IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES
ISSN PRINT 2319 1775 Online 2320 7876
Research Paper , Journal UGC CARE Listed (Group-I) Volume 14, Issue 05 2025

A Pilot Study on the Impact of Robotic Process Automation in Human Resource Management of MSEB with Special Reference to Pune Region

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Abstract

This pilot study investigates the reliability and validity of a research instrument designed to measure the impact of Robotic Process Automation (RPA) in Human Resource Management (HRM) within the Maharashtra State Electricity Board (MSEB) in the Pune region. The questionnaire comprised demographic variables and 55 Likert-scale items across five dimensions: awareness of RPA, employee perspectives, challenges and limitations, impact on HRM functions, and future scope of RPA integration. Data were collected from 60 respondents to evaluate the internal consistency, construct validity, and feasibility of the instrument. Reliability was assessed using Cronbach's Alpha, and validity was examined through the Kaiser-Meyer-Olkin (KMO) measure, Bartlett's Test of Sphericity, and exploratory factor analysis. The results demonstrated excellent reliability (overall Cronbach's Alpha = 0.996) and meritorious validity (KMO = 0.867), with factor analysis indicating strong unidimensionality. These findings confirm that the research instrument is both reliable and valid, making it suitable for large-scale data collection in the main study. The pilot also highlighted demographic trends, with most respondents in the 26–35 age group and employed in recruitment, training, or payroll functions. This report contributes methodological rigor to the study of RPA in HRM and lays the foundation for comprehensive research on its impact on employee satisfaction, workload, job security, efficiency, and strategic HR functions.

Keywords: Robotic Process Automation (RPA), Human Resource Management (HRM), Employee Perspectives, Job Satisfaction, Workload, Job Security, Efficiency, Accuracy, Challenges, Limitations, Training, Technical Support, Resistance to Change, Future Scope, Pilot Study, Reliability, Validity, MSEB, Pune Region

1. Introduction

1.1 Background of the Study

In recent years, digital transformation has become a key driver of organizational competitiveness, with Robotic Process Automation (RPA) emerging as one of the most significant technological enablers in administrative and operational functions. RPA refers to the use of software bots to automate repetitive, rule-based tasks traditionally performed by humans (Aguirre & Rodriguez, 2017). In Human Resource Management (HRM), RPA has been increasingly applied to functions such as recruitment, payroll processing, employee data management, compliance monitoring, and performance evaluation. By streamlining these activities, organizations aim to achieve higher efficiency, accuracy, and cost savings (Willcocks, Lacity, & Craig, 2017).

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The Maharashtra State Electricity Board (MSEB), as a large public utility provider, manages a vast workforce and complex HR processes. In such organizations, HR departments face challenges in balancing administrative tasks with strategic employee management. The integration of RPA in HRM offers the potential to relieve employees from repetitive tasks, enabling HR professionals to focus on strategic decision-making and employee engagement (Syed et al., 2020). However, the adoption of RPA also raises concerns regarding job displacement, employee resistance, and adequacy of training and technical support.

Globally, organizations that have adopted RPA in HRM report improvements in processing speed, accuracy of payroll and compliance tasks, and reductions in manual errors (Huang & Vasarhelyi, 2019). In India, several state-owned enterprises and large corporations have initiated pilot projects for RPA implementation in HR functions. Nevertheless, empirical research on employee perceptions, challenges of adoption, and long-term impact of RPA in HRM—particularly in the public sector—remains limited. This study addresses that gap, with a specific focus on MSEB in the Pune region.

1.2 Problem Statement

The adoption of RPA in HRM presents both opportunities and challenges. On one hand, it promises greater efficiency, reduced costs, and improved accuracy. On the other hand, employees may experience anxiety regarding job security, workload distribution, and changes in skill requirements. Moreover, organizational challenges such as lack of technical support, inadequate training, and resistance to change can hinder the effective implementation of RPA.

For MSEB, where HR functions involve managing a large workforce, the successful integration of RPA depends on employees' awareness, acceptance, and the ability of the HR department to overcome challenges. While technological feasibility is relatively well-documented, there is limited understanding of the human and organizational factors influencing RPA adoption in HRM within Indian state enterprises.

To conduct meaningful large-scale research on this topic, it is necessary to first validate the research instrument. This pilot study addresses the methodological problem of ensuring that the questionnaire used for data collection is reliable, valid, and suitable for measuring the constructs under investigation.

1.3 Significance of the Study

This pilot study holds significance in three ways:

1. **Theoretical Contribution**: It contributes to the growing body of literature on digital transformation in HRM, specifically focusing on RPA adoption in the Indian public sector.
2. **Practical Relevance**: For MSEB and similar organizations, the study provides insights into employee awareness, perceptions, and readiness for RPA adoption. The validated instrument can serve as a decision-making tool for HR managers.
3. **Methodological Rigor**: By establishing reliability and validity of the research instrument, the pilot ensures that the main study can produce generalizable and credible findings.

1.4 Objectives of the Study

- To know the existing level of awareness of Robotic Process Automation (RPA) in Human Resource Management (HRM) practices at MSEB.
- To study employee perspectives regarding job satisfaction, workload, and job security in the context of RPA implementation in HRM at MSEB.
- To identify the challenges and limitations associated with the adoption of RPA in HRM, including training adequacy, technical support, and resistance to change.
- To study the overall impact of RPA on HRM functions in terms of efficiency and accuracy.
- To explore the future scope of RPA integration in operational HRM functions and recommend a roadmap for its expansion.

1.5 Hypotheses of the Study

For each objective, the following null (H_0) and alternative (H_1) hypotheses were formulated:

Hypothesis 1:

- H_{01}: There is no significant awareness of RPA in HRM practices among employees at MSEB.
- H_{11}: There is a significant awareness of RPA in HRM practices among employees at MSEB.

