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Intent-Preserving Neuro-Symbolic Repair for Safe LLM-Driven Financial Transactions

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Abstract: Verifier-guided large language model (LLM) agents can certify that an executed payment satisfies a platform's business rules, yet the certificate says nothing about whether the payment is still the one the customer asked for. When a verifier rejects a command and returns a violation report, the LLM repair step can restore compliance by changing the recipient, the currency or the funding account, producing a rule-compliant but unintended transaction. We call this failure repair-induced intent drift and propose Intent-Preserving Repair (IPR), a neuro-symbolic execution scheme that anchors every user-facing field of the parsed command to evidence in the utterance and computes repairs with answer set programming: anchored fields become fixed facts, only defaulted and procedural fields are searchable, and lexicographic weak constraints select the least intrusive change. When no intent-preserving repair exists, a relaxation program returns a minimum set of conflicting rules that drives a targeted clarification instead of an execution. Building on the Verifier–Actor architecture of VA-NSF, we evaluate on SGD-Fin, 607 real banking and payment dialogues from the Schema-Guided Dialogue corpus paired with seeded platform states and nine business rules. On 296 instances with a grammar-constrained Qwen2.5-0.5B Actor, LLM repair in a re-implemented VA-NSF loop produced intent-mismatched commits for 32.1% of the requests, and 34.6% of its repaired commits on correctly parsed requests changed a user-stated field. IPR raised safe task success from 60.5% to 82.4% ($p < 10^{-19}$), produced no drifted repair, and needed 1.15 instead of 2.49 LLM calls per request.

Keywords: Answer set programming; LLM agents; Neuro-symbolic AI; Constrained repair; Intent preservation; Financial transactions.

1. Introduction

Large language model (LLM) agents now operate external tools and APIs on behalf of users [1]–[3], and finance-specific language models [4], [5] are moving such agents toward transactional use. Transactions differ from most agent tasks in one respect: an action that is wrong is not merely unhelpful, it moves money. Emulation studies of tool-using agents have already exposed risky behaviours that only appear once the agent is allowed to act [6].

Neuro-symbolic executors address this risk by separating language understanding from rule enforcement. In the Verifier–Actor Neuro-Symbolic Framework (VA-NSF) [7], a neural Actor parses an instruction into a typed abstract syntax tree (AST) under grammar-constrained decoding, and a symbolic Verifier evaluates the AST against business rules encoded as answer set programming (ASP) integrity constraints. A compliant AST receives an approval certificate; a non-compliant one yields a structured violation report that is fed back to the Actor for targeted repair, for at most K iterations before escalation to a human. The design makes rule compliance a property of the architecture rather than of the language model.

Rule compliance, however, is only half of a correct transaction. The certificate states that the executed AST satisfies the encoded rules; it does not state that the AST still realises the customer's request, and nothing in a verifier-guided repair loop prevents a repair from satisfying the verifier by editing what the customer said. A repair that, for instance, splits a payment into several sub-threshold payments would satisfy a threshold rule while realising exactly the pattern that anti-money-laundering law prohibits as structuring [8]. The phenomenon has a close analogue in automated program repair, where patches that pass the test suite often break the intended behaviour [9]. Research on LLM self-correction points in the same direction: models improve reliably only with trustworthy external feedback [10]–[12], which is why LLM-Modulo frameworks pair LLMs with sound external critics [13]. A rule verifier is such a critic for compliance, but it is silent about intent.

This paper studies *repair-induced intent drift*, the case in which a repair makes a rejected transaction compliant by changing a field that the user stated, and proposes Intent-Preserving Repair (IPR). IPR keeps the Actor–Verifier interface but changes what happens after a violation. It first anchors the parsed command in the utterance: each user-facing field is *locked* when its value is supported by the user's words, *free* when the user said nothing about it, and *flagged* when the parsed value contradicts the words. Repair is then posed as an ASP optimisation problem in which locked fields are facts, free and procedural fields are chosen from finite domains, the business rules are hard constraints, and weak constraints prefer the fewest and least intrusive changes. If the locked intent makes the rules unsatisfiable, a relaxation program returns a minimum set of conflicting rules, which is turned into a targeted clarification instead of a guessed transaction. The contributions are as follows.

