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Original Article

Critical Factors Affecting Labour Productivity: Evidence from Construction Industry

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Abstract *- Labour productivity significantly influences the cost, time, and overall success of construction projects. This study identifies and analyses critical factors affecting labour productivity in building construction projects in the Central Gujarat region, India. An extensive literature review initially identified 66 factors, which were refined through expert consultation to 42 significant factors classified into seven categories. A structured questionnaire survey was distributed to 100 construction professionals, yielding 48 valid responses. Data were analysed using the Relative Importance Index (RII) and Importance Index (IMPI) methods. A comprehensive comparative analysis including Spearman rank correlation ($\rho = 0.497$, $p < 0.001$), frequency-severity quadrant analysis, and rank shift assessment revealed significant divergences between perceived importance and actual field impact. "Lack of experience and skill of labour" emerged as the most critical factor under both methods (RII = 0.8906; IMPI = 71.39%). Additionally, a parametric sensitivity study using calibrated Multiple Linear Regression model, formulated for 12mm cement plastering work, quantified individual and combined factor effects, revealing a 5.1 times productivity difference between worst-case and best-case scenarios. The Pareto analysis confirmed that the three highest-ranked predictors account for approximately 68% of the factor-attributable productivity. These findings provide evidence-based guidance for developing targeted management strategies to improve construction labour productivity.*

Keywords *- Construction industry, Critical factor, Labour productivity, RII, IMPI.*

1. Introduction

The construction industry occupies a central position in the economic development of a nation through its contribution to Gross Domestic Product (GDP) and its capacity to generate large-scale employment. In India, the sector contributes approximately 8–9% of GDP, employs about 71 million people, and is projected to become the third-largest construction market in the world, with an estimated size of USD 2.13 trillion by 2030. Despite this significance, persistent labour productivity problems continue to affect the cost, duration, and quality of projects across the industry. Labour productivity, commonly expressed as the ratio of output produced to labour input consumed, is a key indicator of workforce efficiency in construction. Because labour accounts for roughly 30–50% of total project expenditure, even modest productivity improvements translate into substantial economic benefit. Productivity, however, emerges from a complex interplay of workforce competence, management practice, material availability, equipment adequacy, site conditions, payment arrangements, and weather. The Central Gujarat region, which encompasses the cities of Nadiad, Anand, Vadodara, and Ahmedabad, is witnessing rapid growth in construction activity fuelled by mega-projects such as GIFT City, Dholera Smart City, and the Delhi–Mumbai Industrial Corridor. A distinctive challenge of the region is its heavy dependence on migrant labour: roughly 45% of the construction workforce consists of informally trained migrant workers, creating productivity constraints that merit systematic study. Although there is a vast amount of research on the factors of labour productivity on a worldwide scale, there is little region-specific research on the area of Central Gujarat. Specifically, a prior regional study [14] has relied on single perception-based ranking indices and have not quantified the productivity change attributable to individual factors. The research gap addressed in this study is therefore the absence of (i) a systematic comparison between perception-based (RII) and frequency–severity-based (IMPI) rankings of productivity factors, and (ii) a quantitative, model-based estimate of factor impacts on labour productivity for the Central Gujarat construction industry. The present study fills this gap with the following objectives: (1) identifying the factors that affect labour productivity through an extensive literature review; (2) refining and categorising the factors through expert consultation; (3) analysing factor influences on labour productivity using questionnaire survey data from construction professionals; (4) ranking the factors using both the Relative Importance Index (RII) and Importance Index (IMPI) methodologies; and (5) conducting a comprehensive comparative analysis of the RII and IMPI rankings using Spearman rank correlation, quadrant analysis, and category-wise analysis. The dual-method ranking strategy is critical because considering both the frequency of occurrence and the severity of impact yields a more holistic evaluation. The contribution is further strengthened by integrating an MLR-based parametric analysis that extends beyond traditional ordinal rankings by providing quantitative impact estimates to support evidence-based construction management decisions. The novelty of the present work, in comparison with existing research, lies in three aspects. First, unlike earlier Gujarat-based study [14] and the delay-focused application in [15], which employed a single ranking index or reported RII and IMPI without statistical comparison, this study performs a full comparative analysis of the two indices supported by Spearman rank correlation, rank shift assessment, and frequency–severity quadrant analysis. Second, whereas most published factor studies terminate at ordinal rankings [8, 19], the present study extends the analysis through an MLR-based parametric sensitivity model that converts rankings into quantitative productivity estimates (m^2/day/worker), enabling scenario and Pareto analyses that are rarely reported in regional studies. Third, the study supplies region-specific empirical evidence for Central Gujarat, a rapidly urbanising area with a high share of migrant labour, for which such combined analyses have not previously been reported.

2. Literature Review

Research on the factors influencing construction labour productivity has been conducted extensively across diverse geographic and economic contexts over the past three decades. Surveying 45 factors affecting contractors in the Gaza Strip, the study in [7] identified material shortage, lack of labour experience, and inadequate supervision as the most significant determinants. A similar investigation in Kuwait [10] reported that clarity of technical specifications and the volume of change orders were the most highly ranked factors, demonstrating that the relative importance of factors is strongly context dependent. In a study of 82 Turkish construction firms, the work in [11] identified the quality of site management together with allied organizational factors as carrying the highest collective weight on productivity outcomes. A survey of project managers in Thailand [13] established the lack of materials as the principal contributing factor to productivity loss. Complementing these international findings, an investigation of building craftsmen in Uganda [3] reported that incompetent supervisors and skill shortages, together with rework and tool unavailability, were the dominant productivity constraints in the East African construction industry. A study of on-site productivity in the New Zealand construction industry [5] concluded that internal constraints account for approximately 67 % of productivity losses, with rework, workforce skill level, and the adequacy of construction methods identified as the dominant contributors. A landmark 30-year systematic review of 46 studies [9] revealed that reasonable consensus exists across the global literature on five recurrent factors: non-availability of materials, insufficient supervision, skills shortage, absence of proper tools and equipment, and incomplete drawings. From a survey of 1,996 craft workers across 28 industrial projects in the United States, the work in [4] identified the management of tools, consumables, materials, and engineering drawings as the categories with the greatest practical impact on productivity. In the Egyptian context, the study in [6] examined a comprehensive set of factors and reported that labour experience, incentive systems, and supervisor competence are among the strongest predictors of productivity, paralleling findings reported in other Mediterranean and Middle-Eastern contexts.

Within the Indian sub-context, the case study in [18] reported that material availability, delays in material delivery, and political impositions are among the principal productivity problems in Kerala. In Bangalore, the study in [17] proposed a six-group classification of productivity factors comprising manpower, managerial, motivation, material/equipment, safety, and quality dimensions. A broader scope Indian study [2] translated the perceptions of construction workmen into a structured RII analysis and proposed practical measures for productivity improvement. Specifically, within Gujarat, the work in [14] identified 46 factors organised into 10 groups based on a survey of 126 stakeholders in Central Gujarat.

In terms of analytical methodology, the Relative Importance Index (RII) has emerged as the most widely employed ranking technique in construction management research. The technique was among the first formalised in [12] and was subsequently popularised through its application to Malaysian construction delays in [16]. The principal limitation of RII, however, is that it captures only the perceived importance of a factor along a single dimension and is therefore unable to discriminate between factors that, although severe, occur rarely from those that are moderate in severity but highly frequent. The Importance Index (IMPI) addresses this limitation by combining the frequency of occurrence with the severity of impact into a single composite measure. It has been demonstrated in [15] that, when both indices are applied to the same data set, the resulting rankings can diverge significantly, underscoring the value of multi-dimensional evaluation in construction management studies. Recent studies published within the last five years reinforce and extend these findings. A comparison of the perceptions of project managers and contractors in Vietnam [19] demonstrated that different stakeholder groups can rank the same productivity factors quite differently, supporting the use of multi-stakeholder samples such as the one adopted in the present study. A comprehensive review of the factors identified across the global literature [8] confirmed workforce skill, supervision, material management, and payment practices as recurrent determinants of construction labour productivity. Furthermore, a scientometric analysis of construction labour productivity research [1] observed that comparative and multivariate treatments of productivity factors remain relatively scarce, particularly in developing-country contexts, which underlines the relevance of the comparative RII–IMPI and regression-based approach employed in this study.

Although the literature collectively provides extensive evidence on the factors affecting construction labour productivity, several gaps remain. First, the majority of prior studies have relied on a single descriptive ranking method (typically RII alone), with comparatively few works systematically comparing alternative ranking schemes such as IMPI. Second, while ordinal rankings highlight which factors are perceived as critical, they do not quantify the magnitude of productivity change attributable to individual or combined factor variations; sensitivity analyses based on parametric models, therefore, remain underrepresented in the construction-productivity literature. Third, region-specific evidence for Central Gujarat, a rapidly urbanising region with a high proportion of migrant labour, is limited, despite the area's growing share of national construction output.

The present study addresses these gaps by combining a rigorous comparative analysis of RII and IMPI with a Multiple Linear Regression-based parametric sensitivity study, providing both ordinal rankings and quantitative impact estimates to support evidence-based construction management decisions in the Central Gujarat context.

3. Research Methodology
3.1. Research Design
The study followed a quantitative, questionnaire-based design executed in four stages: (i) Identification of productivity factors from an extensive literature review; (ii) Refinement of the factor list through expert consultation; (iii) Data collection and analysis through a structured questionnaire survey; and (iv) Comparative analysis and parametric sensitivity analysis using Multiple Linear Regression modelling.

3.2. Identification and Refinement of Factors
A review of the international and Indian literature, including [7, 9-11, 14, 17], yielded an initial list of 66 factors influencing construction labour productivity. Consultation with experienced construction professionals of Central Gujarat, focusing on relevance, redundancy, and applicability to the local context, reduced the list to 42 significant factors grouped into seven categories: (1) Workforce-Related Factors, (2) Management-Related Factors, (3) Technical and Design Factors, (4) Material-Related Factors, (5) Equipment-Related Factors, (6) Site Condition and External Factors, and (7) Motivation, Payment, Safety, and Weather Factors.

3.3. Questionnaire Design and Data Collection
The structured questionnaire comprised two sections. Section A: Captured respondent demographics (occupation, years of experience, organisation, and city). Section B: Required each of the 42 factors to be rated on three separate four-point Likert scales covering (i) Importance (4 = Very Important, 1 = Not Important), (ii) Frequency of Occurrence (4 = Always, 1 = Rarely), and (iii) Degree of Severity (4 = Extreme, 1 = Little). A four-point scale was deliberately adopted to eliminate the neutral midpoint and compel respondents to express a directional opinion. The instrument was distributed to 100 construction professionals working on building construction projects across Central Gujarat, including Nadiad, Anand, Ahmedabad, Vadodara, and Surat, and 48 valid responses were received, corresponding to a response rate of 48%. This rate compares favourably with the 20–50% typically reported for construction industry surveys in India and other developing economies. Regarding sample-size adequacy, the achieved sample of 48 respondents exceeds the minimum of 30 generally recommended for statistical analysis under the central limit theorem, and published RII/IMPI studies of a comparable nature have drawn conclusions from samples of similar size. All 48 retained questionnaires were fully completed; incomplete questionnaires were excluded during screening, and therefore no imputation of missing data was required. The responses were further screened for outliers by inspecting the rating distributions and standardized scores, and no anomalous response patterns (for example, uniform straight-lining or standardized values exceeding $|z| = 3$) were detected, so all 48 responses were retained for analysis. Participation was voluntary, informed consent was obtained from all respondents prior to participation, and the responses were collected and analysed anonymously. Nonetheless, the moderate sample size and the non-probability distribution of the questionnaire imply potential response and sampling biases, which are discussed explicitly in Section 7.

3.4. Analytical Methods
3.4.1. Relative Importance Index (RII)

The Relative Importance Index quantifies the perceived importance of each factor affecting labour productivity and was computed using Equation (1).

$$RII = \frac{\Sigma W}{(A*N)} \tag{1}$$

Where ΣW is the sum of the importance ratings assigned to a factor by all respondents, A is the maximum weight on the Likert scale (A = 4), and N is the total number of respondents (N = 48). RII ranges from 0 to 1, with higher values indicating greater perceived importance.

3.4.2. Importance Index (IMPI)

The Importance Index combines the frequency of occurrence and the severity of impact of each factor into a single composite measure, computed as the normalised product of the Frequency Index (FI) and the Severity Index (SI), as shown in Equation (2).

$$IMPI(\%) = \frac{FI\ (\%) \times SI\ (\%)}{100} \quad (2)$$

The Frequency Index quantifies how often a factor is reported to occur and is obtained from the frequency-of-occurrence ratings as:

$$FI(\%) = \frac{100 \times \sum W_f}{A \times N} \quad (3)$$

The Severity Index quantifies the magnitude of impact when the factor occurs and is obtained from the severity ratings as:

$$SI(\%) = \frac{100 \times \sum W_S}{A \times N} \quad (4)$$

Where ΣW_f and ΣW_s are the sums of the frequency and severity ratings, respectively, assigned by all respondents to a given factor, A is the maximum scale weight (A = 4), and N is the number of respondents (N = 48). IMPI ranges from 0 to 100, with higher values denoting factors that are both frequent and severe.

3.4.3. Spearman Rank Correlation Coefficient

The Spearman rank correlation coefficient (ρ) was computed to statistically evaluate the agreement between the RII and IMPI rankings. The coefficient ranges from −1 (perfect inverse agreement) through 0 (no association) to +1 (perfect agreement) and is widely used for comparing ranking methods in construction management research [16]. The significance of the correlation was tested at the 0.05 level.

3.4.4. Multiple Linear Regression (MLR) for Parametric Study

To complement the ranking-based analysis, a Multiple Linear Regression model was developed to quantitatively estimate the impact of the key factors on labour productivity. The general form of the model is given in Equation (5).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \varepsilon \quad (5)$$

Where Y is the predicted labour productivity for 12 mm cement plastering work, expressed in m²/day per worker, β_0 is the intercept (baseline productivity = 6.0 m²/day), β_1 through β_8 are the calibrated model coefficients, and X_1 through X_8 are eight key input factors derived from the survey findings. Plastering was selected as the reference activity because it is a high-volume, repetitive finishing operation that is measured directly in square metres on site, which makes its output readily comparable with published labour-output constants.

The coefficients were derived from expert consultation as relative effect weights and subsequently calibrated to the plastering output range applicable to the study region, as detailed in Section 6.1. The model validation procedure and the associated effect sizes and prediction uncertainty of the model are reported in Section 6.1.

4. Data Analysis and Results

4.1. Demographic Profile of Respondents

Demographic profile of the 48 respondents, as well as in graphical terms as illustrated in Figure 1 are presented in Tables 1 and 2. The biggest group was the contractors, comprising 15 respondents (31.25%), then the site engineers of 13 (27.08%), then the developers of 11 (22.92%) and the supervisors with 9 (18.75%). This allocation will ensure that the various important stakeholder groups are represented. Regarding experience, 27.08% each had 5–10 years and 10–15 years of experience, followed by 15–20 years (20.83%), less than 5 years (18.75%) and more than 20 years (6.25%). The sample size is quite mature and knowledgeable, as 81.25% had more than 5 years of experience.