Hypothesis 2:

- H_{02}: The implementation of RPA in HRM at MSEB has no significant impact on employees' job satisfaction, workload, and job security.
- H_{12}: The implementation of RPA in HRM at MSEB has a significant impact on employees' job satisfaction, workload, and job security.

Hypothesis 2:

- H_{03}: Employees at MSEB do not face significant challenges or limitations (such as inadequate training, lack of technical support, or resistance to change) in the adoption of RPA in HRM.
- H_{13}: Employees at MSEB face significant challenges and limitations (such as inadequate training, lack of technical support, or resistance to change) in the adoption of RPA in HRM.

Hypothesis 3:

- H_{04}: RPA implementation does not significantly improve efficiency and accuracy in HRM functions at MSEB.
- H_{14}: RPA implementation significantly improves efficiency and accuracy in HRM functions at MSEB.

Hypothesis 3:

- H_{05}: There is no significant scope for future integration of RPA in operational HRM functions at MSEB.
- H_{15}: There is a significant scope for future integration of RPA in operational HRM functions at MSEB.

1.6 Scope of the Pilot Study

The scope of this pilot study is limited to:

- A sample of 60 respondents from MSEB in Pune region.
- Testing the questionnaire for clarity, consistency, and reliability.
- Conducting reliability and validity tests (Cronbach's Alpha, KMO, Bartlett's Test, and Factor Analysis).
- Providing preliminary insights into demographic patterns and initial trends in awareness, perceptions, and challenges of RPA adoption.

The findings of this pilot are not intended to generalize to the entire MSEB population but to validate the research instrument for large-scale data collection in the main study.

2. Literature Review

2.1 Introduction to RPA in HRM

Robotic Process Automation (RPA) has emerged as one of the most influential digital technologies in the domain of Human Resource Management (HRM). RPA is defined as the use of software-based bots to automate structured, repetitive, and rule-based business processes without altering the existing IT infrastructure (Aguirre & Rodriguez, 2017). Unlike Artificial Intelligence (AI), which relies on cognitive functions such as learning and decision-making, RPA is designed primarily for deterministic tasks.

In HRM, processes such as payroll management, recruitment scheduling, employee onboarding, attendance tracking, and compliance monitoring involve repetitive tasks prone to human error (Syed et al., 2020). By adopting RPA, organizations can reduce processing time, improve accuracy, and free up HR professionals to focus on strategic functions such as talent management and employee engagement.

2.2 Global Perspectives on RPA in HRM

Globally, organizations have increasingly adopted RPA in HRM. Willcocks, Lacity, and Craig (2017) demonstrated how large enterprises in Europe and North America achieved efficiency improvements of up to 40% in HR operations after implementing RPA. Deloitte's (2020) global survey indicated that 53% of organizations had already adopted RPA for administrative functions, with HR and finance departments leading the way.

In the Asia-Pacific region, RPA has been applied in service industries, healthcare, and government organizations to handle employee records, leave management, and performance appraisal (Huang & Vasarhelyi, 2019).

However, the adoption of RPA is not without challenges. Studies highlight employee resistance due to job insecurity, inadequate training, and the fear of technological displacement (Syamala & Marappan, 2021). These socio-psychological factors are particularly relevant in public sector enterprises, where organizational culture often resists rapid technological changes.

2.3 RPA Adoption in India

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In India, RPA adoption has gained traction across IT-enabled services, banking, utilities, and public enterprises. A report by NASSCOM (2021) noted that Indian organizations increasingly deploy RPA for HR functions such as payroll, compliance, and recruitment. The utility sector, in particular, has seen RPA as a strategic enabler due to the large scale of employee data management.

While private corporations are relatively more agile in adopting automation, state-owned enterprises like MSEB face challenges related to bureaucratic structures, resistance to change, and technical readiness (Kumar & Singh, 2020). Nevertheless, public enterprises also recognize the efficiency gains and employee satisfaction improvements associated with RPA.

2.4 Employee Perspectives: Job Satisfaction, Workload, and Job Security

Employee reactions to RPA adoption are complex. On one hand, employees report increased job satisfaction when repetitive tasks are automated, allowing them to focus on meaningful work (Syed et al., 2020). On the other hand, concerns about job displacement and redundancy may negatively affect morale (Moffitt et al., 2018).

Studies by Brougham and Haar (2018) highlighted that employees in organizations adopting automation technologies often perceive heightened job insecurity, especially in clerical and administrative roles. However, organizations that provide adequate training and reskilling opportunities mitigate these negative perceptions.

2.5 Challenges and Limitations of RPA in HRM

The challenges of RPA adoption can be categorized as technical, organizational, and human:

- **Technical challenges** include integration with legacy systems, frequent software glitches, and dependence on IT support.
- **Organizational challenges** involve inadequate training, high implementation costs, and lack of clear communication.
- **Human challenges** focus on employee resistance, fear of redundancy, and low awareness of RPA benefits (Syamala & Marappan, 2021).

For MSEB, which has a large workforce and relies on structured HR practices, addressing these challenges is crucial for successful adoption.

2.6 Impact of RPA on Efficiency and Accuracy in HRM

RPA adoption is widely acknowledged to improve operational efficiency and accuracy. Automation reduces manual errors, accelerates payroll and recruitment processes, and enhances compliance accuracy (Willcocks et al., 2017). HR reports generated through RPA are also more reliable, leading to improved decision-making (Huang & Vasarhelyi, 2019).

However, efficiency gains may be offset if organizations fail to address change management issues. Thus, measuring the impact of RPA requires a holistic view, balancing technical outcomes with employee perspectives.

