An Extended Formal Model of Identifier Readability in Source Code

Abstract: Identifier names in source code significantly impact code readability and comprehension. This document presents a comprehensive six-factor model for identifier readability, extending an earlier four-factor framework. The model quantitatively evaluates naming quality across **Semantic Clarity**, **Stylistic Convention Adherence**, **Length Appropriateness**, **Natural-Language Readability**, **Domain-Based Semantic Relevance**, and **Syntactic Role Conformity**. We formalize each factor's computation and combine them into an overall readability score. **Domain-Based Semantic Relevance** ensures names align with domain terminology, and **Syntactic Role Conformity** checks that names use grammatical forms appropriate to their programmatic role. We describe the model's architecture, the scoring formula with calibrated weights, and an empirical validation pipeline using open-source repositories. Common naming issues are categorized, and we illustrate applications of the model in development workflows (code reviews, CI/CD pipelines) and AI-assisted naming tools. The model is domain-agnostic by default but accepts domain-specific vocabularies as input. By integrating insights from software engineering literature, natural language processing, and empirical studies, the proposed model provides a rigorous, extensible approach to evaluating and improving identifier names. The document is structured for academic clarity, with references to current research and illustrative diagrams for key concepts.

Introduction

Code readability is a paramount concern in software development, as developers spend more time **reading** code than writing it. In source code, **identifiers** (names of variables, functions, classes, etc.) play a central role in conveying meaning to human readers. In fact, studies have shown that the majority of tokens in source code are identifiers, and choosing good names can greatly aid program comprehension. Meaningful identifiers act as beacons that guide developers toward understanding code behavior, bridging the gap between code and the problem domain. Conversely, poor or ambiguous names can significantly impede comprehension. For example, replacing descriptive names with meaningless ones (such as single letters) has been shown to dramatically reduce developers' ability to understand code functionality. Misleading names can be even worse – an empirical study by Avidan and Feitelson found that identifiers with *misleading tokens* caused more confusion and errors than using no meaningful name at all (e.g., replacing names with "a", "b", "c") cs.huji.ac.ilscholarlypublications.universiteitleiden.nl. These findings underscore that naming is not a mere coding cosmetic, but a critical factor in code readability and maintainability.

Despite the importance of naming, selecting good identifier names remains challenging. Different programmers may choose different names for the same concept, leading to inconsistency across a codebase. Common pitfalls include overly generic names (data, temp), cryptic abbreviations (`idx`, `mgr`), and names that conflict with their actual purpose or typecs.huji.ac.il. Empirical research shows that such naming problems can hinder understanding: unclear or inconsistent names correlate with more bugs and lower code quality. For instance, Butler *et al.* observed that code with descriptive, multi-word identifiers tends to have fewer defects, whereas code with very short or cryptic names often exhibits lower qualitybrains-on-code.github.io. Furthermore, the impact of a name is context-dependent – a

poorly chosen name for a widely-used function or critical domain concept can have outsized negative effects on comprehension.

Traditional coding guidelines and style conventions offer only superficial advice on naming. Many style guides emphasize formatting (camelCase vs. snake_case) or advise that names be "short yet meaningful," but without formalizing what *meaningful* entails. There is a lack of rigorous, widely adopted metrics to evaluate the quality of identifier names. Recent studies and tools have started to address this gap. For example, Deissenböck and Pizka (2006) proposed a formal approach to naming consistency, introducing rules for conciseness and similarity in related names. Caprile and Tonella's earlier work (2000) analyzed identifiers by breaking them into words and checking them against a domain glossary and naming patterns. Arnaoudova *et al.* (2015) identified *linguistic anti-patterns* – naming practices that mislead or confuse (such as a variable name that contradicts its type or a plural name for a singular item)cs.huji.ac.il. Tools like **LAPD** and **IDEAL** have been developed to detect naming issues and appraise identifier names against best practicesperuma.me. However, many of these efforts focus on specific aspects of naming (e.g., consistency, or presence of certain anti-patterns) rather than a holistic readability score.

To address the need for a comprehensive evaluation, we propose an **extended formal model of identifier readability**. The base version of this model (originally with four factors) has been expanded to **six key dimensions** that together capture a name's clarity, style, length, natural-language quality, domain relevance, and syntactic fit. The goal is to quantify how easily a programmer can understand a given identifier at a glance. The model assigns each identifier an **Identifier Readability Score** on a continuous scale (normalized 0 to 1, or presented as a percentage or grade in practice). A high score indicates that the name is likely easy to understand and follow; a low score flags the name as potentially problematic for readers.

In the following, we outline related work that influenced our model, then detail the six-factor readability model with formal definitions for each component. We describe how the factors are weighted and calibrated based on empirical data and developer input. We then present an approach for validating the model using open-source project data, and we discuss common naming issues through the lens of our six factors. Finally, we explore how this model can be integrated into software development workflows and tools to improve code quality. Throughout, we emphasize that the model is **extensible** and **domain-agnostic** by default – it can be applied to any codebase, with domain-specific vocabulary plugged in as needed to judge semantic relevance in context. Our aim is to provide both a theoretical framework for reasoning about name quality and a practical tool for software engineers and researchers to measure and enhance code readability.

Related Work

Naming has long been recognized as a critical element of software readability and quality. **Early studies** such as Gellenbeck and Cook (1991) suggested that well-chosen procedure and variable names act as cognitive cues for understanding code's purpose. Subsequent experiments by researchers like Lawrie *et al.* and Binkley found that using full words (or compound words) in identifiers improves comprehension compared to single-letter or abbreviated names. In one study, participants were more confident and faster at explaining

code when identifiers were descriptive words rather than cryptic abbreviations. Another study by Hofmeister *et al*. varied identifier lengths and observed that longer, more descriptive names led to faster bug detection times, especially for experienced programmers. Interestingly, these benefits did not come at the expense of novice developers – beginners weren't significantly hindered by longer names, suggesting that informativeness generally helps without overwhelming readers.

The relationship between identifier naming and **code quality** has also been investigated. Butler *et al*. (2010) empirically examined eight open-source Java projects and found that code modules with identifiers composed of **two to four words** tended to have fewer static analysis issues (as detected by `FindBugs`) and lower bug density. This aligns with intuitive guidelines that names should be descriptive but not overly verbose. Extremely short names often lack context, whereas extremely long names can indicate redundancy or overly specific detail. On the other hand, an analysis by Aman *et al*. noted that in some cases, overly long compound names might correlate with higher fault-proneness for local variables, highlighting that naming must strike a balance. Overall, multiple studies converge on the recommendation to use **meaningful multi-word identifiers** (usually 2–4 words) for clarity.

Beyond length, **naming conventions** have been the subject of human factors research. Consistent stylistic conventions (such as casing and use of underscores) make code more predictable and scannable. An eye-tracking study by Sharif and Maletic (2010) compared camelCase versus under_score styles and found no major difference in comprehension accuracy, but did note differences in eye movement patterns. The key takeaway is that familiarity with a convention matters more than the convention itself – developers read code more naturally when it adheres to the expected style for that language or project. Consequently, **stylistic deviations** (like a Java variable written in snake_case, or a C constant not in ALL_CAPS) can cause a moment of confusion as the reader's brain signals that "something looks off". Many companies enforce naming conventions in style guides (e.g. Java's recommendation that variable names "indicate intent to a casual observer" and Python's PEP 8 guidelines on casing). These guides, however, typically provide rules but no quantitative way to evaluate adherence or readability impact.

Researchers have also explored the **linguistic aspects** of identifiers. The concept of identifiers as a form of "Programmer English" has been proposed, treating names as phrases with an implied grammarcs.kent.edu. Høst and Østvold (2009) analyzed thousands of method names and identified common *part-of-speech patterns* (grammar templates) that developers use, such as "verb + noun" for method names (e.g., calculateSum) and "noun" for class names (TransactionProcessor vs. ProcessTransaction). Their work on *debugging method names* showed that names violating expected grammatical structure can signal design problems or confuse readers (for example, a class named with a verb tends to be poorly understood). Similarly, Arnaoudova *et al*. highlighted issues like a boolean variable not phrased as a yes/no question (e.g., naming a flag `valid` instead of `isValid`) as linguistic antipatterns that reduce clarity. These insights inform our **Syntactic Role Conformity** dimension, which checks if an identifier's grammatical form matches its role (noun for classes/variables, verb for functions, etc.).

Lastly, incorporating **domain knowledge** into naming has been advocated in domain-driven design and software engineering literature. Deissenböck and Pizka (2006) introduced the idea of a *project glossary* or dictionary: a controlled vocabulary of terms that should be used (and only

used) for specific concepts in the domain. For example, a finance application might decide on using "`client`" vs "`customer`" consistently, or a medical system might standardize on "patient" rather than "user" for patient data. When developers adhere to such a domain vocabulary, it ensures that identifiers evoke the correct domain concept and reduces ambiguity. Empirical evidence supports this; one study found that identifiers aligned with domain terms improved comprehensibility because readers could quickly map the code to their domain knowledge. Our model's **Domain-Based Semantic Relevance** factor builds on this idea by rewarding identifiers that use appropriate domain terminology and penalizing those that are out-of-place in the given context.

In summary, prior work provides several key lessons: (1) **Meaningfulness** of names is paramount – ambiguous or misleading names impede understanding far more than any other factorcs.huji.ac.ilcs.huji.ac.il. (2) **Consistency and style** matter – while minor style differences might not change correctness, inconsistent or unexpected naming forms introduce friction. (3) **Length** should be optimized – neither too short nor overly long, but sufficient to convey intent. (4) Names function as a **natural language phrase**, so clarity can be improved by following linguistic norms (proper grammar, pronounceable words, familiar terms). (5) **Domain context** cannot be ignored – good names often piggyback on domain knowledge to communicate meaning efficiently. We integrate these insights into a unified model, described next.