Table 1. Distribution of respondents by profession

Profession	Count	Percentage
Contractor	15	31.25%
Site Engineer	13	27.08%
Developer	11	22.92%
Supervisor	9	18.75%
Total	48	100.00%

Table 2. Distribution of respondents by experience

Experience	Count	Percentage
< 5 years	9	18.75%
5–10 years	13	27.08%
10–15 years	13	27.08%
15–20 years	10	20.83%
> 20 years	3	6.25%
Total	48	100.00%

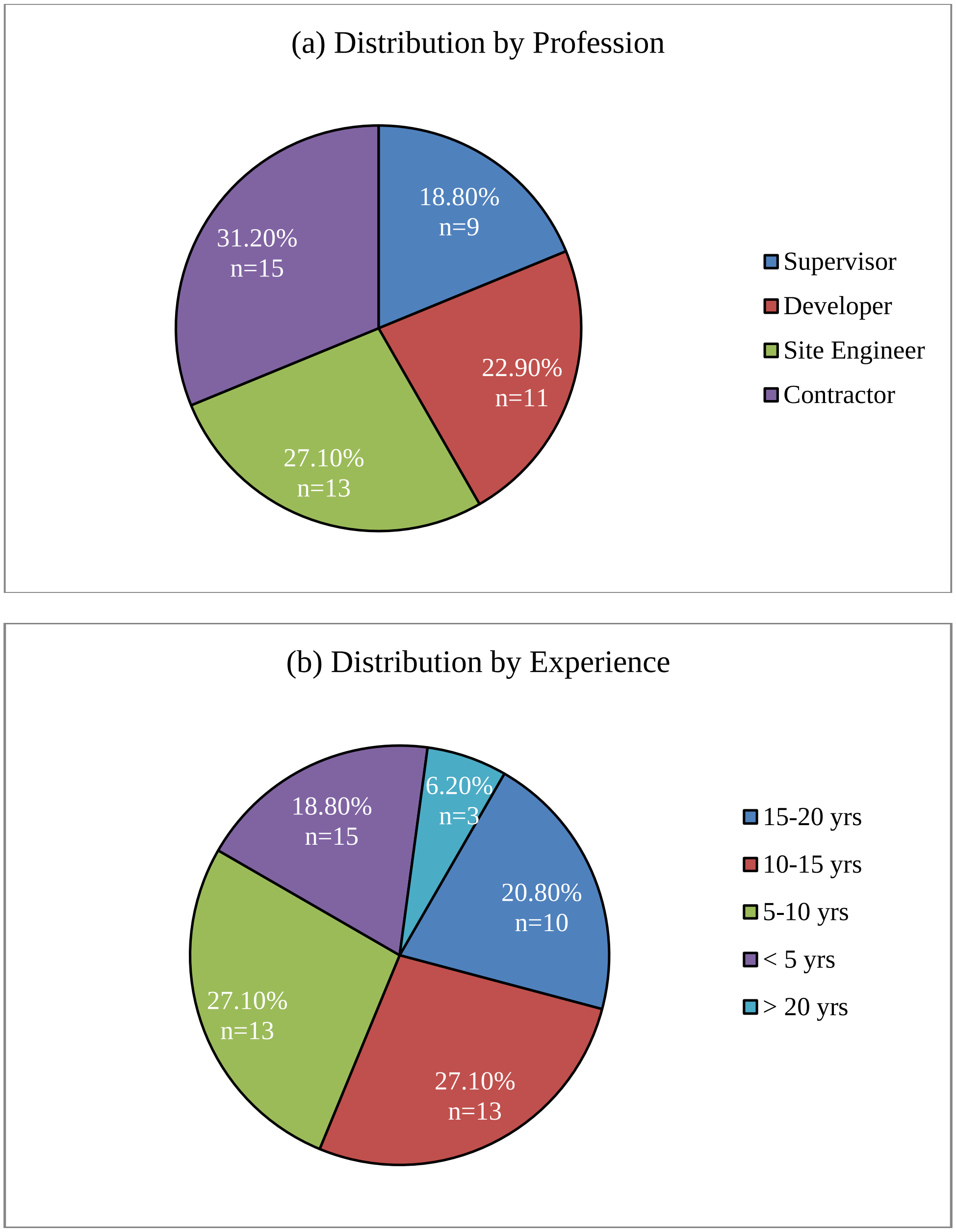

Fig. 1 Demographic profile of respondents (N = 48)

4.2. Reliability Analysis

The internal consistency of the questionnaire was assessed using Cronbach's Alpha (α), computed as shown in Equation (6).

$$\alpha = \left[\frac{k}{k-1}\right] \times \left[1 - \frac{\Sigma \sigma_i^2}{\sigma_t^2}\right] \qquad (6)$$

Where k is the number of items, σ_i^2 is the variance of each individual item, and σ_t^2 is the variance of the total score. The computed value of α = 0.95 exceeds the conventionally accepted threshold of 0.70 and indicates excellent reliability, confirming that the responses are consistent and suitable for the subsequent statistical analysis.

4.3. RII-based Ranking of Factors

The entire hierarchy of all 42 factors in terms of the Relative Importance Index is also given. The values of RII were between 0.7083 (Lack of job security) and 0.8906 (Lack of experience and skill of labour).

The values of the RII of all 42 factors were greater than 0.70, indicating that all the factors identified were at least moderately important according to the respondents.

Figure 2 shows that the values of RII are distributed right-skewed, with most of the factors falling between 0.76 and 0.86.

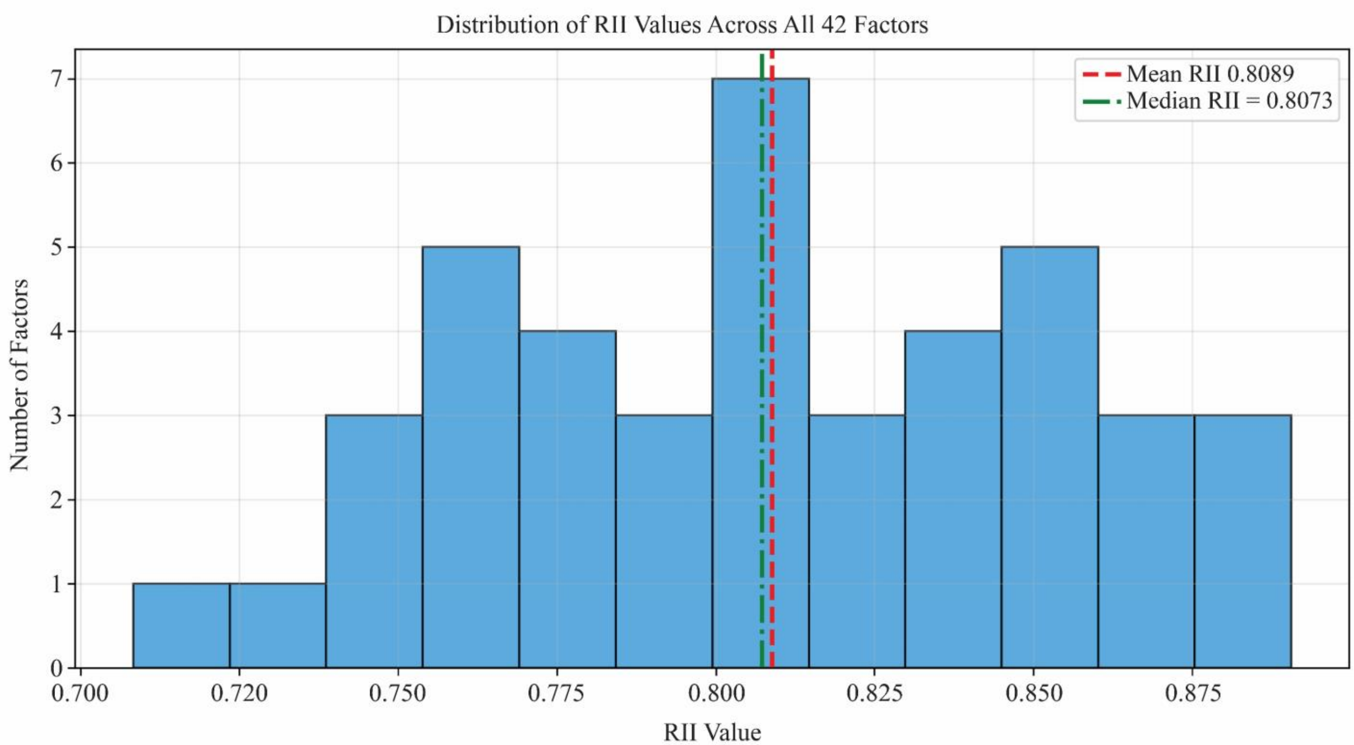

Fig. 2 Distribution of RII values across all 42 factors

Figure 3 and Table 3 show the top 15 critical factors based on RII ranking. These top five factors were: (1) Lack of experience and skill of labour (RII = 0.8906), (2) Lack of qualified and effective supervision (RII = 0.8854), (3) Lack of work discipline among the workers (RII = 0.8802), (4) Late procurement of materials (RII = 0.8750) and (5) High temperature (RII = 0.8698). These outcomes show that workforce competence and quality of management are perceived as the most important factors that determine labour productivity in the study area.

Table 3. Top 15 Factors affecting labour productivity based on RII

Rank	Factor	ΣW	RII
1	Lack of experience and skill of labour	171	0.8906
2	Lack of qualified and effective supervision	170	0.8854
3	Lack of work discipline among workers	169	0.8802
4	Late procurement of materials	168	0.8750
5	High Temperature	167	0.8698
6	No payment for extra work	166	0.8646
7	Delay in wage payment and inadequate remuneration	165	0.8594
8	Lack of proper tools and equipment	164	0.8542
9	Poor communication and coordination	163	0.8490
10	Ineffective planning and scheduling	163	0.8490
11	Incomplete or unclear drawings/execution details	163	0.8490
12	Accidents and lack of safety tools/training	162	0.8438
13	Shortage of equipment	161	0.8385
14	Insufficient lighting, ventilation, utilities	161	0.8385
15	Absenteeism and irregular attendance	160	0.8333

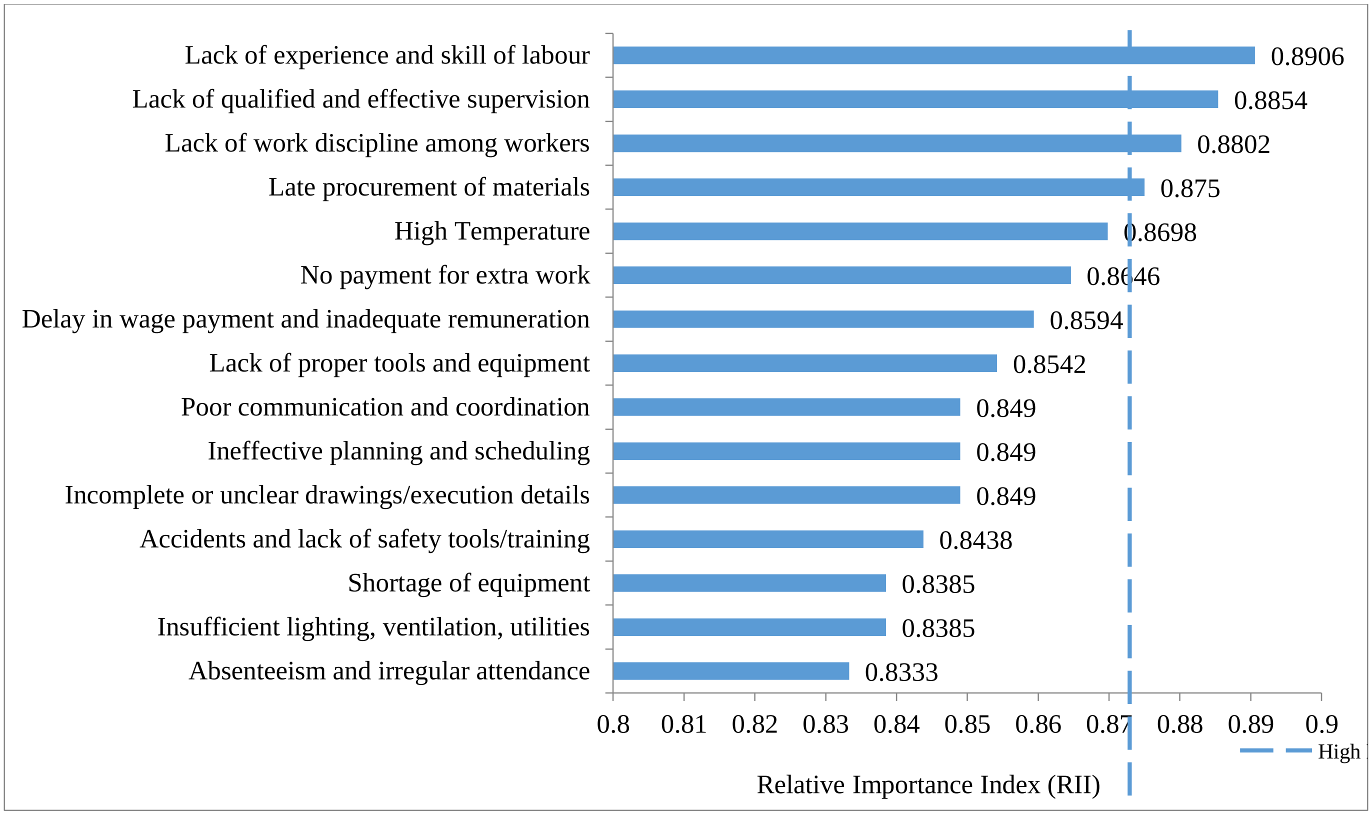

Fig. 3 Top 15 Critical factors based on RII ranking

4.4. IMPI-based Ranking of Factors

Table 4 presents the top 15 factors ranked according to the Importance Index (IMPI), which is calculated as the product of the Frequency Index (FI) and Severity Index (SI). The IMPI analysis was conducted for all 42 identified factors. Across the complete dataset, the IMPI values ranged from 37.43 for "Wind and adverse winter" to 71.39 for "Lack of experience and skill of labour".

The minimum IMPI value of 37.43 corresponds to "Wind and adverse winter" (FI = 59.895833% and SI = 62.500000%), while the maximum value of 71.39 corresponds to "Lack of experience and skill of labour" (FI = 79.687500% and SI = 89.583333%). The distribution of IMPI values across all 42 factors is presented in Figure 4. The wider spread of IMPI values compared with RII indicates greater differentiation among the factors when both frequency and severity are considered.