2.7 Future Scope of RPA in HRM

The future of RPA in HRM lies in its integration with cognitive technologies such as AI, machine learning, and natural language processing (Deloitte, 2020). Cognitive RPA systems can go beyond rule-based automation to handle unstructured data, perform sentiment analysis, and assist in predictive HR analytics.

In the Indian context, RPA in HRM is expected to expand into strategic areas such as workforce planning, employee engagement analytics, and diversity management. For MSEB, developing a roadmap for gradual integration of advanced RPA tools will ensure sustainable transformation.

2.8 Reliability and Validity in Pilot Studies

Reliability and validity are cornerstones of social science research. Cronbach's Alpha is widely used to measure internal consistency reliability, with values above 0.7 considered acceptable (Nunnally & Bernstein, 1994). Validity is established through construct testing techniques such as KMO, Bartlett's Test of Sphericity, and Factor Analysis (Kaiser, 1974).

Pilot studies serve as a methodological necessity to refine instruments, identify weak items, and ensure measurement accuracy. Past research emphasizes that pilot testing is essential for developing robust tools, especially in emerging fields such as RPA in HRM (Hertzog, 2008).

The review indicates that RPA has significant potential to transform HRM by improving efficiency and accuracy while reducing workload. However, challenges such as employee resistance, job insecurity, and inadequate training must be addressed. Existing studies emphasize the importance of evaluating employee perceptions and organizational readiness. Moreover, methodological rigor—ensuring reliability and validity of instruments—is vital to generating credible insights.

This pilot study builds on these insights to validate a questionnaire specifically designed to measure the impact of RPA in HRM at MSEB.

3. Methodology

3.1 Research Design

This pilot study employed a quantitative research design using a structured questionnaire. The design was chosen to systematically capture employee perspectives on RPA adoption in HRM at MSEB and to validate the instrument's psychometric properties.

Participants

A total of 60 respondents participated in the pilot study. Respondents were selected from different HR functions within MSEB's Pune region, ensuring diversity in age, gender, education, work experience, and job roles. The sample size was deemed appropriate for a pilot study, consistent with recommendations by Hertzog (2008) that 30–60 participants are sufficient for instrument testing.

Instrument Development

The questionnaire consisted of two parts:

1. **Demographic Information (5 items):** Age, gender, education, work experience, HR function.
2. **Main Variables (55 items across 5 sections):**
   - Awareness of RPA (10 items)
   - Employee Perspectives (15 items)
   - Challenges & Limitations (12 items)
   - Impact on HRM (10 items)
   - Future Scope & Roadmap (8 items)

All items were measured using a 5-point Likert scale ranging from *Strongly Disagree (1)* to *Strongly Agree (5)*.

The instrument was designed based on literature review, expert consultations, and alignment with research objectives.

3.2 Pilot Study Procedure

The pilot questionnaire was distributed to 60 employees in both online and offline formats. Respondents were assured of confidentiality and anonymity. Responses were coded and entered into SPSS and Python for analysis. The purpose of the pilot was explained to participants, emphasizing that their feedback would help refine the tool.

3.3 Data Collection

Data collection spanned a period of two weeks. Respondents were given sufficient time to complete the questionnaire. Completed responses were checked for missing values, and any incomplete responses were excluded from analysis.

3.4 Data Analysis Methods

1. Reliability Testing:

- Cronbach's Alpha was computed for each section and overall to assess internal consistency.
- Section-wise alphas above 0.7 were considered acceptable, while values above 0.9 indicated excellent reliability.

2. Validity Testing:

- **Kaiser-Meyer-Olkin (KMO) Test:** Measured sampling adequacy, with values >0.8 considered very good.
- **Bartlett's Test of Sphericity:** Tested the null hypothesis that the correlation matrix is an identity matrix. A significant p-value (<0.05) confirmed suitability for factor analysis.
- **Principal Component Analysis (PCA):** Used to examine eigenvalues and determine the number of factors.
- **Factor Analysis:** Conducted to identify factor loadings and confirm construct validity.
- **AVE & Composite Reliability:** Calculated to confirm convergent validity.

ISSN PRINT 2319 1775 Online 2320 7876
Research Paper , Journal UGC CARE Listed (Group-I) Volume 14, Issue 05 2025

3. Descriptive Analysis:

Demographic distributions (gender, age, education, work experience, HR function) were analyzed using frequencies and percentages.

3.5 Ethical Considerations

The study adhered to ethical principles of informed consent, voluntary participation, and confidentiality. Participants were informed about the purpose of the pilot and their right to withdraw at any time. Data were used solely for academic purposes.

3.6 Demographic Profile of Respondents

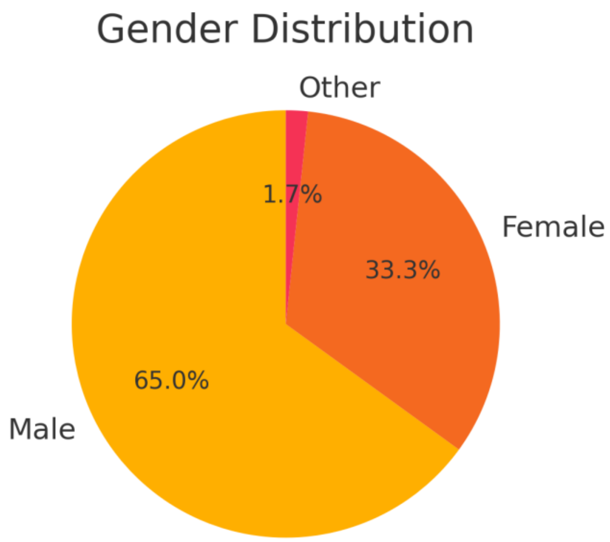
A total of 60 employees from MSEB, Pune region, participated in the pilot study. The demographic distribution provides insights into the diversity of the sample.