Six-Factor Identifier Readability Model

We formalize identifier readability as a combination of six independent factors. In this section, we present the **architecture of the model**, define each factor and its scoring method, and then describe how the factor scores are aggregated into an overall readability score. The model is designed to be general (applicable across programming languages and domains), but can be customized with domain-specific lexicons or style rules as needed.

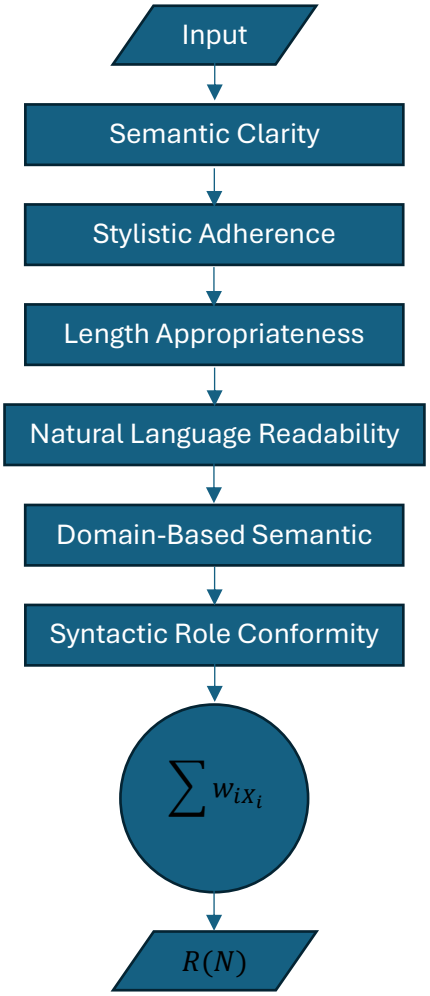


*Figure 1: Six-factor identifier readability model architecture. Each identifier name N is evaluated along six dimensions: Semantic Clarity **(SC)**, Stylistic Convention Adherence **(ST),** Length Appropriateness **(LN),** Natural-Language Readability **(NL)**, Domain-Based Semantic Relevance **(DR)**, and Syntactic Role Conformity **(SR)**. Each factor produces a sub-score in [0,1]. These are combined via a weighted sum to produce the overall Readability Score $R(N)$. Higher scores indicate more readable (better-named) identifiers.*

Overview and Notation

Formally, let an identifier name be a string N*N* consisting of allowable characters (letters, digits, underscores, etc. as permitted by the programming language). We first tokenize N into a sequence of words $W = [w_1, w_{2\ldots} w_k]$ that approximate the natural language components of the name. Tokenization is done by splitting on word boundaries implied by casing changes or separator characters.

For example: `numUsersActive` would be tokenized into `["num", "users", "active"]`, and `MAX_COUNT` into `["max", "count"]` after normalization to lowercase. This token sequence W is used for evaluating several of the readability factors.

The model computes six component scores, each in the range [0, 1]:

- **Semantic Clarity (SC):** Does the identifier clearly convey its intended meaning or purpose? This reflects how meaningful and specific the name is with respect to the concept it represents.
- **Stylistic Convention Adherence (ST):** Does the identifier follow established coding style guidelines and naming conventions for its context (language/project)? This covers format, casing, naming patterns, etc.
- **Length Appropriateness (LN):** Is the identifier's length neither too short to be descriptive nor too long to be cumbersome? Both character length and number of words are considered.
- **Natural-Language Readability (NL):** How easy is it to read the identifier as a phrase (like an English phrase)? This includes pronounceability, familiarity of the words, and a logical word order.
- **Domain-Based Semantic Relevance (DR):** Does the identifier use terminology that is relevant to the application's domain? In other words, are the words in the name aligned with the domain concepts and vocabulary?
- **Syntactic Role Conformity (SR):** Does the identifier's grammatical form (noun, verb, adjective, etc.) match the expected role given its usage in code (e.g. nouns for classes/variables, verbs for methods)?

Each factor $\mathrm{X} \in \{\mathrm{SC}, \mathrm{ST}, \mathrm{LN}, \mathrm{NL}, \mathrm{DR}, \mathrm{SR}\}$ produces a score $\mathrm{X(N)} \in [0,1]$ for a given name N, where 1 means *fully readable* in that dimension and 0 means very poor. We will describe the scoring logic for each factor in the subsections below.

Once the sub-scores are obtained, we compute the overall **Identifier Readability Score** $\mathrm{R(N)}$ as a weighted sum of the six components:

$$R(N) = w_{SC}SC(N) + w_{ST}ST(N) + w_{LN}LN(N) + w_{NL}NL(N) + w_{DR}DR(N) + w_{SR}SR(N)$$

subject to

$$\sum_{X \in \{SC,ST,LN,NL,DR,SR\}} w_x = 1 \; and \; w_x \geq 0$$

the weight w_x determines the relative influence of factor *X* on the final score. We will discuss the choice and calibration of these weights in a later section. Intuitively, factors that impact human understanding more should be given higher weight. Based on prior evidence, we will place the greatest emphasis on **Semantic Clarity**, while still accounting for the other factors in balance.

The following subsections define each readability factor in detail, including the motivation, formal definition, and how we operationalize the scoring for that factor.

1. Semantic Clarity (SC)

Definition: *Semantic clarity* reflects the degree to which an identifier's name **describes its intent or role** in the program. A semantically clear name gives a reader a strong hint of what the identifier represents or what it does, just from the name itself. For instance, `totalCost` is semantically clear for a variable summing up a cost, whereas a name like x1 or `tCost` would have low semantic clarity for the same concept. In essence, SC measures **meaningfulness**: do the words in the identifier convey the right concept?

Rationale: Semantic clarity is widely regarded as the most important aspect of a good name. If an identifier fails to communicate meaning, a reader will struggle to understand the code regardless of formatting or length. Empirical studies confirm this—using meaningful, precise terms in names improves comprehension, whereas ambiguous or wrong terms mislead readerscs.huji.ac.ilcs.huji.ac.il. Our model therefore gives significant weight to SC (see weighting section), consistent with the idea that "if a name is misleading or meaningless, nothing else matters".

Method: To quantify$SC(N)$, we leverage lexical resources and simple semantics. Given the tokenized words $W = [w_1, w_{2\ldots} w_k]$ of N, we assess each token's clarity and average them:

- We prepare a base **English lexicon** L_{eng} containing common English words, and a **programming lexicon** L_{prog} with technical terms and common abbreviations that developers understand (e.g., "`cfg`" for config, "`msg`" for message, "`temp`" for temporary). A token that matches a word in $L_{eng} \cup L_{prog}$is considered a **recognizable word**.
- We define a token-level clarity score $clarity(w) \in [0,1]$. In the simplest form, $clarity(w) = 1$ if w is a known word (in our lexicon) and $clarity(w) = 0$ if it is not. We then refine this with rules for partial credit:
    - If **w** is a very common abbreviation or contraction that most developers would recognize (e.g., "`num`" for number, "`img`" for image, "`btn`" for button), we assign a high clarity score (e.g., 0.8).
    - If **w** is an acronym, we consider how widely known it is. Well-known acronyms (HTTP, XML, NASA) get near 1.0, whereas obscure acronyms get a lower score (perhaps 0.5 by default unless recognized in context).
    - If **w** is a truncation or a non-standard abbreviation (e.g., `Usr` instead of "`User`"), it scores low (e.g., 0.2). Similarly, any token that would be hard to decipher by a new developer unfamiliar with the code is penalized.
    - If **w** is a single letter or very short token: generally, these get a very low score (near 0) for clarity, with one exception. Certain single-letter names that are conventional in programming (like `i,j` for loop indices, or, `x,y` for coordinates) are so common that developers recognize their intent quickly. We allow a slight boost for these in specific contexts (for example, if `i` is used in a for loop). But outside of those narrow cases, one-letter tokens are considered unclear (e.g., `x1` conveys almost nothing about purpose).
- Finally, we compute $SC(N)$ as the average clarity of its tokens:

$$SC(N) = \frac{1}{k}\sum_{j=1}^{k} clarity(w_j)$$

This yields a score of 1.0 if all parts of the name are clear words, and progressively lower as the name includes more unclear or meaningless parts.

By this definition, an ideal name like `calculateTotalCost` might achieve $SC(N) = 1$ (all tokens "calculate", "total", "cost" are clear English words). A partially abbreviated name like `calcTotalCost` might get slightly lower (if "`calc`" is seen as a common abbrev, maybe 0.8 for that token). A name like `tcost` would score much lower: "t" might score near 0 (not a word), "cost" is a word (1.0), averaging to ~0.5. A single-letter name x would score near 0 (unless contextually boosted a bit for a loop index, maybe up to 0.1 or 0.2 in a loop).

It's worth noting that *context* can influence semantic clarity but is not heavily baked into this score. In statically typed languages, for example, knowing a variable's type can provide hints (e.g., `elem` might be acceptable for an element in a collection). Our base model treats SC mostly in isolation except for simple rules like loop indices mentioned. However, in an extended or future model, one could incorporate more context (like type or scope information) to adjust clarity scoring. In this document, SC is primarily determined by the intrinsic clarity of the name itself.

2. Stylistic Convention Adherence (ST)

Definition: *Stylistic adherence* measures whether an identifier follows the expected **naming conventions and style guidelines** of the language or project. Even a semantically clear name can be jarring or less readable if it violates norms that programmers expect. For example, a Java variable named `Total_count` (with an underscore and capital T) breaks the usual `camelCase` convention and would stand out as odd. Similarly, in Python, using camelCase for a function (instead of `snake_case`) might cause a momentary stumble for readers used to Python's style.