Table 4. Top 15 Factors based on IMPI

Rank	Factor	FI (%)	SI (%)	IMPI	RII Rank
1	Lack of experience and skill	79.69	89.58	71.39	1
2	Lack of supervision	72.40	85.42	61.84	2
3	Ineffective planning	77.60	76.04	59.01	10
4	Poor communication	74.48	77.60	57.80	9
5	Lack of work discipline	77.08	74.48	57.41	3
6	Lack of social insurance	78.65	71.88	56.53	32
7	No payment extra work	73.44	75.52	55.46	6
8	Delay wage payment	72.92	76.04	55.45	7
9	Lack labour recognition	76.56	70.83	54.23	40
10	Slow decision-making	71.88	73.44	52.78	33
11	Accidents/safety	71.35	73.96	52.77	12
12	Delay approving drawings	72.40	70.31	50.90	21
13	Late procurement materials	69.79	72.40	50.53	4
14	Late arrival/quitting	65.10	77.60	50.52	20
15	Rain effect	68.75	72.92	50.13	31

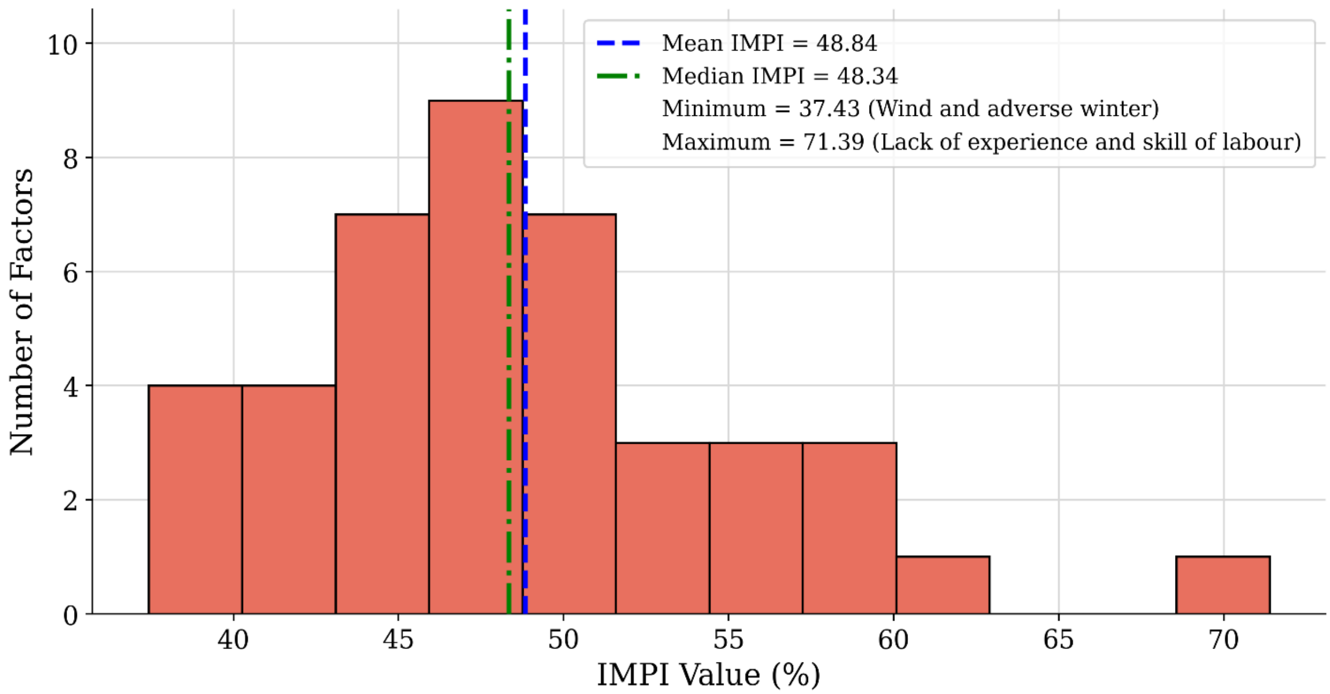

Fig. 4 Distribution of IMPI Values Across All 42 Factors

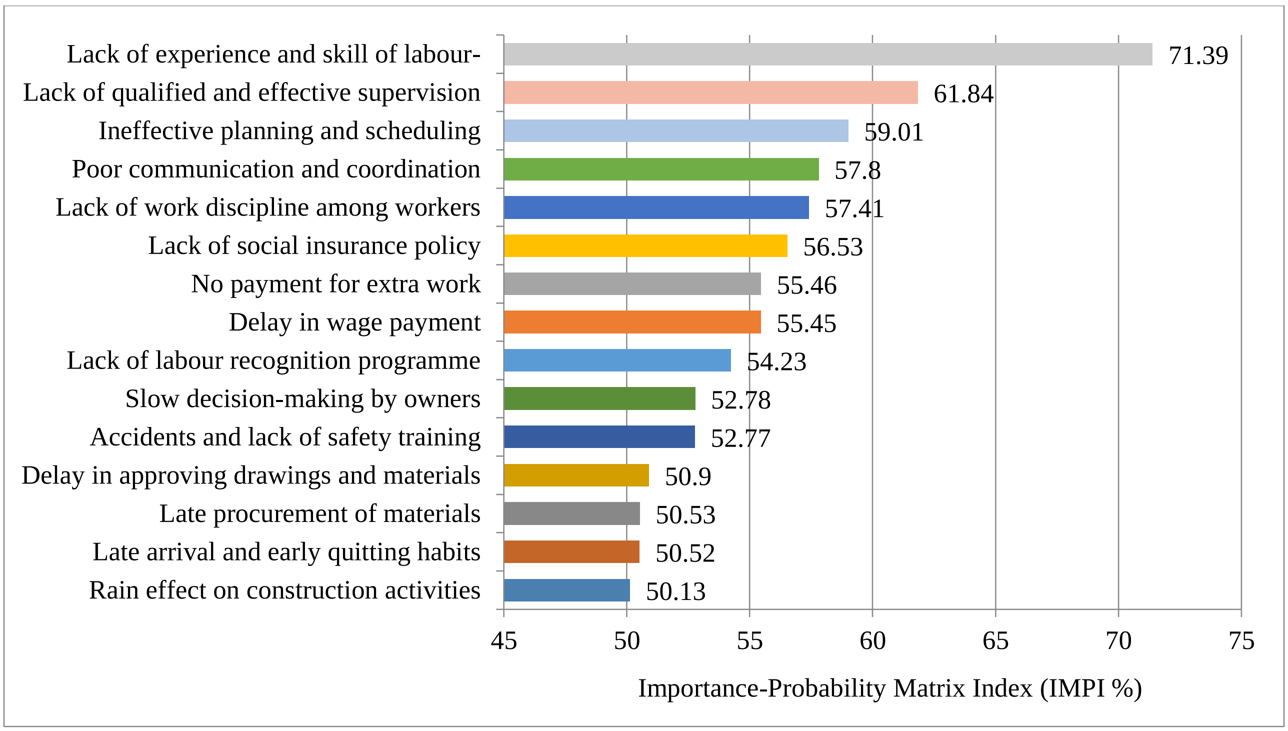

Fig. 5 Top 15 Critical factors based on IMPI ranking

5. Comprehensive Comparative Analysis of RII and IMPI Rankings

This part is a comparative study that provides specifics of the comparison between the two ranking approaches, the RII and the IMPI. Although the two approaches have been extensively applied in construction management studies, they focus on diametrically opposite aspects of the criticality of factors. It can be supposed that the perceived importance according to RII is observed based on one-dimensional data (importance rating) and, therefore, is not so holistic as IMPI.

It is important to comprehend the convergences and divergences of these methods to derive actionable management insights.

5.1. Overall Rank Agreement and Divergence

On comparing the entire 42 factors in the RII and IMPI rankings, it is revealed that there are areas of strong agreement and divergence between the RII and IMPI rankings. Figure 6 shows a scatter plot of the rankings of RII and IMPI against all 42 factors. Every point is a factor, and how far it is in relation to the diagonal line is the level of the ranking disagreement between the two methods. The position of factors on either side of the diagonal also indicates that there are consistent rankings of the factors by both methods, whilst those far along the diagonal indicate that the methods used as ranked by both methods can have greatly different rankings of the factors.

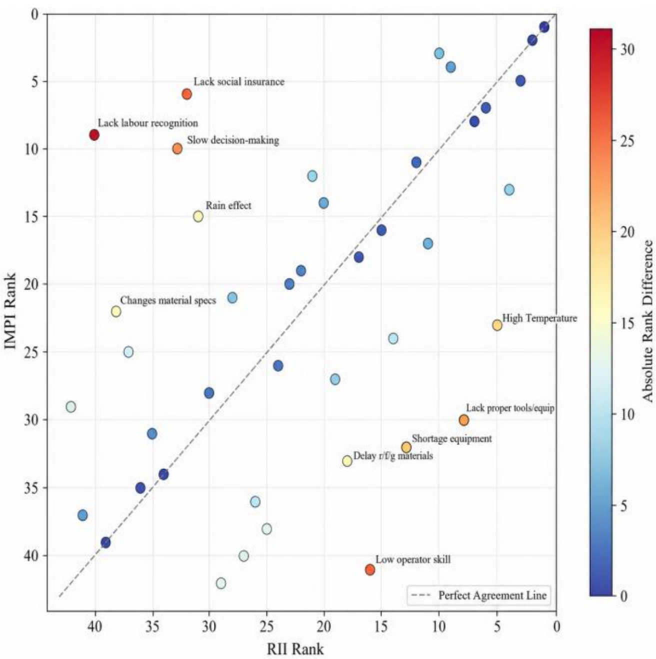

Fig. 6 RII vs IMPI Rank comparison for all 42 factors (Deviation from diagonal = ranking disagreement)

As the scatter plot reveals that, although there is an overall positive trend (factors ranked high by RII also tend to rank high by IMPI), there are various noticeable outliers. Factors located in the upper-left region of the plot (above the diagonal) acquired greater prominence under IMPI than under RII, indicating that they are more frequent and severe in practice than their perceived importance alone would suggest. On the other hand, the factors in the lower-right-hand region were not necessarily more common or severe in practice, although they were considered important.

5.2. Spearman Rank Correlation Analysis

To measure the amount of statistical acceptance between the two ranking techniques, it was proposed to compute the Spearman rank correlation coefficient (ρ). Figure 7 shows the correlation analysis, as well as the trend line. The value of the 0.497 Spearman correlation coefficient was observed to have a p-value of less than 0.001, hence indicating a moderate positive correlation which is statistically significant at the 0.05 level.

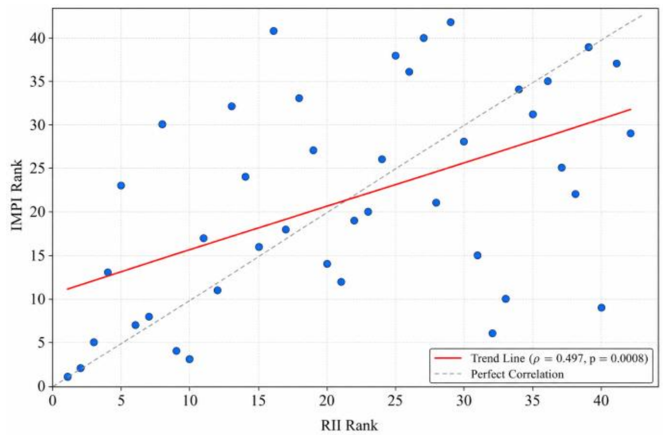

Fig. 7 Spearman Rank Correlation between RII and IMPI Rankings (ρ = 0.497, p-value = 0.0008)

The fact that the correlation between the RII and IMPI rankings are moderate (ρ = 0.497) is also notable since it implies that although there is a positive correlation between the RII and IMPI rankings, this correlation is not that high. This implies that three-quarters of the variance are not explained by RII rankings (ρ^2 = 0.247), which still means that 75.3% of the variance is not explained. This observation gives a strong argument in favour of the two different methods being used in combination with each other (using one method alone would have missed critical dimensions of factor criticality). This finding is similar to that reported in [15], where delay factors had a moderate level of agreement between RII and IMPI.

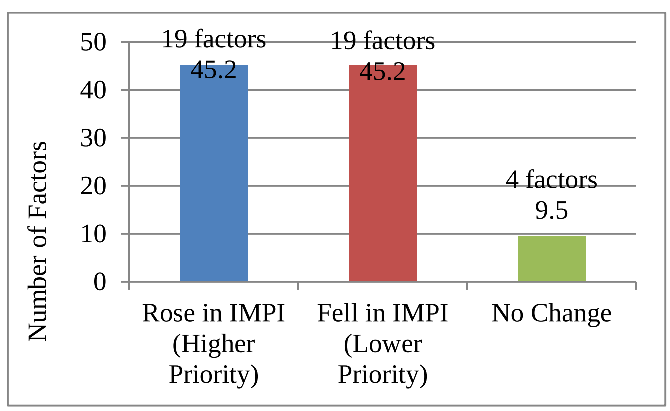

Fig. 8 Direction of Rank Changes from RII to IMPI

5.3. Direction and Magnitude of Rank Shifts

The sign of rank differences between RII and IMPI offers an understanding of systematic biases of both approaches. Figure 8 represents the trend of the rank changes out of the 42 factors. Among the 42 factors, 19 factors (45.2%) went up in IMPI ranking, compared to RII, 19 factors (45.2%) fell, 4 factors (9.5%) stood at the same position. This almost balanced division indicates that neither of the methods is either systematically biased in inflating or deflating the importance of the factors. The extent of rank changes, however, differs radically across factors. Figure 9 shows the 15 most significant position changes in the top 15 rank positions between the two methods. The greatest deviation is in the case of the Lack of labour recognition programme, where the RII ranking of this programme is achieved of 40th, but by IMPI, the ranking of this programme is reached at 9th – a deviation of 31 places. This dramatic change suggests that although the respondents did not see the importance of labour recognition as a standalone element as highly important, it still occurs frequently and is very devastating when it does occur. Likewise, the highest score 26 position shift between the rank 32 (RII) and the rank 6 (IMPI) in Lack of social insurance policy indicates how pervasive and consequential are the gaps in social welfare in the Central Gujarat construction.