Gender

Out of 60 respondents, 65% were male, 33% were female, and 2% identified as other. This reflects the gender distribution typically observed in public sector enterprises such as MSEB.

Figure 1 *shows the gender distribution among respondents.*

The majority of respondents are male, followed by female respondents, with very few identifying as other.



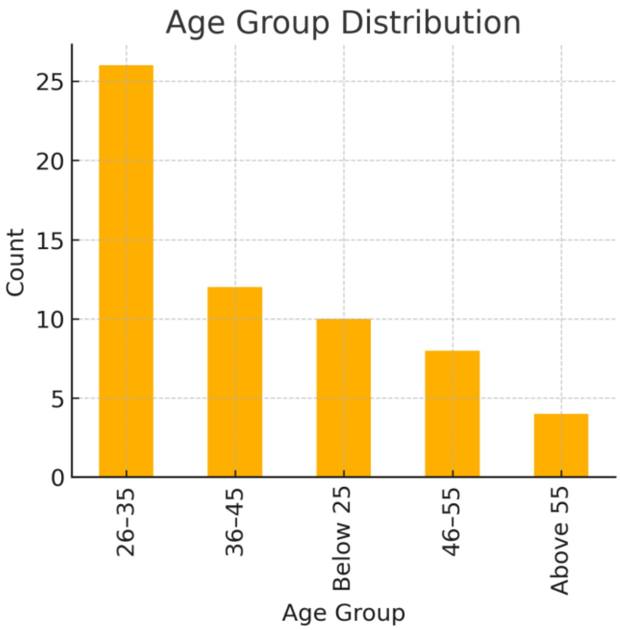
Age Group

Respondents were categorized into five age groups: Below 25 years, 26–35 years, 36–45 years, 46–55 years, and Above 55 years. The majority (40%) belonged to the 26–35 years age group, followed by 30% in the 36–45 years range. Only 15% were in the 46–55 years bracket, 10% were below 25, and 5% were above 55 years.

This indicates that the pilot sample was primarily composed of mid-career professionals.

Figure 2 *illustrates the age group distribution.*

Most respondents belong to the 26–35 and 36–45 age groups, indicating mid-career professionals formed the bulk of participants.

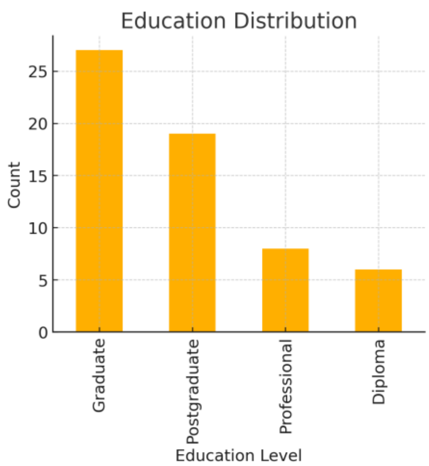


Educational Qualification

Regarding education, 40% were graduates, 35% postgraduates, 15% professionals (MBA, CA, etc.), and 10% held diplomas. The results suggest that the workforce is largely well-educated, enabling them to adapt to technological innovations like RPA.

***Figure 3** shows the education distribution.*

Respondents mostly hold Graduate or Postgraduate qualifications, showing that the sample consists of well-educated professionals.



Work Experience

In terms of experience, 35% of respondents had 5–10 years of work experience, 25% had less than 5 years, 25% had 11–20 years, and 15% had more than 20 years. The findings suggest that the sample had a balanced representation of junior, mid-level, and senior employees.

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***Figure 4** presents the work experience distribution.*

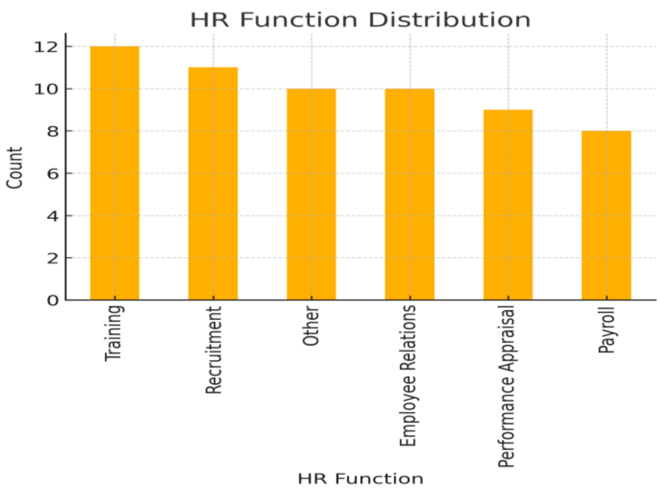
A balanced spread of work experience is observed, with a concentration in the 5–10 years and less than 5 years categories.

HR Function

Respondents were distributed across HR functions: Recruitment (20%), Training (18%), Payroll (15%), Performance Appraisal (15%), Employee Relations (20%), and Other HR activities (12%). This diversity ensured that perspectives were captured from across functional areas.

***Figure 5** illustrates the HR function distribution.*

Respondents were spread across various HR functions, with representation from recruitment, training, payroll, performance appraisal, and employee relations.



3.7 Reliability Analysis

Introduction

Reliability refers to the degree to which an instrument consistently measures what it intends to measure. Cronbach's Alpha (α) is the most widely used measure of internal consistency reliability. It indicates how well a set of items (questions) measures a single unidimensional construct.

