On the Relationship Between Code Verifiability and Understandability

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Common Wisdom

easier to verify -> **easier to understand**

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"**rewrite your code to be simpler** for the checker to analyze; this is likely to make it easier for people to understand, too."

- Checker Framework manual

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"**success in checking the consistency of the specifications and the code** will depend on... the **complexity and style** in which the code and specifications are written"

- OpenJML manual

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But **how do we know** that this is true?

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Our goal: **fill this gap** in the literature with an empirical study

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- Our hypothesis:
  - ***“There is a correlation between code that is hard to verify and code that is hard for humans to understand.”***

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Auxiliary benefit of verification:
points to hard-to-understand code

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- For the **users** of verification tools:
  - refactor to avoid warnings
- For **code understanding researchers**:
  - there is a semantic component to human code understanding
  - explains ineffectiveness of traditional, syntactic metrics like cyclomatic complexity

Empirical study design

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  - must use **proxies**

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- “unannotated” = “no specifications”
  - but still trying to prove e.g., absence of buffer overflows
- “correct” so that no warnings correspond to real bugs
  - that is, all warnings are **false positives**

Choosing verifiers

- We selected **four** “verifiers”:

CHECKER framework

Infer

JML

OpenJML

Java Typestate Checker

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All tools have **sound cores**: internally, they try to construct a proof (= “do verification”).

Proxy for understandability

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Metrics for understandability from **prior work**

- this is a **pragmatic** decision: don’t run another human study!
  - but studies in the literature don’t use the same set of metrics

Prior studies

- we used **6** prior studies

Prior studies: descriptive stats

Table 1: Datasets (DSs) of code snippets and understandability measurements/metrics used in our study. The metrics types are "C" for correctness, "R" for ratings, "T" for time, and "P" for physiological.

DS	Snippets	NCLOC	Participants	Understandability Task	Understandability Metrics	Meas.
1 [81]	23 CS algorithms	6 - 20	41 students	Determine prog. output	**C:** *correct_output_rating* (3-level correctness score for program output) **R:** *output_difficulty* (5-level difficulty score for determining program output) **T:** *time_to_give_output* (seconds to read program and answer a question)	2,829
2 [70]	12 CS algorithms	7 - 15	16 students	Determine prog. output	**P:** *brain_deact_31ant* (deactivation of brain area BA31ant) **P:** *brain_deact_31post* (deactivation of brain area BA31post) **P:** *brain_deact_32* (deactivation of brain area BA32) **T:** *time_to_understand* (seconds to understand program within 60 secs.)	228
3 [16]	100 OSS methods	5 - 13	121 students	Rate prog. readability	**R:** *readability_level* (5-level score for readability/ease to understand)	12,100
6 [77]	50 OSS methods	18 - 75	50 students and 13 developers	Rate underst./answer Qs	**R:** *binary_understandability* (0/1 program understandability score) **C:** *correct_verif_questions* (% of correct answers to verification questions) **T:** *time_to_understand* (seconds to understand program)	1,197
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mix of classic algorithms and open source

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almost all students;
# of participants varies

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- instead, use **random-effects meta-analysis**
    - technique for combining medical studies on different populations and proxies

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Brute force is **safe**, but **throws away** the benefit of multiple metrics per study

