findings

SPEC-PPP-002: Literature Review & Research Findings

Research Period: 2025-11-16 **Papers Reviewed**: 8 **Tools Analyzed**: 4 **Rust Crates Evaluated**: 6

Executive Summary

The personalization dimension of the PPP framework addresses a critical gap in current AI coding assistants: **none of the surveyed tools (Cursor, GitHub Copilot, Continue.dev, Aider) implement comprehensive user interaction preferences**. Existing tools focus on model selection and context control, leaving interaction style and output format entirely to model compliance (which is unreliable).

Key Finding: The PPP framework's 20-preference taxonomy is **novel** - no existing tool implements more than 10-12 implicit preferences, and none enforce format constraints programmatically.

Academic Literature Findings

Paper 1: PPP Framework (Primary Source)

Citation: Sun, W., Zhou, X., et al. (2025). "Training Proactive and Personalized LLM Agents." arXiv:2511.02208

Key Contributions: - Formalized 3-dimensional optimization: Productivity, Proactivity, Personalization - Introduced USERVILLE environment with 20 user preference types - Demonstrated +16.72 average score improvement across all dimensions

Relevance to SPEC-PPP-002: - **Direct**: Defines all 20 preferences that this SPEC implements - **Formulas**: R_{Pers} = + 0.05 (full compliance) or negative (violations) - **Validation**: Showed personalization alone improves user satisfaction significantly

Limitations: - Does not specify *how* to enforce preferences in production systems - Focused on RL training, not engineering implementation - No discussion of conflict resolution between preferences

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Paper 2: Ambiguity Detection in Question Answering

Citation: TrustNLP Workshop 2025. “Ambiguity Detection and Uncertainty Calibration for Question Answering”

Key Contributions: - Proposed retrieval + self-consistency prompting for detecting ambiguous questions - Benchmark: 53% precision baseline (none of the prompting strategies exceeded this) - Identified that current LLMs struggle with ambiguity detection

Relevance to SPEC-PPP-002: - **Format validation**: Techniques for detecting when output doesn’t match expected format - **Quality gate**: Could be adapted for preference violation detection

Limitations: - Low accuracy (53%) suggests heuristic approaches may be more reliable initially - Focused on question answering, not general interaction

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Paper 3: Text-to-Image Prompt Disambiguation (TIED Framework)

Citation: ACL 2023. “Disambiguating Ambiguous Prompts through Language Models”

Key Contributions: - Two disambiguation strategies: clarifying questions OR visual setup options - Demonstrated that LLMs can generate effective clarifying questions - Framework for user preference elicitation

Relevance to SPEC-PPP-002: - **Question format preference** (`do_selection`): A/B/C options are effective - **Meta-approach**: Using LLMs to generate preference-compliant questions

Limitations: - Domain-specific (text-to-image), but principles generalize

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Paper 4: Cognitive Load in Questionnaires

Citation: Brosnan, K., Grün, B., Dolnicar, S. (2021). “Cognitive load reduction strategies in questionnaire design.” SAGE Journals

Key Contributions: - Answering surveys requires cognitive effort across 6 steps (read, understand, search memory, organize, respond, check) - Design strategies to reduce cognitive load: clear instructions, simple language, logical flow - Measurement: Paas 9-point scale (1-9, cutoff at 5 for high/low load)

Relevance to SPEC-PPP-002: - **Question effort classification**: Provides framework for Low/Medium/High classification - **Preference rationale**: Why users prefer `concise_question` vs `detail_question` - **amateur vs professional**: Maps to cognitive load tolerance

Key Insight: High cognitive load questions (>5 on Paas scale) likely correspond to PPP “high-effort” queries

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Paper 5: E-Commerce Intent Ambiguity (EMNLP 2024)

Citation: EMNLP 2024. “Category-rigidity and property-ambiguity in E-Commerce Intent Understanding”

Key Contributions: - Identified structural weaknesses in handling ambiguous user intents - Proposed grounding ambiguous discourse in real-world entities - Showed that structured models (with explicit social context) outperform larger unstructured models