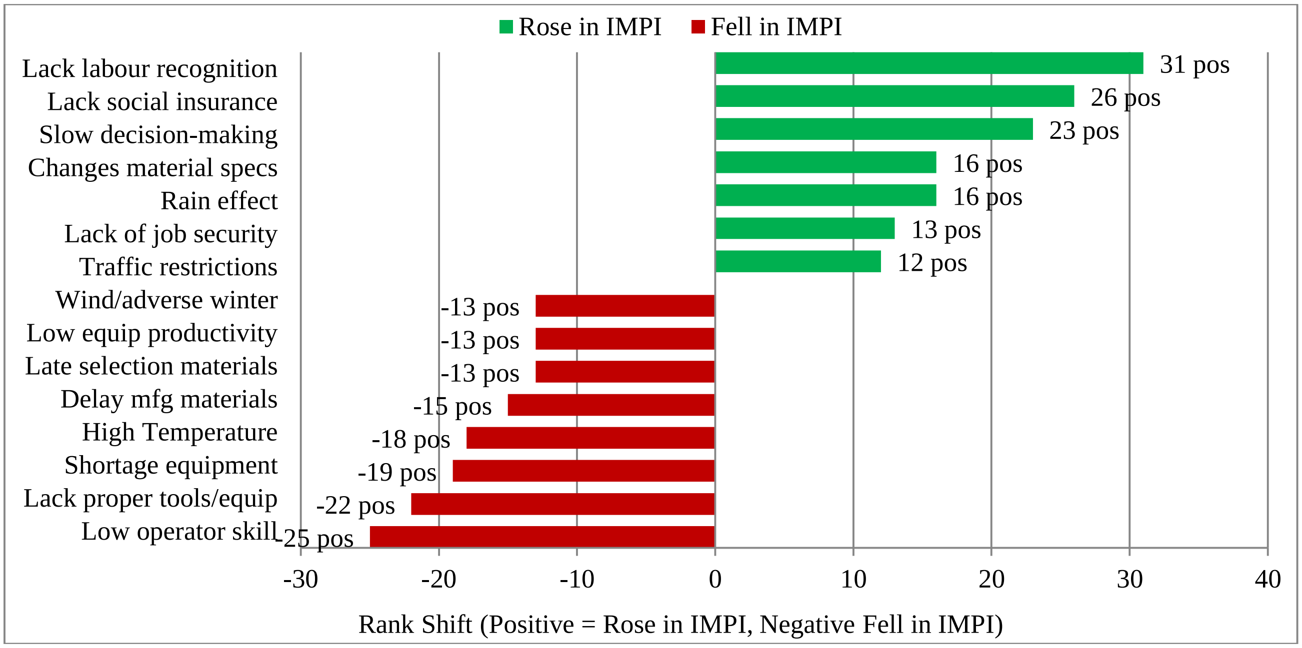

Fig. 9 Top 15 most significant rank shifts between RII and IMPI

At the far opposite end, some of the factors which were rated as highly important by the respondents were found to have considerably lower IMPI rankings. Ten factors had shifts of 15 or more positions between the two methods, as summarised in Table 5. The lack of the proper tools and equipment that dropped rank 8 (RII) to rank 30 (IMPI), a decrease of 22 positions, suggesting that while respondents recognise the theoretical importance of equipment, actual equipment shortages are either infrequent or less severe than perceived in practice. High Temperature lost by 18 positions (high-ranking High Temperature statuses dropped to low-ranking Impact statuses within the scale), causing the factor to be ranked 23rd (IMPI) instead of 5th (RII), indicating that seasonal and not persistent effects are at work. Low level of equipment-operators skill, a rank of 16 dropped 25 places to rank 41, the largest negative change of rank.

Table 5. Factors with rank shifts of 15 or more positions

Factor	RII Rank	IMPI Rank	Shift	Direction
Lack of labour recognition	40	9	+31	↑ Rose
Lack of social insurance	32	6	+26	↑ Rose
Low operator skill	16	41	−25	↓ Fell
Slow decision-making	33	10	+23	↑ Rose
Lack of proper tools/equipment	8	30	−22	↓ Fell
High Temperature	5	23	−18	↓ Fell
Shortage of equipment	13	32	−19	↓ Fell
Rain effect	31	15	+16	↑ Rose
Changes in material specs	38	22	+16	↑ Rose
Delay manufacturing special materials	18	33	−15	↓ Fell

5.4. Grouped Comparison of Top 15 Factors

Figure 10 shows a bar chart which is grouped by considering the values as normalized by RII. This compared the normalized RII values (scaled by 100 to allow an exact comparison) and the IMPI values to the top 15 factors as ranked by RII. This visualization shows the difference between the perceived impact (importance) and the actual impact (frequency-severity impact) of each factor. Factors with high perceived importance but of less than normalized RII are those that have less real-world impact.

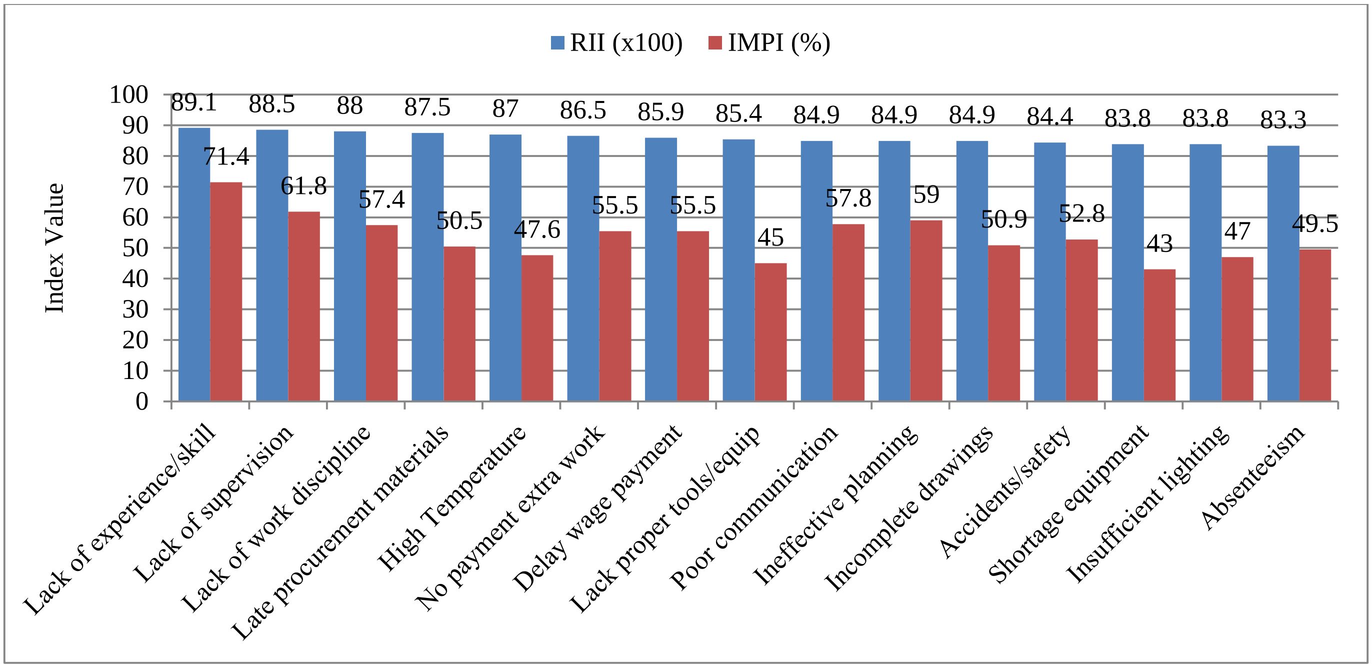

Fig. 10 Comparative analysis - RII (×100) vs IMPI (%) for Top 15 factors by RII

The chart reveals that "Lack of experience and skill of labour" has the smallest gap between normalized RII (89.06) and IMPI (71.39), indicating strong consistency between perceived importance and actual field impact.

In contrast, "Lack of proper tools and equipment" exhibits the largest gap among all 15 factors (85.42 vs 45.00), suggesting that while respondents consider equipment highly important in principle, actual equipment shortages are either infrequent or less severe in practice within the Central Gujarat context. "High Temperature" also shows a substantial gap (86.98 vs 47.62), confirming the seasonal rather than persistent nature of temperature effects despite high perceived importance.

5.5. Radar Comparison of Top 5 Factors

Figure 11 includes a radar chart of normalized RII and IMPI for five critical factors that featured prominently across both ranking methods. The radar visualisation reveals that the swing of the remaining factors is varied in terms of converging to the 'Lack of experience and skill of labour' factor.

The values of IMPI of all five factors are regularly lower than normalized RII values, which is not surprising since the value of IMPI is the multiplicative interaction of frequency and severity (both values that are less than 100%), whereas the value of RII is the rating along a single dimension that tends to cluster at the higher values.

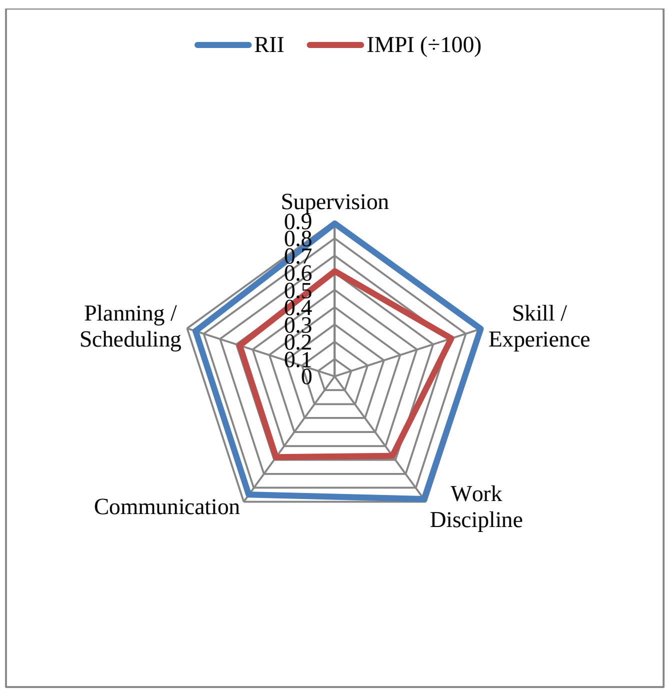

Fig. 11 Radar comparison – RII vs IMPI (Normalized) for Top 5 factors

5.6. Frequency-Severity Quadrant Analysis

In a bid to offer more insight to the frequency and severity distributions of factors, a quadrant analysis has been performed. Figure 12 gives each of the 42 factors, and the position is indicated by colour intensity, which indicates the IMPI value. There are four strategic quadrants of the plot represented by the mean FI (68.10%) and mean SI (70.86%). Quadrant I (High Frequency, High Severity) has the most crucial elements that need to be addressed at the managerial level. This quadrant includes "Lack of experience and skill of labour" (FI = 79.69%, SI = 89.58%) and "Lack of qualified supervision" (FI = 72.40%, SI = 85.42%). All these factors are pervasive and influential, and they are the most priority intervention targets. This quadrant was identified to have six factors, which together contributed 14.3% of all factors.

Quadrant II (Low Frequency, High Severity) comprises factors that are severe when they do but not as common. This includes "Lack of proper tools and equipment" (FI = 60.42%, SI = 74.48%) and "Absenteeism and irregular attendance" (FI = 65.63%, SI = 76.04%). These are the monitoring of the warrants and contingency planning. This quadrant was found to have twelve factors.

Within the High Frequency, Low Severity range (Quadrant III), those factors that may be occurring regularly but that cause a lesser impact are included. "Location of site and distance from workers' homes" (FI = 70.31%, SI = 60.94%) and "Frequent change orders" (FI = 70.31%, SI = 68.75%) fall here. The advantages are the improvements on a system-wide basis. Nine factors were identified in this quadrant.

The factors in Quadrant IV (Low Frequency, Low Severity) have a lower combined impact, e.g. "Wind and adverse winter" (FI = 59.90% and SI = 62.50%). These can be controlled in the routine procedures. This quadrant had 15 factors that constituted 35.7% of all factors.

Figure 13 shows the same FI-SI distribution with colour-coded by the category of factor and with the resulting spatial pattern of clustering. Factors related to management are more clustered (high frequency, high severity), whereas those related to Equipment are more dispersed and tended to yield lower frequency values.