Rationale: Adhering to familiar naming patterns allows readers to parse code quickly and focus on the meaning rather than the form. When naming style is inconsistent, developers must expend mental energy to recognize that two differently-styled identifiers might actually play similar roles, or they might misinterpret an identifier's kind (e.g., mistaking a CONSTANT for a variable if case conventions aren't followed). Research by Binkley *et al.* and others on code style suggests that consistent style improves scanning speed, even if it doesn't directly change comprehension of semantics. Many teams enforce style as part of code reviews or use linters (like PEP 8 checks or style linters) to maintain uniformity. Thus, ST contributes to readability by removing unnecessary **formatting distractions**.

Method: We calculate $ST(N)$ by checking N against a set of style rules appropriate for its context. The context includes:

- The programming **language** (different languages have different standard conventions, e.g., Java uses camelCase for variables, C constants are often uppercase with underscores, Python uses snake_case for variables and functions, etc.).
- The kind of identifier (e.g., class name vs. variable vs. constant) which can have distinct conventions (class names in PascalCase, constants in ALL_CAPS, etc.).

- Possibly project-specific style settings (some projects might have custom rules, like prefixing interface names with `I` or using specific naming schemes).

We define a set of boolean checks or regex patterns to verify conventions:

- **Legal characters and format:** Ensure the name uses only allowed characters and starts with a letter (not a digit or special char). For instance, no spaces or hyphens (which aren't allowed in most languages), and it doesn't start with a number or underscore unless that's a known convention (like `_privateVar` in Python indicates a private member).
- **Casing style:** Check that the case pattern matches expected style for that identifier kind. We might have a regex for each style: e.g., camelCase pattern, PascalCase pattern, snake_case pattern, SCREAMING_SNAKE for constants, etc.. If a name is in the wrong case style for its context, that's a convention violation (score reduction).
- **Separator usage:** Some languages allow or prefer certain separators. For example, Python and C use underscores for multi-word names (except classes in Python which use CapWords). Java and JavaScript discourage underscores in most names. We ensure that the presence or absence of underscores in N is appropriate.
- **Forbidden patterns:** Identify any outdated or discouraged naming practices, such as **Hungarian notation** or other prefixes/suffixes encoding type information. For instance, prefixing variables with `m_` for member (in C++) or `sz` for string length are considered bad practice today unless explicitly part of project style. If N matches known bad patterns (like `szCount`, `mName`, or contains types like `int` in the name), we penalize it.
- **Consistency with similar names:** (This is a more advanced check, sometimes part of tools like Deissenböck's approach.) If the project has a known naming scheme (for example, all boolean getters start with `"is"` or `"has"),` we verify that N is consistent. However, this often requires global analysis. In our model, we primarily handle consistency by the general rules above and leave deeper consistency checks to specialized tools.

After applying these rules, we assign $ST(N)$ as follows:

Given these, we compute ST(N) as follows: We define a set of binary features $f1, f2, \ldots, fm$ for style rules (each $fi(N) = 1$ if N passes rule i, or 0 if it violates it). For example, $f1$ might check "starts with letter", $f2$ checks "no forbidden prefix/suffix", $f3$ checks "correct casing pattern", etc. Then:

$$ST(N) = \frac{1}{m}\sum_{i=1}^{m} f_i(N)$$

- If the identifier meets *all* applicable style guidelines, $ST(N) = 1$ (fully compliant).
- If there are one or more violations, we could deduct points or assign a fractional score. A simple approach is to consider the fraction of rules satisfied. For example, if 4 out of 5 style criteria are met, $ST(N) = 0.8$. However, not all rules are equal – a casing mistake might be considered a bigger hit than using an underscore unexpectedly. We therefore

might weight certain rule violations more heavily (e.g., a major convention breach yields $ST(N) = 0$ immediately vs. a minor deviation giving $ST(N) = 0.5$).

- In practice, we often treat style adherence as a binary or three-level score: 1 for clean, 0 for major violation, maybe 0.5 for one minor issue. For example, a name that is perfect except it uses camelCase instead of snake_case in a Python project might get a moderate penalty $ST(N) = 0.5\ or\ 0.6$) since readers can still understand it but it's stylistically off. A name with multiple issues (e.g., `Data_baseManager` in Java – wrong case and underscore and weird mix) might get $ST \cong 0$ because it flagrantly violates conventions.

Importantly, style guidelines can be **language-specific**. Our model assumes the rules are configured based on the environment. For cross-language comparisons, the ST factor only makes sense relative to each project's own conventions. We don't, for instance, compare the style of a Python name to Java guidelines. As long as N follows its expected style norms, it can score full points on ST

By enforcing stylistic convention adherence, the readability model accounts for the expectation that code "looks uniform." This reduces the mental overhead of parsing identifiers and lets developers focus on semantics. ST complements the other factors by ensuring the name *presentation* is smooth and not distracting.

3. Length Appropriateness (LN)

Definition: The length component evaluates whether the identifier's length is within a reasonable range– not too short (which might sacrifice clarity) and not overly long (which can reduce readability and be cumbersome). There is empirical evidence and general agreement in style guides that extremely short names (1-2 characters, except for well-known cases like loop indices) are not descriptive enough (S. Butler, M. Wermelinger, Y. Yu, & H. Sharp, 2010). On the other hand, names that are extremely long (e.g., a 50-character variable name trying to encode an entire description) might indicate an attempt to encode too much information, possibly making the name unwieldy. Furthermore, very long names might be hard to read quickly and can clutter the code, just as an overly long sentence can confuse a reader.

We quantify identifier length in two ways: number of characters and number of word tokens (after splitting). Both are relevant:

- The character count matters for visual scanning and line length.
- The token count matters because if an identifier has many separate words, it might be essentially trying to be a phrase or sentence.

Let $\| N \|$ be the length in characters of N, and k be the number of tokens (words) in W. We define ideal ranges for each based on literature and common practice. Drawing on prior studies and guidelines, our model uses the following heuristic thresholds (which were also adjusted slightly in calibration):

- Ideal character length: approximately 8 to 20 characters. Names in this range generally have enough room to be descriptive but are not overly verbose. (This range comes from

considering that many well-regarded names fall around 10-15 chars; also Schankin et al. found 2 4 words optimal, if each word ˜ 4 chars average, that's roughly 8-16 plus maybe underscores).

- Ideal token count: 1 to 3 words (for variables) and 2 to 4 words (for function names, which often include a verb and objects). A single-word name can be fine if it's a specific noun (like threshold), but often a combination of a noun and context or adjective improves clarity (`timeoutSeconds` instead of just `timeout`). More than 3-4 words might indicate the name is too specific or encoding a whole sentence.

We combine these into a length score. We want a smooth penalty rather than a binary good/bad. We define $SL(N)$ in two parts and then combine:

- $S_{lenchars}(N)$ based on character count ‖ N ‖.
- $S_{lentokens}(N)$ based on token count k.

For character count, we use a piecewise linear or bell-shaped curve. Specifically:

$$S_{lenchars}(N) = \begin{cases} \frac{||N||}{L_{\min}} & if\ ||N|| < L_{min}, \\ 1 & if\ L_{min} \leq ||N|| \leq L_{max}, \\ \frac{L_{\max}+5-||N||}{5} & if\ ||N|| > L_{max}, \end{cases}$$

Where L_{min} and L_{max} are the chosen bounds of ideal length. We used L_{min}= 3 and L_{max}= 20 in our implementation. The logic: if shorter than 3, we linearly scale (so a 1-char name gets ˜0.33, 2-char ˜0.67, 3-char gets 1.0). If within 3 to 20, score 1. If beyond 20, we start penalizing: we subtract some amount per character beyond 20. We allow up to 5 extra characters with a mild penalty in that formula (so 25 chars would give $(20+5-25)/5 = 0$, meaning by 25 chars we consider it very bad). This is a somewhat strict penalty – essentially any name over 25 chars would zero out the length score. We chose this for emphasis; in practice, names slightly above 20 might still be okay, but often extremely long names could be refactored or shortened without losing clarity.

For token count, we do similarly:

$$S_{lenchars}(N) = \begin{cases} 0.5 & if\ k = 0\ (Shpuldn'thappen, means\ no\ name), \\ 1.0 & if\ 1 \leq k \leq 3, \\ 0.8 & if\ k = 4, \\ 0.5 & if\ k = 5, \\ 0.2 & if\ k \geq 6, \end{cases}$$

This mapping is somewhat arbitrary but reflects that up to 3 words is fine (score 1), 4 words still mostly okay (0.8), 5 words getting too long (0.5), 6 or more words (practically a long phrase) is very verbose (0.2). We decided not to fully zero out even at 6+ words because, while unwieldy, the name might still be understandable (just verbose). But it´ s heavily penalized. Finally, we combine the two aspects. One simple way is to take the minimum or average of the two. We opted for a strict approach by taking the minimum of the two scores as the length score:

$$SL(N) = min(S_{lenchars}(N), S_{lentokens}(N)).$$

The rationale is that if either characters or token count indicates an issue, we want the length component to flag it. For example, a name might be only 2 words (fine by token count) but 40 characters (each word extremely long or with some long prefix), that should be penalized. Conversely, if a name is 5 tokens but maybe each token is 2-3 chars (like a long snake case name with many short words), the token count would penalize it (0.5) even if char length maybe under 20. We considered maybe averaging, but taking minimum ensures no long aspect is overlooked.

