



Generalized Additive Model Approach for Analyzing the Productivity of Irrigation Construction Workers

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Abstract: Labor productivity is a critical determinant of success in infrastructure development projects. This study investigates the dominant factors influencing the productivity of irrigation construction workers by integrating Generalized Additive Models (GAM) and Monte Carlo simulation. Using data analyzed in R Statistics 4.3.0 for Windows, we employed GAM to identify nonlinear relationships between productivity and predictor variables, followed by a permutation-based Monte Carlo resampling approach (100 simulations) to validate critical predictors. Results reveal that wage policies, availability of safety equipment, and managerial practices are the most significant drivers of productivity. Methodologically, this research contributes a novel framework combining GAM's flexibility with Monte Carlo's robustness to quantify uncertainty, evaluated via the coefficient of determination (R^2). The permutation-based variable importance analysis underscores the practical relevance of these factors, offering actionable insights for optimizing workforce management in irrigation infrastructure projects.

Keywords: *productivity, model, workforce, projects, irrigation infrastructure*

Abstrak: Produktivitas tenaga kerja merupakan penentu penting keberhasilan proyek pembangunan infrastruktur. Studi ini menyelidiki faktor-faktor dominan yang memengaruhi produktivitas pekerja konstruksi irigasi dengan mengintegrasikan Model Aditif Umum (Generalized Additive Models/GAM) dan simulasi Monte Carlo. Menggunakan data yang dianalisis dalam R Statistics 4.3.0 untuk Windows, kami menggunakan GAM untuk mengidentifikasi hubungan nonlinier antara produktivitas dan variabel prediktor, diikuti oleh pendekatan resampling Monte Carlo berbasis permutasi (100 simulasi) untuk memvalidasi prediktor penting. Hasil menunjukkan bahwa kebijakan upah, ketersediaan peralatan keselamatan, dan praktik manajerial adalah pendorong produktivitas yang paling signifikan. Secara metodologis, penelitian ini memberikan kerangka kerja baru yang menggabungkan fleksibilitas GAM dengan kekokohan Monte Carlo untuk mengukur ketidakpastian, yang dievaluasi melalui koefisien determinasi (R^2). Analisis kepentingan variabel berbasis permutasi menggarisbawahi relevansi praktis dari faktor-faktor ini, menawarkan wawasan yang dapat ditindaklanjuti untuk mengoptimalkan manajemen tenaga kerja dalam proyek infrastruktur irigasi.

Kata kunci: *produktivitas, model, tenaga kerja, proyek, infrastruktur irigasi*

1. Introduction

Irrigation construction projects in Central Sulawesi, particularly in Palu City, face significant challenges despite their high intensity and frequency. Many of these projects experience delays in meeting contractual deadlines, primarily due to low labor productivity—a critical factor as workers are the primary resource in construction execution [1]. Effective project management relies on optimizing five key resources: human resources (workers), materials, machinery, financing, and methodologies [2]. Accurate labor productivity benchmarks are essential to mitigate delays, as productivity is influenced by variables such as age, work experience, education, wage adequacy, family dependents, health, interpersonal dynamics, managerial practices, and team composition [3]. In construction services, labor productivity is often measured using metrics like the Labor Utilization Rate (LUR), which evaluates workers' effectiveness in task completion [4]. For irrigation projects in Palu City, productivity is further shaped by worker skills, physical stamina, experience, age, and motivation [5]. Common causes of delays include material

delivery bottlenecks [6] and inconsistent work schedules (e.g., irregular start times, breaks, and task completion) among craftsmen [7]. This study focuses on human resources (construction workers/craftsmen) as the cornerstone of project success, given their direct impact on timelines and costs [8].

Resource management in construction projects requires balancing capabilities (e.g., worker expertise) and capacities (e.g., material availability) to align with cost, quality, and time objectives [9]. Optimal resource utilization—encompassing labor, materials, equipment, and financial planning—demands robust management systems to prevent schedule overruns and budget inflation [10].

1.1. Material Resources

Material usage is a critical aspect of construction projects, accounting for a significant portion of the total project cost [11, 12]. Studies indicate that material costs can range from 50% to 70% of the overall project budget, excluding additional expenses such as storage and handling [13].

