

From Papers to Progress: Rethinking Knowledge Accumulation in Software Engineering

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Abstract

Software engineering research has experienced sustained growth in both output and participation over the past decades. Yet concerns persist about the field's ability to accumulate, integrate, and reuse knowledge in ways that support long-term progress. To better understand how the community itself perceives these challenges, we analyze responses from the ICSE 2026 Future of Software Engineering pre-survey, which captures perspectives from a globally distributed and highly experienced set of researchers. Our analysis reveals a tension between increasing research productivity and the limited mechanisms available for synthesizing results, tracking evolving claims, and supporting cumulative understanding over time.

Building on these observations, we diagnose four interrelated structural breakdowns: papers function as isolated knowledge units with claims embedded in prose; context and provenance are lost as knowledge moves through the publication pipeline; claims evolve without systematic tracking; and incentive structures favor novelty over consolidation. We argue that addressing these barriers requires rethinking the fundamental properties of research artifacts.

We articulate four technology-agnostic principles for future research artifacts: structured and interpretable representations of claims and evidence; inspectable and provenance-aware documentation of methodological decisions; long-lived and reusable substrates that evolve beyond publication; and governance mechanisms that align individual incentives with collective knowledge-building goals. We discuss implications for research practice, publication norms, and community infrastructure, positioning FOSE as a venue for experimenting with alternative artifact designs that support cumulative scientific progress.

CCS Concepts

- Software and its engineering → Software creation and management; Empirical software validation;
- General and reference → Empirical studies.

Keywords

knowledge accumulation, research artifacts, software engineering, cumulative progress, research infrastructure

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1 Introduction

Software engineering research has experienced remarkable growth over the past decades. Conference submissions have increased, publication venues have proliferated, and the community has become truly global. By many measures, the field is thriving: researchers are productive, techniques are advancing, and new areas of inquiry continue to emerge. Yet beneath this surface of activity lies a persistent challenge: the difficulty of building cumulative knowledge that connects, consolidates, and extends prior work in ways that support long-term scientific progress.

This challenge is not new, nor is it unique to software engineering. Across many scientific disciplines, researchers have observed that increasing publication rates do not automatically translate into deeper understanding or more integrated knowledge [5, 8]. In software engineering specifically, concerns about fragmentation, replication, and the ability to synthesize results across studies have been raised repeatedly [11, 12]. Despite these concerns, the structural factors that limit cumulative progress—and the properties that future research artifacts might need to address them—remain underexplored.

This paper offers a community-informed perspective on knowledge accumulation challenges in software engineering. Grounded in responses from 280 ICSE 2026 FOSE pre-survey participants—an experienced (57% with 10+ years), productive (44% with 11+ papers in 3 years), globally distributed community—we diagnose four interrelated structural breakdowns: papers as isolated units, lost context and provenance, untracked claim evolution, and misaligned incentives favoring novelty over consolidation. In response, we propose four technology-agnostic design principles for research artifacts: structured and interpretable representations, inspectable and provenance-aware documentation, long-lived and reusable substrates, and community-governed infrastructures. This FOSE contribution synthesizes community observations into a diagnosis of structural limitations and principles to guide future work, without prescribing specific tools or claiming to solve the challenges we identify.

2 Community Signals from the ICSE 2026 FOSE Pre-Survey

To ground our diagnosis in community perspectives, we draw on the ICSE 2026 Future of Software Engineering pre-survey ($n=280$). The respondents represent a mature, productive, and globally distributed research community: 57% have 10+ years of experience, 44% authored 11+ papers in the past three years, and participation spans six geographic regions (Europe 50%, North America 25%, Asia 15%, others 10%).

This profile is critical to our argument. If knowledge accumulation remains limited despite significant expertise, productivity, and global participation, then the barriers must be *structural* rather than individual. The community is not lacking effort or output

117 capacity—respondents themselves recognize systemic challenges
 118 in knowledge synthesis, with concerns about fragmentation across
 119 resubmissions, difficulties building on prior work, and systems that
 120 reward novelty over consolidation. These observations motivate
 121 the structural diagnosis that follows.

122 3 Where Knowledge Accumulation Breaks 123 Down

125 If the software engineering community is experienced, productive,
 126 and globally distributed, yet faces persistent challenges synthesizing
 127 results and building on prior work, then the barriers must be
 128 structural. We diagnose four interrelated breakdowns arising from
 129 how research artifacts are currently produced, represented, and
 130 connected.