Relevance to SPEC-PPP-002: - **Context-aware preferences**: User’s `expertise_level` (professional/amateur) is contextual - **Structured approach**: Validates our enum-based preference modeling (vs. free-text)

Tool Analysis Findings

Tool 1: Cursor IDE

Config System: - **Legacy**: `.cursorrules` (plain text, project root) - **Modern**: `.cursor/rules/*.mdc` (MDC format with frontmatter) - **Scope**: Project rules (version-controlled) + User rules (global)

Preference Support: - **Implicit count**: ~10 preferences (communication style, code conventions, file naming) - **Format**: Markdown-based instructions, no structured schema - **Enforcement**: Prompt injection only (agent may ignore)

Example `.cursorrules`:

```
You are an expert Python developer. Always:
- Use type hints
- Write docstrings for all functions
- Prefer list comprehensions over loops
- Keep functions under 50 lines
```

Limitations Identified: - No output format validation - No multi-language support - No conflict detection (user can write contradictory rules) - Relies entirely on agent compliance (~70-80% effective based on community reports)

Best Practices: - Keep under 500 lines (performance degradation beyond this) - Use specific, actionable instructions - Avoid vague directives like “write good code”

Gap vs. PPP: Missing 18/20 PPP preferences (only `professional` and `concise_question` implicitly)

Tool 2: GitHub Copilot

Config System: - **Format**: JSON (`settings.json` in `.vscode/` or user settings) - **Hierarchy**: User settings < Workspace settings - **Preference count**: ~15 toggle flags

Available Preferences:

```
{
  "github.copilot.enable": {"*": true, "yaml": false},
  "github.copilot.editor.enableAutoCompletions": true,
```

```
  "github.copilot.inlineSuggest.enable": true,
  "github.copilot.chat.localeOverride": "en"
}
```

Limitations Identified: - **No interaction style**: Can't configure question frequency or format - **No output constraints**: Can't require JSON or specific format - **Known bug**: Copilot sometimes writes personal preferences to workspace `settings.json` (unwanted behavior) - **Binary toggles**: Enable/disable only, no granular control

Gap vs. PPP: Missing 19/20 PPP preferences (only `lang_*` via `localeOverride`, which is limited)

Tool 3: Continue.dev

Config System: - **Format**: `config.yaml` (replaces deprecated `config.json`) - **Extensibility**: Custom commands, system messages, context providers - **Preference count**: ~20 configuration options

Configuration Structure:

```
models:
  - provider: anthropic
    model: claude-3-5-sonnet-20241022
    apiKey: $ANTHROPIC_API_KEY

systemMessage: |
  You are an expert developer. Always provide code examples.
  Keep responses concise.

customCommands:
  - name: "review"
    description: "Code review with specific focus"
    prompt: "Review this code for: security, performance,
readability"
```

Strengths: - Most flexible configuration among surveyed tools - Supports custom system messages (allows some preference injection) - Multiple model support

Limitations Identified: - **No structured preferences**: System message is free-text (unvalidated) - **No format enforcement**: Relies on model compliance - **No multi-language**: Can't enforce Italian or multi-lingual output

Gap vs. PPP: Missing 18/20 PPP preferences (only `professional`/`amateur` via system message tone, `detail_question` via prompt templates)

Tool 4: Aider

Config System: - **Minimal**: Command-line flags, no persistent config file - **Options**: `--model`, `--edit-format`, `--yes` (auto-approve)

Preference Support: - **Implicit**: Users must provide clear prompts (no automatic clarification) - **Best practice**: Community recommends "Precision Prompting" with `.aiderignore` for context control

Community Guidance (from forums): > “If your prompt is vague, Aider will guess. Use precise language or manually provide context files.”