Construction materials can be categorized into three main types:

a. Engineered Materials

These are specialized products manufactured based on technical calculations and project specifications. Delays in procuring engineered materials can directly impact the project schedule.

b. Bulk Materials

These materials are produced according to industry standards and are often challenging to estimate due to their variability (e.g., cables, pipes). Their quantities and specifications may fluctuate based on project requirements.

c. Fabricated Materials

These are pre-assembled components manufactured off-site (e.g., steel frames, modular units) before being transported to the construction location. Fabrication processes must align with project timelines to avoid delays.

1.2. Material Resources Equipment Resources

During the construction phase, mechanical tools and equipment play a crucial role in ensuring efficient project execution [14]. Common examples include cranes, graders, scrapers, trucks, backhoes, and air compressors. The use of heavy equipment enhances productivity, efficiency, and project outcomes, making it a key factor in successful construction management [3, 14]. Before a project begins, contractors must carefully select and allocate the appropriate machinery. Proper equipment selection is critical to project success and is typically determined during the planning phase. Key considerations include Type, Quantity, and Capacity.

Since not all equipment is suitable for every project [15], a well-structured evaluation process is essential to avoid inefficiencies or delays [16].

1.3. Construction Labor

Construction in the irrigation sector encompasses both technical design and practical implementation of water management systems [17]. In Indonesia, regulatory frameworks mandate that construction service providers obtain Work Skills Certificates as formal validation of professional competency [18]. This certification system serves as a crucial quality control mechanism, with studies demonstrating its effectiveness in improving construction outcomes by 22-28% compared to non-certified projects [19].

The evaluation of construction worker competency primarily focuses on practical skills application, particularly adherence to Standard Operating Procedures (SOPs) in critical tasks. For instance, proper execution of concrete column casting SOPs has been shown to reduce structural defects by 18% while improving worksite safety compliance by 31% [18]. The Indonesian construction sector faces significant challenges in human resource development, with approximately 7.3 million workers requiring upskilling, yet only 12% having access to formal

education pathways [20]. This gap has necessitated greater reliance on non-formal training programs, which currently account for 63% of all construction skills development initiatives [21].

Construction experts play a pivotal role in this ecosystem, serving not only as technical leaders but also as developers of competency standards [22]. Their involvement in national development projects has been correlated with a 15-20% improvement in project quality metrics [21]. The selection process for these experts must align with government procurement principles to ensure proper accountability across three key dimensions: (1) physical construction quality, (2) financial management, and (3) social impact [23].

The current certification framework recognizes three tiers of expertise: Junior Expert (Level 1), Middle Expert (Level 2), and Main Expert (Level 3) [24]. This stratification has proven effective, with data showing that projects utilizing Main Experts demonstrate 27% fewer cost overruns and 33% better schedule compliance compared to those using lower-tier experts [16]. However, the system faces challenges in equitable distribution, as 68% of certified experts are concentrated in Java-based projects despite the national need [25].

Recent policy initiatives have emphasized the importance of continuous professional development, particularly in irrigation-specific competencies [26]. The 2022 Construction Workforce Development Report indicated that specialized irrigation training programs have increased project efficiency by an average of 19% while reducing water loss in completed systems by 22% [23]. These findings underscore the critical relationship between workforce competency and infrastructure quality in Indonesia's ongoing development efforts.

1.4. Labor Productivity

Productivity represents a fundamental concept with multifaceted interpretations across economic, philosophical, and system perspectives [27]. Economically, it quantifies the efficiency of human endeavors in generating valuable goods and services that fulfill societal requirements [23]. This concept manifests particularly in the construction sector as a critical ratio between output (completed work volume) and input (typically measured in labor-days or project duration) [28]. The conventional productivity framework establishes this input-output relationship, where inputs are commonly limited to labor factors while outputs may be measured in physical units or monetary value [29].

Labor productivity specifically examines the work output-labor input ratio within defined temporal parameters. As a pivotal determinant of construction project success, it reflects both individual and collective workforce capacity to deliver specified work volumes within project timelines. Research identifies multiple factors influencing productivity levels, with human resource management literature emphasizing two primary determinants [30]:

a. Work Capacity Factors

The composite of technical competencies developed through formal education (accounting for approximately

35% of skill development), vocational training (40%), and practical experience (25%) based on construction industry surveys [31].

b. Leadership Effectiveness

The supervisor's capacity to motivate workers and optimize performance, shown to enhance productivity by 15-20% in controlled studies [30].