132 3.1 Papers as Isolated Knowledge Units

134 Research papers package claims, evidence, and context into narrative
 135 prose optimized for dissemination. While effective for presenting
 136 new ideas, this format creates barriers to cumulative building.
 137 Claims are embedded in paragraphs, interleaved with motivation
 138 and methods, making extraction and comparison across papers
 139 require reading entire documents and reconciling terminological
 140 differences. Evidence linkages remain implicit—readers must infer
 141 which results support which claims under what assumptions.
 142 Even when artifacts are shared, results are static at publication
 143 time; updates to datasets or baselines require new papers citing
 144 the old, while original claims remain unchanged. The consequence
 145 is fragmentation: each paper is an island connected only through
 146 citations and prose, requiring repeated manual synthesis that does
 147 not scale as literature grows.

148 3.2 Loss of Context and Provenance

150 Research involves countless contextual decisions: which dataset to
 151 use, how to split data, which baselines to compare, how to handle
 152 edge cases. Papers describe these choices but often omit the rationale
 153 due to space constraints. As work is cited and summarized,
 154 motivation and assumptions fade—carefully qualified findings become
 155 unqualified facts in subsequent literature. Methodological
 156 decisions must be reverse-engineered, sometimes revealing that
 157 subtle choices significantly impacted results. Papers present polished
 158 final versions, hiding the evolutionary path from hypothesis
 159 to result. When context and provenance are lost, later researchers
 160 must either accept prior work at face value or invest substantial
 161 effort reconstructing reasoning, slowing progress and increasing
 162 misapplication risk.

163 3.3 Claims Evolve Without Tracking

165 Scientific claims are refined, qualified, contradicted, and superseded as
 166 evidence accumulates, yet the publication system provides limited tracking mechanisms. The literature may contain
 167 conflicting claims—technique A outperforms B in one paper, the reverse in another—but contradictions are not systematically flagged.
 168 Researchers discovering conflicts must investigate causes themselves, often finding subtle methodological differences account
 169 for divergence. Refinements are implicit: a follow-on paper may qualify a prior claim, but the original remains unchanged. Claim

175 relationships—does one extend, contradict, or depend on another?—
 176 are expressed only in natural language like “building on [12]” or “in
 177 contrast to [34].” Without structured representations, knowledge
 178 remains fragmented and ambiguous, requiring extensive manual
 179 synthesis to determine what is currently believed, under what conditions, and with what confidence.

181 3.4 Incentive Structures Favor Novelty Over 182 Accumulation

183 The final breakdown is embedded in incentive structures. Publication
 184 venues, hiring criteria, and funding mechanisms reward
 185 novelty and originality [10, 13]. Conference and journal reviews
 186 prioritize new techniques and findings; replication studies, negative
 187 results, and syntheses face higher acceptance bars even when they
 188 would advance collective understanding [3]. Researchers investing
 189 in replication, dataset curation, or shared infrastructure face opportunity
 190 costs—these efforts may not yield top-venue publications or count heavily in promotion reviews [4]. Building knowledge repositories,
 191 ontologies, and interoperability layers requires sustained effort often led by small groups without commensurate recognition.
 192 The result is a collective action problem: everyone benefits from better infrastructure, but individuals are disincentivized from
 193 contributing. As long as novelty is privileged over accumulation,
 194 knowledge remains fragmented and progress constrained.

195 These four breakdowns reinforce one another, creating a system
 196 where knowledge accumulates slowly despite community expertise
 197 and productivity. Incremental fixes—better citation practices, more
 198 replications, improved repositories—are necessary but insufficient.
 199 Addressing these barriers requires rethinking the fundamental properties of research artifacts themselves.

200 4 Rethinking Research Artifacts for 201 Cumulative Progress

202 The structural barriers arise from design choices in how artifacts
 203 are produced and shared. Addressing them requires reconsidering
 204 fundamental artifact properties. We articulate four technology-
 205 agnostic principles describing properties that systems, tools, or
 206 practices aiming to support knowledge accumulation should strive
 207 for. Implementations will vary across domains, but these principles
 208 provide a shared foundation for evaluating research infrastructure.

209 4.1 Principle 1: Structured and Interpretable

210 **Principle:** Research artifacts should make claims, evidence, and
 211 context explicit and directly accessible, not only embedded in prose.

212 The first breakdown—papers as isolated units—stems from the
 213 fact that claims and evidence are woven into narrative text. While
 214 prose is valuable for explaining motivation and argumentation,
 215 it is not optimal for supporting cumulative synthesis. A reader
 216 wishing to compare claims across papers must extract and interpret
 217 statements from natural language, a process that does not scale as
 218 the literature grows.

219 Artifacts should represent claims, evidence, and context as structured,
 220 first-class entities. A claim should be identifiable: “Technique
 221 X improves metric Y on dataset Z by δ under conditions C.” Evidence
 222 and context should be explicitly linked, not buried in prose.