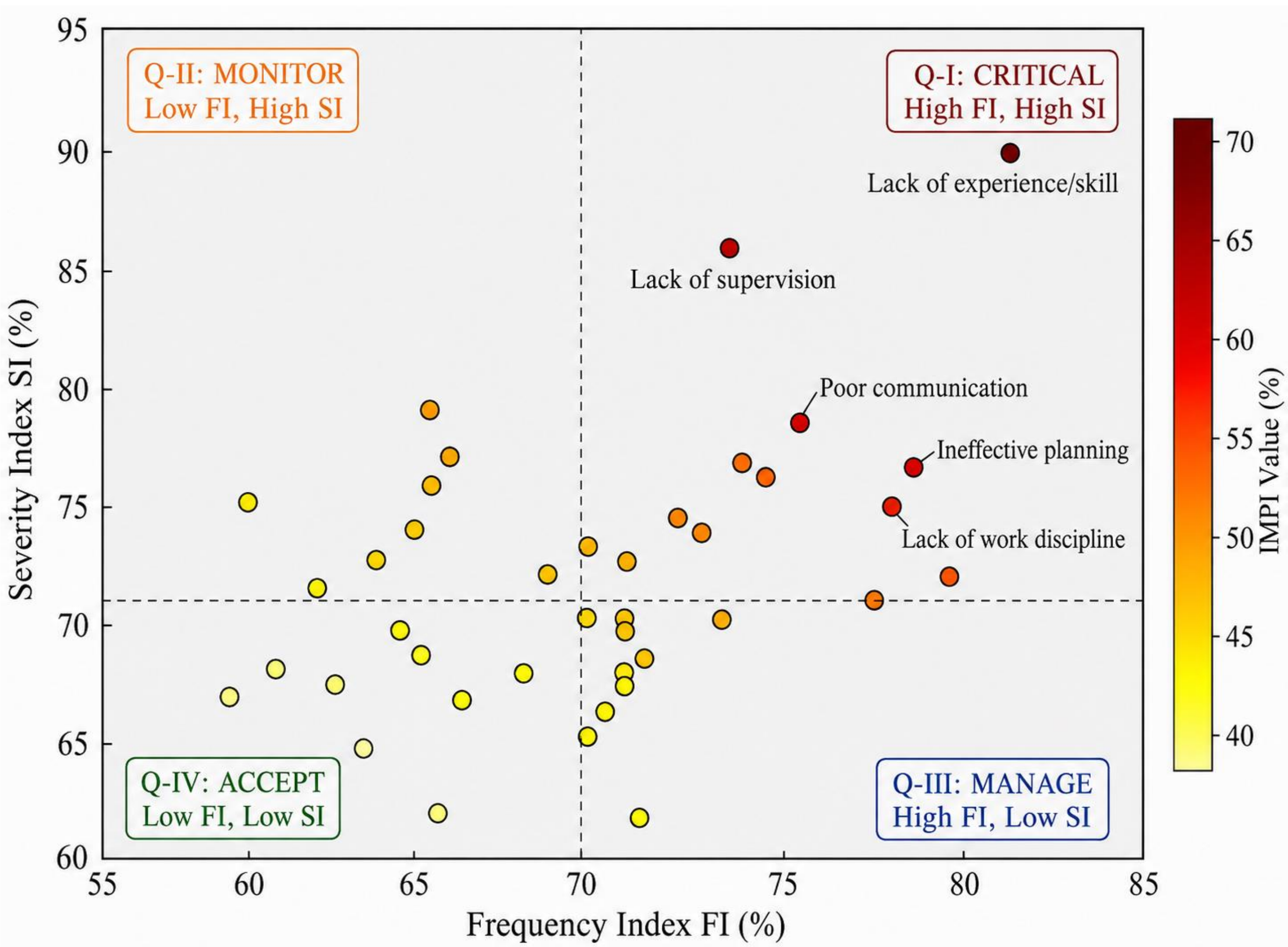

Fig. 12 Frequency-Severity quadrant analysis of all 42 factors

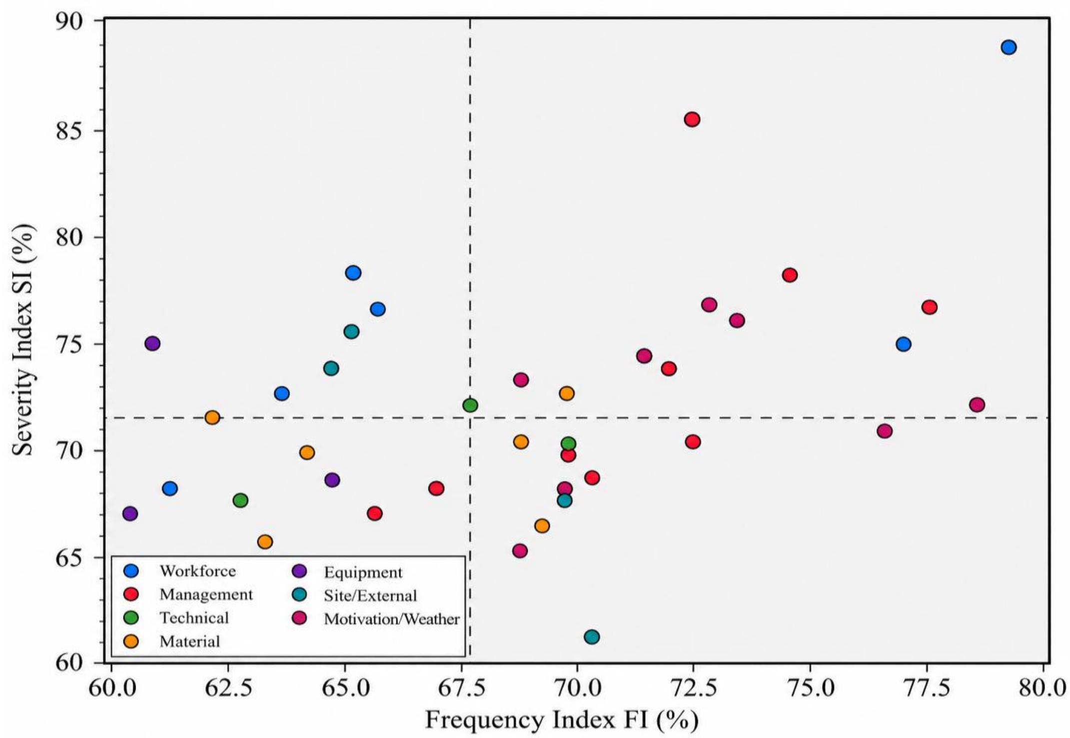

Fig. 13 FI-SI distribution by factor category

5.7. Category-wise Comparative Analysis

The category-wise analysis gives a deeper level of analysis of the relative importance of various groups of factors. Figure 14 shows mean of the RII by category with error bars of standard deviation. The factors that had highest mean RII (0.8246) are the Workforce-related factors, followed by Technical factors (0.8177) and Equipment factors (0.8104). The respective mean IMPI values per category are shown in Figure 15. Notably, the category hierarchy is rearranged in the IMPI analysis: Management-related factors, which attain only moderate RII rankings, record the second-highest mean IMPI.

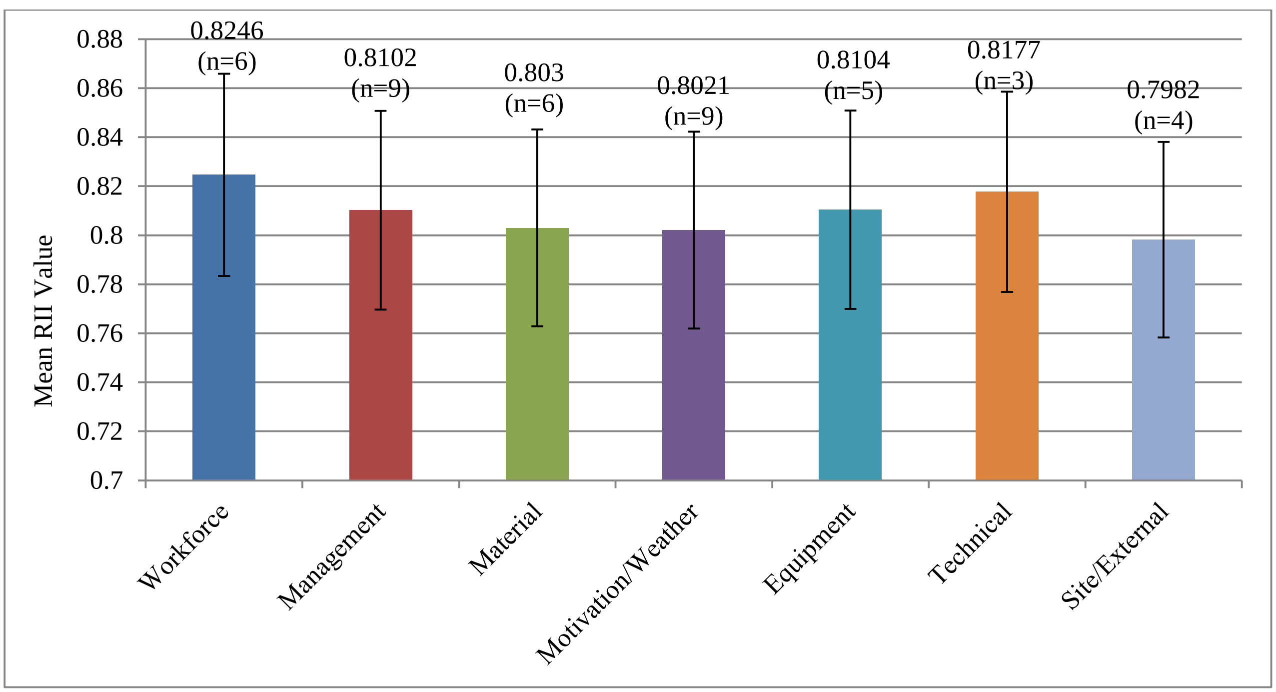

Fig. 14 Category-wise mean RII with Standard Deviation

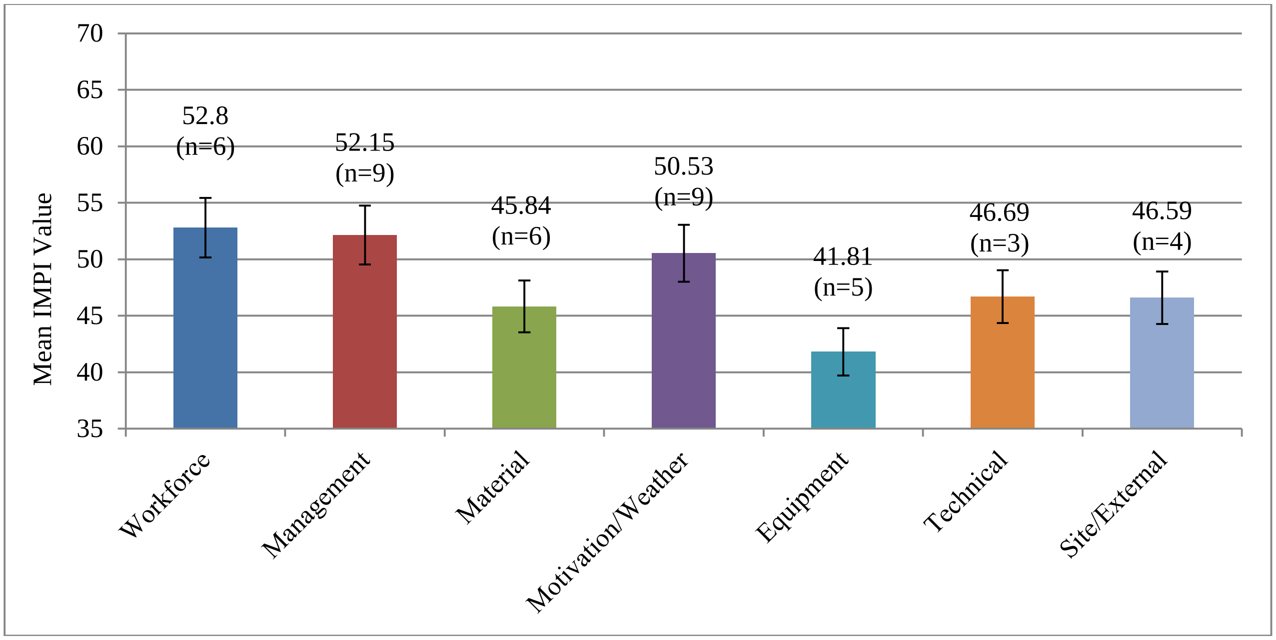

Fig. 15 Category-wise mean IMPI with Standard Deviation

The entire statistical summary of means, standard deviations, and sample size of both the RII and IMPI were summarized in the category-wise Table 6. As the data show, factors that relate to the Workforce do not just rank top in both methods; more importantly, the standard deviation (SD) in RII is the broadest (SD = 0.0540), which implies that in this group of factors, there are not just different, but very different perceptions. Contrarily, the Equipment-related factors depict lowest average IMPI (41.81) with the low SD (2.41), which confirms a comparatively low frequency-severity profile to all the equipment-related problems. Figure 16 directly compares normalized values of RII and IMPI by taking all the values individually in a grouped bar diagram. As Table 6 shows, Management and Motivation/Weather categories exhibit the least difference between mean RII and mean IMPI, suggesting that these factors are both perceived to be important and actually to have a significant frequency-severity profile in practice. Equipment and Technical categories show the largest gaps, indicating that they may have been overvalued in their perception relative to their actual frequency-severity picture in practice.

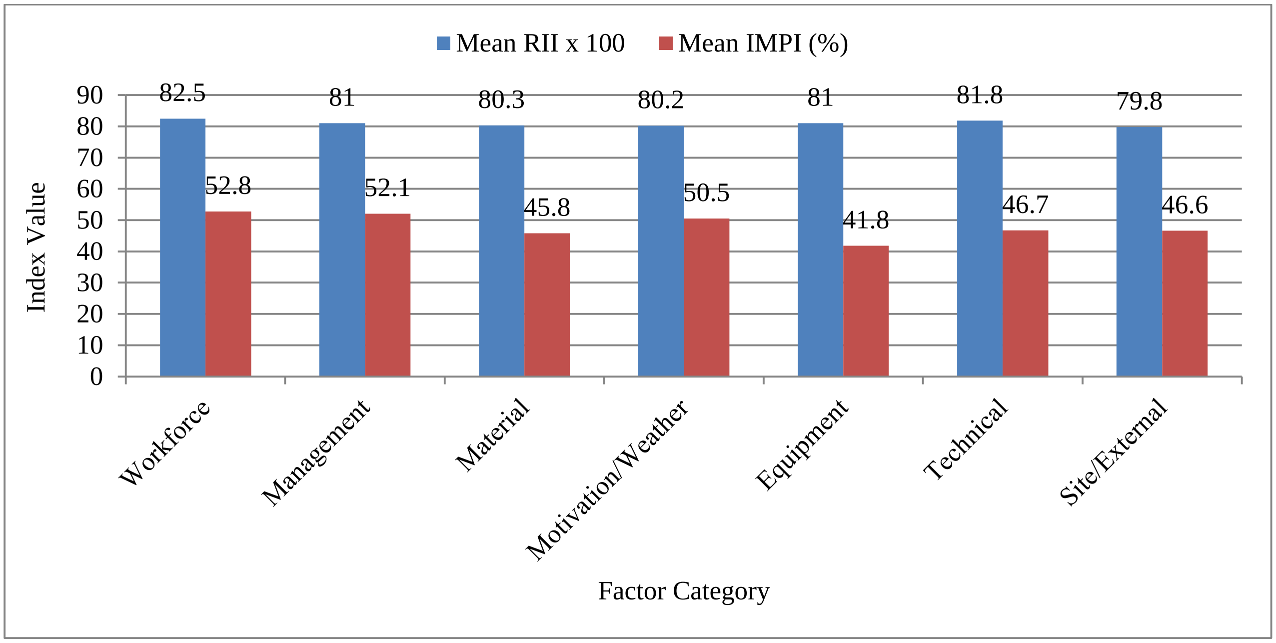

Fig. 16 Category-wise comparison - mean RII (×100) vs mean IMPI (%)

Table 6. Summary of Category-wise RII and IMPI Statistics

Category	n	Mean RII	SD RII	Mean IMPI	SD IMPI
Workforce	6	0.8246	0.0540	52.80	8.90
Management	9	0.8102	0.0378	52.15	5.06
Technical	3	0.8177	0.0268	46.69	3.54
Material	5	0.8030	0.0376	45.54	3.56
Equipment	5	0.8104	0.0431	41.81	2.41
Site/External	4	0.7982	0.0277	46.59	2.40
Motivational/Weather	10	0.8021	0.0527	50.53	6.23

5.8. Variability Analysis by Category

Box plots were drawn for both RII and IMPI values by category to examine the level of within-category variability. The box plot in Figure 17 shows that the RII values are relatively concentrated across the categories, with the interquartile ranges (IQRs) varying from 0.0260 in the Technical category to 0.0886 in the Motivation/Weather category. The Motivation/Weather category, therefore, exhibits the widest RII interquartile range, whereas the Technical category shows the narrowest. The overall RII values range from 0.7083 to 0.8906, indicating relatively limited dispersion within the 4-point importance-rating scale.The box plot of the IMPI values is presented in Figure 18. The IMPI distributions show greater differentiation among factors than the RII distributions because IMPI incorporates both frequency and severity. The Workforce category has the widest overall IMPI range, from 41.58 to 71.39, while the Motivation/Weather category ranges from 37.43 to 56.53. Within the Motivation/Weather category, the minimum value of 37.43 corresponds to “Wind and adverse winter”, whereas the maximum value of 56.53 corresponds to “Lack of social insurance policy”. The Equipment category has a comparatively narrow IMPI range of 39.39 to 45.00. Overall, the category-wise box plots demonstrate that IMPI provides greater differentiation among factors by incorporating both the frequency and severity of productivity-affecting factors.