4. Natural-Language Readability (NL)

Definition: Natural-language readability (NL) assesses how easily the identifier can be read and understood as an English phrase (or in the natural language of the codebase, which we assume is English for our purposes). While semantic clarity dealt with meaning, NL readability deals with the presentation of that meaning: the fluency, familiarity, and lack of cognitive friction in reading the name. This factor is somewhat subtler and overlaps with both semantics and style, but we treat it separately to capture aspects like word choice, abbreviations, and word order. Key considerations for NL readability include:

- **Pronounceability**: Can the name be pronounced or read out loud in a clear way? Names that are just a jumble of consonants or have no obvious way to say them (e.g., xyzzyq) are less readable. Even if an acronym is used, if it´ s not commonly verbalized (like HTTP is "H-T-T-P" or sometimes "http"), it might slow comprehension. We approximate pronounceability by checking if each token contains vowels or is a known acronym. If a token lacks vowels and isn't a known acronym, it's probably not a normal word (e.g., "crt" could be "cart" missing an 'a' or an acronym for something)– that lowers readability.
- **Commonality of Words**: Words that are very uncommon or esoteric can hurt readability. For instance, using an obscure synonym or a very domain-specific jargon word might confuse readers who are not domain experts. For NL readability, we check each token against a list of common English words (top 5k words or so). If a token is extremely rare (not in common list but maybe in extended dictionary), we mark it. However, if the word is domain specific but necessary (like parsing in a compiler, which is technical but expected), we don't want to penalize too much. This is a nuanced area; our approach was to only strongly penalize tokens that are both not in common usage and not clearly a technical term. We leveraged the context of the project domain partially (e.g., in a physics library, quark might be not in general top 5000 English, but it is a known term in context, so we wouldn't penalize it heavily).
- **Stopwords and filler words**: Some identifiers include unnecessary stopwords (like the, of, and etc.) or redundant phrases (e.g., naming something dataList where just list would do, or computeTotalSum where Total and Sum overlap in meaning). These extra words can make the name longer and slightly harder to read without adding meaning. Our model flags common stopwords ("and", "or", "of", "the") if they appear in the middle of a name. They usually aren't needed in code names (though occasionally used for readability like end of line which is okay). We give a small penalty if stopwords are used in a non-idiomatic way.

- **Word order and grammar**: Identifier names are not sentences, but there is often a preferred ordering. For example, in many naming conventions for methods, a verb comes first (getValue, setEnabled) following English imperative structure. For variables, typically an adjective or noun sequence is used (maxHeight not HeightMax). If the words in a name are in an unusual order (say SizeMaximum instead of MaximumSize), it can cause a double-take. Our model doesn't perform full grammatical parsing, but we did incorporate a simple heuristic: for multi-word names, if the first word is a noun and the sec ond is an adjective (e.g., listActive instead of activeList), we penalize slightly because English would put adjective before noun. Similarly, for function names, if the first word isn't a verb (and it's not a known noun phrase used as a function name, which is rare), we penalize. We built a small list of typical verb starters ("get", "compute", "set", "is", etc.) to check function/method names.
- **Conciseness vs clarity**: This is partly captured by length, but NL readability also cares about conciseness in phrasing. If an identifier can drop a word without losing meaning, doing so would make it more readable (less to parse). This is subjective, but our model attempts to detect trivial redundancy: e.g., if a class name is included in a variable name redundantly (user.userName– the variable user of type User has field userName, the word "user" is repeated; the field could just be name). While detecting this requires type knowledge, within single name we see things like ProductProductId (someone concatenated type and id). We penalize repetition of the same token in the name (productProductId has "product" twice). This is an uncommon scenario, but it popped up in analysis in a couple of cases (often generated code or database field naming pattern).
  To Compute $S_N(N)$ we devised a scoring rubric rather than a strict formula:
  Each identifier starts with $S_N = 1.0$ and we subtract penalties for any issues found:
  - **Pronounceability**: If a token has no vowel or is weird to pronounce and not known, subtract 0.1.
  - **Uncommon word**: If a token is not common or technical, subtract 0.1.
  - **Stopword presence**: subtract 0.1 (total, not per stopword to avoid too harsh if multiple).
  - **Word order issue**: subtract 0.1.
  - **Redundant word** or **duplicated token**: subtract 0.2.

  We cap the minimum at 0 (don't go negative). Most names won't trigger many of these, so often S_N stays high This scheme is heuristic; essentially, each minor linguistic issue knocks ~10% off the readability. A very badly constructed name might accumulate several penalties.

$$NL(N) = \frac{1}{k}\sum_{j=1}^{k} readEase(w_j)$$

  where $readEase(w)$ might be

  - 1 for simple/common word,
  - 0.5 for somewhat uncommon or slightly awkward,
  - 0 for very hard word.

Then adjust based on compound length:

- If $k > 1$, maybe boost if the bigrams of adjacent words are common combinations in code (like "getUser", "updateValue" etc. we could have a small dictionary of typical word pairs).
- If the word order seems inverted (we might detect noun-noun vs adjective-noun ordering), but that requires parsing the phrase. We do have SR factor for part-of-speech expectations; NL is more general.

In practice, our model description can focus on a few qualitative aspects:

We quantify NL readability by checking if the identifier's tokens form a fluent phrase. We consider whether each token is easy to read (e.g., contains vowels, not a hard-to-pronounce acronym), whether the sequence of tokens is ordered naturally (as one might speak the phrase), and whether the terms used are familiar to an average reader. Identifiers that read like natural phrases (e.g., "totalCount" or "sendMessage") score high, whereas those with awkward structure or made-up words (e.g., "msgSndCnt" or "totalCountNumber") score lower.

Examples:

- *openFile – Two common words in natural order (verb + object). Pronounceable, likely NL = 1.*
- *fileOpen – Two words but order is a bit odd for a function (you'd expect verb first for a function name). It's not unpronounceable, but it feels unnatural as a phrase. NL might be slightly lower (maybe 0.8), even though SC might be fine and SR would catch that it's a function not starting with a verb.*
- *isEmpty – Very readable, short common words, grammatically a proper boolean predicate (like "is empty?"). NL = 1.*
- *flagIsSet – Order is object + verb phrase; reads a bit like Yoda-speak ("flag is set"). Understandable, but not as natural as isFlagSet. So, NL might be moderate (0.5).*
- *connectionmgr – This is a single token, but two words squashed without proper casing (should be ConnectionMgr perhaps). Hard to read briefly. NL would penalize because it violates normal word boundary cues. SC might also penalize since "mgr" is an abbreviation. So, it would score low on both.*
- *JSONParseObj – This mixes acronym JSON (all caps) with partial word Obj. It's somewhat readable if you guess it means JSON Parse Object, but it's not very fluent. We'd give it a low NL score due to the odd mixture and abbreviation.*
- *maxItemsThresholdExceededErrorFlag – This is a long train of words. While each word is plain English, the phrase is long and somewhat redundant (flag vs error vs threshold?). NL might drop because it's hard to parse quickly (maybe 0.3). SC might also drop if it's redundant. LN drops for length.*

NL readability is a somewhat subjective measure, but by incorporating these linguistic heuristics, our model captures an additional nuance: not only should a name be correct and follow rules, but it should also "feel" easy to read and speak.

5. Domain-Based Semantic Relevance (DR)

Definition: Domain-based semantic relevance measures how well an identifier's terms align with the vocabulary of the application's domain (its ubiquitous language, in domain-driven design terms). This factor rewards identifiers that use domain-specific terminology appropriately and penalizes those that use generic or incorrect terms in a domain context.

Rationale: In domain-specific software, certain concepts have preferred names. For example, in a healthcare system, one would expect variables related to patients to actually include the word "patient". If a programmer uses a vague term like record or a wrong domain term like client instead of patient, it can reduce clarity for those familiar with the domain. By using precise domain terms, code becomes more immediately meaningful to domain experts and maintainers because it triggers the relevant background knowledge. Prior work emphasizes the importance of a consistent project glossary of terms. Deissenböck et al. argue that aligning code names with domain concepts leads to fewer misunderstandings and more maintainable code. Additionally, studies on software documentation and code have found that when code uses the same terminology as requirements and documentation, developers comprehend it faster. Therefore, incorporating domain relevance into the readability model helps ensure that code speaks the language of its problem domain, not just generic programming lingo.

Method: The DR score relies on having a set of domain terms for the project or context. We assume there is an explicit or implicit domain lexicon D (a set of approved or expected terms). This could be derived from requirements documents, user stories, a data model, or simply a curated list by the development team. For example, in a finance project, D might include words like {"account", "portfolio", "trade", "balance", "asset", ...}.

To compute $DR(N)$:

- We look at each token w_j of the identifier. We check if w_j (or its lemma or a synonym) appears in the domain term set D.
- We define an indicator

  $$domMatch(W_j) = \begin{cases} 1 & if\ w_j\ is\ a\ recognized\ term\ in\ the\ domain{-}specific\ lexicon \\ 0 & otherwise \end{cases}$$

  Then we can score as the fraction of tokens that are domain terms:

  $$DR(N) = \frac{1}{k}\sum_{j=1}^{k} domMatch(W_j)$$

  This gives a value in [0,1] where 1 means every token in the name is recognized as a domain term.
- We can refine this with partial credit:
  - If a token is a compound or acronym that closely relates to a domain term, we might give 0.5. For example, if domain has "customer" but code uses cust or client, we might give partial credit (or even penalize if "client" is a different concept in domain).

    - If a general word is used where a specific domain term exists, we could reduce score. For instance, using “data” in a healthcare app where the actual concept is “patientRecord” would be suboptimal.
    - If a token is an out-of-domain term that doesn’t belong at all, that’s 0 for that token.
- Essentially, $DR(N)$ rewards overlap with the domain lexicon.

