessments became a standard part of the recruitment process.

Section 2: HR Performance in Employee Selection (HRPES)

Please rate your agreement with the following statements on a scale of 1 (Strongly Disagree) to 5 (Strongly Agree):

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

HRPES1: The efficiency of the hiring process improved during the pandemic.
HRPES2: The quality of hires was maintained during virtual recruitment.
HRPES3: Virtual interviews were as effective as in-person interviews.
HRPES4: The time taken for recruitment decreased during the pandemic.

Section 3: COVID-19 Pandemic Effects (COV)

Please rate your agreement with the following statements on a scale of 1 (Strongly Disagree) to 5 (Strongly Agree):

COV1: The pandemic led to a reduction in hiring demand.
COV2: Work-from-home policies affected the selection process.
COV3: Budget constraints impacted the recruitment process.
COV4: The hiring process was delayed due to lockdowns.

Section 4: Candidate Availability and Preferences (CAP)

Please rate your agreement with the following statements on a scale of 1 (Strongly Disagree) to 5 (Strongly Agree):

CAP1: There was an increase in job applications during the pandemic.
CAP2: More candidates preferred remote work positions.
CAP3: Skill gaps among candidates increased during the pandemic.
CAP4: Competition for roles in the IT sector intensified.

Section 5: Government and Industry Regulations (GIR)

Please rate your agreement with the following statements on a scale of 1 (Strongly Disagree) to 5 (Strongly Agree):

GIR1: Government policies on remote hiring influenced our selection process.
GIR2: Compliance with data privacy laws impacted virtual recruitment.
GIR3: Industry standards for virtual hiring practices were adopted.

Section 6: Changes in HR Policies (CHR)

Please rate your agreement with the following statements on a scale of 1 (Strongly Disagree) to 5 (Strongly Agree):

CHR1: New policies for remote interviews were implemented.
CHR2: The use of contract-based hiring increased.
CHR3: Onboarding processes were adapted for remote settings.
CHR4: Performance evaluation methods changed due to remote work.
CHR5: Policies for flexible work arrangements were introduced.
CHR6: Employee training was shifted to virtual platforms.