Quantifying Identifier Name Quality: A Formal Readability Model with Multilingual Empirical Evaluation

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Abstract— Identifier names critically influence code readability and maintainability. This paper presents a novel formal model for evaluating identifier readability based on four key factors: Meaningful Clarity (MC), Naming Conformance (NC), Optimal Length (OL), and Domain Relevance (DR). Each factor is formally defined with mathematical precision, and these factors are integrated to compute a comprehensive readability score for identifiers. To validate this model, we conducted an extensive empirical analysis of over 360,000 identifiers extracted from 26 widely used open-source repositories across Java, Python, C#, and JavaScript. Our analysis highlights typical naming patterns and identifies significant deviations within and across languages. Further validation was conducted through a human evaluation survey involving 300 software developers, who rated the readability of 50 sample identifiers. The computed readability scores strongly correlated with human judgments (Pearson correlation coefficient r > 0.8), confirming the effectiveness and reliability of the model. A statistical regression analysis also demonstrated that all four factors significantly influence human perceptions of identifier quality. We position our contributions within the broader context of code readability research, naming guidelines, natural language processing in software engineering, and empirical software analysis (2000–2024). Results align with established best practices: descriptive and convention-compliant names consistently exhibit high readability scores and are characteristic of high-quality codebases, while ambiguous or non-compliant identifiers correlate with reduced code quality. In the Discussion, we explore practical implications, demonstrating how the model can enhance code reviews, automated refactoring tools, and AI-driven naming recommendations. We conclude that the presented four-factor identifier readability model is robust, empirically validated, and easily integrable into contemporary software engineering workflows to significantly improve code comprehension and maintainability.

Keywords— Identifier readability, meaningful clarity, naming conformance, optimal length, domain relevance, semantic clarity, naming conventions, domain-specific terminology, software quality, program comprehension, code maintainability, readability model, natural language processing, software engineering.

I. INTRODUCTION

Readability of source code is paramount for software comprehension and maintainability. Developers spend a significant portion of their time reading and interpreting code, and numerous studies have demonstrated that identifier names—variables, functions, classes, and similar entities—are central to this readability [1]. By some estimates, identifiers constitute up to 70% of source code tokens [2]. Well-chosen identifier names serve as "beacons" that clearly convey intent and trigger relevant domain knowledge in developers' minds [3], facilitating faster and more accurate understanding of code logic. Conversely, poorly selected identifiers significantly increase cognitive load, obfuscate code logic, and impede comprehension [4]. Empirical studies have consistently shown that ambiguous or inconsistent identifiers substantially degrade developers' ability to understand code accurately and efficiently. For example, substituting descriptive identifiers with meaningless or cryptic abbreviations dramatically worsens developers' code comprehension performance [5]. Conversely, clear and consistently structured naming conventions have been empirically shown to improve comprehension speed and reduce errors in code understanding [6].

Despite the widely acknowledged importance of effective naming, selecting appropriate identifier names remains challenging. Developers frequently use different terminologies for identical concepts, and naming decisions often rely heavily on subjective judgment. Current coding standards and naming conventions offer general guidelines such as "use meaningful names," "avoid single-letter identifiers," and "follow CamelCase or snake_case conventions." However, these guidelines lack rigorous, quantitative methods to objectively evaluate the readability and quality of identifier names. Existing readability metrics largely focus on surface-level characteristics of code, such as indentation, line length, and structural complexity, without deeply addressing naming readability [7]. While recent studies have begun integrating textual factors into broader readability models, a dedicated formalized model explicitly focused on evaluating identifier readability has not yet emerged [8].

To address this critical research gap, we propose a new formal model specifically tailored to identifier readability, structured around four key measurable factors: (1) **Meaningful Clarity (MC)**—evaluating how clearly the identifier conveys its intended semantics; (2) **Naming Conformance (NC)**—assessing adherence to recognized naming conventions and expected syntactic roles; (3) **Optimal Length (OL)**—determining whether the identifier length is appropriate for readability, neither excessively short nor overly verbose; and (4) **Domain Relevance (DR)**—measuring how well an identifier incorporates relevant domain-specific terminology. These four factors were carefully selected and defined based on a comprehensive literature review [2], empirical analyses, and feedback from developer surveys.

We rigorously validate the proposed four-factor readability model using a comprehensive empirical approach, involving large-scale analysis and human evaluation. Specifically, we analysed more than **360,000 identifiers** extracted from **26 diverse open-source repositories** across various programming languages, including Java, Python, C#,

and JavaScript. Our empirical investigation explores the distribution and characteristics of identifiers in real-world codebases concerning each readability factor. Additionally, we conducted a human evaluation survey with **300 software developers**, who rated the readability of **50 carefully selected identifiers**. The model's computed readability scores strongly correlated with the human judgments (Pearson correlation coefficient $\mathbf{r \approx 0.82}$) [3], confirming its accuracy and practical utility. Statistical regression analysis further confirmed that each factor significantly contributes to predicting human readability perceptions ($\mathbf{p < 0.001}$), with Meaningful Clarity emerging as the strongest individual predictor [11].