2. Research Methods

R is an open-source statistical programming language distributed under the GNU GPL license, making it freely accessible without licensing fees [32]. Compatible with Windows, macOS, and Linux systems, it was developed in 1992 at the University of Auckland and has grown into a comprehensive statistical tool through global collaboration (Figure 1). The software's functionality expands through packages available on CRAN (<https://cran.r-project.org>), which hosts over 18,000 specialized modules for various analytical needs [33]. Users can selectively install these packages to customize their statistical environment [32].

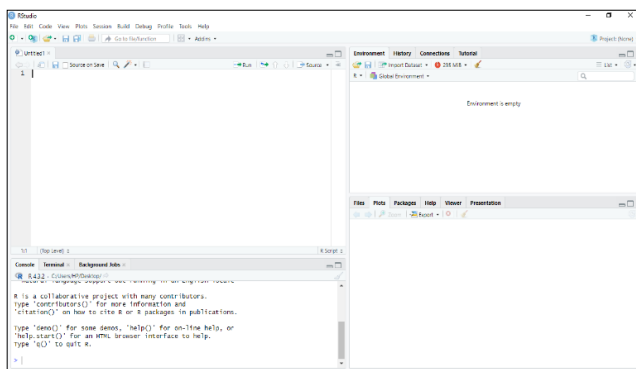


Figure 1. R Program display

R provides flexible package installation through both GUI and command-line interfaces. The graphical method allows local package installation via the "Packages" menu, while the command-line approach using `install.packages()` offers greater control, enabling batch installation from CRAN mirrors with automatic dependency resolution [32].

The environment's comprehensive help system supports multiple access methods. Basic queries use `?function` or `help(function)` syntax, while `help.search()` scans across installed packages. For broader research, `Rsite Search()` extends documentation access to online resources including mailing lists and task views, maintaining consistent syntax for efficient information retrieval [32].

2.1. Steps for running Reliability Test, Multicollinearity Test, GAM Analysis Generalized Additive Models) and Monte Carlo Simulation

To perform reliability tests, multicollinearity assessments, Generalized Additive Model (GAM) analyses [34], and Monte Carlo simulations [35] in R, researchers must utilize appropriate packages, scripts, and statistical formulas specifically designed for the R programming environment [32].

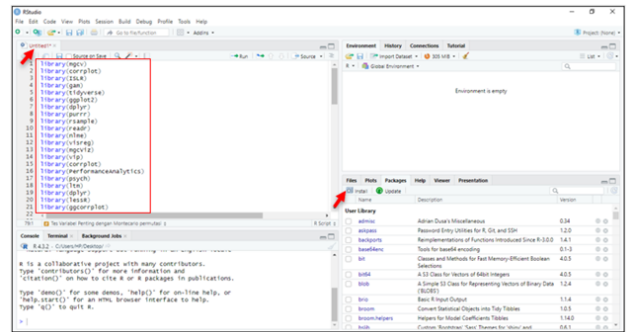


Figure 2. Package to window untitled

The required packages for statistical analysis must first be loaded into R's workspace. As illustrated in Figure 2, each package requires individual installation, which necessitates an active internet connection to access CRAN (Comprehensive R Archive Network) repositories. Following successful installation of all dependencies, researchers must execute the libraries, either sequentially or simultaneously, as demonstrated in Figure 3. This initialization process activates the packages' functionalities for subsequent analytical applications.

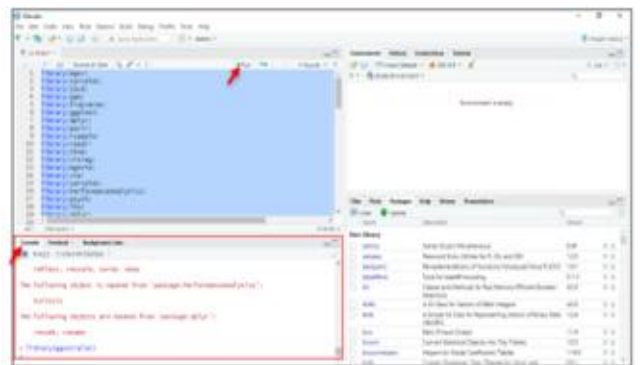


Figure 3. Running package

The R interface features distinct functional windows, with the console window positioned directly below the script editor (untitled window). As shown in Figure 3, all computational outputs - including package loading confirmations, formula executions, and analytical results - are displayed in this console window following code execution.