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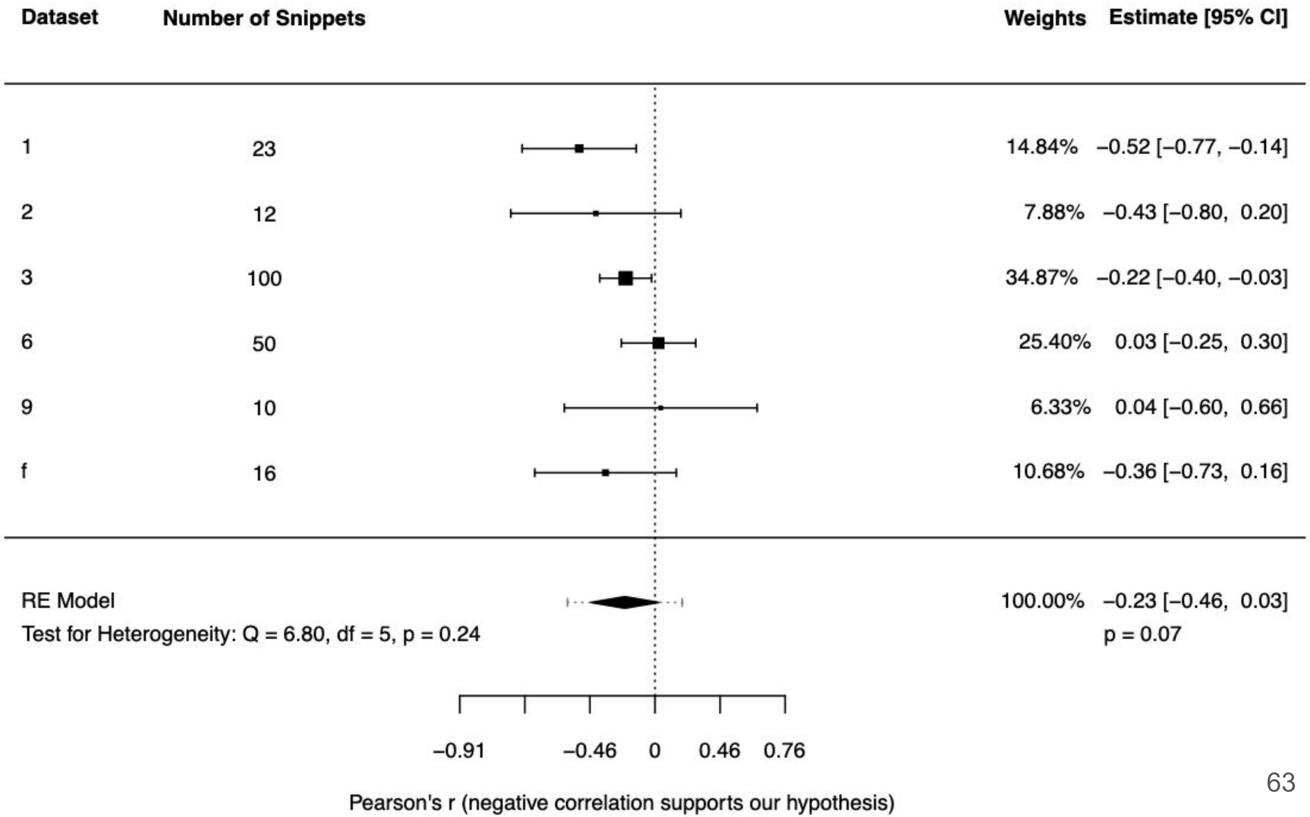

