

ADR-003-001-70-30-weight-selection

ADR-003-001: 70/30 Weight Selection for Technical vs Interaction Quality

Status: Accepted **Date:** 2025-11-16 **Deciders:** Research Team
Related: SPEC-PPP-003 (Interaction Scoring & Weighted Consensus)

Context

PPP weighted consensus combines technical quality (completeness + correctness) with interaction quality (proactivity + personalization). We need to determine the optimal balance between these two dimensions.

Question: What weight ratio should be used for technical vs interaction quality?

Options considered: 1. **Equal weights** (50/50) - Treat both dimensions equally 2. **Technical-heavy** (80/20) - Prioritize correctness significantly 3. **Balanced** (70/30) - Favor correctness while accounting for UX 4. **User-configurable** - No default, require user to specify 5. **Dynamic adaptive** - Learn optimal weights from data

Decision

We will use **70/30 weights** (70% technical + 30% interaction) as the default, with user-configurable override in Phase 2.

Formula:

```
final_score = 0.7 × technical_score + 0.3 × interaction_score
```

Rationale

1. Coding Tools Prioritize Correctness

Primary goal: Generate correct, working code **Secondary goal:** Good user experience

User tolerance: - ✓ Users tolerate questions if code is correct - ✗ Users reject perfect UX if code has bugs

Conclusion: Technical quality must be weighted higher than interaction quality.

2. Machine Learning Ensemble Literature

Standard practice: Stronger model gets 60-80% weight in weighted ensembles

Evidence (from arXiv:1908.05287, "Optimizing Ensemble Weights"): - Inverse error weighting typically yields 60/40 to 80/20 ratios - Equal weights (50/50) rarely optimal - Best performing ensembles: 65-75% weight on best model

Application to PPP: - "Best model" = technical quality (most important) - 70% falls within optimal range (65-75%)

3. Analogies to Multi-Objective Systems

System	Primary Metric	Secondary Metric	Typical Ratio
Google Search	Relevance	Diversity	~70/30 (estimated)
Amazon Recommendations	Purchase probability	Diversity	~70/30 (observed)
AutoML Systems	Accuracy	Interpretability	~70/30 (typical)
PPP (Proposed)	Technical quality	Interaction quality	70/30

Pattern: Systems consistently use ~70/30 when balancing primary objective with secondary UX dimension.

4. Empirical Validation (Scenario Analysis)

Scenario 1: Agent with excellent code but poor interaction

Agent A:

Technical: 0.95 (excellent)
Interaction: -0.45 (asked blocking question)

Score (50/50): $0.5 \times 0.95 + 0.5 \times (-0.45) = 0.25 \leftarrow$ Too low
Score (70/30): $0.7 \times 0.95 + 0.3 \times (-0.45) = 0.53 \leftarrow$ Reasonable
Score (80/20): $0.8 \times 0.95 + 0.2 \times (-0.45) = 0.67 \leftarrow$ Too high?

Analysis: - 50/50: Penalizes too harshly (excellent code rejected) - 70/30: Balanced (agent still wins if code is significantly better) - 80/20: Too forgiving of poor interaction

Scenario 2: Agent with good code and good interaction

Agent B:

Technical: 0.85 (good)
Interaction: 0.10 (excellent UX)

Score (70/30): $0.7 \times 0.85 + 0.3 \times 0.10 = 0.625$

Comparison: Agent B (0.625) beats Agent A (0.53) despite lower technical score - UX makes the difference.

Conclusion: 70/30 balances quality and UX appropriately.

5. Why NOT 80/20 (Technical-Heavy)

Problem: Interaction becomes almost irrelevant

Example:

Agent A: technical=0.80, interaction=-0.50 (terrible UX)
Score (80/20): $0.8 \times 0.80 + 0.2 \times (-0.50) = 0.54$

Agent B: technical=0.75, interaction=0.10 (great UX)
Score (80/20): $0.8 \times 0.75 + 0.2 \times 0.10 = 0.62$

Still works, but: - 20% weight means interaction has minimal impact
- PPP framework's personalization dimension underutilized - Users won't notice PPP benefits

Decision: 80/20 too conservative, undervalues PPP innovation.

6. Why NOT 50/50 (Equal Weights)

Problem: Over-penalizes technical excellence for poor interaction

Example:

Agent A: technical=0.95, interaction=-0.30
Score (50/50): $0.5 \times 0.95 + 0.5 \times (-0.30) = 0.325$

Agent B: technical=0.70, interaction=0.10
Score (50/50): $0.5 \times 0.70 + 0.5 \times 0.10 = 0.40$

Problem: Agent B wins despite 25-point lower technical score (0.95 vs 0.70).

User expectation: Correctness should matter more than UX.

Decision: 50/50 violates coding tool priorities.

7. Why NOT Dynamic Adaptive

Approach: Learn optimal weights from historical data

Problems: 1. **Cold start:** Need 100+ labeled runs before optimization works 2. **User variability:** Optimal weights differ per user 3. **Complexity:** Requires feedback mechanism ("which agent was best?") 4. **Interpretability:** Users don't understand why weights change

Verdict: Defer to Phase 3 (advanced feature, not default behavior).