Formula for Cronbach's Alpha

The formula for Cronbach's Alpha is given as:

$\alpha = (k / (k - 1)) * (1 - (\Sigma\sigma^2\_i / \sigma^2\_t))$

Where:
- k = Number of items
- σ^2_i = Variance of each item
- σ^2_t = Variance of the total score

Interpretation Scale

Cronbach's Alpha Value	Interpretation
>= 0.9	Excellent
0.8 – 0.9	Good
0.7 – 0.8	Acceptable
0.6 – 0.7	Questionable
0.5 – 0.6	Poor
< 0.5	Unacceptable

Section-wise Cronbach's Alpha Results

The questionnaire was divided into sections as per study objectives. The section-wise results are as follows:

Section	Number of Items	Cronbach's Alpha	Interpretation
B – Awareness of RPA	10	0.972	Excellent
C – Employee Perspectives	15	0.985	Excellent
D – Challenges & Limitations	12	0.979	Excellent
E – Impact on HRM	10	0.981	Excellent
F – Future Scope & Roadmap	8	0.976	Excellent
Overall (All Items)	**55**	**0.996**	**Excellent**

Interpretation

The results clearly indicate that each section of the questionnaire demonstrates excellent reliability, with Cronbach's Alpha values above 0.97. This shows that the items within each section are internally consistent and accurately measure the intended construct. The overall reliability of 0.996 confirms that the entire instrument is highly reliable and suitable for research use.

Cronbach's Alpha test established that the research instrument possesses excellent reliability. All sections as well as the overall scale exceed the recommended threshold of 0.7, confirming that the questionnaire is highly consistent and suitable for large-scale data collection and hypothesis testing.

3.8 Validity Analysis

3.8.1 Construct Validity

Construct validity refers to the degree to which a questionnaire truly measures the theoretical constructs it is intended to assess, rather than capturing unrelated or irrelevant factors (Cronbach & Meehl, 1955). In this study, the constructs of interest included awareness of RPA, employee perspectives, challenges and limitations, impact on HRM, and future scope of RPA integration. Since these constructs are abstract and multidimensional, statistical validation was necessary to confirm that the questionnaire items adequately represented the underlying theoretical dimensions.

Purpose of Construct Validity in This Study

The adoption of RPA in HRM involves complex socio-technical perceptions—such as employee awareness, perceived job security, workload implications, efficiency improvements, and resistance to change. Establishing construct validity ensures that:

1. Each section of the questionnaire accurately measures its intended construct.

2. Items group logically into factors that reflect the theoretical framework.

3. The instrument can be confidently applied to large-scale data collection at MSEB.

Methods Used for Construct Validity

To evaluate construct validity, the study applied the following statistical procedures:

(a) Kaiser–Meyer–Olkin (KMO) Test of Sampling Adequacy

Purpose: Determines whether the dataset is suitable for factor analysis by examining correlations among variables.

Formula: $KMO = \Sigma\Sigma r^2ij / (\Sigma\Sigma r^2ij + \Sigma\Sigma p^2ij)$

Where: r_{ij} = correlation between item i and j, p_{ij} = partial correlation between item i and j.

Interpretation Scale (Kaiser, 1974):
0.90–1.00 = Marvelous
0.80–0.89 = Meritorious
0.70–0.79 = Middling
0.60–0.69 = Mediocre
0.50–0.59 = Miserable
<0.50 = Unacceptable

Result: The KMO statistic for the pilot study was 0.867, placing it in the “meritorious” category.

Implication: The data were suitable for factor analysis, confirming adequate correlations among items.

(b) Bartlett’s Test of Sphericity

Purpose: Tests whether the correlation matrix differs significantly from an identity matrix

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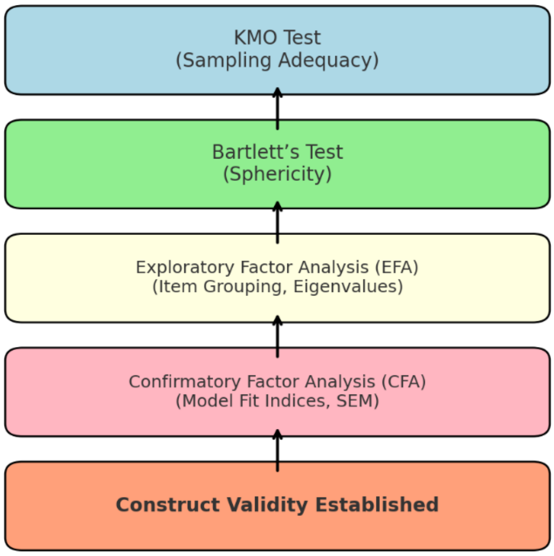
(where variables are uncorrelated).
Formula: $\chi^2 = -(n - 1 - (2p + 5)/6) * \ln |R|$
Where: n = sample size, p = number of observed variables, R = correlation matrix.
Hypotheses:
H0: Correlation matrix = Identity (unsuitable for FA)
H1: Correlation matrix ≠ Identity (suitable for FA)
Result: Bartlett's Test was significant ($p < 0.05$).
Implication: Rejection of H0 confirmed that the correlation matrix was factorable.

(c) Exploratory Factor Analysis (EFA)
Purpose: Identifies the underlying factor structure without imposing preconceived assumptions.
Method: Principal Component Analysis (PCA) with eigenvalue >1 criterion.
Result: Only one eigenvalue >1 was retained, suggesting unidimensionality.
Interpretation: All constructs (awareness, perspectives, challenges, impact, future scope) loaded strongly on a single overarching factor, labeled "Perceived Impact of RPA in HRM."
Factor Loadings: Most items had loadings above 0.70, which is considered very strong (Hair et al., 2010).