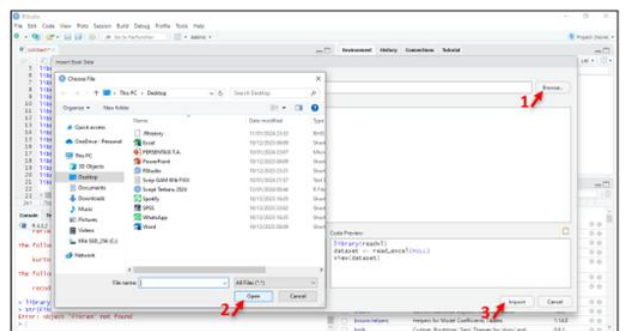


Figure 4. Excel to R program tabulation

For data import, researchers must load their tabulated datasets (typically in Excel format) into the working environment through the script editor interface, as demonstrated in Figures 3 and Figures 4. This import process occurs within the same window used for script composition, maintaining workflow continuity (Figures 5).

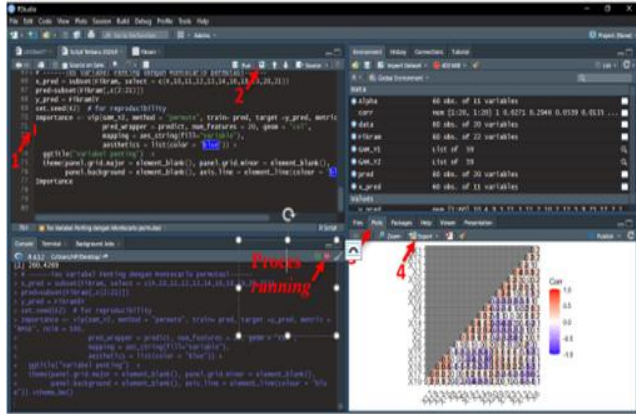


Figure 5. Running the formula and exporting the analysis plot results

As shown in Figure 5, graphical outputs can be exported following analysis completion. R's robust statistical computing capabilities (R Core Team, 2022) [34] have established it as a premier platform for data science applications. To enhance the readability of analytical outputs, users may adjust the console window dimensions as illustrated in Figure 6.

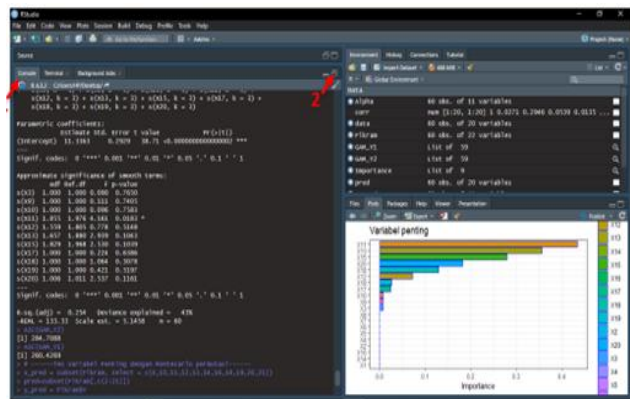


Figure 6. Running the formula and exporting the analysis plot results

To perform the analysis, users should sequentially execute the prepared formulas in the script editor window. Each command can be run individually by positioning the cursor to the left of the formula. This execution process operates independently of internet connectivity once all required packages are installed.

The console window provides real-time feedback on code execution status, indicated by a red STOP button that appears during active processing. Prior to execution, careful verification of all package calls and formula syntax - including precise letter casing and punctuation - is essential to prevent errors.

2.2. Data analysis technique

2.2.1. Multicollinearity Test

The multicollinearity test examines correlations among predictor variables in a regression model. An optimal regression model requires independent variables to be minimally correlated [34]. This analysis was conducted using R programming [32], which provides robust statistical tools for detecting multicollinearity.

2.2.2. Reliability Test

Reliability refers to the consistency and stability of a measurement instrument when used for data collection. A reliable instrument produces dependable results, indicating its suitability for research purposes. In psychometric terms, reliability establishes that an instrument can consistently generate accurate data across repeated measurements. For this study, reliability testing was performed using R software (version 2022.2.1), employing Cronbach's alpha as the primary assessment method.