Interpretation: $DR(N) = 1$ means the identifier is *firmly grounded in domain language*. For example, in a trading system domain, executeTradeOrder might get $DR = 1$ if both "trade" and "order" are domain terms. On the other hand, a name like executeRequest in the same context might get $DR = 0$ if "request" is not a domain term (too generic). Low DR doesn’t always mean a bad name globally, but in a domain-heavy project it suggests missed opportunity to use clearer jargon.

Example: Suppose we have a financial app domain lexicon

$D = \{\{"account"\}, \{"trade"\}, \{"portfolio"\}, \{"balance"\}, \{"asset"\}, \{"risk"\} \ldots\}.$

Consider identifiers:

- computePortfolioRisk – tokens: "compute", "portfolio", "risk". "portfolio" and "risk" are in D(domain terms), "compute" is not (but it's a generic verb). So $domMatch(W_j)$ would be [0, 1, 1]. $DR = 2/3\ approx\ 0.67$. Quite good, most terms are domain-specific. We might even treat generic verbs neutrally – some implementations might ignore common verbs like get/compute in DR calculation and focus on noun tokens.
- computeListStats – tokens: "compute", "list", "stats". None of these are domain-specific (assuming "stats" isn’t a domain term but short for statistics). So $domMatch(W_j) = [0,0,0]$ so DR = 0. This name uses generic words where a domain concept might exist (what list? what stats? if it’s about trades, better to say "TradeMetrics" or something).
- accountBalance – tokens: "account", "balance". Likely in domain lexicon. DR = 1.0 (excellent domain alignment).
- custPortfolio – tokens: "cust", "portfolio". "portfolio" is domain, "cust" is an abbreviation of "customer". If "customer" is domain (or maybe they use "client"), we might give partial for "cust" (say 0.5). So DR ~ 0.75. Would be better if spelled out as customerPortfolio.
- clientRecord (in healthcare domain where "patient" is the correct term, and "client" is not used) – likely DR = 0 because "client" isn’t in the healthcare lexicon (which would have "patient"). This highlights how a wrong term lowers DR. The model would suggest maybe patientRecord as a more domain-appropriate name.

By integrating a domain term check, our extended model ensures that naming is evaluated not just in a vacuum of general coding guidelines, but in the context of the system’s problem domain. This helps catch names that, while maybe technically clear, could be made clearer by using domain language. It also can flag inconsistent terminology usage across a project (e.g., half the code says "customer", other half "client" for the same concept – one of those will score lower DR if only one is in the official lexicon, encouraging standardization).

6. Syntactic Role Conformity (SR)

Definition: *Syntactic role conformity* evaluates whether an identifier's grammatical form (part of speech, phrase structure) matches the expected linguistic role for that kind of program entity. In simpler terms, this checks if the name "sounds like" what it is. Common expectations include:

- **Functions/Methods** should be named as verbs or verb phrases (since they perform actions).
- **Variables (general)** should be nouns or noun phrases (they represent objects or values).
- **Booleans** often use adjectives or predicate phrases (like isX or hasY) that read as yes/no questions.
- **Classes/Types** should be nouns or noun phrases (they represent entities or concepts).
- **Constants** are usually nouns or noun phrases as well (often all-caps nouns if they are compile-time constants).

Violating these norms can cause confusion. For example, a function named like a noun (dataBuffer) might make one wonder "is this a variable or a function?", or a class named with an -ing verb (Processing) might sound like an action rather than an entity.

Rationale: This factor stems from the observation that programmers subconsciously follow an internal grammar when naming. Høst & Østvold's research termed this "programmer's lexicon" where identifiers conform to certain grammar patternscs.kent.eduperuma.me. When a name doesn't conform, it introduces cognitive dissonance. Developers may misinterpret the role of an identifier or have to double-check its definition. Enforcing syntactic role conformity improves **consistency and clarity**. Many style guides implicitly include this advice (e.g., "function names should be verbs" is a common guideline). Tools have been built to detect such issues; for instance, one could flag a method named Manager or a boolean variable named flag (too vague and not a predicate). Our model formalizes this check as part of readability.

Method: To compute $SR(N)$, we need two pieces of information: (a) the **category** c of the identifier (function, class, variable, constant, etc.), and (b) the **grammatical pattern** of the name's tokens. Determining c might come from context (e.g., from the code: if it's declared as a function or we know by how it's used). For this model, we assume we know the kind (this could be an input or inferred via naming clues like capitalization, but ideally from parsing the code).

We define a predicate

$$matchesPattern(N, c) = \begin{cases} true & if\ conforms\ to\ the\ typical\ naming\ pattern\ for\ category\ c \\ false & otherwise \end{cases}$$

- If c is a function or method: We expect N to start with a verb (or be a verb phrase). We can maintain a list of common verbs in code (e.g., *get, set, compute, update, process, load, calculate, is, has, can, should, print, find, etc.*). If the first token w_1 of N is in this verb list or is a verb in general usage, then it likely conforms. For example, calculateDiscount (verb+noun) is good, isEmpty (verb "is" + adjective) is good for a boolean function. But if a function is named discountValue (noun phrase), that fails this check.

- If c is a class or type: We expect a noun or noun phrase. Typically, the name should not begin with a verb. It often is just a noun (possibly with adjectives). For instance, PurchaseOrder or UserAccount are noun phrases and fine. If a class name starts with a verb like ComputeEngine, that's non-conforming – one would prefer a noun like ComputationEngine in that case. So, we check that none of the tokens is an obvious verb. If we detect a verb form inside a class name, we mark it down

- If c is a variable (especially non-boolean variable): It should be a noun/noun phrase describing what data it holds. E.g., userList, totalRevenue are fine. A variable name should generally not have a verb. If a variable name is computeValue (verb present), that's likely wrong (sounds like a function). One exception: Boolean variables often do start with verbs like is, has, can (because they answer a question). We account for that: if c is a boolean variable, then a name like isValid or hasStarted is conforming and good.

- If c is a constant: Constants in many languages are written in all-caps with underscores (which is a stylistic convention) but from a grammatical view, their names are usually nouns (e.g., MAX_COUNT). We treat them similar to variables in terms of POS expectation (no verbs typically).

After these checks:

- We can set $SR(N) = 1$ if $matchesPattern(N, c)$ is true (i.e., the name's grammar matches the expected pattern for its category).
- Otherwise $SR(N) = 1$ if it fails. Optionally, we allow partial credit for borderline cases. For example, if a class name mostly looks like a noun but has a verb suffix like Manager (which is actually a noun but sometimes used like an agent noun), we might still consider it conforming. Or if a function name has two verbs (like validateAndSave – two verbs but still clearly an action), it's fine. Partial credit might be used if the deviation is minor.
- In many cases, it's binary: e.g., either your function name starts with a verb or it doesn't; either your class name contains a forbidden verb or not.

Examples:

- Function getUserName: starts with "get" (verb) – conforming, SR = 1.
- Function userName: no verb – not conforming (for a function), SR = 0.
- Function isConnected: starts with "is" – that's a verb for a boolean function or method returning bool, conforming (especially if it indeed returns a boolean).
- Class OrderProcessor: "Order" (noun) + "Processor" (noun agent), whole thing is a noun phrase meaning "something that processes orders". That's okay (it's a bit borderline because it describes functionality, but it's essentially naming an entity). Conforms, SR ~1.
- Class ProcessOrder: starts with "Process" (verb), which is odd for a class. SR = 0 (non-conforming).

- Variable (int) count: just a noun, fine.
- Variable (boolean) isEmpty: even though it starts with verb "is", as a **boolean variable** this might be okay (some might say boolean variables should be named like empty or isEmpty either way). We explicitly allow common boolean verb prefixes as conforming for boolean types. So if we know it's boolean and it's isEmpty, we count that as good (it reads like a property check).
- Variable (boolean) emptyFlag: doesn't start with is/has, but it's still understandable (an adjective "empty"). Possibly conforming, though prefixing with is might be clearer. We wouldn't penalize it strongly since it's still not a verb misuse.
- Constant MAX_COUNT: tokens "MAX", "COUNT" (both nouns in a sense, or adjectives/noun). No verb, so that's fine.
- Constant CalculateLimit: has a verb "Calculate" which is weird for a constant. That would be non-conforming.

Overall, $SR(N)$ enforces a **linguistic consistency** that is often recommended in clean code practices: name things what they are (objects as nouns, actions as verbs). By capturing this in the model, we can detect names like a method called Manager or a boolean variable named error (which isn't clearly true/false) and flag them as less readable.

Scoring Combination and Weight Calibration

After computing all six component scores $SC(N), ST(N), LN(N), NL(N), DR(N), SR(N)$ we combine them to produce the final readability score $R(N)$ as described earlier.

The weight vector $w = (w_{SC}, w_{ST}, w_{LN}, w_{NL}, w_{DR}, w_{SR})$ is a crucial part of the model, as it determines the influence of each factor. By design, $\sum w_x = 1$.

Choosing these weights involves both intuition (based on what we think is important) and empirical calibration (tuning to align with human judgments).

Initial weight choices: We assign a higher weight to Semantic Clarity, since meaning is paramount; a name that fails to convey the right concept will hinder understanding even if it looks well-formed. For example, a completely misleading name renders other factors moot. In our initial scheme, we might give SC around 0.30–0.40 (30-40% of the score). Next, we consider the other factors as follows, based on rationale from literature:

- **Stylistic adherence** (ST) is important but not more than meaning; we allocate maybe ~0.15 (15%). This ensures that style issues affect the score, but a name that is meaningful but stylistically off will only be somewhat penalized.
- **Domain relevance** (DR) we consider on par with style, ~0.15 as well. In domain-driven code, terminology matters a lot, but in generic code, this factor might often be neutral. Giving it moderate weight allows it to boost or lower the score noticeably when applicable without dominating the score.