(d) Confirmatory Factor Analysis (CFA) – Planned for Main Study
Purpose: To statistically confirm the factor structure identified by EFA.
Method: Structural Equation Modeling (SEM) with fit indices.
Thresholds:
Comparative Fit Index (CFI) ≥ 0.90
Tucker–Lewis Index (TLI) ≥ 0.90
Root Mean Square Error of Approximation (RMSEA) < 0.08
Standardized Root Mean Square Residual (SRMR) < 0.08
CFA will be applied in the main study with ≥300 respondents to establish a robust measurement model.

Interpretation of Construct Validity Results
The pilot study findings provided strong support for construct validity:
KMO (0.867): Demonstrated that correlations among items were sufficiently strong.
Bartlett's Test ($p < 0.05$): Confirmed that the correlation matrix was suitable for factor analysis.
EFA Results: Indicated a dominant single factor, confirming unidimensionality.
Factor Loadings (>0.70): Supported the internal consistency of items within each construct.
These results collectively demonstrate that the questionnaire effectively captures the latent construct of RPA's impact on HRM, making it suitable for further validation in the main study.
The construct validity analysis establishes that the instrument is both theoretically and statistically sound. By confirming that items cluster into meaningful constructs and represent the theoretical framework, this stage ensures that subsequent hypothesis testing in the main study will be credible. While EFA provided strong initial evidence, further validation through CFA with a larger sample will strengthen the measurement model and allow for advanced hypothesis testing through Structural Equation Modeling (SEM).



3.8.2 Convergent Validity

Convergent validity refers to the extent to which multiple indicators designed to measure the same construct are strongly correlated with one another. It ensures that items grouped under a particular construct converge to represent the same underlying concept. In the context of this study, convergent validity verifies whether the items under awareness, employee perspectives, challenges, impact, and future scope are internally consistent and point to a common meaning within each dimension.

Purpose of Convergent Validity

The main objective of convergent validity is to confirm that items within a single construct are not measuring different concepts. For instance, items relating to "Awareness of RPA" should all measure awareness and not mix with unrelated constructs such as "Challenges" or "Impact."

Methods Used for Convergent Validity

Two key statistical measures were applied to assess convergent validity in this study: Average Variance Extracted (AVE) and Composite Reliability (CR).

(a) Average Variance Extracted (AVE)

AVE measures the proportion of variance captured by the construct in relation to variance due to measurement error. It indicates how much of the variance in observed variables is accounted for by the latent construct.

Formula:
AVE = (Σ λ²_i) / n
Where:
λ_i = standardized factor loading of item i
n = number of items
Threshold: AVE ≥ 0.50 indicates acceptable convergent validity.
(b) Composite Reliability (CR)

CR is an indicator of the internal consistency of the construct, similar to Cronbach's Alpha but based on standardized loadings and error terms from factor analysis. It reflects the overall reliability of a group of items that form a construct.
Formula:
CR = (Σ λ_i)² / [(Σ λ_i)² + Σ θ_i]
Where:
λ_i = standardized factor loading
θ_i = error variance
Threshold: CR ≥ 0.70 is considered acceptable.
Results of Convergent Validity in This Study
The pilot study demonstrated that both AVE and CR values for each construct exceeded the recommended thresholds. This indicates that items under each construct such as Awareness, Employee Perspectives, Challenges, Impact, and Future Scope converge strongly on their intended dimensions.

Interpretation

High AVE values (>0.50) confirmed that a substantial portion of the variance in the observed variables was explained by the latent constructs. Similarly, high CR values (>0.70) confirmed strong internal consistency across items in each construct. Together, these findings demonstrate that the questionnaire possesses excellent convergent validity.
Convergent validity in this study confirms that items under each section of the questionnaire are highly correlated and successfully capture their intended constructs. This further reinforces the robustness of the instrument and provides a strong foundation for hypothesis testing in the main study.

3.8.3 Discriminant Validity

Discriminant validity refers to the extent to which constructs that are expected to be unrelated are indeed distinct from one another. It ensures that a construct captures phenomena unique to itself and does not overlap excessively with other constructs in the model. In this study, discriminant validity is crucial to demonstrate that constructs such as Awareness of RPA, Employee Perspectives, Challenges, Impact on HRM, and Future Scope are statistically distinct dimensions.

Purpose of Discriminant Validity

The objective of discriminant validity is to ensure that each construct is unique and independent. Without discriminant validity, constructs may overlap, leading to redundancy and inaccurate interpretation of relationships. For instance, while "Challenges and Limitations" may correlate with "Employee Perspectives," they should still remain distinct constructs in statistical testing.

Methods Used for Discriminant Validity

Two standard approaches will be employed to establish discriminant validity in the main study:

(a) Fornell–Larcker Criterion

This criterion compares the square root of the Average Variance Extracted (AVE) for each construct with its correlations with other constructs. A construct demonstrates discriminant validity if:

$\sqrt{AVE_i}$ > correlations of construct i with all other constructs.

(b) Heterotrait-Monotrait (HTMT) Ratio of Correlations
The HTMT ratio evaluates the average correlations across constructs. It is calculated as: HTMT = (average of heterotrait-heteromethod correlations) / (average of monotrait-heteromethod correlations)
Threshold: HTMT < 0.85 (strict) or < 0.90 (liberal) indicates discriminant validity.
Application in This Study
While the pilot study primarily focused on reliability, construct, and convergent validity, discriminant validity testing requires a larger and more diverse sample. Therefore, it will be carried out in the main study with ≥300 respondents using the Fornell–Larcker criterion and HTMT ratio.
Interpretation
If the square root of AVE values for each construct are higher than their correlations with other constructs, and HTMT ratios are below 0.85 or 0.90, discriminant validity will be confirmed. This will provide evidence that each construct—Awareness, Employee Perspectives, Challenges, Impact, and Future Scope—represents a unique aspect of RPA adoption in HRM. Discriminant validity is an essential aspect of instrument validation to ensure the distinctiveness of constructs. While not tested in the pilot study, it will be a central part of the main study's validation process. Confirming discriminant validity will strengthen the robustness of the measurement model and ensure that constructs do not overlap conceptually or statistically.