233 Structured representations enable direct comparison and reasoning: conflicting claims become visible and resolvable by examining
 234 structured evidence, and claims referencing updated datasets can
 235 be systematically reevaluated. Instantiations could include semantic
 236 annotations (machine-readable metadata describing claims and
 237 results) or knowledge graphs [9, 14] (entities with typed relationships
 238 enabling queries like “Which papers claim improvements on
 239 dataset D?”). Structure should complement prose, making knowl-
 240 edge directly accessible while preserving narrative’s explanatory
 241 power.
 242

244 4.2 Principle 2: Inspectable and 245 Provenance-Aware

246 **Principle:** Research artifacts should preserve the full provenance
 247 of claims—from raw data through methodological decisions to final
 248 results—and make this provenance inspectable.

249 The second breakdown—loss of context and provenance—occurs
 250 because reasoning behind decisions fades as knowledge moves
 251 through publication. Papers report final results but often omit the
 252 path taken: why this dataset, baseline, or protocol. Later researchers
 253 must reconstruct this reasoning, often discovering subtle choices
 254 had significant consequences.

255 Artifacts should document not only what was found but how
 256 and why. Every claim should trace to its sources: data, code, config-
 257 uration, assumptions. Methodological decisions should be explicitly
 258 justified, and when results are updated, the provenance chain should
 259 track changes [6]. Provenance enables trust: researchers can inspect
 260 a claim’s lineage, verify evidence, and understand conditions. When
 261 claims conflict, provenance diagnoses divergence sources. Instanti-
 262 ations could include versioned computational artifacts (code and
 263 data in version control with clear lineage) or provenance graphs
 264 (explicit representations linking claims to experiments to data). Arti-
 265 facts should be transparent about origins and decisions, enabling
 266 future work to build on solid foundations.

268 4.3 Principle 3: Long-Lived and Reusable

269 **Principle:** Research artifacts should support evolution and reuse,
 270 not remain static at the moment of publication.

271 Papers are snapshots frozen in time. Once published, they do not
 272 update when evidence emerges, datasets are revised, or methods
 273 improve. Follow-on work cites and describes differences in prose,
 274 but original claims remain unchanged.

275 Artifacts should be living substrates that can be updated, ex-
 276 tended, and reused. When datasets are corrected, dependent claims
 277 should be re-evaluatable. When techniques are refined, prior results
 278 should be comparable to new results. When claims are qualified,
 279 these relationships should be reflected in the artifact. This does
 280 not mean rewriting papers—rather, underlying structured represen-
 281 tations should decouple from narrative documents. Narratives
 282 remain stable as historical records while structured substrates
 283 evolve. Instantiations could include living knowledge bases (reposi-
 284 tories where claims and datasets are versioned and updated) or
 285 executable benchmarks (evaluation frameworks rerun with updated
 286 data). Knowledge should outlive individual papers, accumulating in
 287 shared substrates that reduce redundancy and enable direct build-
 288 ing.
 289

291 4.4 Principle 4: Governed with Human 292 Oversight

293 **Principle:** Research artifacts and infrastructures should be gov-
 294 erned by community processes that ensure quality, integrity, and
 295 ethical responsibility.

296 Even with perfect technical infrastructure, cumulative progress
 297 requires coordination: quality standards, conflict resolution mech-
 298 anisms, and recognition for consolidation work. Artifacts cannot
 299 govern themselves—structured representations and provenance
 300 tracking are valuable only if the community trusts, maintains, and
 301 uses them responsibly. This requires human oversight: peer review
 302 for knowledge contributions, curation, dispute resolution processes,
 303 and credit systems valuing infrastructure work alongside novel re-
 304 search.

305 Governance also addresses ethical concerns about ownership, at-
 306 tribution, bias, and access. Who controls shared knowledge bases?
 307 How is credit assigned for incremental contributions? How do
 308 we prevent infrastructures from perpetuating biases? These social
 309 and ethical questions require community deliberation and ongoing
 310 stewardship. Instantiations could include community curation pro-
 311 cesses (peer-reviewed contributions with clear criteria) or credit
 312 systems recognizing infrastructure, replication, and consolidation
 313 work. Cumulative progress is a collective endeavor—technical so-
 314 lutions must be embedded in social practices aligning individual
 315 incentives with collective goals.

317 4.5 From Principles to Practice

318 These principles are aspirational, requiring significant changes in
 319 how research is conducted, reviewed, and rewarded. They provide
 320 a framework for evaluating incremental steps: Does a proposed tool
 321 or practice make artifacts more structured, inspectable, reusable, or
 322 better governed? The principles are technology-agnostic—knowledge
 323 graphs, computational notebooks, and repositories are potential
 324 instantiations, but the principles describe *properties* that artifacts
 325 should have, leaving room for diverse implementations. The chal-
 326 lenge is designing systems and reforming incentives to make cu-
 327 mulative knowledge building not only possible but rewarded.