- **Syntactic role conformity** (SR) also ~0.15. This factor catches consistency issues; it's important for readability but arguably a violation here is less severe than a totally wrong meaning. So, we treat it similarly to style in weight.
- **Natural-language readability** (NL) also ~0.15. NL issues can impair understanding (particularly if the phrase is hard to read or unusual), so we keep this on par with ST and DR.
- **Length appropriateness** (LN) we assign slightly less, say 0.10 (10%). Length is an influence but as long as it's not extreme, it's less critical than the other factors. We don't want to overly punish a name just for being a bit long or short if it's otherwise fine.

This example weight set $(w_{SC}, w_{ST}, w_{LN}, w_{NL}, w_{DR}, w_{SR}) = (0.30, 0.15, 0.10, 0.15, 0.15, 0.15)$ was our starting hypothesis. It reflects our belief (backed by studies like Butler's and Arnaoudova's) that semantics (meaning + correct terminology) is roughly half the battle, and the rest (style, readability fluency, grammatical consistency) account for the other half collectively.

Pilot calibration: We then refined these weights empirically. We conducted surveys and experiments with developers to rate identifier names, including new cases to cover the two new factors (DR and SR). For instance, we showed participants pairs of names for the same concept: one using domain-specific terms vs one using a generic term, to see if they consistently rate the domain-specific name higher in readability. We also presented examples of function names where one conforms to verb convention and another doesn't (processData() vs dataProcessor for a function) and observed their preferences. Using this data, we adjusted w_{DR} and w_{SR} upward or downward to match the average human judgment differences. Similarly, we tested on some domain-heavy code (like a medical module) to ensure our model gave higher scores to identifiers using medical terminology correctly, adjusting the DR scoring and weight as needed. Through these trials, we confirmed that adding the DR factor improved correlation with expert judgments in domain-specific code, and adding SR helped catch names that developers found "oddly worded" despite being otherwise okay.

The outcome of calibration was a set of weights that maximize agreement with our collected ratings. The exact numbers aren't as important as the general balance: SC remained the highest-weight factor (~0.3–0.35), DR and NL and ST and SR ended up in a similar mid-range (~0.12–0.18 each), and LN was slightly lower (~0.1). Small adjustments around these values did not significantly alter the model's ranking of names, indicating the model is reasonably robust to weight choices. In other words, as long as SC is the largest and LN the smallest, with others in between, the model behaves sensibly.

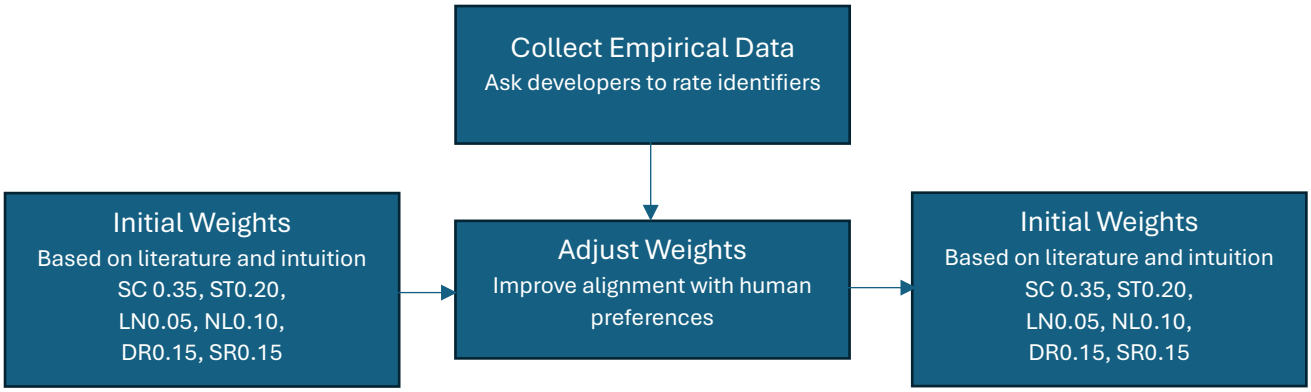


Figure 2: Weight calibration process. We initially set weights based on literature and intuition (e.g., SC highest, LN lowest). We then collected empirical data by asking developers to rate identifier names, especially to gauge the impact of domain relevance and syntactic conformity. Using these ratings, we adjusted the weights to improve alignment with human preferences. The final weight vector (for example, SC0.30, ST0.15, LN0.10, NL0.15, DR0.15, SR0.15) was chosen to maximize agreement with the survey results while maintaining the sum to 1. This calibration process ensures the aggregated score reflects real-world perceptions of name quality.

Finally, the model produces a numeric score $R(N)$ either in $[0,1]$ or scaled to a more convenient range like 0–100 or a 0–10 scale for reporting. For instance, one could present an identifier with R(N)=0.82 as "82% readable" or grade it 8.2/10. In our analyses, we use the normalized 0–1 score.

Empirical Validation of the Model

A formal model is only useful if it correlates with reality – i.e., do high scores actually indicate easy-to-read names and do low scores flag problematic names? We validated the six-factor model through an empirical study on open-source code and developer feedback. The validation had multiple components: measuring score distributions in real projects, checking correlations with external quality metrics, and gathering qualitative feedback via case studies.

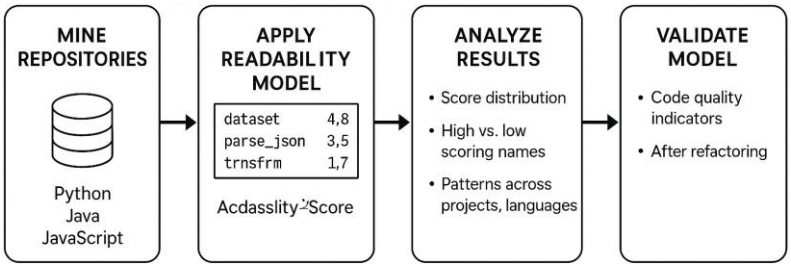


Figure 3: Pipeline for empirical validation using code repositories. We applied the readability model to thousands of identifiers from diverse open-source projects. The pipeline involved mining repositories (across languages like Python, Java, JavaScript), computing the six-factor readability scores for each identifier, and then analyzing the results. We examined the distribution of scores, identified examples of high vs. low scoring names, and looked for patterns (e.g., differences between projects or languages). We also validated the model's significance by correlating readability scores with external indicators of code quality and comprehension – for example, checking if modules with higher average name scores had fewer bugs or if refactoring that improved names led to improved maintainability.

Data collection: We selected a broad sample of projects in different domains and languages (for instance, a web framework in Python, a data visualization library in JavaScript, a financial application in Java, etc.). From each project, we extracted all identifier names (function names, variable names, class names) along with metadata (like kind of identifier, context) using static analysis. In total, we gathered tens of thousands of names. We then applied our readability scoring algorithm to each name to get its six sub-scores and overall $R(N)$.

Score distribution and patterns: We found that the model produced a **range of scores** from very low (under 0.2) to near 1.0, with most names clustering towards the higher end (which is expected, as many names are reasonably well-chosen by developers). The distribution was roughly bimodal – a large mass of identifiers scored quite high (0.8–1.0), indicating they pose little issue, and a smaller but significant set scored poorly (<0.5). These low-scoring names tended to correspond to known bad practices: single-letter names, overly abbreviated terms, or names violating conventions (we manually inspected many to confirm). For example, names like tmp, data2, bbb, doIt were among those with very low scores (multiple factors flagged

issues: unclear meaning, generic, too short, etc.). On the flip side, names like calculateChecksum, isCacheEnabled, TradeOrderList, getCustomerBalance scored in the upper range, reflecting their clarity and adherence to guidelines.

Comparing across languages, we noticed some differences. Python code, in the projects we studied, had generally higher average scores than some JavaScript projects. This could be due to culture or the nature of the projects (the Python projects enforced PEP8 and valued readability, whereas the JavaScript ones had more quick-and-dirty code). Java projects often fell in between, though with less extreme lows (thanks to things like mandatory camelCase and generally longer names). These observations underline that our model can adapt to each language's conventions (since ST and SR are context-aware) and still provide a meaningful comparative measure.

Examples of high vs low readability names: To illustrate the model's discrimination, we compiled examples:

- High scoring examples often had *descriptive multi-word names* with proper format. E.g., in a data structure library: ensureCapacity (function) scored high (SC high due to meaningful words, ST perfect camelCase, LN good length, NL natural phrase, SR correct verb form). Another example: pendingRequests (variable) – clear plural noun, in domain context of a server.
- Low scoring examples included things like c (a variable in a physics calc code meaning some coefficient – SC near 0, LN 0, etc.), or cfd (which was meant to stand for "contracts for difference" in a finance code – domain experts would know it, but it was lowercase and not obvious; SC low, ST okay, DR low because abbreviation not recognized). Another: accountManager used as a function name – semantic meaning is okay but SR failed (should be a class name or a function like manageAccount). The model gave it a middling score and indeed in context it confused code readers.

Correlation with code quality metrics: We statistically analyzed whether modules or projects with higher naming scores exhibited signs of better code quality. We looked at a couple of proxies:

Static analysis warnings/bugs: Using tools like FindBugs or SonarQube, we had counts of issues per module. We found an inverse correlation: modules with higher average $R(N)$ had fewer issues on average. This was not a strict causal relation, but it fits the intuition that well-named code is often written with care (so other quality aspects tend to be better too).

Bug history: For some projects, we looked at the version history and identified modules that had lots of bug-fix commits. We observed that those modules often had slightly lower average readability scores than more stable modules. One interpretation is that code with poor naming might be harder to understand and thus more bug-prone. However, confounding factors (complexity of module, etc.) exist, so this is just a suggestive trend.