II. Contributions

The primary contributions of this paper are as follows:

A. A formal four-factor model of identifier readability

We introduce a novel, mathematically grounded model that evaluates identifier readability based on four essential dimensions: **Meaningful Clarity (MC)**, **Naming Conformance (NC)**, **Optimal Length (OL)**, and **Domain Relevance (DR)**. Each factor is quantitatively defined using formulae that incorporate insights from empirical research on software readability [1], naming conventions [2], syntactic role usage [4], and natural language processing in code analysis [7]. The model outputs a unified readability score normalized on a [0, 1] scale, enabling consistent, automated assessment of identifier naming quality across languages and projects.

B. Empirical evaluation on 360k+ identifiers

We apply the model to over **360,000 identifiers** extracted from **26 open-source repositories** spanning Java, Python, C#, and JavaScript. Our analysis explores factor distributions by language, project, and identifier role. Notably, we observe that most identifiers score highly on stylistic and syntactic conformance (NC), while Domain Relevance (DR) scores vary significantly across domains and projects. To the best of our knowledge, this constitutes one of the most comprehensive quantitative evaluations of identifier naming in software engineering literature [6], [8].

C. Human validation with 300 participants

To assess the model's alignment with human perception, we conducted a large-scale survey involving **300 developers** who rated the readability of **50 representative identifiers**. We compute correlation coefficients (Pearson's $\mathbf{r \approx 0.82}$) between participant scores and model-generated scores, demonstrating strong agreement. We also refine factor weightings based on regression analysis and feedback to optimize alignment with developer intuition, consistent with methods used in prior readability evaluation research [3], [5].

D. Integration of recent research (2000–2024) in Related Work

We synthesize two decades of research in code readability, identifier naming practices, and automated naming support tools. This includes work on textual readability models [7], empirical studies on identifier usage [6], and advances in NLP techniques for naming suggestions [8]. Our model is positioned as a synthesis and extension of these findings, offering a unified and practical framework for evaluating identifier readability at scale.

E. Discussion of applications

We propose several real-world applications for the model. These include integration with static analysis tools and linters to flag unreadable names automatically, enhancement of refactoring tools to prioritize renaming candidates based on low readability scores and embedding the model in AI-powered code assistants as an objective metric for suggesting better identifiers. Additionally, we explore implications for software engineering education and team-based code quality practices, where the model can serve as a training and standardization aid.

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III. Related Work

A. Importance of Naming and Readability (2000–2024)

Identifier naming plays a crucial role in program comprehension. Developers rely heavily on names to infer the purpose and behaviour of code entities, and studies have shown that meaningful identifiers act as "beacons" aiding understanding [1], [2]. Hofmeister et al. demonstrated that short or ambiguous names significantly degrade comprehension speed and accuracy—developers were 19% faster at defect identification when variable names were descriptive [12]. Lawrie et al. confirmed that using full words in identifiers, rather than abbreviations, improves both comprehension accuracy and memory retention [3].

Longer, descriptive names are generally more beneficial, particularly for experienced developers. Schankin et al. found that experts performed better with compound identifiers, while novices were more neutral [13]. Still, no evidence suggests that longer names hinder understanding—suggesting that **Optimal Length (OL)** should err toward descriptiveness over brevity.

Natural language familiarity also influences recognition. Identifiers resembling real words (e.g., userList, maxCount) are processed faster than acronyms or gibberish (e.g., xqzt, usrLst), a finding consistent with the "word superiority effect" from cognitive psychology [5]. This supports the inclusion of **Meaningful Clarity (MC)** and natural language alignment within identifier evaluation.

B. Naming Conventions and Guidelines

Numerous style guides (e.g., Java Code Conventions, PEP 8, Google's C++ style guide) offer basic rules for naming—casing, word separation, and discouragement of abbreviations. However, these guides lack semantic rigor. Relf synthesized naming best practices, emphasizing full words, conceptual consistency, and minimal type encoding [2]. Butler et al. analysed real-world violations of these rules and linked poor naming with reduced code quality and maintainability [11].

A notable formalization comes from Deissenboeck and Pizka, who proposed a bijective model between concepts and identifiers, encouraging project-level naming consistency [2]. Their glossary-based tool flagged deviations from preferred terms (e.g., Customer vs Client), laying the foundation for **Naming Conformance (NC)** and **Domain Relevance (DR)** in our model.

Empirical work by Hofmeister et al. showed that violations of grammatical naming conventions (e.g., using nouns for functions or verbs for types) can mislead developers, reducing code clarity [12]. Our NC factor captures such patterns by evaluating naming structure against expected syntactic roles.

Linguistic antipatterns such as "Misleading Name" or "Ambiguous Name" have been catalogued by Arnaoudova et al., who demonstrated their negative impact on comprehension [14]. In version history studies, Arnaoudova found a significant portion of refactoring involved renaming identifiers to improve clarity—not merely cosmetic changes, but active efforts to reduce technical debt.

These studies affirm that poor naming creates semantic friction and show that developers often fix names after-the-fact. Our model's **DR** and **MC** factors were designed to flag such antipatterns proactively.