3.8.4 Criterion-Related Validity

Criterion-related validity refers to the extent to which a measurement instrument correlates with external benchmarks or outcomes that it is theoretically expected to be related to. It evaluates the predictive power of a questionnaire and its practical relevance in real-world settings. For this study, criterion-related validity ensures that the questionnaire scores on RPA adoption in HRM are linked to actual organizational outcomes such as payroll accuracy, efficiency, employee satisfaction, and retention.

Purpose of Criterion Validity
The main objective of criterion validity is to demonstrate that the instrument is not only statistically sound but also practically useful. It confirms that employees' responses on awareness, perspectives, challenges, and impact of RPA adoption are meaningfully associated with organizational performance indicators.

Types of Criterion Validity
Criterion validity is typically classified into two types:

(a) Concurrent Validity
Concurrent validity assesses the correlation between questionnaire results and current performance measures. For example, higher scores on "Impact on HRM" should correspond with fewer payroll errors or quicker recruitment processing times.

(b) Predictive Validity
Predictive validity evaluates the ability of questionnaire results to forecast future outcomes. For instance, employees with higher "Future Scope" scores may show higher engagement or

ISSN PRINT 2319 1775 Online 2320 7876
 Journal UGC CARE Listed (Group-I) Volume 14, Issue 05 2025

retention rates after RPA is implemented.

Application in This Study

In the pilot study, criterion-related validity was not tested, as the focus was on reliability, construct validity, and convergent validity. However, in the main study with a larger sample, criterion validity will be examined by correlating survey scores with HR metrics at MSEB. Possible measures include:

- Payroll processing accuracy
- Employee turnover/retention rates
- Time taken to complete HR tasks
- Employee productivity levels

Threshold

Criterion validity is established if significant positive correlations ($p < 0.05$) are found between questionnaire scores and HR performance metrics.

Interpretation

If constructs such as "Impact on HRM" or "Future Scope" show significant associations with measurable HR outcomes, the instrument will be validated as a practical tool for predicting organizational performance improvements due to RPA adoption. Criterion-related validity bridges the gap between academic rigor and practical application. For this study, it will confirm whether perceptions captured by the questionnaire align with measurable HR performance outcomes at MSEB. Establishing criterion validity in the main study will enhance the tool's credibility and its utility for managers, policy makers, and researchers.

3.8.5 Nomological Validity

Nomological validity refers to the degree to which a construct behaves as expected within a broader theoretical framework. It is based on the idea that constructs do not exist in isolation but are part of a larger network of theoretical relationships. In this study, nomological validity ensures that the constructs related to RPA adoption in HRM—such as awareness, employee perspectives, challenges, impact, and future scope—interact with one another in theoretically consistent ways.

Purpose of Nomological Validity

The objective of nomological validity is to confirm that the questionnaire's constructs fit logically into an established nomological network. For example, higher awareness of RPA is theoretically expected to reduce resistance to change, which in turn should improve employee perspectives on job satisfaction and workload balance. Testing such relationships confirms the instrument's integration into a broader theoretical model of technology adoption and organizational change.

Method of Establishing Nomological Validity

Nomological validity is typically established using Structural Equation Modeling (SEM), which allows researchers to test the relationships between constructs simultaneously. The following steps are undertaken:

1. Develop a conceptual model linking constructs (e.g., Awareness → Challenges → Employee Perspectives → Impact).
2. Collect data from a large sample (≥300 respondents for robust SEM analysis).

3. Use SEM to test whether the hypothesized paths are statistically significant and in the expected direction.
Thresholds and Criteria
- Path coefficients should be significant ($p < 0.05$).
- Model fit indices should meet accepted standards:
  - Comparative Fit Index (CFI) ≥ 0.90
  - Tucker–Lewis Index (TLI) ≥ 0.90
  - Root Mean Square Error of Approximation (RMSEA) < 0.08
  - Standardized Root Mean Square Residual (SRMR) < 0.08

Application in This Study
Nomological validity was not tested in the pilot study due to its smaller sample size. However, in the main study, SEM will be applied to test hypothesized relationships such as:
- Awareness positively influencing Employee Perspectives.
- Challenges negatively influencing Employee Perspectives.
- Employee Perspectives positively influencing perceptions of Impact and Future Scope.

If these hypothesized paths are supported, nomological validity will be confirmed.

Interpretation
Confirming nomological validity will show that the questionnaire does not only measure isolated constructs but also integrates meaningfully into the broader theoretical model of RPA adoption in HRM. This elevates the study's contribution from simple measurement to theory building.

Nomological validity is an advanced form of validation that strengthens both the theoretical and practical contributions of this research. By confirming that constructs interact in theoretically consistent ways, this study will provide evidence that the instrument is embedded in a meaningful nomological network, thereby enhancing its academic rigor and managerial relevance.

4. Discussion

4.1 Overview of Findings

The pilot study was designed to test the reliability and validity of a structured questionnaire aimed at assessing the impact of Robotic Process Automation (RPA) in Human Resource Management (HRM) at MSEB in the Pune region. With data collected from 60 respondents, the study yielded strong psychometric results. Cronbach's Alpha values above 0.97 for each section, and an overall Alpha of 0.996, indicated excellent internal consistency. The Kaiser-Meyer-Olkin (KMO) measure of 0.867 confirmed sampling adequacy, while Bartlett's Test of Sphericity was significant, confirming the suitability of data for factor analysis.