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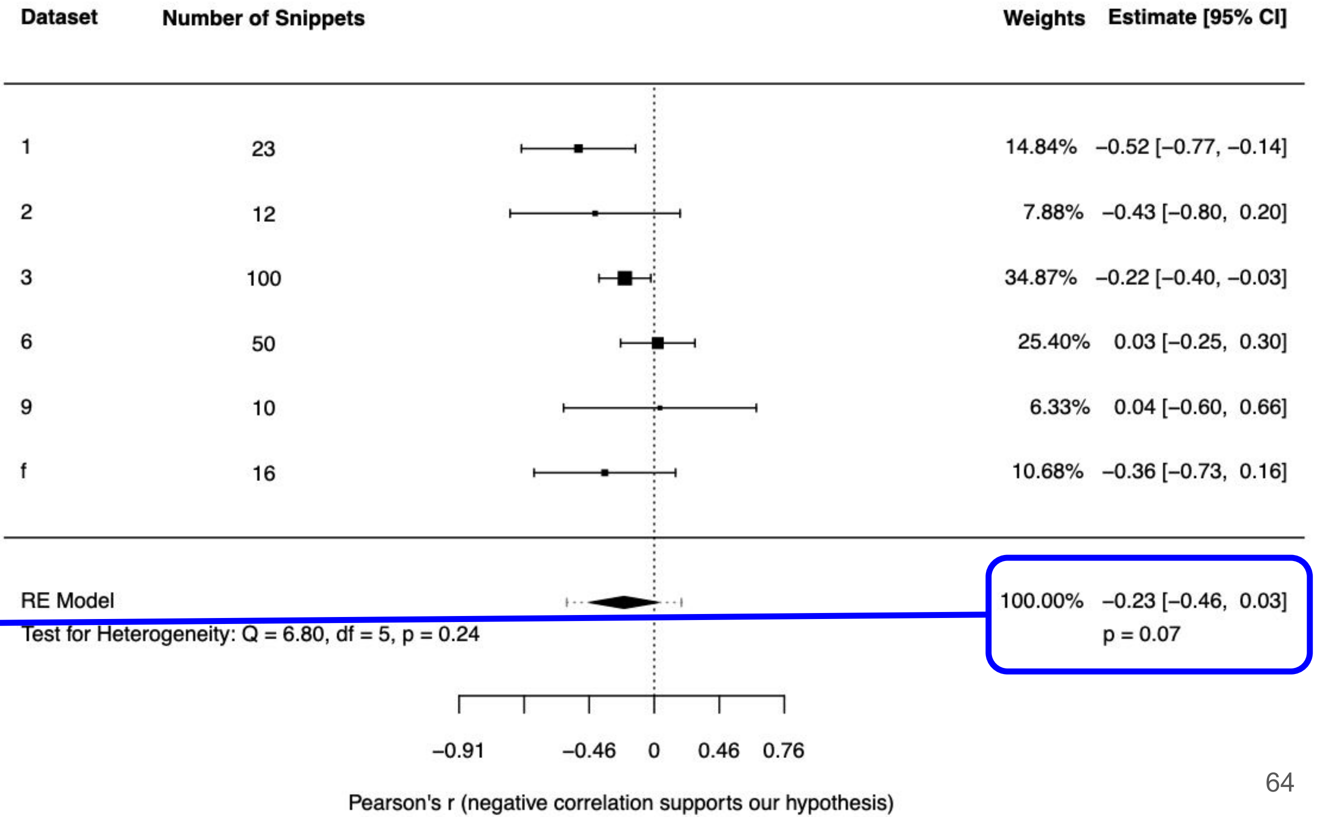
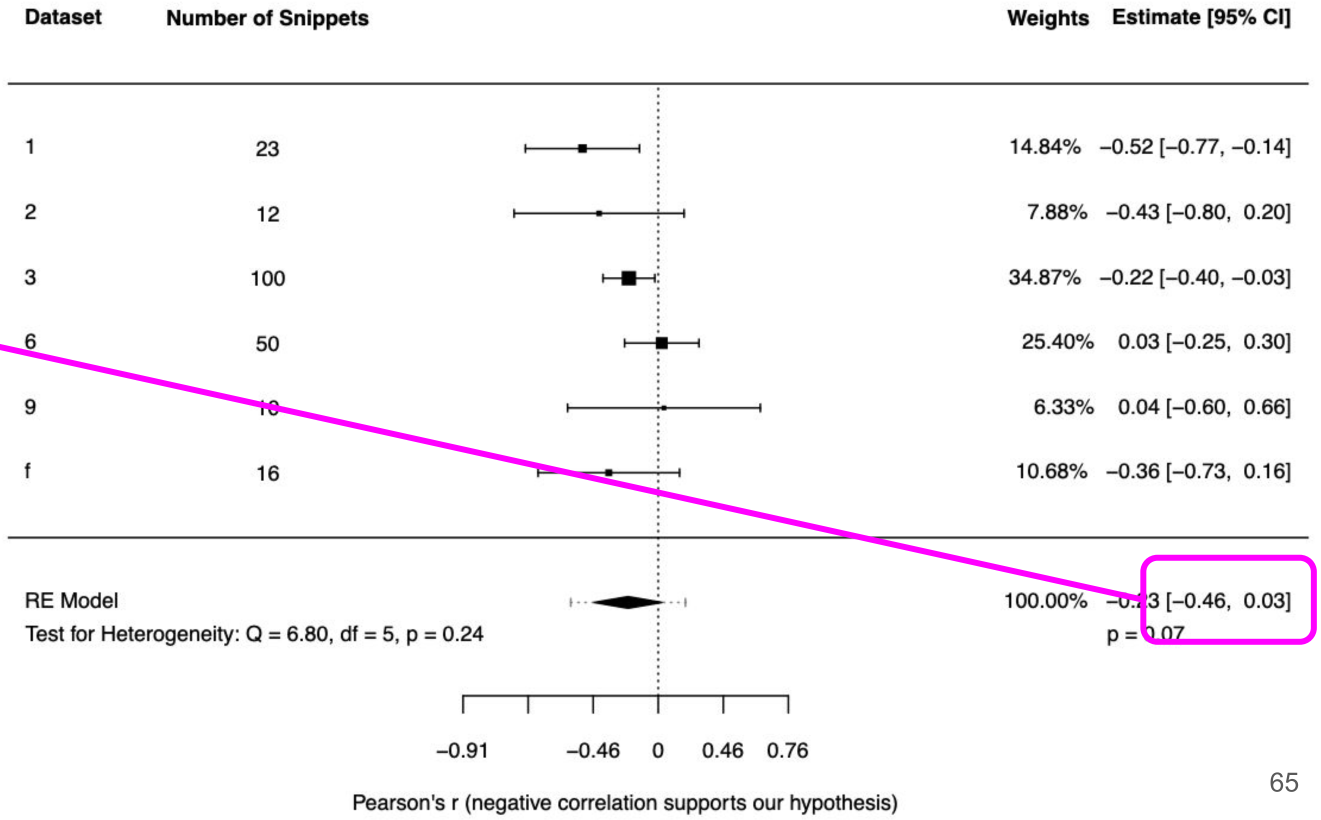


overall correlation of *r*=0.23 (small effect size)