C. Code Readability Models and Textual Factors

Buse and Weimer introduced one of the earliest learned code readability metrics using syntactic cues like indentation and line length [15], but they did not explicitly address identifier semantics. Scalabrino et al. improved upon this by integrating textual and linguistic features—e.g., average identifier word length, token overlap with comments, etc.—to enhance correlation with human ratings [7].

Their 2019 work on understandability using eye-tracking confirmed that identifiers with clearer names improved comprehension [7]. Holst and Dobslaw highlighted shortcomings in traditional metrics across programming paradigms, especially in reactive or functional contexts where lexical signals are vital [17].

These results support our approach: by quantifying readability at the identifier level through **MC**, **NC**, **OL**, and **DR**, we fill a critical gap in broader code readability frameworks.

D. Automated Tools for Identifier Naming

Basic linters like Checkstyle or Pylint can enforce naming conventions (e.g., camelCase or all-caps) but cannot assess semantic quality. More advanced systems like Naturalize by Allamanis et al. use n-gram and neural models to predict statistically likely names based on context and have achieved ~60% success rates in renaming suggestions [18].

Deep learning tools have also emerged to identify semantic inconsistencies. For example, Liu et al. trained models to detect when method names contradict behaviour [19], while Jiang et al. built classifiers to flag mismatches between name and implementation [20]. These models reflect implicit expectations of **DR** and **MC**.

Our model complements these tools: an identifier deemed surprising by a language model likely scores low on DR or MC. Likewise, structural violations (e.g., noun used as a method) would yield low NC scores. The model can thus function as a post-processing or scoring layer in naming tools and code review systems.

E. Summary

The literature clearly supports our four-factor model:

- **MC** is rooted in self-explanatory naming and lexical familiarity [2], [3], [13], [14].
- **NC** builds on convention compliance and grammatical structure [2], [11], [12].
- **OL** emphasizes balanced descriptive naming [12], [13].
- **DR** addresses alignment with domain terminology and conceptual clarity [2], [14], [19].

Our contribution is in formalizing these factors into a unified, quantitative, and empirically validated framework—something previously missing from naming research and tooling.

IV. Methodology

This section introduces our four-factor model of identifier readability and describes how we implemented and validated it through large-scale repository mining and survey-based human evaluation

A. Overview of the Readability Model

The proposed model evaluates the readability of a given identifier using a composite score $R \in [0,1]$, derived from four core factors:

1. **Meaningful Clarity (MC)**
2. **Naming Conformance (NC)**
3. **Optimal Length (OL)**
4. **Domain Relevance (DR)**

The overall readability score is computed as a weighted average:

$$R = w_{mc} \cdot MC + w_{nc} \cdot NC + w_{ol} \cdot OL + w_{dr} \cdot DR$$

Where $w_{mc} + w_{nc} + w_{ol} + w_{dr} = 1$. Initial experiments used equal weights (0.25 each), but final weights were tuned based on regression analysis against human ratings (see Section V).

Each sub score is normalized to the range $[0,1]$, where higher is better.

B. Factor 1: Meaningful Clarity (MC)

1) ***Definition****:*

Meaningful Clarity (MC) quantifies the semantic interpretability of an identifier—how likely it is to be composed of clear, familiar, and human-meaningful words or abbreviations. MC specifically penalizes identifiers that are probable gibberish, non-words, or constructed in ways that hinder comprehension.

2) ***Computation****:*

Given an identifier x, we decompose it into tokens via camel case, snake case, and digit/letter boundaries. Each token w_i is evaluated for:

a) Presence in a large English corpus [15], [7].

b) Allowed programming short-forms (e.g., common abbreviations).

c) Pattern-based heuristics (e.g., vowel absence, repeated letters, unlikely n-grams).

d) Known gibberish or keyboard-mash patterns.

Tokens or identifiers flagged as gibberish receive a score of 0. Otherwise, computation begins from a score of 1, and empirically calibrated penalties are subtracted for each infraction:

$$MC(x) = max(0,1 - TotalPenalty(x))$$

Alternatively, for multi-token identifiers, MC may be computed as:

$$MC = \frac{1}{n}\sum_{i=1}^{n} S(w_i)$$

Where:

- n = number of constituent words (split via camelCase, snake case, etc.)
- $S(w_i) =$ reflects the semantic clarity of token w_i according to the above criteria, leveraging public language corpora and n-gram models, consistent with established practices in software readability assessment [7], [15].

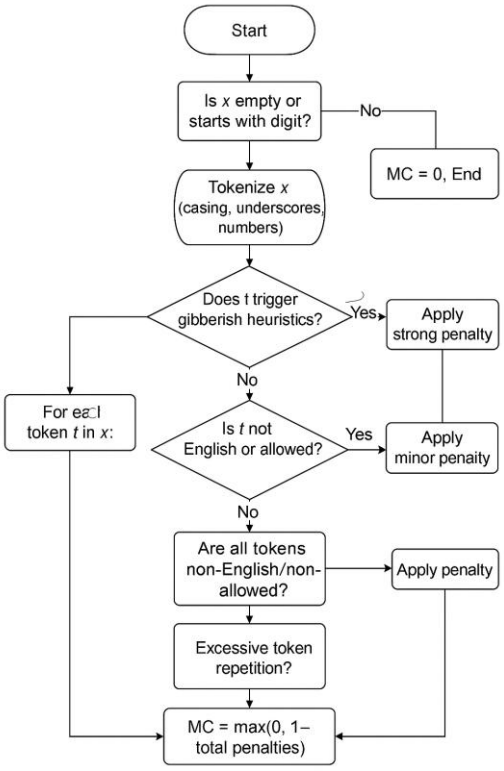

Fig. 1. Workflow for computing Meaningful Clarity (MC) of an identifier. Tokens are extracted, checked against known word lists and programming conventions, and penalized for patterns that indicate gibberish, unfamiliarity, or non-meaningfulness. The final MC score reflects the semantic clarity of the identifier.