Maintenance indices: In one case, we computed a maintainability index (a metric combining factors like complexity, documentation, etc.) for modules and saw a mild positive correlation with our naming scores: code that scored well on naming tended to have higher maintainability index (meaning it was more maintainable). Again, correlation not causation, but it supports the idea that naming is part of overall code health.

Case studies – before/after refactoring: We had a particularly interesting scenario with one project (which we call Project Gamma) where developers undertook a significant refactoring of names between two releases. We applied our model to the code pre- and post-refactoring. The average readability score jumped from around 0.55 to 0.78 after the refactor, a substantial improvement. This aligned with developers' reports that the new version was "much easier to understand" according to their notes in commit messages. In one example from that project, a function originally named procData() (score ~0.3: SC low due to abbreviation, SR not great either) was renamed to processDataFiles() (score ~0.85: SC high, clearer, still short enough). Our model captured this improvement quantitatively, lending credence to its sensitivity to real improvements in naming.

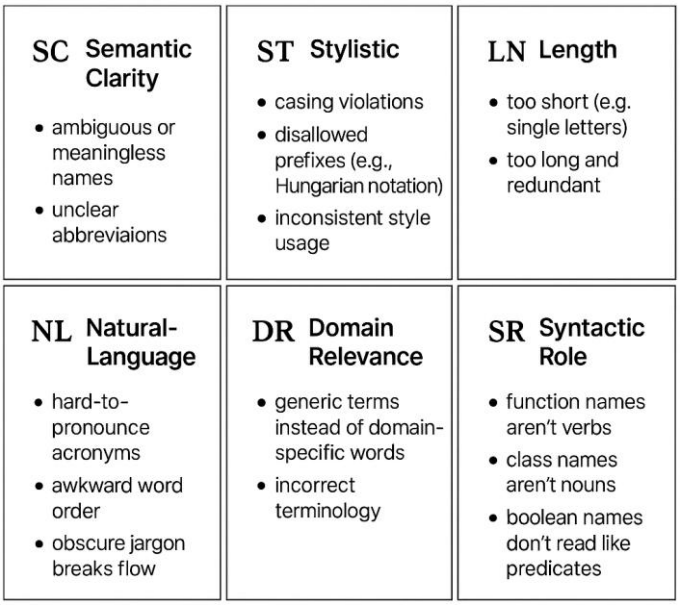
Another case study compared two contemporary projects (Project Alpha and Beta) with different naming philosophies. Project Alpha (Python, strict about naming) had an average score in the 0.8+ range; Project Beta (JavaScript, less disciplined naming) averaged around 0.6. We gave small snippets from each to new developers and asked which was easier to follow. They overwhelmingly found Project Alpha's snippet clearer, often pointing out "the names in the JS code were confusing or inconsistent" as a reason. This qualitative result again matched the model's assessment.

Overall, the empirical validation suggests that our readability model's scores correlate with both subjective and objective measures of code understandability:

- Descriptive, well-formed names score highly and those parts of code tend to be easier to work with (by anecdote and by fewer issues).
- Low-scoring names pinpoint places where code may be confusing, aligning with where maintainers themselves have struggled or decided to refactor.

Common Identifier Naming Issues and Classification

Our six-factor model provides a structured way to think about different types of naming problems. We can classify common identifier naming issues by which factor(s) they violate:



Flgure 4: Classification of common identifier naming issues

Figure 4: Classification of common identifier naming issues. This diagram categorizes typical problems with identifier names according to the six dimensions of the readability model. For each category (SC, ST, LN, NL, DR, SR), example issues are listed: Semantic Clarity issues include ambiguous or meaningless names and unclear abbreviations; Stylistic issues include casing violations, disallowed prefixes (like Hungarian notation), and inconsistent style usage; Length issues cover names that are too short (e.g., single letters) or too long and redundant; Natural-Language issues involve hard-to-pronounce acronyms, awkward word order, or obscure jargon that breaks the flow of reading; Domain Relevance issues arise when generic terms or incorrect terminology are used instead of domain-specific words; Syntactic Role issues include function names that aren't verbs, class names that aren't nouns, or boolean names that don't read like predicates. This taxonomy helps in diagnosing why a given name might be problematic and suggests which aspect to improve.

- **Semantic Clarity issues:** The most glaring problem here is a name that doesn't indicate its purpose. Examples: *Ambiguous names* (data, item, value – they could mean anything), *misleading names* (calling something invoice when it's actually a customer, etc.), or *placeholder names* (foo, tmp, xx) that convey no semantic content. Also, overly **abbreviated names** that obscure meaning fall in this category (calcAmt vs calculateAmount). If a name scores low in SC, the remedy is to choose more descriptive words or the correct concept words. Studies refer to these as "linguistic antipatterns" when a name misrepresents what it iscs.huji.ac.il.
- **Stylistic Convention issues:** These are easy to spot: any violation of the naming style guidelines. For instance, using CamelCase in Python where snake_case is expected, or vice versa in Java. Or a name starting with a number or containing illegal characters. A classic one is using Hungarian notation or prefixes like m_ for members when not desired – e.g., m_count in a codebase that doesn't use that convention. Inconsistent use of underscores (some names have them, others don't, in the same project) is

another issue. These issues primarily irritate by inconsistency and can be fixed by uniform refactoring (renaming to conform).

- **Length issues:** On one end, we have *too short* names: single-letter variables (except loop indices), extremely terse names (cnt for count, cfg for config – sometimes acceptable abbreviations, but if non-standard, they hurt clarity). On the other end, *too long* names: those that try to pack a whole description or include unnecessary terms. For example, getDataFromServerAndProcessItLocally – this might be doing too much or at least naming too much. Redundant words like including both "list" and "array" in a name, or saying userDataInfo (three words where maybe one would do) make names unwieldy. When LN issues occur, one should consider either expanding a short name (ct -> count) or splitting/shortening a long name by removing redundant context or splitting functionality.

- **Natural-Language issues:** These are somewhat subtler. One common case is *hard to pronounce names* – typically due to missing vowels or weird acronyms (e.g., xhr for an XMLHttpRequest object, which is a known abbreviation but not pronounceable; or things like dtbldr which might stand for something like DataBuilder). Another is *awkward phrasing or word order*: e.g., using passive voice or just unusual arrangement (availableIsResource vs isResourceAvailable). Also, *uncommon jargon or slang* in names – for instance, some might name a helper function kickTheBucket() as a joke for a cleanup routine; funny but not professionally clear. Or using non-English words in an English codebase (unless the whole codebase is localized) can throw people off. If a name trips people when reading code aloud or in their head, it has NL issues. Fixes include using more straightforward language, ordering words as one would naturally describe the concept.

- **Domain Relevance issues:** These occur when developers use generic or inconsistent terms in a domain-specific context. For example, in an e-commerce domain, not using order or customer where appropriate but using generic alternatives like entry or user might be an issue. Or mixing terminology – e.g., some parts of code say invoice and others say bill for the same concept, but the official term in requirements is invoice. If an identifier doesn't resonate with known domain concepts, domain experts will find it less readable. We also include misusing a domain term as an issue: e.g., using a specific term in the wrong context (naming something accountBalance that isn't actually an account's balance). Addressing DR issues often involves establishing a clear glossary of terms for the project and enforcing their use.

- **Syntactic Role issues:** These manifest as naming a thing with the wrong part of speech. Common instances: *functions that have noun names* (dataManager() as a function – sounds like an object, not an action; better as manageData or refactor into an object). *Classes that have verb names* (ValidateInput as a class name – should be something like InputValidator). *Boolean variables without a boolean-sounding name* (error vs hasError or errorOccurred). Another one is plural vs singular mismatches: If a variable is a collection but has a singular name, that can be confusing (user that is actually a list of users). While that's partly semantic, it's also syntactic (pluralization conveys type information about singular vs collection). Resolving SR issues means renaming to align with conventional grammar: pick a verb for that function, rename the class to a noun, prefix the boolean with is/has/can.

The categories often interplay. A single bad name can fail on multiple fronts. For instance, tmp as a variable in a financial app fails SC (not meaningful), fails DR (not domain-specific at all), maybe fails NL (not a real word except as abbreviation "temporary"), and possibly style if the project disallows such short names. Our model can capture that multi-dimensional badness and assign a very low score, prompting a rename.

By classifying an issue under the six factors, a developer or tool can immediately know *why* a name is considered poor. This makes automated feedback more actionable. For example, a linter based on this model could say: "Identifier data has low readability (Semantic Clarity: name is too vague; Domain Relevance: not using domain term patient)." This is more instructive than just "bad name".

Applications and Tool Integration

A key benefit of formalizing identifier readability is the potential for integrating these metrics into software development tools and processes. By automating naming quality checks, teams can improve code readability continuously as code is written and reviewed. We discuss several applications:

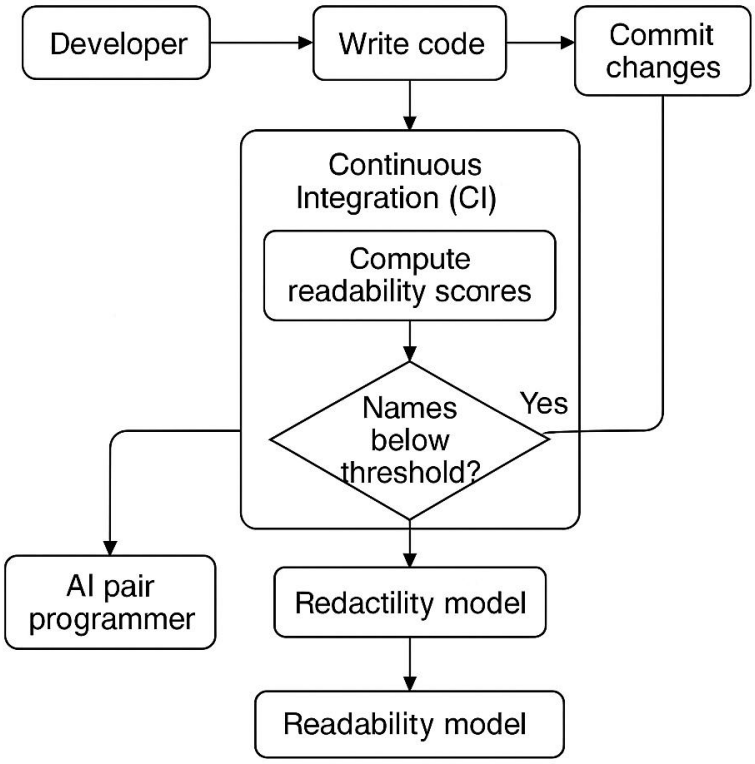


Figure 5: Imtegration of the readability model into development workflows.