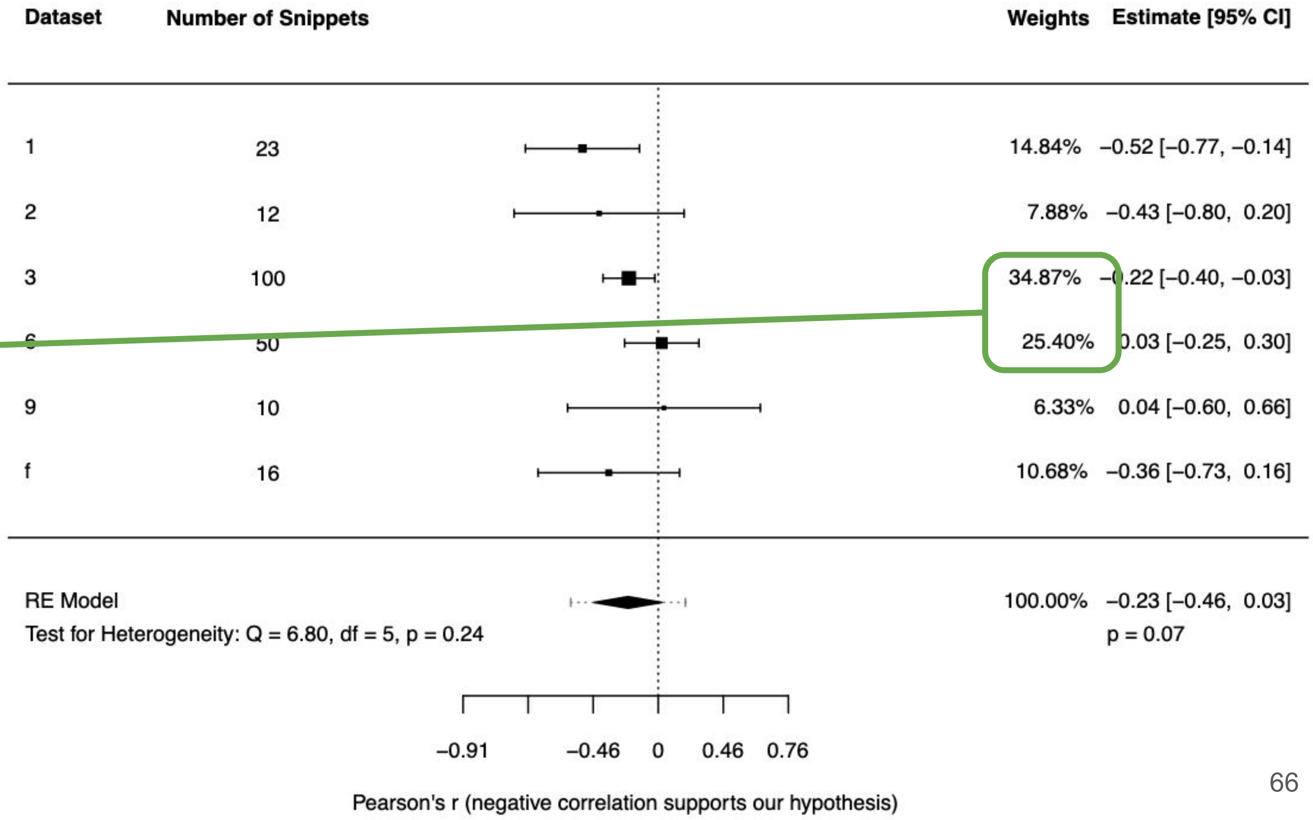
Results: overall

95% confidence interval is wide [-0.46, 0.03], but most of it supports our hypothesis



Results: overall

meta-analysis weights these two datasets (with 50 and 100 snippets) much higher than the others



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- Our results give **mild but suggestive** support for our hypothesis
  - especially given our **relatively conservative** statistical methods
- The main limitation preventing us from making stronger conclusions is **the small number of snippets** in prior work
  - future work: new study with a **larger number of snippets**

Results: secondary analyses

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- **per-tool** analysis:
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Results: secondary analyses: per-tool

- **per-tool** analysis:
  - same meta-analysis using one tool's warnings
  - results were **similar**:
    - all tools have same pattern of correlations
    - gives us **a bit more confidence**

Results: secondary analyses: ablation

- **leave-one-out ablation** analysis:
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Results: secondary analyses: ablation

- **leave-one-out ablation** analysis:
  - same meta-analysis without the warnings from each tool
  - results **nearly identical**, implying no one tool dominates

Results: secondary analyses: categories

- **per-metric-category** analysis:
    - same meta-analysis, but with only metrics from one category
    - correctness, rating, time, and physiological categories

Results: secondary analyses: categories

- **per-metric-category** analysis:
  - same meta-analysis, but with only metrics from one category
  - correctness, rating, time, and physiological categories
  - similar results; **too-wide** confidence intervals (except rating)

Contributions

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Thanks to my fabulous collaborators!