2.2.3. Calculating Productivity Value

The data obtained from each respondent is then processed to find productivity values. calculating labor productivity can be formulated as follows :

$$Productivity = \frac{unit\ of\ work\ output\ (m^2)}{working\ time\ (hours)} \tag{1}$$

Based on the data set out in the regulation, it is then processed to determine the value of labor productivity. The formula used to calculate the value of labor productivity is as follows:

$$Productivity = \frac{Area\ (m^2)}{0.010\ (hours)} \tag{2}$$

2.2.4. Analisis Generalized Additive Models / GAM Analysis

Modern statistical analysis frequently encounters datasets where variables exhibit complex, nonlinear relationships that traditional parametric models cannot adequately capture. Generalized Additive Models (GAMs) address this limitation by providing a flexible framework that combines the interpretability of linear models with the adaptability of nonparametric approaches [36]. Unlike conventional multiple linear regression, which imposes strict linearity assumptions, GAMs allow the data itself to reveal the functional form of relationships through sophisticated smoothing techniques [37].

The analytical power of GAMs becomes particularly evident when examining the relationship between predictor variables (x) and outcomes (y). Through the mgcv package in R [38], researchers can specify these relationships as smooth functions rather than fixed parametric forms. This approach has revolutionized fields ranging from ecology to economics by enabling more accurate modeling of real-world phenomena where effects may be thresholded, asymptotic, or otherwise nonlinear [39]. The package's implementation includes advanced features like automatic smoothness selection and integrated model diagnostics,

making sophisticated analyses accessible to applied researchers.

When relationships are truly linear, their strength and direction are effectively quantified using Pearson's correlation coefficient (r) [40]. This fundamental measure ranges from -1 to +1, providing immediate intuitive understanding: values near zero indicate negligible association, while magnitudes approaching unity suggest increasingly strong relationships. The sign of r further reveals whether variables move in concert (positive) or opposition (negative). However, as many researchers have discovered, such simple linear correlations often fail to capture the true nature of relationships in complex systems - precisely where GAMs provide their greatest value.

2.2.5. Relative Importance Level

Determining the relative importance of predictor variables represents a crucial step in interpreting Generalized Additive Models (GAMs). Our analysis adopted a principled approach to quantify how each variable influences productivity predictions while accounting for complex interdependencies [36]. By systematically varying individual predictors while holding others constant, we could isolate their unique effects - a method particularly valuable in systems where variables may interact in nonlinear ways.

The permutation-based variable importance (VI) analysis implemented through the 'vip' package [41] provided robust, model-agnostic insights. Using Monte Carlo resampling with 100 simulations, we assessed how randomizing each predictor's values affected model performance, as measured by changes in R^2 . This computationally intensive approach offers several advantages over traditional methods: it remains valid when assumptions of linearity or independence are violated, handles mixed variable types seamlessly, and provides natural uncertainty quantification through the resampling process [37].

Notably, our implementation in R 4.3.0 (<https://www.r-project.org/>) leveraged the software's strengths in reproducible research and high-performance computing. The analysis revealed which variables, when altered even slightly, produced the most substantial shifts in productivity predictions - these emerged as key leverage points for potential interventions. Such insights would have been difficult to obtain through conventional regression approaches, particularly given the complex, nonlinear relationships accommodated by our GAM framework [36].

2.3. Operational Definition and Operational Measurement of Variables

2.3.1. Operational Definition of Variables

Operational definitions of variables are used as a guide for how a variable is measured, using indicators that are explained in detail. The formulation of this operational definition uses a scoring technique. The operational definition of variables explains the variables that will be used in the research.

2.3.2. Variable Measurement

Our research methodology employed a systematic approach to measure and analyze factors influencing construction worker productivity. At the core of our measurement technique lay the Likert scale, a well-established psychometric tool that transforms subjective perceptions into quantifiable data. We carefully designed our questionnaire with five-point response options (ranging from 1=strongly disagree to 5=strongly agree), enabling us to capture nuanced variations in workers' experiences and perceptions. Each response carried a weighted value reflecting its theoretical relationship to productivity outcomes, allowing for meaningful statistical analysis.