329 5 Implications for the Future of Software 330 Engineering

331 Realizing these principles would require changes in how research
 332 is conducted, reviewed, published, and rewarded.

335 5.1 Research Practice and Publication

336 Research practice would shift toward documenting process along-
 337 side outcomes: recording methodological decisions, their ratio-
 338 nales, and impacts using computational notebooks, version control,
 339 and workflow platforms. Researchers would supplement narrative
 340 papers with structured representations—semantic annotations or
 341 knowledge graph entries—making contributions directly accessible
 342 for synthesis. Designing for reuse would become standard: datasets
 343 documented with schemas, code modular and documented, proto-
 344 cols reproducible. Structured artifacts would enable new collabora-
 345 tion forms, with researchers contributing incrementally to shared
 346 knowledge bases rather than isolated papers.

Publication and review would need to value consolidation alongside novelty. Papers that resolve contradictions, curate benchmarks, or provide infrastructure should be recognized. Conferences could establish expectations for structured artifacts as first-class contributions, not optional supplements. If artifacts evolve post-publication, papers become snapshots while living artifacts accumulate evidence and track refinements, requiring new norms for citing evolving work.

5.2 Community Infrastructure

The community would need platforms for storing, querying, and updating structured artifacts—knowledge graphs, benchmark repositories, collaborative platforms—maintained through community governance [2]. Shared standards (ontologies, schemas, reporting protocols) would enable reuse across studies [15]. Infrastructure contributions, replications, and refinements would require recognition through alternative metrics, tenure criteria changes, or contribution-tracking platforms [1]. Governance structures would manage stewardship: maintaining repositories, resolving disputes, updating standards, addressing ethical concerns. Building such infrastructure requires sustained investment and coordination, but without it, the principles remain aspirational.

5.3 FOSE as a Venue for Experimentation

The Future of Software Engineering track is positioned to support experimentation with alternative artifact types. FOSE could encourage submissions experimenting with structured artifacts or living documents, judged on potential to demonstrate new knowledge-organizing approaches rather than solely novelty. FOSE sessions could facilitate dialogue about infrastructure needs and governance models, and track experiments over time to inform broader community decisions about adopting new norms.

6 Limitations

This paper diagnoses structural barriers and proposes principles for future research artifacts, but does not provide complete solutions. We acknowledge several limitations.

Survey limitations. Our analysis draws on 280 FOSE pre-survey responses, representing a small, self-selected fraction of the global community. The data are descriptive, not causal—they establish that the community is experienced and productive, supporting our argument that barriers are structural, but do not prove specific breakdowns. The survey reflects perspectives at one moment; community concerns evolve over time.

Feasibility challenges. Realizing these principles faces practical barriers. Producing structured, provenance-aware artifacts requires effort that researchers may not have without reduced demands or increased support. The needed infrastructure—shared repositories, standards, governance—does not yet exist in many areas and requires sustained investment and coordination [7]. Adoption depends on changing incentives at multiple levels (funding agencies, universities, conferences), which is difficult and slow. Cultural norms resist change, especially from those who succeed under current systems.

Ethical concerns. Structured knowledge infrastructures raise questions about ownership (who controls shared knowledge bases?),

bias (artifacts may perpetuate creators' biases if diversity is lacking), access (resources may concentrate in well-funded institutions), and privacy (structured data about research processes requires ethical use and consent). These are not purely technical issues—they require community deliberation, ethical oversight, and ongoing stewardship. Any future infrastructure must address these concerns.

7 Conclusion

Software engineering research is productive and globally distributed, yet knowledge accumulation lags behind knowledge production. This paper has argued that the barriers are structural: papers function as isolated documents, provenance is lost, claims evolve without tracking, and incentives favor novelty over consolidation. Addressing these barriers requires rethinking research artifacts themselves. We have proposed four principles—structured and interpretable, inspectable and provenance-aware, long-lived and reusable, and governed with human oversight—to guide future work.

These principles are aspirational and technology-agnostic. Realizing them requires changes in practice, publication norms, infrastructure, and incentives. The challenges are significant, but the alternative—continuing with practices optimized for dissemination rather than accumulation—will perpetuate fragmentation as the field grows.

The Future of Software Engineering track provides space for this conversation. Next steps include experimenting with alternative artifact designs, developing infrastructure aligned with these principles, and revising recognition systems to value consolidation alongside novelty. Most importantly, the community must engage in dialogue about what cumulative progress requires and what trade-offs are acceptable.

The future of software engineering depends not only on what we discover but on how we organize and preserve what we know. Building infrastructures that support cumulative knowledge building—making it rewarded, not just possible—is essential to ensuring the next generation inherits not just a literature to read but a knowledge base to build upon.

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