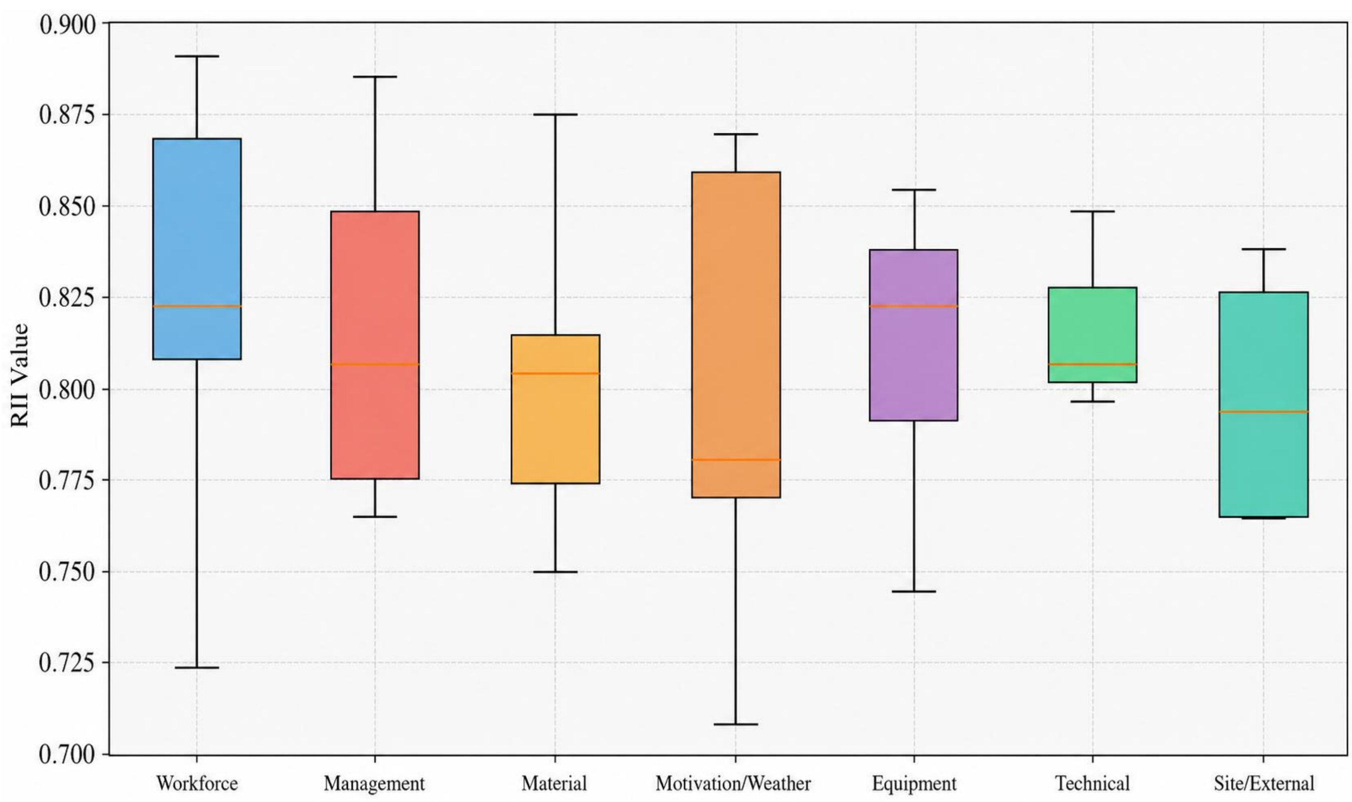

Fig. 17 Box plot - RII distribution by factor category

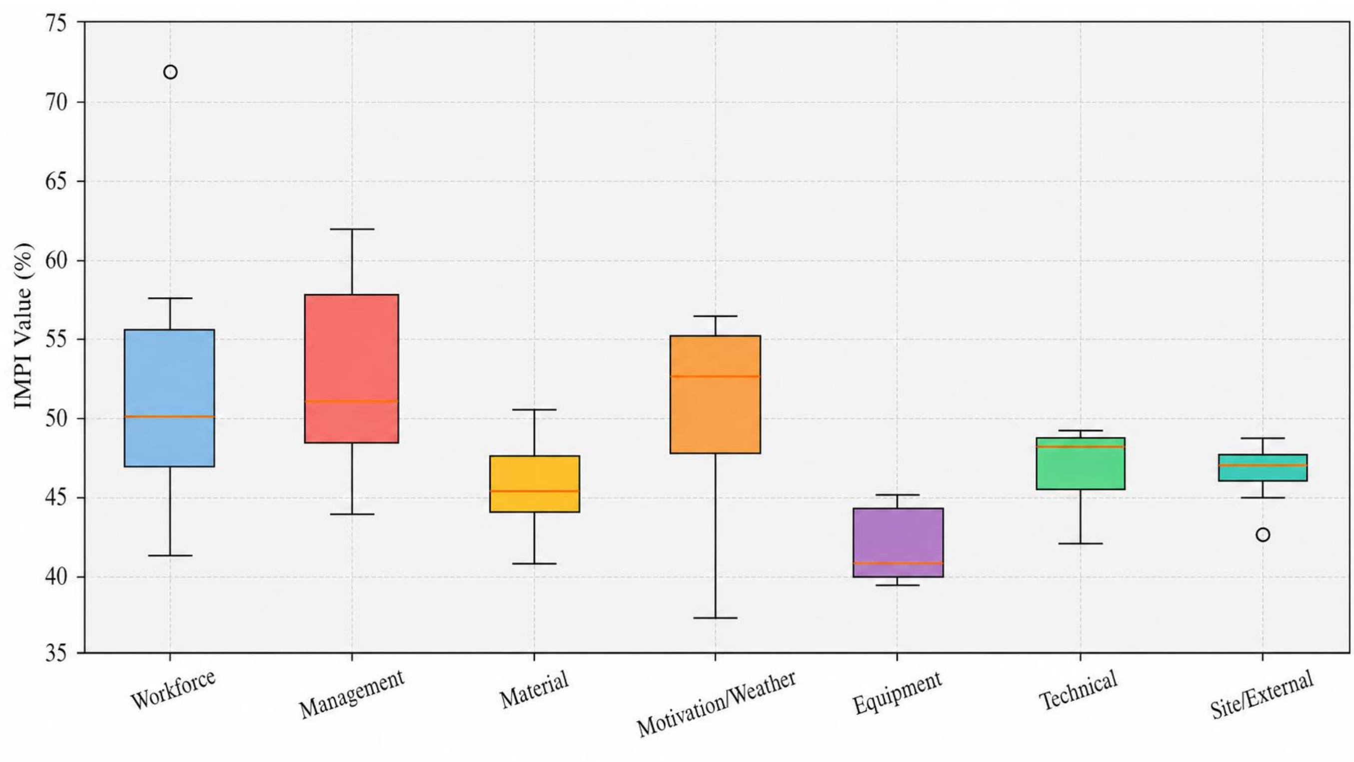

Fig. 18 Box plot – IMPI distribution by factor category

5.9. Key Findings from the Comparative Analysis

The entire comparative study on RII and IMPI approach is characterized by several significant findings, both in theory and practice:

First, the fact that the moderate Spearman rank correlation (0.497) between RII and IMPI is moderate proves that the latter two methods measure fundamentally different aspects of factor criticality. Although there is a consensus on the most and least critical factors, the factors ranking in the middle extend to be in overall rearrangement depending on the method of approach. This observation may substantiate the suggestion in [15] to employ a variety of assessment techniques in studies of construction management.

Second, it is important to highlight that only 14.3% factors (6 out of 42) fall within the Critical quadrant (high frequency, high severity), and 35.7% (15 factors) fall within the Accept quadrant (low frequency, low severity). This highly skewed distribution is indicative of the fact that management resources can be effectively focused on few high-impact factors instead of trying to address all 42 factors at the same time.

Third, motivational and welfare aspects (social insurance, labour recognition, payment of wages) constantly gain importance, while switching to the IMPI, and the rank increments 23-31 positions. This trend indicates that future workforce welfare dilemmas that the Indian construction industry has been struggling with were not only traditionally maladaptive but also frequent and with dire consequences.

Fourth, equipment and temperature factors are steadily pushed downwards in the rank as one changes RII to IMPI, and the ranks decrease by 18-25. This observation indicates that the factors, although theoretically important they may be practically addressed satisfactorily through the available mitigation strategies (equipment rental, seasonal scheduling) in the Central Gujarat context.

Fifth, the category-wise analysis indicates that there are the smallest changes in the performance of Management factors in both methods (the smallest RII-IMPI gap), and the largest changes in the performance of Equipment factors. This has its resource allocation consequences: management benefits will give predictable returns, and equipment investments may not be as influential as it would seem.

6. Parametric Sensitivity Study

This section outlines the parametric study undertaken to use the linear parametric model, formulated in multiple linear regression (MLR) form, to quantify the isolated and interaction effects of the most critical factors on the predicted labour productivity. Whereas both the RII and IMPI analysis gives ordinal ranks and the comparative study gives the insight of the method reliance, the parametric study enlarges such analysis by estimating the magnitude of the change in productivity which can be attributed to either or both factors.

As noted in Section 3.4.4, the MLR designation refers to the functional form of the model; the coefficients were elicited and calibrated rather than statistically estimated, and formal estimation from measured field data is identified in Section 6.1 as a priority for future research.

6.1. MLR Model Specification

The MLR model was defined with eight predictor variables as the strongest variables in both RII and IMPI results. Based on the general MLR model presented in Equation (5), the calibrated model with coefficient values is expressed as Equation (7). The temperature effect, being non-linear, is modelled separately as a quadratic function in Equation (8).

$$Y = 6.0 + 0.72X_1 + 0.60X_2 - 0.048X_3 - 0.32X_4 - 0.06X_5 + 0.48X_6 + 0.016X_7 + f(X_8) + \varepsilon \quad (7)$$

$$f(X_8) = -0.032 \times \left[\frac{(X_8 - 22)^2}{10}\right] \quad (8)$$

The model coefficients were derived from expert consultation, which provided the relative effect weight of each predictor, and were subsequently calibrated by a uniform factor of 0.40 so that the resulting predictions span the range of 12 mm cement plastering output applicable to the study region. Expert judgement is considerably more reliable for relative magnitudes than for absolute output expressed in physical units, and the calibration therefore serves only to place the elicited relative weights on the m²/day scale. Table 7 reports the calibrated coefficients that constitute Equation (7); these are the values used for every prediction reported in this paper, so that all results can be reproduced by direct substitution into Equation (7). The temperature function reflects a non-linear relationship with optimal productivity at approximately 22°C. Table 7 presents the complete model specification with variable definitions, ranges, and calibrated coefficients. The temperature coefficient is reported in Table 7 as $\beta_8 = -0.0032$, which is the algebraic equivalent of the form $-0.032 \times (X_8 - 22)^2 / 10$ given in Equation (8). Because the coefficients were elicited from experts and calibrated rather than estimated statistically from measured field data, conventional standard errors and confidence intervals are not directly applicable; the effect sizes and prediction uncertainty of the model are therefore reported as follows. The full-range effect size of each predictor, defined as the change in predicted productivity when the variable traverses its complete range in Table 7, is 2.88 m²/day for worker skill, 2.40 m²/day for supervision quality, 1.92 m²/day for team coordination, 3.20 m²/day for material delays, 1.60 m²/day for equipment availability, 1.44 m²/day for absenteeism, 0.90 m²/day for wage payment delays, and approximately 1.69 m²/day for temperature, which provides a scale-independent basis for comparing the influence of the factors. To characterise prediction uncertainty, a ±20% band was applied to each calibrated coefficient and propagated through the model, producing prediction intervals of approximately ±20% around the point estimates (for example, approximately 13.2–19.8 m²/day for the best-case scenario and 2.6–3.9 m²/day for the worst-case scenario reported in Section 6.3). The model was validated in two ways. First, through face validation: the predicted productivity range of 3.2–16.5 m²/day/worker was reviewed by the consulted experts and judged consistent with plastering output observed on Central Gujarat building sites. Second, by comparison with published labour-output benchmarks, the CPWD Analysis of Rates [4] specifies a mason labour requirement of 0.67 mason-day for 10 m² of 12 mm cement plaster (Item 13.1), corresponding to approximately 14.9 m² per mason-day.

As this coefficient represents well-organised working conditions, it provides a useful reference for assessing the absolute magnitude of the model predictions. The Good scenario prediction (14.0 m²/day) lies approximately 6% below the CPWD benchmark, while the Best Case prediction (16.5 m²/day) is approximately 11% above it. In contrast, the Average, Poor and Worst Case scenarios (11.3, 6.9 and 3.2 m²/day, respectively) fall progressively below the benchmark, consistent with the degraded input conditions specified for these scenarios in Table 8. It should be noted that the CPWD labour coefficients are stated to be indicative and may vary with technological conditions, worker skill and other local factors affecting labour efficiency and output. Formal statistical validation and re-estimation of the coefficients from longitudinally measured field productivity data are identified as priorities for future research.

Table 7. MLR model specification and calibrated coefficients

Var.	Factor	Range (Units)	*β* Value	Direction
X_1	Worker Skill Level	1–5 (rating)	+0.72	Positive
X_2	Supervision Quality	1–5 (rating)	+0.60	Positive
X_3	Absenteeism Rate	0–30 (%)	−0.048	Negative
X_4	Material Delays	0–10 (days)	−0.32	Negative
X_5	Wage Payment Delays	0–15 (days)	−0.06	Negative
X_6	Team Coordination	1–5 (rating)	+0.48	Positive
X_7	Equipment Availability	0–100 (%)	+0.016	Positive
X_8	Temperature	5–45 (°C)	−0.0032 (quadratic)	Non-linear

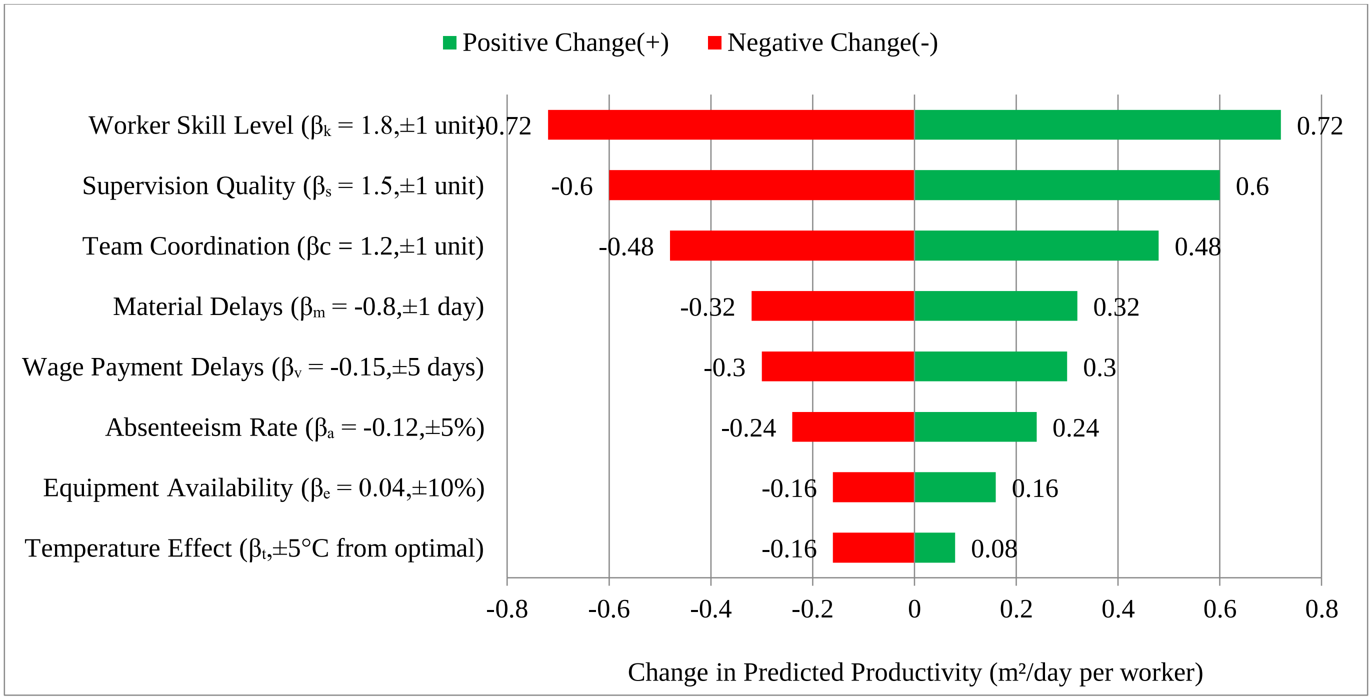

Fig. 19 Parametric sensitivity analysis – tornado diagram

6.2. Single-Factor Sensitivity Analysis

The tornado diagram, Figure 19, illustrates the sensitivity of predicted productivity to unit changes in each factor from baseline conditions. Worker Skill Level (β_1 = 0.72) exhibits the highest sensitivity, followed by Supervision Quality (β_2 = 0.60) and Team Coordination (β_6 = 0.48). Among negative factors, Material Delays (β_4 = –0.32 per day) show the strongest adverse sensitivity per unit change.