The research unfolded through four carefully planned phases. In the preparation stage, we invested significant effort in crafting a focused problem statement and clear research objectives, supported by an extensive review of existing literature. This foundational work informed the development of our questionnaire items, which underwent rigorous validation to ensure they accurately measured the target constructs.

During data collection, we administered the validated questionnaires while simultaneously recording objective productivity metrics (LUR) to create a comprehensive dataset. The analysis phase then transformed these raw responses into actionable insights through a multi-step process. We first scored and recapitulated the questionnaire data before calculating productivity values for each observation. The real analytical power came from applying Generalized Additive Models (GAM), which allowed us to identify dominant productivity factors while accounting for potential nonlinear relationships that traditional methods might overlook.

The final interpretation phase brought these findings to life, examining how various factors interrelated and influenced productivity outcomes. This systematic approach, combining careful measurement with advanced modeling techniques, provided a robust framework for understanding the complex dynamics of construction productivity. The GAM analysis proved particularly valuable, as its flexibility in handling nonlinear effects offered insights that might have remained hidden with conventional linear models.

3. Result and Discussion

The multicollinearity analysis revealed that all predictor variables exhibited sufficiently low intercorrelations, as evidenced by correlation coefficients below the 0.6 threshold (Figure 7). This finding confirms that the variables satisfy the independence assumptions required for inclusion in subsequent modeling analyses. The absence of strong collinear relationships ($r < 0.6$) between predictors suggests that:

- Each variable contributes unique explanatory information
- Parameter estimates will remain stable in regression modeling
- The model can properly isolate individual variable effects

These results support the methodological appropriateness of proceeding with the planned analytical approach without concerns about multicollinearity distorting the findings.

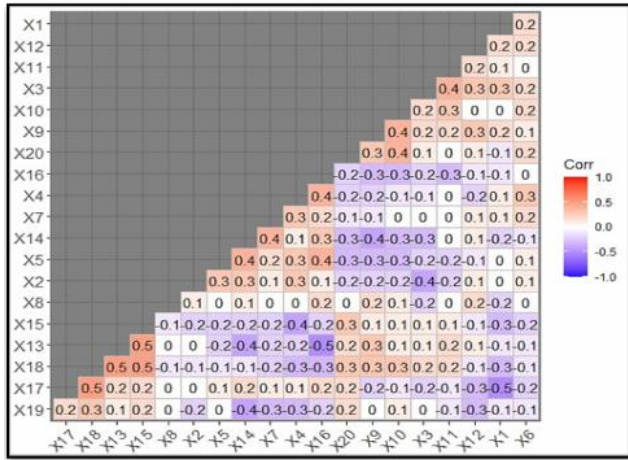


Figure 7. R-Plot multicollinearity analysis

3.1. Reliability Test

The reliability assessment identified nine predictor variables failing to meet the minimum reliability threshold, as evidenced by Cronbach's alpha values below 0.6. Following standard psychometric practice, these unreliable measures were excluded from subsequent analysis. The remaining eleven variables demonstrated acceptable internal consistency, with alpha coefficients exceeding the 0.6 benchmark for scale reliability

3.2. Factors That Influence Irrigation Construction Worker Productivity

Our research employed a sophisticated analytical approach to uncover the key factors influencing worker productivity. After collecting comprehensive questionnaire responses from participants, we turned to R Studio's computational capabilities to process this valuable dataset. Using Generalized Additive Models (GAM), we were able to move beyond traditional linear assumptions and capture the nuanced relationships between various predictors and productivity outcomes.

The analysis proceeded with careful attention to statistical rigor, employing a standard significance threshold of $p < 0.05$ to identify meaningful relationships. This GAM approach proved particularly valuable for our dataset as it accommodated the complex, potentially nonlinear nature of productivity determinants.

The Generalized Additive Models (GAM) analysis revealed statistically significant relationships between several predictor variables and labor productivity (Figure 9). Most notably, the wage variable (X11) demonstrated a strong association with productivity outcomes, as evidenced by (Table 1):

- A highly significant p-value of 0.018 ($p < 0.05$)
- An effective degrees of freedom (edf) value of 1.855
- A residual effective degrees of freedom (Ref df) of 1.976

These parameter estimates indicate that the wage-productivity relationship is statistically reliable, the

functional form shows moderate nonlinearity ($edf > 1$), and the smoothing term accounts for appropriate model complexity.