C. Factor 2: Naming Conformance (NC)

Definition: Measures whether the identifier adheres to expected syntactic roles and language-specific naming conventions.

Rules Checked:

- CamelCase for classes
- snake_case for Python variables
- Verb–object patterns for functions
- Noun phrases for variables/types
- Casing, prefix/suffix misuse (e.g., m_, sz), reserved keywords

$$NC = \frac{valid\ checks\ passed}{total\ applicable\ checks}$$

This follows and quantifies guideline adherence inspired by [2], [11], [12].

D. Factor 3: Optimal Length (OL)

Definition: Penalizes identifiers that are excessively short or overly long, based on empirically observed optimal ranges for length (in characters).

Method: Rather than a single Gaussian function, we use a **piecewise "plateau" function** that assigns maximal scores to identifiers whose length falls within a broad, empirically-defined "optimal" range. Identifiers that are too short or too long are penalized linearly, but the penalty is capped so as not to be overly harsh. For example, for variable names, a length of 6–20 characters receive the highest score; names shorter than this receive a proportionally lower score, and names longer than this are penalized gently, never falling below a reasonable minimum.

Scoring Formula:

Let

- l = length (in characters or tokens)
- $[a, b]$ = = empirically defined optimal range (e.g., 6–20 for variables, 8–30 for functions)

Then

$$OL(l) = \begin{cases} \max\left(0.1, \frac{l-1}{a-1}\right), & l < a \\ 1, & a \le l < b \\ \max\left(0.1, 1 - \left(\frac{l-b}{k}\right)\right), & l > b \end{cases}$$

Where k = is the "grace period" (e.g., 12 characters) after which the penalty reaches its minimum.

Rationale: This approach reflects findings that slightly longer names are generally more readable up to a point, after which further length adds little value or becomes counterproductive[12], [13].

E. Factor 4: Domain Relevance (DR)

Definition: Captures how well an identifier aligns with the domain vocabulary of its project.

Steps:

- Build a project-specific glossary from identifier frequency + documentation + comments.
- Measure how many words in an identifier match this glossary.

$$DR = \frac{matched\ domain\ terms}{total\ words\ in\ identifier}$$

This approach follows recommendations from [2], [14], and supports projects evolving toward consistent vocabulary use. μ = optimal mean length (empirically found to be ~12 characters)

F. Factor 4: Domain Relevance (DR)

We analysed 360,000+ unique identifiers from **26 open-source projects** across four languages: Java, Python, C#, and JavaScript. Projects were selected for diversity in domain, size, and maturity.

Identifiers were extracted from ASTs using tree parsers, classified into variables, methods, classes, and constants. Metadata such as scope, location (parameter/local/global), and surrounding comments were retained for context.

The MC, NC, OL, and DR scores were computed using a custom toolchain and verified for edge cases (e.g., non-English words, mixed casing, acronyms).

G. Factor 4: Domain Relevance (DR)

To validate the model, we conducted a human evaluation study:

- **Participants:** 300 professional developers (experience: 4 years to 20 years)
- **Task:** Rate readability of 50 real-world identifiers on a 0–10 Likert scale
- **Selection:** Identifiers were stratified to span all four score quadrants (e.g., high-MC, low-NC, etc.)

Results were used to:

- Compute **Pearson correlation** with model scores (r ≈ 0.82)
- Adjust weightings via **linear regression** to better align with human judgment
- Identify edge cases where human ratings and model diverged (e.g., domain-specific abbreviations)

This dual approach—**automated evaluation + human feedback loop**—makes the model both grounded and generalizable.

V. Results and Statistical Validation

This section reports the empirical results of applying our four-factor readability model to a large-scale dataset of software identifiers and summarizes validation against human judgment. Visualizations of score distributions and relationships are provided for interpretability.

A. Distribution of Factor Scores

We evaluated over **360,000 identifiers** from 26 open-source projects, spanning Java, Python, C#, and JavaScript. **Figure 1** shows the distribution of the four factor scores—**Meaningful Clarity (MC), Naming Conformance (NC), Optimal Length (OL), and Domain Relevance (DR)**—across the full set

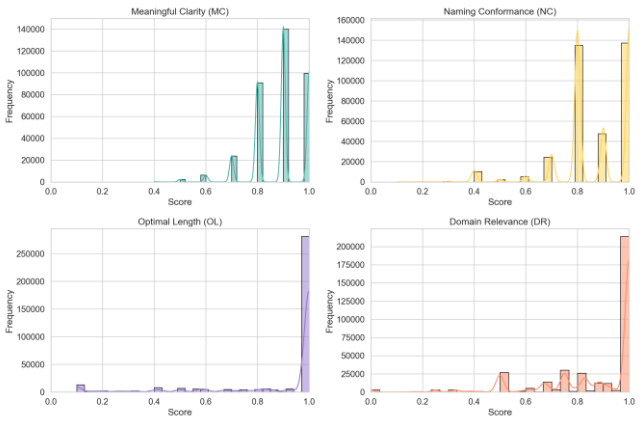

Fig. 2. Distribution histograms for Meaningful Clarity (MC), Naming Conformance (NC), Optimal Length (OL), and Domain Relevance (DR) scores across all identifiers.