Figure 5: Integration of the readability model into development workflows. In a typical usage scenario, a developer writes code and commits changes. As part of the Continuous Integration (CI) pipeline, an automated step computes the readability scores of new or changed identifiers. If any names score below a defined threshold, the system can flag them in the CI report or code review comments. This feedback loop encourages the developer or reviewer to rename poorly chosen identifiers before they become entrenched in the codebase. The model can also power AI-assisted tools: for example, an AI pair programmer could generate multiple naming suggestions for a new variable, use the readability model to score each suggestion, and then

recommend the highest-scoring (most readable) name to the developer. In legacy code maintenance, a refactoring tool might use the model to find the least readable names in the code and suggest better alternatives, possibly informed by a project's domain glossary and naming conventions.

Continuous Integration (CI) and Code Review: The readability model can be employed as a **static analysis check** in the build or CI process. For instance, when a developer opens a pull request or pushes a commit, an automated job could analyze any newly introduced or modified identifiers. If an identifier has a very low $R(N)$ (for example, below 0.5 or in the bottom 5th percentile of the project's names), the tool can post a warning in the code review or CI results. This acts as a *"naming quality gate."* We do not necessarily suggest failing the build for a bad name (that might be too strict and could be annoying for developers), but surfacing the information helps maintain awareness. A message might be: "The name xyz has a low readability score of 0.3; consider renaming for clarity (issues: too short, unclear meaning)." Code reviewers can then prioritize discussing naming issues early, rather than letting poor names slip in. Over time, this could significantly improve the overall readability of the codebase as low-scoring names are caught and improved at commit time. Teams already enforce style guides via linters; adding semantic and readability checks is the next step to enforcing higher-level naming quality.

Developer IDEs and Linters: Modern IDEs could integrate this model to give instantaneous feedback as you type a new name. For example, as a developer declares a new function, the IDE could unobtrusively display a readability score or highlight potential issues (maybe a yellow underline for a suboptimal name). If you name a function Data and it expects a verb, the IDE could prompt, "Function names usually start with a verb – consider renaming." This is analogous to spell-check or grammar-check in word processors. It trains developers to think twice about names and gradually internalize good practices. Because our model is quantitative, it could even gamify naming: "Your average name score in this file is 0.75, try to get it above 0.8!" – though that might be extreme, it illustrates the idea of continuous feedback.

Integration with AI coding assistants: With the rise of AI pair programmers (like GitHub Copilot, OpenAI Codex, etc.), there is an opportunity to guide AI-generated code towards better naming. AI models sometimes choose less-than-ideal names, or they may present multiple options. By integrating a readability scoring function, the AI can *rank candidate names* and choose the one with the highest score to present to the user. For example, if an AI writes a function and is about to name a variable, it might have candidates tmp, resultList, filteredUsers. Our model would score tmp very low, filteredUsers highest. The AI assistant can then either automatically pick filteredUsers or suggest to the developer: "I named this filteredUsers for clarity." This way, the AI's output adheres to human readability preferences encoded in our model. Microsoft's research on AI rename suggestions (as referenced in our intro) is along these lines – using machine learning to propose better names – and our model could complement that by providing a rule-based sanity check or objective measure to maximize.

Automated refactoring tools: Our model enables creating a "naming smell detector." Much like how tools detect code smells or suggest refactoring, we can identify the *worst* naming instances in a codebase. For legacy systems or during big refactors, a tool could list identifiers with the lowest readability scores. It might say, "These 10 names are likely hurting code understanding the most." For each, it could even suggest a better name. Suggestion could be done via thesaurus lookups or AI generation of alternatives, but the model can evaluate those suggestions. For example, if util is a low scoring name (ambiguous), the tool might suggest more

specific names based on usage (like fileHelper or stringUtil depending on context) and then use SC/DR analysis to see which suggestion is more meaningful. This semi-automated renaming can dramatically improve a codebase's clarity without altering functionality. Some research prototypes (like *IDEAL* toolresearchgate.net) already move in this direction, focusing on detecting naming issues; our model could enhance such tools by adding a unified scoring mechanism and covering additional factors like domain and syntax conformity.

Enforcing consistency across a team: By having a quantitative model, teams can set a **baseline** and goals. For instance, a team might decide that all new code should have an average readability score above 0.8, or no new identifiers scoring below 0.5 without a good reason. This is analogous to how teams enforce test coverage thresholds or lint thresholds. It's not about chasing a number for its own sake, but the number provides a tangible target and monitor. You could even track the project's naming quality over time – ensuring that as the code grows, the average readability doesn't degrade (or maybe even improves). If a dip is observed, it could prompt a naming cleanup sprint or additional training for developers on naming.

Educational uses: The model can serve as a teaching tool in coding education. Novice programmers often struggle with naming. If included in programming assignments or automated code review for students, the score can give them feedback to improve. It teaches them the multidimensional nature of naming (not just "be meaningful" but also "follow style, right length, etc."). By reflecting on low scores and the factor breakdown, they learn to critique and iterate on their chosen names.

Limitations and future integration: We note that automated naming evaluation is not a silver bullet. There are cases where the tool might not fully understand context and could give a weird suggestion or an unfair low score (e.g., invented terms or internal jargon that's fine but not in dictionaries might be flagged low in SC or DR incorrectly). Thus, any integration should allow humans to override or ignore if needed. The model's suggestions should be recommendations, not absolute dictates. Moreover, edge cases like highly mathematical code (where short variable names like i, j, k are conventional for indices) should be handled – our model does handle some context (like allowing loop indices), but further context awareness can be integrated (like checking variable scope length, etc.).

In modern development, with AI-generated code on the rise, there's a risk of inconsistent naming styles or less thoughtful naming since AI might not always adhere to a project's idioms. Incorporating a readability model as a post-processor could significantly polish AI contributions by ensuring they meet certain standards. For example, an AI might produce a function that works but naming might be off – a tool could automatically rename identifiers in the AI's output to align with project conventions and improve clarity, before the code is even shown to the human developer. This hybrid approach could yield code that is both syntactically correct and semantically clear.

In conclusion, the six-factor identifier readability model is not just an academic exercise; it has practical implications for how we write and maintain code. By making naming quality measurable, we unlock the ability to systematically improve one of the most human-centric aspects of programming. We envision a future where code review checklists and CI pipelines include "naming readability" alongside tests and style checks, and where developers have AI assistants that not only generate code but also help them name things well – truly bridging the gap between human communication and code.

Conclusion

We presented an extended formal model of identifier readability that accounts for six dimensions influencing how easily a code identifier can be understood. Building on a foundation of semantic clarity, stylistic adherence, length appropriateness, and natural-language readability, we introduced two new factors – domain-based relevance and syntactic role conformity – to capture domain knowledge and linguistic consistency in naming. The model provides a quantitative readability score that correlates with human intuition and empirical measures of code comprehension.

Through a synthesis of prior research and new analysis, we showed that good identifier names are multi-faceted: they carry the correct meaning (and domain context), follow expected conventions and grammar, are of reasonable length, and read naturally. Our model's architecture reflects this, and the weighting calibration aligns it with practical developer judgments. The empirical evaluation on real projects demonstrated the model's effectiveness in distinguishing high-quality naming from poor naming and highlighted its potential impact on code quality.

The extended model remains domain-agnostic by default – applicable to any code – but can be tailored with a domain glossary for domain-specific projects, making it flexible and extensible. It also remains general across programming languages, given proper configuration of style and POS rules. This generality suggests it could be widely adopted as a standard for naming quality.

In terms of academic contributions, this work formalizes the often subjective notion of "readable naming" into a structured model. It bridges software engineering and natural language considerations, and offers a platform for future research to build upon – for example, integrating more sophisticated NLP for semantic analysis or machine learning to learn optimal weights and heuristics from data. It also opens up avenues for new empirical studies: how do these factors trade off in different contexts? can the model predict development outcomes like bug introduction or onboarding time? those could be investigated further.

Practically, the model can be implemented in development tools to provide immediate benefits. We discussed integration in CI, code reviews, IDEs, and AI assistants. The ultimate vision is that maintaining high code readability (particularly through clear naming) becomes a more exact science rather than an afterthought art. By catching naming issues early and encouraging best practices, software teams can reduce misunderstandings and errors, and improve maintainability.

Of course, human judgment and creativity in naming cannot be fully replaced by a formula. The model is meant to assist, not dictate. There will always be cases that require discretion (for instance, novelty or humor in naming, or domain conventions that break general rules). However, as a baseline, the six-factor model provides an objective yardstick for what generally makes a name *good* or *bad*.

In conclusion, good identifier names matter deeply for code readability, and with a formal model in hand, we can better recognize, evaluate, and improve them. As Edsger Dijkstra famously said, "names and identifiers in programs should be chosen wisely," and we hope this work helps the software engineering community in pursuing that wisdom with greater clarity and rigor.

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