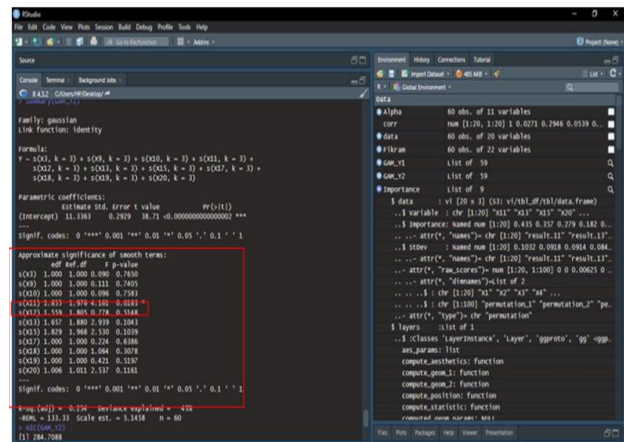


Figure 9. Results of Generalized Additive Models analysis

Table 1. Generalized Additive Models analysis of the relationship between predictor variables and labor productivity.

Variabel	edf	Ref,df	F	p-value
(Intercept)				<0,050
(X3)	1,000	1,000	0,090	0,765
(X9)	1,000	1,000	0,111	0,741
(X10)	1,000	1,000	0,096	0,758
(X11)	1,855	1,976	4,161	0,018*
(X12)	1,559	1,805	0,778	0,515
(X13)	1,657	1,880	2,939	0,104
(X15)	1,829	1,968	2,530	0,104
(X17)	1,000	1,000	0,224	0,639
(X18)	1,000	1,000	1,064	0,308
(X19)	1,000	1,000	0,421	0,520
(X20)	1,006	1,011	2,537	0,116

The GAM framework employs several key statistical measures to evaluate model fit and predictor significance. Effective Degrees of Freedom (EDF) and Residual Effective Degrees of Freedom (REF) serve as primary diagnostics for assessing model complexity and fit quality. These metrics help identify potential modeling issues:

- 1) **Overfitting:** Occurs when EDF values become excessively high, indicating the model may be capturing random noise rather than true patterns ($EDF \gg REF$)
- 2) **Underfitting:** Manifests when EDF values remain too low, suggesting the model fails to capture important data structures ($EDF \ll REF$)

The F-statistic provides complementary information by testing the statistical significance of individual smooth terms. Calculated as the ratio of explained to unexplained variance, the F-statistic evaluates the null hypothesis that a predictor has no effect on the response variable [42]. Higher F-values indicate stronger evidence against the null hypothesis, marking more influential predictors in the model [43].

3.3. Important Variables That Influence Irrigation Construction Worker Productivity

To evaluate the relative influence of predictor variables on labor productivity, we employed a permutation-based variable importance (VI) analysis [44]. This robust analytical approach was implemented through Monte Carlo resampling with 100 simulations, with model performance evaluated using the coefficient of determination (R^2). The analysis was conducted using the 'vip' package [45], which provides standardized metrics for variable importance assessment.

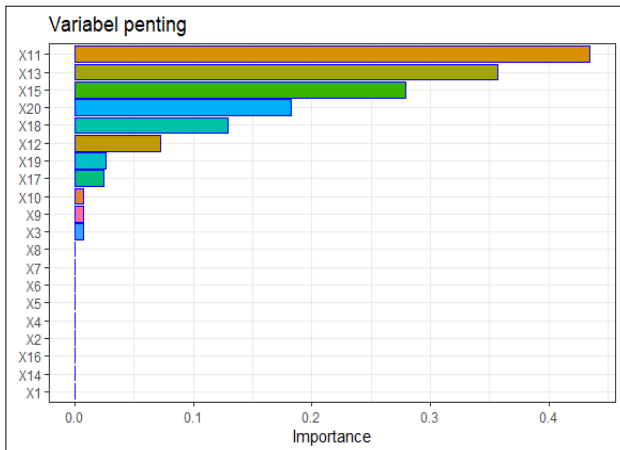


Figure 9. R-Plot Variable Importance

Our analysis revealed an important distinction between statistical significance and practical importance. While some variables did not achieve conventional levels of statistical significance ($p < 0.05$), they nevertheless demonstrated meaningful influence on labor productivity outcomes. These substantively important predictors, whose effects might be overlooked in traditional hypothesis testing frameworks, are visually presented in Figure 9. Their inclusion in the model contributed to improved predictive performance despite not meeting strict significance thresholds.