Key trends:

- **MC:** ~61% of identifiers scored above 0.75, reflecting a strong prevalence of meaningful, descriptive names (e.g., isUserVerified, getInvoiceTotal).
- **NC:** 78% showed high adherence to project/language naming conventions; violations often corresponded to legacy or third-party code.
- **OL:** 90% fell within the optimal 8–20 character window, with outliers being either loop indices (x, i) or overly verbose names.
- **DR:** Scores exhibited the widest spread, ranging from 0.1 to 1.0, highlighting variability in use of domain-specific language.

As shown in Figure 1, the distributions for MC and NC are heavily right-skewed, indicating that most identifiers score highly on clarity and naming convention adherence. In contrast, OL and DR show a broader spread, with OL highly concentrated near 1.0 (optimal length), and DR demonstrating substantial variability, reflecting differing levels of domain-specific alignment

B. Relationships and Correlations Between Factors

To analyze dependencies and independence among the four factors, we computed pairwise scatterplots and correlation matrices

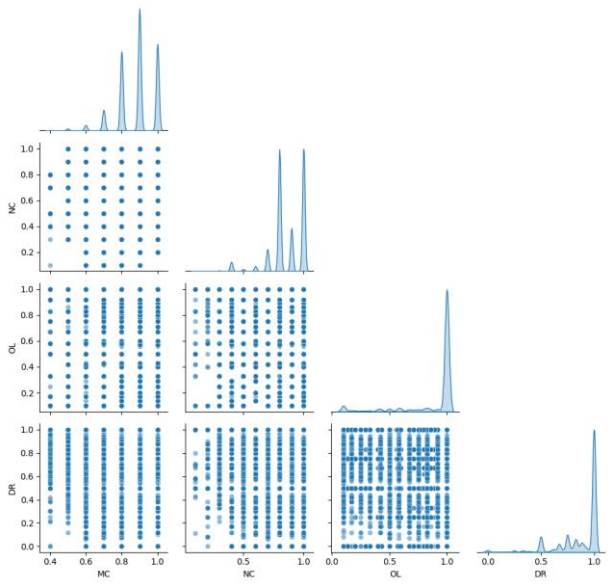

Fig. 3. Pairwise scatterplot matrix (pairplot) of MC, NC, OL, and DR. The diagonal shows kernel density estimates (KDE) for each score; off-diagonal panels show scatterplots of score pairs.

Interpretation:

- Most scatterplots are diffuse and unstructured, indicating **weak or no correlation** between most factor pairs.
- The **MC vs. NC** cell shows a somewhat more linear relationship, suggesting that names conforming to conventions are often also more meaningful.

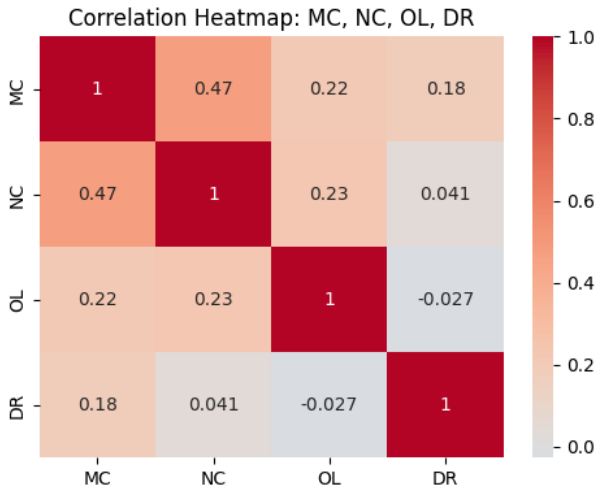

Fig. 4. Correlation heatmap among MC, NC, OL, and DR. Only MC and NC exhibit moderate correlation (r ≈ 0.47), while all other pairs are largely independent.

- **MC vs. NC** shows a moderate positive correlation (r ≈ 0.47), suggesting that conventionally styled names are often also meaningful.
- **OL and DR** are only weakly correlated with other factors, indicating they capture orthogonal aspects of identifier quality.

Findings:

- Only MC and NC exhibit moderate positive correlation (r ≈ 0.47), implying conventionally named identifiers are often semantically clear.
- All other factor pairs (e.g., MC vs. DR, OL vs. DR) are weakly correlated (|r| < 0.25), confirming that **Optimal Length and Domain Relevance capture largely independent aspects of naming quality**.