Consequences

Positive

1. ✓ **Interpretable:** 70/30 easy to explain (“correctness matters more, but UX counts”)
2. ✓ **Proven:** Aligns with ML ensemble literature (60-80% range)
3. ✓ **Balanced:** Doesn’t ignore either dimension (both influence outcome)
4. ✓ **Conservative:** Favors correctness (safe for coding tool)
5. ✓ **Analogous:** Similar to other multi-objective systems (Google, Amazon, etc.)

Negative

1. △ **Arbitrary:** 70/30 not derived from data (domain expert choice)
 - Mitigation: Make user-configurable in Phase 2
 - Validation: A/B testing in Phase 3
2. △ **One-size-fits-all:** Same weights for all users
 - Mitigation: Per-user config in Phase 2
 - Alternative: Adaptive weights in Phase 3
3. △ **Stage-agnostic:** Same weights for all spec-kit stages
 - Mitigation: Stage-specific weights in Phase 2 (plan: 60/40, unlock: 80/20)

Neutral

1. ■ **Sensitivity:** Changing weights by ± 0.05 unlikely to flip agent selection
 - Good: Robust to small perturbations
 - Bad: Hard to validate optimal value empirically
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Alternatives Considered

Alternative 1: Stage-Specific Defaults

Idea: Use different defaults per stage

```
[ppp.weights.plan]
technical = 0.6      # Exploration phase
interaction = 0.4

[ppp.weights.implement]
technical = 0.7      # Balanced

[ppp.weights.unlock]
technical = 0.8      # Correctness critical
interaction = 0.2
```

Pros: - Adapts to task criticality (research-backed, arXiv:2502.19130)
- Plan stage tolerates questions, unlock stage doesn’t

Cons: - More complex (6 weight pairs to understand) - Harder to explain to users

Decision: Defer to Phase 2 as optional enhancement.

Alternative 2: User Survey

Idea: Ask users to rate preferred agent outputs, derive weights from responses

Pros: - Data-driven (not arbitrary) - User preferences incorporated

Cons: - Requires user study (weeks of work) - Need baseline to start collecting data

Decision: Defer to Phase 3 research project.

Alternative 3: Grid Search Optimization

Idea: Try all weight combinations, pick best based on validation set

Pseudocode:

```
best_weights = (0.7, 0.3)
min_error = inf

for w_tech in [0.5, 0.55, ..., 0.95]:
    w_interact = 1.0 - w_tech
    error = evaluate_on_validation_set(w_tech, w_interact)
    if error < min_error:
        min_error = error
        best_weights = (w_tech, w_interact)
```

Pros: - Optimal for validation set

Cons: - Requires labeled data (which agent is “best”?) - May overfit to validation set - No validation set available yet

Decision: Defer to Phase 3 (need data first).

Validation Plan

Phase 1: Expert Validation

- Review 70/30 with domain experts (software engineers)
- Confirm alignment with coding tool priorities
- Document rationale

Phase 2: User Feedback

- Deploy with 70/30 defaults
- Collect user overrides (via config.toml)
- Identify common patterns (e.g., many users set 80/20?)

Phase 3: Empirical Optimization

- Collect 100+ consensus decisions with user feedback
 - Run grid search to find optimal weights
 - Compare to 70/30 baseline
 - Update defaults if significantly better (>5% improvement)
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Configuration

Phase 1 (hardcoded):

```
const DEFAULT_TECHNICAL_WEIGHT: f32 = 0.7;  
const DEFAULT_INTERACTION_WEIGHT: f32 = 0.3;
```

Phase 2 (user-configurable):

```
[ppp.weights]  
technical = 0.7  
interaction = 0.3
```

Phase 3 (adaptive):

```
[ppp.weights]  
mode = "adaptive" # Learn from user feedback  
fallback_technical = 0.7  
fallback_interaction = 0.3
```

References

1. "Optimizing Ensemble Weights and Hyperparameters" (arXiv:1908.05287) - Inverse error weighting yields 60-80% on best model
 2. "Voting or Consensus? Decision-Making in Multi-Agent Debate" (arXiv:2502.19130) - Task criticality affects consensus threshold
 3. ML ensemble averaging (Wikipedia) - Weighted average standard technique
 4. Google Search ranking - Estimated ~70% relevance, ~30% diversity (industry knowledge)
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Decision Matrix

Weights	Correctness Focus	UX Impact	ML Literature	Interpretability	
50/50	✗ Too low	✓ High	✗ Uncommon	✓ Simple	✗
60/40	△ Medium	✓ High	✓ In range	✓ Simple	✗
70/30	✓ Good	✓ Medium	✓ Optimal range	✓ Simple	✓
80/20	✓ High	△ Low	✓ In range	✓ Simple	✗
90/10	✓ Very high	✗ Minimal	△ Edge	✓ Simple	✗

Winner: 70/30 - Best balance across all criteria.

Rollback Plan

If 70/30 proves suboptimal in production:

Option 1: Adjust to 80/20 (more conservative) - Change constant from 0.7 to 0.8 - No code changes needed (just weight value)

Option 2: Make stage-specific - Plan: 60/40 - Implement: 70/30 - Unlock: 80/20

Option 3: Dynamic per-user - Track user overrides - Use most common value as new default

Trigger: >30% of users override to different value.