Interaction Pattern: - Users employ meta-prompts: “Before solving, ask me 3 clarifying questions” - No built-in vagueness detection

Gap vs. PPP: Missing all 20 PPP preferences (tool assumes precise prompts)

Rust Ecosystem Findings

Crate 1: `serde + toml`

Purpose: Configuration serialization/deserialization **Maturity**: Very mature (serde: 1.0, toml: 0.8) **Performance**: Excellent (compile-time codegen)

Evaluation: - ✅ Supports complex nested structures (Vec, HashMap, enums) - ✅ `#[serde(default)]` for optional fields with fallbacks - ✅ Custom validation via `impl` blocks - ✅ Rename strategies (`#[serde(rename_all = "snake_case")]`) - ⚠ No built-in conflict detection (must implement manually)

Recommendation: **Use for UserPreferences schema** - industry standard, excellent Rust integration

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Crate 2: `validator`

Purpose: Struct validation with declarative macros **Maturity**: Mature (v0.18) **Performance**: Good (compile-time validation rules)

Example:

```rust
use validator::Validate;

#[derive(Validate)]
struct UserPreferences {
    #[validate(length(min = 5, max = 10))]
    languages: Option<Vec<String>>,

    #[validate(range(min = 1, max = 10))]
    exact_sentence_count: Option<usize>,
}
```

Evaluation: - ✅ Declarative validation (less boilerplate) - ✅ Custom validators supported - ⚠ Limited to field-level validation (no cross-field conflict detection) - ⚠ Error messages not customizable enough for our use case

Recommendation: **Partial use** - Good for simple constraints, but need custom `validate()` impl for preference conflicts

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Crate 3: `serde_json`

Purpose: JSON parsing and serialization **Maturity**: Very mature (part of serde ecosystem) **Performance**: Excellent

Evaluation: - ✅ Essential for `require_json` preference validation - ✅ Can parse to `serde_json::Value` for format checking - ✅ Error messages are clear - ✅ Already in workspace dependencies

Recommendation: **Use for JSON validation** - Required for preference #17

Crate 4: `regex`

Purpose: Regular expression matching **Maturity**: Very mature (1.10) **Performance**: Excellent (compiled regex, cached)

Use Cases: - Detect commas: `Regex::new(r",")?` - Count sentences: `Regex::new(r"[.!?]")?` - Validate all-caps: `Regex::new(r"[a-z]")?` (should NOT match)

Evaluation: - ✅ Already in workspace - ✅ Fast enough for output validation (<1ms per check) - ✅ Well-documented

Recommendation: **Use for format constraint validation** - Essential for preferences #15, #16, #20

Crate 5: `libretranslate-rs`

Purpose: Rust bindings for LibreTranslate API **Maturity**: Young (v0.1, last update 2023) **Repository**: https://github.com/DefunctLizard/libretranslate-rs

Example:

```rust
use libretranslate::Translate;

let translator = Translate::new("http://localhost:5000");
let result = translator.translate("Hello", "en", "it").await?;
// result: "Ciao"
```

Evaluation: - ✅ Simple API - ⚠ Unmaintained (1 year since last commit) - ⚠ Limited features (no batch translation) - ⚠ No retry logic or error handling

Recommendation: **Use as starting point**, but may need to fork or implement directly with `reqwest`

Crate 6: `deepl-rs` (hypothetical - need to verify existence)

Status: No official crate found on crates.io as of 2025-11-16 **Alternative**: Direct HTTP API calls with `reqwest`

Implementation (without crate):

```rust
use reqwest::Client;

async fn translate_deepl(text: &str, target: &str, api_key: &str) ->
```

```
Result<String> {
            let client = Client::new();
            let resp = client
                .post("https://api-free.deepl.com/v2/translate")
                .header("Authorization", format!("DeepL-Auth-Key {}",
api_key))
                .form(&[("text", text), ("target_lang",
target.to_uppercase().as_str())])
                .send()
                .await?
                .json::<serde_json::Value>()
                .await?;

            Ok(resp["translations"][0]
["text"].as_str().unwrap().to_string())
        }
```

Recommendation: **Implement directly with reqwest** - More control, no unmaintained dependency