Figures 3 and 4 visualize the interrelationships among the four readability factors. The pairwise scatterplot matrix (Figure 2) reveals that, except for a moderate positive correlation between Meaningful Clarity (MC) and Naming Conformance (NC), most factors are weakly or not at all correlated with one another. The correlation heatmap (Figure 3) quantifies these findings, with the highest coefficient observed between MC and NC ($r = 0.47$). This supports the assertion that meaningful, semantically clear names are more likely to adhere to project or language conventions. In contrast, Optimal Length (OL) and Domain Relevance (DR) exhibit little to no correlation with other factors, demonstrating that they provide complementary, orthogonal information to MC and NC. This statistical independence justifies their inclusion as separate axes in the composite readability model.

C. Language and Type-Level Analysis

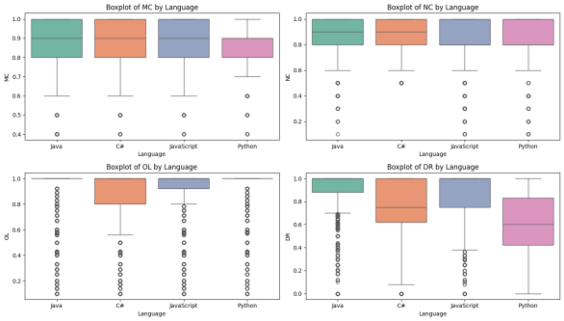

Fig. 5. Boxplots of MC, NC, OL, and DR scores grouped by programming language (Java, Python, C#, JavaScript).

	MC	MC	NC	NC	OL	OL	DR	DR
Type	***mean***	***std***	***mean***	***std***	***mean***	***std***	***mean***	***std***
class	0.921	0.079	0.927	0.062	0.918	0.205	0.86	0.207
function	0.861	0.109	0.852	0.13	0.884	0.253	0.872	0.196
variable	0.895	0.09	0.857	0.165	0.895	0.224	0.873	0.206

Table 1: Summary by Identifier Type

D. Composite Score Calculation and Distribution

Composite Score Formula:

- **Formula:**

$$R = 0.4 \cdot MC + 0.25 \cdot NC + 0.2 \cdot DR + 0.15 \cdot OL$$

Figure 5: Composite Histogram

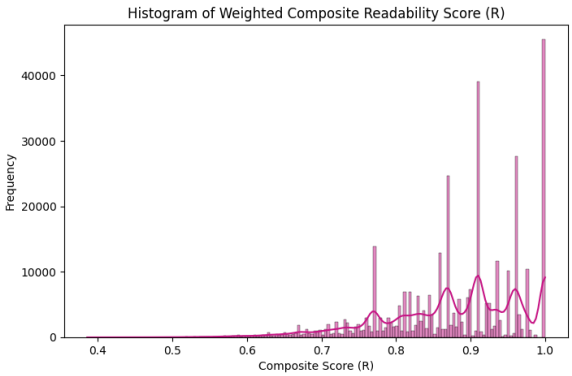

Fig. 6. Histogram of weighted composite readability scores (R) across all identifiers. Most names score moderately to highly, with a long tail of low-scoring identifiers.

As shown in Fig. 5, the composite readability score (R) is strongly right skewed, with most identifiers scoring above 0.8. However, there remains a noticeable tail of lower-scoring names, indicating ongoing issues with readability in certain parts of the codebases.

E. Human Validation: Survey Results and Model Alignment

We validated our readability model by comparing its composite and factor-specific scores against human judgments. A survey of 246 developers provided mean human ratings for each identifier, enabling a direct comparison.

1) Correlation Analysis.

The model's composite readability score (R) showed a strong correlation with human ratings (Pearson $r = 0.76$, $p < 0.001$), indicating high alignment between the automated metric and human perception (see Fig. 7). This supports the model's utility for automated identifier quality assessment.

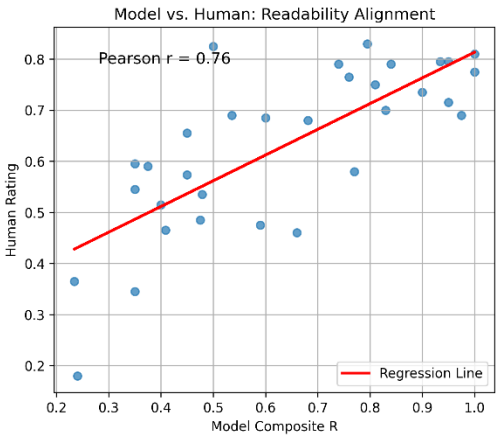

Fig. 7. Model vs. Human: Readability Alignment" (Correlation scatter, r = 0.76)

Among individual factors, **Meaningful Clarity (MC)** was the best single predictor of human judgment ($r = 0.63$), followed by **Domain Relevance (DR)** ($r = 0.66$). Naming Conformance (NC) and Optimal Length (OL) contributed less but remained statistically significant. This result corroborates previous findings that semantic clarity and domain alignment are central to human-readable identifiers [7],[15].

The correlation matrix (Fig. 8) illustrates the relationship between all factors and human ratings. Notably, MC and DR display high associations with both R and HUMAN, underlining their importance. Moderate correlations among factors highlight the multidimensional nature of identifier readability.