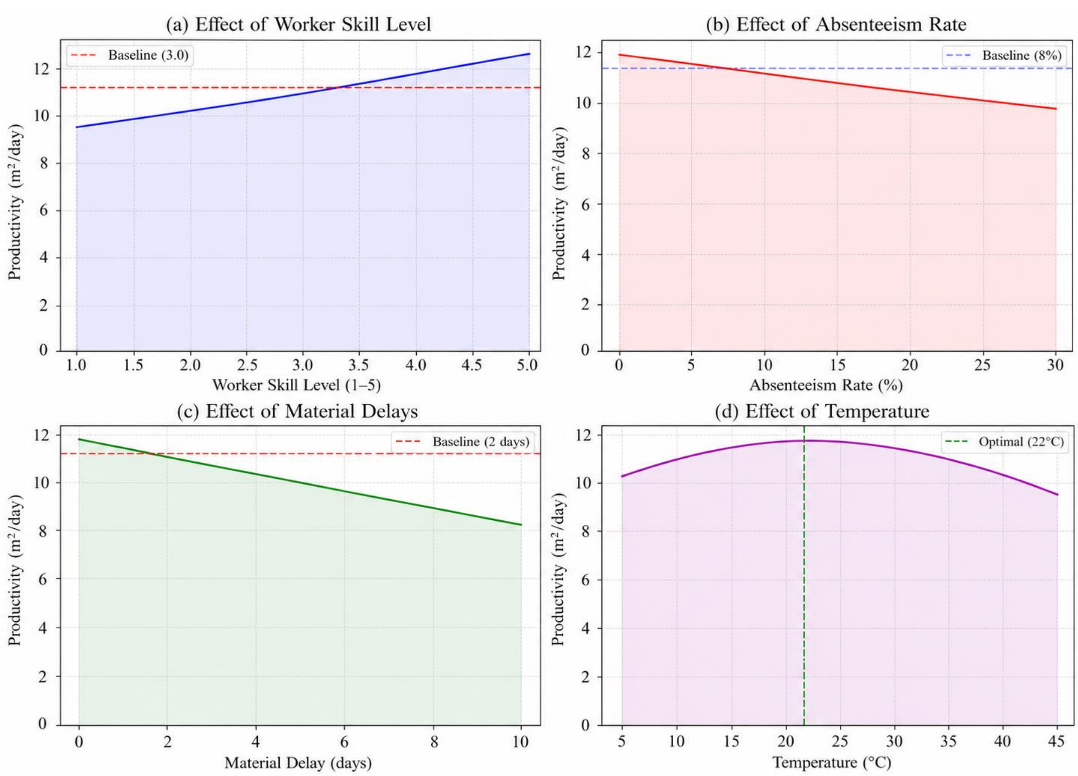

Fig. 20 Single-factor sensitivity analysis – primary factors

Figure 20 shows single-factor sensitivity curves in more detail on four representative factors. In Panel (a), the positive relationship between the skill level of the worker and his/her productivity is nearly linear, with a minimum value of about 9.8 m²/day at skill level 1, and a maximum value of 12.8 m²/day at skill level 5.

The slow decrease with an increase in absenteeism is depicted in panel (b). The significant impact of material delays can be seen in panel (c). The inverted-U correlation, with temperature as the independent variable and productivity as the resulting variable, appears inverted in Panel (d).

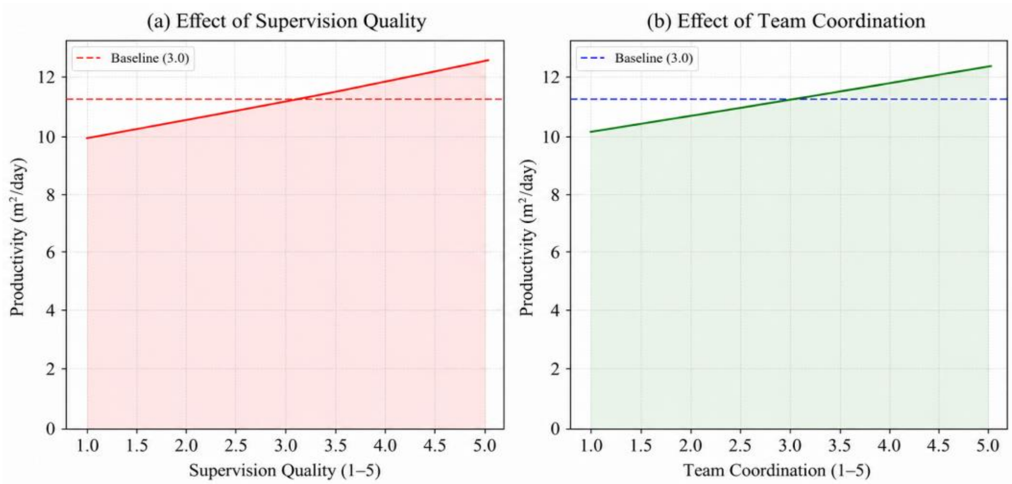

Fig. 21 Sensitivity analysis - management factors (supervision and coordination)

Figure 21 shows sensitivity curves of the two other management factors: supervision quality and team coordination. They both have strong positive linear relationships with productivity, and supervision has a steeper slope (β_2 = 1.50) than coordination (β_6 = 1.20), which is consistent with the ranking of both RII and IMPI analysis. Figure 22 shows the sensitivity curves on wage payment delay and equipment availability. The wage delays have a linear declining productivity (β_5 = –0.06 per day) and the equipment have a slow positive slope (β_7 = +0.016 per percentage point). This is supported by the fact that the relatively smooth weight of the slope of equipment availability indicates the realization of the results of the comparative analysis, according to which equipment factors have a moderate real-life effect.

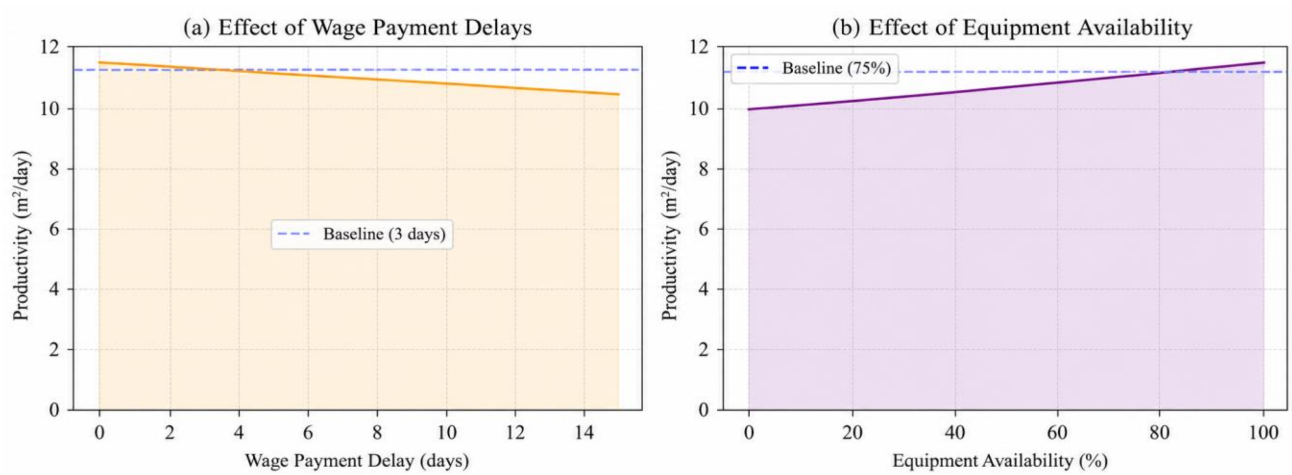

Fig. 22 Sensitivity analysis – resource and payment factors

6.3. Multi-Factor Scenario Analysis

Five representative scenarios were established in case of worst case, best case and various territories. In Table 8, the scenario definitions and expected productivity results are given. The results are presented in a graphical manner in Figure 23.

All scenario predictions were obtained by direct substitution of the input values into Equation (7), with the error term set to zero (ε = 0), so that the reported values represent the expected (mean) predicted productivity for each specified set of input conditions rather than the outcome of an individual observation.

Table 8. Scenario Definitions and Predicted Productivity

Scenario	X_1 (Skill)	X_2 (Supv.)	X_3 (Abs.%)	X_4 (Mat. Days)	X_5 (Wage Delay Days)	X_6 (Coord.)	X_7 (Equip.%)	X_8 (Temp.)	Y (m²/d)
Worst Case	1.0	1.5	25%	8	12	1.5	40%	42°C	3.2
Poor	2.0	2.0	15%	5	7	2.0	55%	38°C	6.9
Average	3.0	3.0	8%	2	3	3.0	75%	28°C	11.3
Good	4.0	4.0	4%	1	1	4.0	85%	25°C	14.0
Best Case	5.0	5.0	1%	0	0	5.0	98%	22°C	16.5

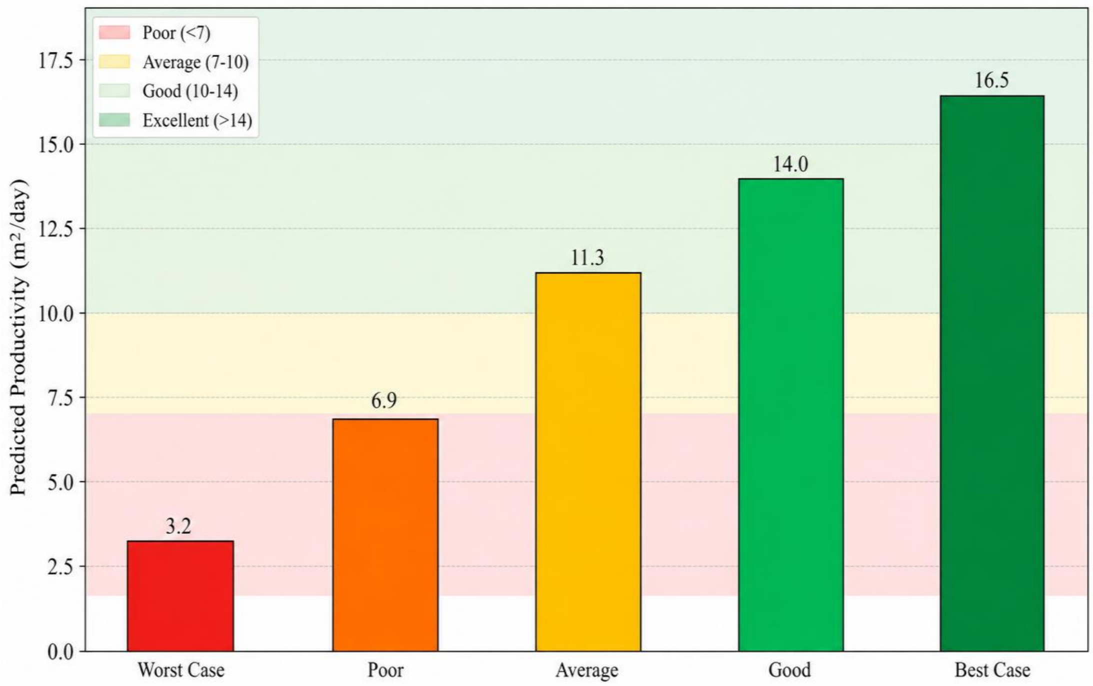

Fig. 23 Multi-factor scenario analysis

The range of productivity (based on the scenario analysis) is 3.2 to 16.5 m²/day/worker (a 5.1 times difference). This yields 4.4 m²/day of gain on the transition of Poor to that of Average; and 2.7 m²/day on the transition of Average into that of Good. This is because, as marginal returns decline, the largest gains can be attained by raising the lowest-performing factors.

To confirm the calculation procedure, a worked example is presented for the Best Case scenario of Table 8, for which $X_1 = 5.0$, $X_2 = 5.0$, $X_3 = 1\%$, $X_4 = 0$ days, $X_5 = 0$ days, $X_6 = 5.0$, $X_7 = 98\%$ and $X_8 = 22°C$. Since X_8 equals the optimum of 22°C, the temperature term of Equation (8) evaluates to $f(X_8) = -0.032 \times (22 - 22)^2 / 10 = 0$. Substituting these values into Equation (7) with $\varepsilon = 0$ gives:

$$Y = 6.0 + (0.72 \times 5.0) + (0.60 \times 5.0) - (0.048 \times 1) - (0.32 \times 0) - (0.06 \times 0) + (0.48 \times 5.0) + (0.016 \times 98) + 0$$

$$Y = 6.000 + 3.600 + 3.000 - 0.048 - 0.000 - 0.000 + 2.400 + 1.568$$

$$Y = 16.52 \approx 16.5 \text{ m}^2/\text{day}$$

Applying the identical procedure to the remaining scenarios of Table 8 yields 3.22 m²/day for the Worst Case, 6.92 m²/day for the Poor scenario, 11.28 m²/day for the Average scenario and 13.96 m²/day for the Good scenario, which correspond to the values of 3.2, 6.9, 11.3 and 14.0 m²/day reported in Table 8 and plotted in Figure 23. Every predicted value reported in this paper is therefore reproducible by direct substitution into Equation (7) with $\varepsilon = 0$.

6.4. Factor Interaction Effects

The combination effects matrix, Figure 24, shows the possible combined effects of pairs of factors. The most probable high-potential relationship is between Worker Skill Level and Supervision Quality ($0.72 \times 0.60 = 0.432$), implying the most successful workforce skills investing is when it is accompanied by a high standard of supervision.