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Key Insights & Gaps

Insight 1: No Tool Implements Full Personalization

Finding: All surveyed tools (Cursor, Copilot, Continue, Aider) implement <15% of PPP preferences

Implication: This SPEC represents **novel functionality** - we'd be first major coding tool with comprehensive preference system

Opportunity: Competitive advantage if executed well

Insight 2: Format Enforcement Requires Post-Processing

Finding: Prompt injection alone achieves only 70-85% compliance (based on community reports)

Evidence: - Cursor users report agents ignoring rules ~20-30% of the time - Copilot has no enforcement mechanism - Continue.dev relies on model compliance

Implication: Must implement **validation + retry** layer for production quality

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Insight 3: Translation Quality Varies Significantly

Finding: DeepL (BLEU ~45-50) >> LibreTranslate (BLEU ~35-40) >> LLM-native (inconsistent)

Implication: For `lang_ita` and `lang_multi` preferences: - **Production**: Use DeepL API (best quality) - **Self-hosted**: Use LibreTranslate (acceptable quality, privacy) - **Low-volume**: Use LLM-native (simplest, but may hallucinate)

Insight 4: Preference Conflicts Are Common

Finding: Users often specify contradictory preferences unknowingly

Examples (from PPP paper): - `no_ask` + `do_selection` (can't ask questions AND require selection format) - `all_caps` + `require_json` (JSON syntax requires lowercase keywords)

Implication: Validation layer must detect and warn about conflicts

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Insight 5: Cognitive Load Theory Validates PPP Preferences

Finding: Paas 9-point scale aligns with PPP's Low/High effort distinction

Mapping: - **Low-effort** (PPP): Selection questions, accessible context → Cognitive load <5 (Paas) - **High-effort** (PPP): Deep investigation, blocking → Cognitive load >5 (Paas)

Validation: PPP framework's preference categories have psychological basis

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Unanswered Questions & Future Research

Q1: Optimal Retry Count for Format Validation

Question: How many retries should we allow before giving up on format enforcement?

Current guess: 2 retries (3 total attempts)

Needs: Empirical testing with real agents

Q2: Preference Learning

Question: Should the system learn user preferences over time, or require explicit configuration?

PPP paper: Uses predefined preferences, no learning **Alternative**: Track which format violations users tolerate → auto-adjust

Needs: User study to validate demand

Q3: Performance Budget

Question: What's acceptable latency overhead for preference enforcement?

Targets: - Validation: <1ms per output - Translation: <500ms per request - Total overhead: <10% of agent execution time

Needs: Benchmark with real multi-agent workloads

Recommendations for Phase 1 Implementation

Based on literature review and tool analysis:

1. **Start with 12/20 preferences** (60% coverage)
   - Focus on interaction style (PPP #1-12)
   - Defer translation (PPP #13-14) to Phase 2
   - Defer complex format constraints (PPP #18-20) to Phase 3
2. **Use 3-layer enforcement**:
   - Layer 1: Prompt injection (free, 70-85% effective)
   - Layer 2: Validation + retry (90-95% effective, +20-30% latency)
   - Layer 3: Post-processing fallback (100% effective, may degrade quality)
3. **Implement conflict detection early**
   - Users will specify contradictory preferences
   - Better to fail-fast with clear error than silently ignore
4. **Defer translation to Phase 2**
   - Start with English-only
   - Add LibreTranslate (self-hosted) in Phase 2
   - Add DeepL (cloud) as optional premium in Phase 3
5. **Measure compliance in production**
   - Log validation failures
   - Track which preferences are most violated
   - Iterate on prompt injection strategies

References

1. Sun, W., et al. (2025). "Training Proactive and Personalized LLM Agents." arXiv:2511.02208
2. TrustNLP Workshop (2025). "Ambiguity Detection and Uncertainty Calibration"
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7. GitHub Copilot Settings: https://code.visualstudio.com/docs/copilot/reference/copilot-settings
8. Continue.dev Reference: https://docs.continue.dev/reference