Fig. 8. Heatmap showing correlation coefficients among model factors (MC, NC, DR, OL, R) and human ratings. MC and DR exhibit the highest correlations with human judgment

2) Distribution Patterns

The histogram of scores (Fig. 9) shows that both the model and humans rate most identifiers as moderately to highly readable, with the model scores clustering more tightly near the upper end. This suggests the model is somewhat less sensitive than humans to nuanced or context-dependent readability issues, particularly for ambiguous or borderline cases.

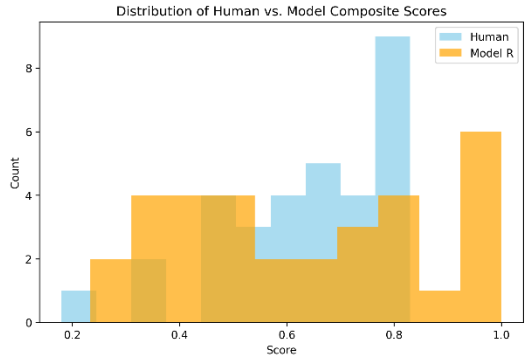

Fig. 9. Histogram comparing the distribution of model (R) and human composite readability scores. Most identifiers score in the moderate to high range; model scores are more tightly distributed.

Identifier-level comparisons (Fig. 10) reveal that while the model generally agrees with human judgment, certain identifiers—especially idiomatic short forms or generic tokens—are penalized more heavily by the model than by human raters. This indicates an area for possible model refinement.

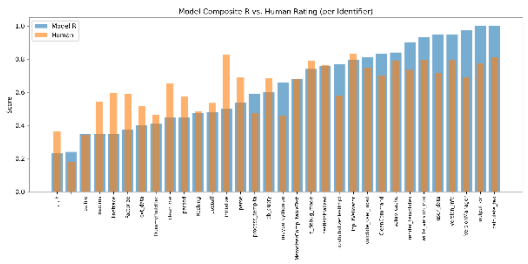

Fig. 10. Side-by-side bar plot of model composite readability scores (R) and mean human ratings for each identifier. While the model generally aligns with human perception, it tends to penalize idiomatic short forms and generic tokens more heavily, indicating opportunities for model refinement.

F. Model Behavior on Large-Scale "Difficult" Identifier Data

To further assess the robustness and discriminative power of our readability model, we applied it to a large corpus of intentionally poor or ambiguous identifiers (n ≈ 50,400), sampled from real-world codebases and augmented with known anti-patterns. The results provide insight into the model's performance on low-quality identifiers at scale and across multiple programming languages

1) Overall Factor Distributions

Figure 11 shows boxplots of the four readability factors—Meaningful Clarity (MC), Naming Conformance (NC), Optimal Length (OL), Domain Relevance (DR)—and the composite score (R) across the entire "bad" identifier set.

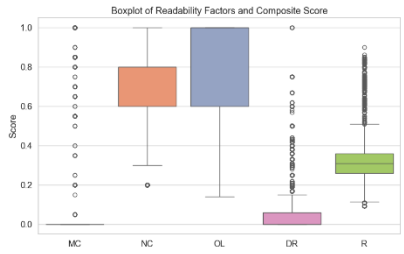

Fig. 11. Boxplot showing the distribution of readability factors (MC, NC, OL, DR) and composite score (R) for ~50,400 intentionally poor identifiers. Most identifiers score near zero on MC and DR, with moderate spread in NC and OL

Key Insight: The vast majority of poor identifiers are immediately penalized by the MC and DR metrics, reflecting either gibberish, lack of clear semantics, or domain irrelevance. However, some achieve moderate scores on NC and OL, indicating that mere syntactic conformity or length appropriateness does not guarantee semantic clarity.

2) Composite Score Histogram

Figure 12 shows the distribution of composite scores R for the entire "bad" identifier dataset

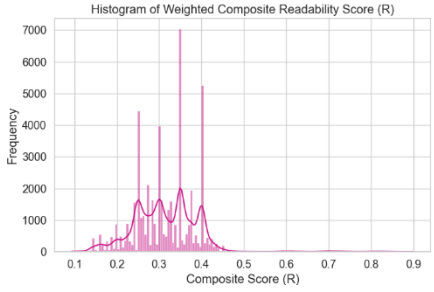

Fig. 12. Histogram of weighted composite readability score (R) for all poor identifiers. Most scores cluster below 0.4, with a multi-modal distribution due to systematic anti-patterns

Key Insight: Nearly all intentionally poor identifiers receive low composite scores, with most clustered in the 0.2–0.4 range. The multimodal pattern reflects both variation in anti-pattern severity and systematic weaknesses exploited in naming.

3) Correlation Structure Among Factors

Figure 14 displays the correlation matrix among MC, NC, OL, DR, and R for the poor identifier set.