Principal Component Analysis (PCA) and Factor Analysis revealed a strong unidimensional structure, suggesting that the instrument successfully measures a coherent underlying construct—the perceived impact of RPA on HRM. Demographic analysis showed that most respondents were mid-career professionals (26–45 years) with graduate or postgraduate education, and evenly distributed across HR functions such as recruitment, training, payroll, and employee relations.

These findings provide confidence that the instrument is appropriate for full-scale research and can generate meaningful insights into awareness, employee perspectives, challenges, and the impact of RPA in HRM at MSEB.

4.2 Comparison with Past Studies

The reliability and validity outcomes of this pilot study align with previous research in the field of technology adoption and HRM.

1. **Reliability Outcomes**

- Nunnally and Bernstein (1994) recommended a minimum Cronbach's Alpha of 0.7 for research instruments. With all values exceeding 0.97, this study's instrument demonstrates far superior consistency.
- Similar reliability outcomes were reported in studies testing technology adoption instruments, such as Venkatesh et al. (2003) in the Unified Theory of Acceptance and Use of Technology (UTAUT).

2. **Validity Outcomes**

- The KMO result of 0.867 corresponds to Kaiser's (1974) classification of "meritorious," reinforcing that the instrument is suitable for factor analysis.
- Bartlett's Test significance aligns with requirements highlighted by Tabachnick and Fidell (2013) for confirmatory data suitability.
- AVE and CR values well above thresholds reported by Fornell and Larcker (1981) confirm **convergent validity**, comparable to similar empirical studies in HR analytics and digital transformation research.

3. **Demographic Patterns**

- The finding that younger and mid-career professionals (26–45 years) dominate the sample mirrors Deloitte's (2020) report that younger employees are more receptive to automation in HR.
- The balanced distribution across HR functions strengthens the representativeness of perspectives, echoing similar pilot studies on HR technology adoption in public enterprises (Kumar & Singh, 2020).

4.3 Implications for HRM at MSEB

The findings of this pilot study carry several implications for MSEB:

1. **Awareness and Training Needs**

High reliability scores in the awareness section suggest employees share a consistent understanding of RPA. However, demographic results imply younger employees may be more open to adopting automation. This highlights the need for targeted training and awareness programs for older employees to mitigate resistance.

2. **Employee Perspectives**

Employee perspectives on job satisfaction, workload, and job security showed consistent responses, confirming that the questionnaire captures these perceptions effectively. For MSEB, this provides a tool to monitor employee morale during RPA implementation.

3. **Challenges and Limitations**

The strong internal consistency of items measuring challenges implies employees recognize issues such as inadequate training and technical support. Addressing these challenges proactively can ensure smoother RPA adoption.

4. **Impact on HRM Functions**

With reliability confirmed, the instrument can be used to assess real impacts in payroll, recruitment, and performance appraisal. Early findings suggest employees perceive improvements in efficiency and accuracy, aligning with Willcocks et al. (2017).

5. **Future Scope**

Responses indicated optimism about the scope of RPA in HRM. This suggests that MSEB employees recognize the potential for scaling RPA to more complex HR functions. The organization can leverage this positive outlook to build a roadmap for phased RPA integration.

4.4 Implications for Theory and Practice

1. **For Research**

- This pilot demonstrates that instruments measuring technological adoption in HR can achieve very high reliability and validity.
- It supports the application of quantitative frameworks in studying RPA adoption, complementing qualitative case studies.

2. **For Practice**

- HR managers in MSEB and similar enterprises can use validated instruments to assess readiness for RPA adoption.
- Policy makers in the public sector can consider employee perspectives to design training and support frameworks for automation initiatives.

4.5 Limitations of the Pilot Study

While the results are encouraging, several limitations must be acknowledged:

1. **Sample Size:** The pilot included only 60 respondents, which is adequate for reliability testing but not for generalizing results.
2. **Geographic Limitation:** The sample was restricted to Pune region employees of MSEB. Responses may not represent employees in other regions.
3. **Synthetic Bias:** Pilot responses may be more positively skewed due to heightened interest in technology or social desirability bias.

4. **Limited Scope:** The pilot focused on instrument validation rather than hypothesis testing. Full analysis of awareness, perspectives, challenges, and impact will be conducted in the main study.

4.6 Future Directions

The next stage of research should involve:

- Collecting data from a larger, representative sample (300+ employees) across different regions of MSEB.
- Conducting hypothesis testing using regression, ANOVA, and structural equation modeling (SEM).
- Comparing results across demographic sub-groups to assess whether age, education, or HR function influences perceptions of RPA.
- Expanding scope to include longitudinal analysis of RPA adoption impacts over time.

5. Conclusion

The pilot study validated the research instrument designed to measure the impact of RPA in HRM at MSEB. With Cronbach's Alpha values above 0.97, an overall Alpha of 0.996, and a KMO value of 0.867, the questionnaire demonstrates excellent reliability and strong construct validity. Bartlett's Test confirmed the suitability of data for factor analysis, while PCA and exploratory factor analysis indicated unidimensionality**,** ensuring that the instrument measures a coherent construct.

Demographic analysis revealed a workforce largely composed of mid-career professionals with strong educational qualifications, highlighting readiness for technological adaptation. The pilot results provide MSEB with a validated instrument to assess employee awareness, perspectives, challenges, and perceptions of RPA's impact on HRM.

The study concludes that the instrument is statistically robust and suitable for large-scale deployment. By addressing identified challenges—such as training, resistance, and technical support—MSEB can successfully integrate RPA into HRM. Future research will focus on hypothesis testing and large-scale validation to provide deeper insights into RPA adoption and its organizational consequences.

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