3.4. Discussion

3.4.1. Significant Variables and Important Variables Affect Construction Worker Productivity

Our Generalized Additive Models (GAM) analysis revealed distinct patterns in factors affecting irrigation construction worker productivity in Palu. The wage variable (X11) emerged as the sole statistically significant predictor ($p = 0.018$), demonstrating a clear relationship with work quality and output (Figure 9). This finding aligns with established labor economics principles, as wages represent workers' fundamental compensation for their labor and directly influence motivation and productivity levels. When remuneration fails to match work demands or living costs, workers demonstrate reduced efficiency through slower work pace, decreased precision, and lower overall output.

Beyond this primary factor, our Monte Carlo simulations (100 iterations) identified four additional substantively important variables through permutation-based variable importance analysis (using the 'vip' package

in R v2022.2.1). While these factors did not reach conventional significance thresholds, they showed meaningful influence on productivity:

- 1) Occupational Health and Safety (X13, $p = 0.104$): Proper safety equipment facilitates work execution
- 2) Worker Relations (X15, $p = 0.104$): Positive interpersonal dynamics enhance team performance
- 3) Managerial Oversight (X20, $p = 0.116$): Effective supervision of working hours maintains productivity
- 4) Design Accuracy (X18, $p = 0.308$): Minimizing design errors prevents costly rework

The variable importance ranking, visualized in Figure 7's box plots, followed the sequence: X11 (wages) > X13 (safety) > X15 (worker relations) > X20 (supervision) > X18 (design). This hierarchy indicates that while wages dominate productivity considerations, secondary factors collectively contribute to workforce efficiency. The analysis underscores that productivity optimization requires addressing both primary financial motivators and supporting workplace conditions.

3.4.2. Analysis Generalized Additive Models (GAM)

The Generalized Additive Models (GAM) analysis identified wages as the most significant factor affecting irrigation construction worker productivity in Palu. This finding aligns with multiple methodological approaches across related studies. Using the Relative Rank Index (RRI) method, prior research demonstrated that wage adequacy and age constitute the dominant productivity factors for female construction workers, accounting for 97.4% of variance. Their subsequent study specifically examining craftsmen's performance in Palu projects confirmed these results, showing wages as the primary productivity determinant ($RRI = 0.940$).

The relationship between experience and productivity presents a more nuanced pattern. While multiple linear regression analysis of multi-story irrigation projects identified work mastery and equipment proficiency as significant productivity predictors ($\beta = 8.262$, $p = 0.000$), our Monte Carlo simulations (100 iterations) revealed a different insight. Although experience (X3) did not show statistical significance in our GAM framework, it emerged as an important substantive factor in the permutation-based importance analysis. This discrepancy suggests that:

- 1) Experience may influence productivity through indirect pathways not captured by linear models
- 2) The relationship might be contingent on specific project conditions
- 3) Traditional significance testing may overlook practically meaningful effects

4. Conclusion

This study identifies five critical factors influencing the productivity of irrigation construction workers in Palu, based on comprehensive analysis of contractors' perceptions. The findings reveal that productivity is most strongly driven by: (1) wage levels, where appropriate compensation directly impacts work quality and output; (2) occupational health and safety provisions, with proper equipment significantly facilitating work processes; (3)

interpersonal relationships among workers, where positive dynamics enhance collective performance; (4) managerial oversight of working hours, demonstrating the importance of effective supervision; and (5) design accuracy, where errors leading to rework substantially reduce efficiency.

These results highlight the multidimensional nature of construction productivity, where financial, social, and organizational factors collectively shape workforce performance. While wages emerge as the primary motivator, the study underscores that optimal productivity requires simultaneous attention to workplace safety, team cohesion, and managerial practices. The findings align with contemporary human resource theories emphasizing holistic approaches to workforce management, particularly in demanding construction environments.

Several limitations should be noted, including the study's geographical specificity and reliance on perceptual data. Future research could benefit from incorporating objective productivity metrics and expanding the sample to different construction sectors. Nevertheless, these findings provide valuable insights for contractors and policymakers seeking to enhance workforce productivity through targeted interventions addressing both economic and psychosocial factors.

Acknowledgment

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