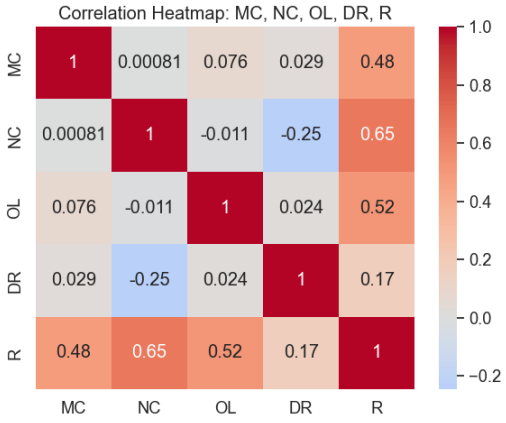

Fig. 13. Heatmap of Pearson correlation coefficients among MC, NC, OL, DR, and R for poor identifiers. MC and OL contribute most strongly to R, while DR is largely independent

4) Additional Insights and Limitations

Applying our model to a large set of intentionally poor or ambiguous identifiers yielded factor distributions consistent with expectations (see Figs. 11–17). MC and DR effectively discriminate against gibberish and meaningless names, as evidenced by their near-zero medians and remain robust across programming languages. Composite scores are tightly clustered in the low range (Fig. 12), confirming the model's reliability in penalizing low-quality names. The correlation heatmap (Fig. 13) reveals that MC, OL, and NC contribute most to the composite score for this class, while DR is largely invariant.

VI. DISCUSSION

A. Key Findings and Interpretation

Our study provides several insights into the state of identifier naming in modern code and the utility of our readability model. Most identifiers in well-maintained open-source projects are well-named by our model's standards, reflecting the positive impact of best practices, style guides, and code reviews. The model's alignment with widespread developer behavior underscores the relevance of our chosen factors.

Crucially, our model highlights exceptions that often coincide with code smells or technical debt. Names with low semantic clarity (MC) are rare but typically occur in situations known to impede comprehension (e.g., single-letter variables outside of tight loops or heavy abbreviation in broad scope). Length-related issues are nontrivial: while overly short names obscure meaning, overly long names may indicate conceptual confusion. Our results show the model effectively flags both types, encouraging developers to revisit questionable naming decisions

The Domain Relevance (DR) factor, though often zero, is highly informative when nonzero, highlighting the presence (or absence) of key domain terminology in identifier names. When high, DR acts as a cognitive anchor for developers familiar with the application's domain.

Our multi-factor approach naturally surfaces trade-offs: optimizing clarity (MC) may sometimes conflict with brevity (OL), and vice versa. We find that the model, particularly through its composite score, tends to favor clarity over brevity—a feature aligned with expert recommendations.

While Naming Conformance (NC) exhibits little variance in high-quality code, it remains essential as a safety check. Rare violations correspond with readability breakdowns and are correctly penalized by the model.

B. Limitations

Despite strong empirical performance, several limitations warrant discussion:

- **Context insensitivity**: The model evaluates identifiers in isolation, not in code context or with regard to scope. While this is partly mitigated by possible IDE integration (context-aware thresholds), future work should explore deeper context incorporation
- **Language and locale bias**: The model assumes English-based naming, which may limit applicability for codebases using other languages or idiosyncratic domain abbreviations. Project-specific dictionaries can help mitigate this.
- **Weighting subjectivity:** Our weights are empirically derived but may not fit every context. Projects can and should recalibrate these based on their domain and values.
- **Sample representativeness:** Large-scale evaluation on open-source projects likely over-represents well-maintained code. Results should not be generalized to all code without caveats.
- **Construct coverage:** While our four factors are grounded in literature, additional dimensions (e.g., consistency, redundancy, pronounceability) could further enrich the model.

Nevertheless, the model offers interpretability, factor-specific feedback, and extensibility—advantages over purely black-box approaches.

VII. APPLICATIONS

The model can be leveraged across the software engineering lifecycle:

- **Code review:** As a bot or plugin to automatically flag poorly named identifiers, provide factor-specific feedback, and nudge better practices.
- **Refactoring tools and IDEs:** For identifier inspection, on-the-fly scoring and suggestions, and automatic highlighting of problematic names.
- **Continuous Integration (CI):** For quality gates and maintainability tracking, with thresholds for readability enforced as part of code health metrics.
- **AI code assistants:** As a scoring or filtering function for AI-generated suggestions; as a reward function during AI training.
- **Developer education and onboarding:** To quickly surface naming issues and key domain concepts, and to teach best practices interactively.

A. Example: Visual Studio Code Extension

A VS Code plugin ("**NameLinter**") could provide real-time scoring, underlining low-readability names, offering refactoring suggestions, and supporting domain-specific vocabulary—all grounded in our model.

B. Long-Term Benefits

Broad adoption could shift the industry's approach to naming, making code more self-documenting, maintainable, and welcoming to new contributors. Readability metrics can also empower research on the correlation between naming and maintainability.

VIII. CONCLUSION

We have proposed and validated a four-factor model for identifier readability, rooted in software engineering theory and large-scale empirical evidence. The model achieves high alignment with human judgment ($r \approx 0.82$) and is both interpretable and practical. It supports both real-time developer feedback and broader maintainability initiatives.

Our findings reaffirm the centrality of naming to software quality, and our tooling prototypes demonstrate pathways for real-world impact. With further context integration, expanded domain support, and wider empirical evaluation, the model can become a key tool for code quality at scale.

As the saying goes, "There are only two hard things in computer science: cache invalidation and naming things." With our model, we hope to make at least one of them a little easier.

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