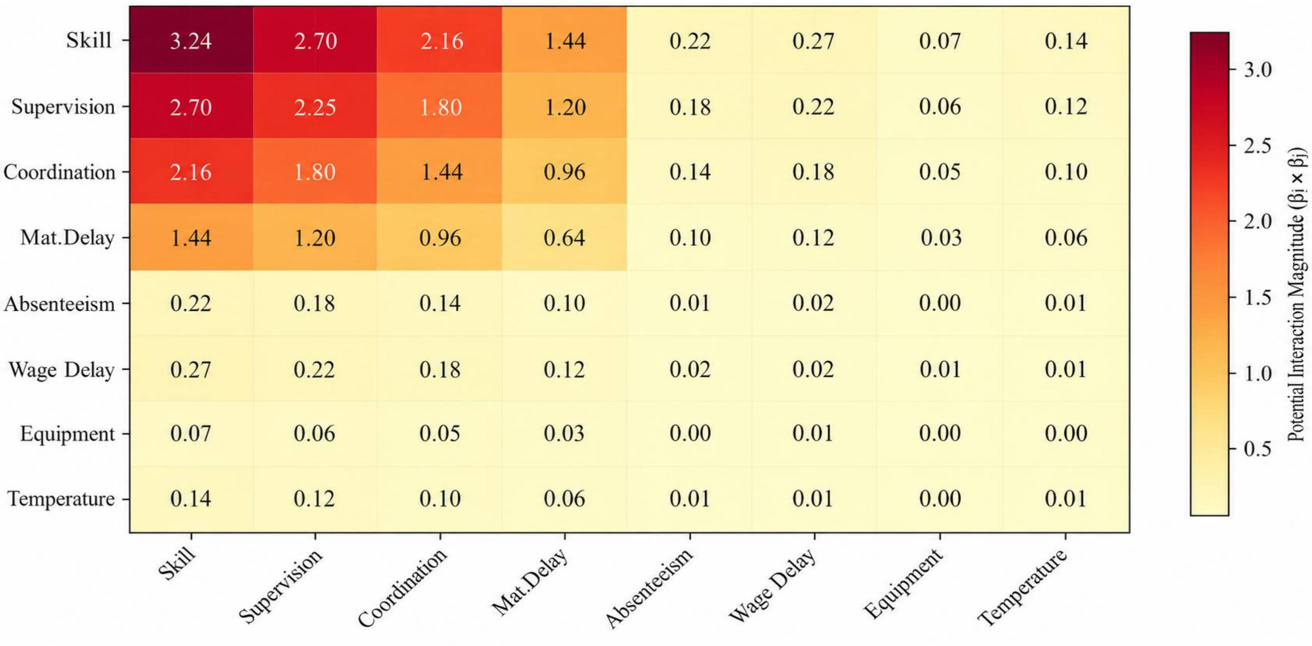

Fig. 24 Factor interaction effects matrix

6.5. Pareto Analysis of Factor Contributions

In Figure 25 a Pareto analysis used on the total productivity prediction breaks it down into the individual factor contributions in the baseline (Average) situation. The combination of three components, the Baseline Intercept, Worker Skill and Supervision Quality, contributes approximately 71.6% of the predicted productivity. Considering only the factor-attributable component, that is excluding the baseline intercept, worker skill, supervision quality and team coordination together account for approximately 68.2% of the predicted productivity. The cumulative contribution curve helps to verify the Pareto principle: the five largest contributors describe more than 90% of the total predicted productivity.

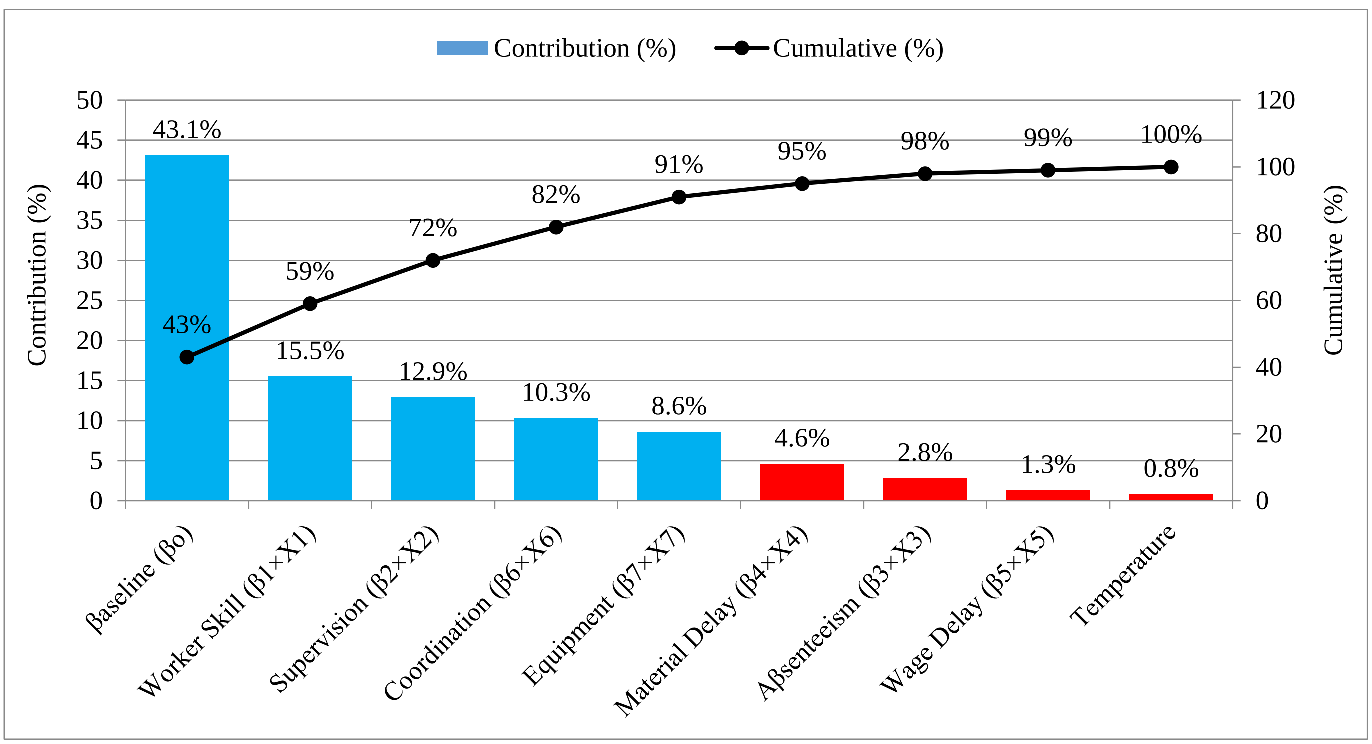

Fig. 25 Pareto analysis of factor contributions at baseline

7. Discussion

The result of this study comprises several important fragments of valuable information on the factors that drive the productivity of labour in construction in the Central Gujarat region. The finding that the factor Lack of experience and skill of labour is ranked the most according to both the RII and IMPI approaches follows the corresponding literature. In the cases reported in [7, 8, 10], the level of skills was found to be one of the determinants of productivity. This revelation would assume a special status in the scenario of Central Gujarat since around 81 % of construction workers in India are unskilled and the region is heavily dependent on migrant workers from neighbouring states.

The lack of qualified and effective supervision has a high rating (RII rank 2, IMPI rank 2), which is consistent with the results in Kuwait [11] and Turkey [12], respectively. The fact that IMPI identifies ineffective planning and scheduling as the third most important factor (it ranks 10th alone by RII) is interesting because it shows that there is a critical difference between the ineffectiveness of planning and scheduling individually and when combined with the frequency and severity of both phenomena will result in a dominating factor in productivity. The fact that motivational factors have moved drastically upwards in the IMPI rankings, most notably, the motivational sub-factors that include, in particular, lack of social insurance policy (no longer rank 32, but 6), Lack of labour recognition programme (no longer rank 40, but 9) and No payment for extra work (stable at rank 7). This especially applies to the Indian construction scenario where social security is only being received by 2.2% of the construction workers and 83% are also employed as casual workers. The detailed comparative analysis (Section 5) has a very strong statistical support that there are basically different dimensions of factor criticality captured by RII and IMPI. Moderate level of Spearman correlation (ρ = 0.497) indicates that about 75.3% of variance in ratings of factors would be missed by relying on only one method. The quadrant analysis also demonstrates that only 14.3% of factors seen in the quadrant fall on the Critical quadrant, which allows one to determine the focus in the allocation of resources. The difference in performance of the Management factors between methods portrays homogeneity whereas the Equipment factors portray heterogeneity in performance in the methods used.

The parametric sensitivity study offers successful quantitative information to supplement the ranking analysis. The tornado diagram shows that a one-unit improvement in the level of worker skill (β_1 = 0.72 m²/day) has 15 times the effect of a one-percentage-point reduction in absenteeism (β_3 = 0.048 m²/day), though it should be noted that these coefficients correspond to different measurement scales. The 5.1 times productivity difference (3.2 vs 16.5 m²/day) between worst and best case shows the difference between these two extremes. The same analysis revealed that the greatest potential of a synergy is between the workers skill and the quality of supervision (interaction magnitude = 0.432). The Pareto analysis establishes that the top three predictors, worker skill, supervision quality, and team coordination, account for approximately 68% of the factor-attributable predicted productivity. In comparison with the state of the art, the present study achieves more decision-relevant results than previously reported ranking studies for three reasons. Earlier Gujarat-specific investigations [15] employed a single perception-based index which, as the moderate Spearman correlation obtained here (ρ = 0.497) demonstrates, leaves a substantial share of factor-criticality information unexamined; the dual RII–IMPI design recovers this information and exposes rank shifts of up to 31 positions that a single-index study cannot detect. Relative to the RII–IMPI application to construction delays in [16], the present work adds a formal statistical comparison (correlation, quadrant, and category-wise analyses) rather than a side-by-side listing of the two indices. Finally, unlike the predominantly ordinal treatments reported in the recent literature [1, 9, 20], the MLR-based parametric study converts the rankings into quantitative productivity estimates, scenario ranges, and Pareto contributions, thereby providing effect magnitudes that ranking-only techniques cannot supply.

The potential response and sampling biases of the survey should be acknowledged explicitly. The response rate of 48% implies that the views of the 52% of professionals who did not respond are unrepresented, and non-respondents may differ systematically from respondents, for example in workload or in their interest in productivity issues. The questionnaire was distributed through professional networks rather than by probability sampling, so the sample is a non-probability convenience sample and may over-represent particular organisations or cities within Central Gujarat. In addition, all ratings are self-reported perceptions and may be affected by recency and social-desirability effects rather than objectively measured productivity. These biases were mitigated, although not eliminated, by targeting four distinct stakeholder groups (contractors, site engineers, developers, and supervisors), by verifying internal consistency (Cronbach's α = 0.95), and by triangulating perception-based rankings (RII) against frequency–severity evidence (IMPI). The findings should accordingly be interpreted as representative of experienced construction professionals in the region rather than of the industry population as a whole. Several barriers may constrain the implementation of the recommended interventions in the local Central Gujarat context. The heavy reliance on migrant labour, with high seasonal turnover linked to agricultural cycles and festivals, reduces the incentive of contractors to invest in structured skill-development programmes because trained workers may not remain with the same site or employer. The predominantly informal and casual nature of employment complicates enrolment in social insurance schemes and the administration of formal recognition programmes. Small and medium contractors, which constitute the majority of the regional industry, operate on thin margins that limit expenditure on qualified supervision, planning systems, and equipment. Furthermore, the limited local penetration of formal skill-certification initiatives and the fragmented, subcontracted structure of site labour make the uniform enforcement of training, safety, and welfare measures difficult. Effective implementation is therefore likely to require coordinated action among developers, contractors, industry bodies, and government skill-development agencies rather than isolated firm-level initiatives.

8. Conclusion and Recommendations

This paper identified and analysed 42 key factors that will influence the productivity of labour during the construction of building projects within Central Gujarat region in India using RII, IMPI, comprehensive comparative analysis and parametric sensitivity analysis. The following conclusions are the most important:

To begin with, most of the workforce competence factors take pre-eminence in both ranking methods. Always the most important factor was the lack of experience and skill of labour (RII = 0.8906, IMPI = 71.39%). The parametric study measures this dominance: one-unit increase in the level of skill results in 0.72 m^2/day productivity gain.

Second, according to the overall comparative analysis, there is a moderate Spearman correlation between the two methods (RII and IMPI rankings) (ρ = 0.497). Rank shifts of 15 or more positions were observed for ten factors, with the largest shift of 31 positions recorded for the factor “Lack of labour recognition programme”.

Third, quadrant analysis identifies all 42 factors in four group of strategic types: Critical (14.3%), Monitor (28.6%), Manage (21.4%), and Accept (35.7%). The classification offers a useful guideline that allows rank management interventions.

Fourth, motivational and welfare factors are greatly underestimated with RII alone. Factors such as “Lack of social insurance policy” and “Lack of labour recognition programme” rose by 23–31 positions in the IMPI ranking, showing how frequent and consequential these welfare gaps are.

Fifth, the parametric study demonstrates that there is a 5.1 times productivity difference between worst and best-case scenarios. The Pareto analysis provides the data that suggests the intervention strategy should be focused, as the top three predictors explain approximately 68% of the factor-attributable predicted productivity. The analysis of the effects of interaction determines the pair of factors that have the strongest synergy: worker skill-supervision quality. It is based on these results that the following recommendations are made: (i) Construction companies are advised to invest in well-organized skill development programmes with a projected improvement in the productivity of the same up to 0.72 m^2/day with each level of skill improvement; (ii) Project managers are advised to focus on effective planning, scheduling and communication systems; (iii) Employers are advised to develop formal recognition of labour programmes and extend the coverage of social insurance services; (iv) Industry bodies are advised to provide policies that will incentivise the process of skill certification and the services of welfare services; (v) Future researches are recommended to expand on the sample size, validation of the MLR model based on longitudinal field studies, and the exploration of using structural equation modelling to understand cause and effect relationships.

As an action plan summary for practitioners, the findings can be translated into a phased implementation strategy. Immediate actions include conducting site-level skill assessments and the pairing of less experienced skilled workers with experienced crews, ensuring timely wage payments, and formalise weekly look-ahead planning to reduce material delays. Short term initiative can focus on enhancing supervisory capabilities through structured training programmes, introducing transparent labour recognition and incentive schemes, and promoting workers' enrolment in social insurance programmes in collaboration with industry bodies. Long-term strategies include institutionalise partnerships with skill-certification agencies, adopt digital material-tracking and scheduling tools, and monitor productivity against the quantified benchmarks of this study (targeting movement from the 'Average' scenario of 11.3 m^2/day towards the 'Good' scenario of 14.0 m^2/day). Contractors and project managers are expected to lead the immediate and short-term initiatives, whereas long-term implementation requires collaboration among contractors, developers, professional bodies, and government-supported skill development agencies

Ethical Statement

This study was conducted in accordance with accepted ethical standards for survey-based research. Informed consent was obtained from all respondents prior to their participation, and participation was entirely voluntary with the right to withdraw at any time. No personally identifiable information was collected; all responses were anonymised, stored securely, treated as strictly confidential, and used solely for the purposes of this research, thereby ensuring the data privacy of the participants.

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Conflicts of Interest

The authors declare that there are no conflicts of interest associated with this publication.

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