1) We define intent anchoring and repair-induced intent drift for LLM-driven transaction execution, and we show on real user requests that LLM repair in a VA-NSF-style loop produces rule-compliant but intent-violating commits.

2) We present IPR, which combines utterance-grounded

field locking with an intent-locked, minimal-change ASP repair program and a relaxation-based minimum conflict explanation. Executed transactions are compliant and agree with the anchored intent by construction, and rule-based escalations on grounded parses are provably necessary.

3) We construct SGD-Fin, a benchmark of 607 money-transfer episodes extracted from the Schema-Guided Dialogue corpus with seeded platform states, nine business rules and an independent policy oracle.

4) On 296 instances, IPR raises safe task success from 60.5% to 82.4%, eliminates drifted repairs and needs less than half of the LLM calls of the repair loop; ablations isolate the roles of the intent lock and of evidence grounding.

2. Related Work

2.1. LLM Agents for Financial Operations

Tool-augmented LLMs learn when and how to call APIs [2], [3], and agent benchmarks show that multi-step, environment-changing tasks remain error-prone [1]. Finance-specific pre-training [4] and open financial LLMs [5] improve domain language understanding but do not by themselves constrain what an agent executes, and ToolEmu [6] shows that many failures of tool-using agents become visible only through their actions. VA-NSF moves the safety argument from the model to a symbolic verifier; IPR extends that argument from rule compliance to intent fidelity. Yue et al. introduce an evidence-based multi-agent debate framework for financial statement fraud analysis, showing the value of grounding complex financial reasoning in traceable evidence [28].

2.2. Neuro-Symbolic Reasoning with Solver Feedback

Logic-LM translates problems into symbolic programs and revises the formalisation using solver error messages [14], and LINC delegates deduction to a first-order prover [15]. NeurASP integrates neural outputs as probabilistic facts of answer set programs [16], and LLMs can draft answer set programs from natural-language descriptions [17]. In these systems the solver returns a verdict or an error message on the formalisation. The closest design is the Verifier–Actor loop, in which violation reports guide an LLM repair; our results show that this guidance is precisely what makes the model edit the reported field, including fields the user specified. Yang et al. also provide a useful neural-symbolic retrieval architecture that organizes structured and semantic evidence for downstream reasoning tasks [29].

2.3. Self-Correction and Repair Overfitting

Iterative self-feedback improves many generation tasks [10], yet without external signals LLMs often fail to correct reasoning errors [11], and a critical survey concludes that reliable external feedback is the main enabler of self-correction [12]. LLM-Modulo frameworks combine LLM generators with sound external critics [13]. Program repair offers a cautionary parallel: a patch that satisfies the oracle can still be incorrect [9]. IPR addresses the analogous problem by constraining the repair space instead of the critic.

2.4. Constrained Decoding and Database Repairs

Grammar-constrained decoding guarantees syntactically valid outputs through finite-state or incremental parsing [18]–[20]; we use it, as VA-NSF does, to obtain well-formed ASTs. Minimal repair under integrity constraints originates in database theory, where repairs of an inconsistent database are minimally different consistent instances [21], including attribute-level updates [22]. IPR adapts update-based repair to a single transaction and adds the ingredient that agents need: which attributes may be updated is decided by the user's utterance. ASP under the stable model semantics [23] provides the declarative encoding [24], and clingo [25] provides grounding, optimisation and model enumeration.

3. Problem Formulation

Let u be a user instruction, σ the platform state (accounts with status and balance, a payee directory with KYC status and accepted currencies, per-customer limits and a 24-hour transaction log) and R a set of business rules. A transaction is a typed AST a = (cp, amt, cur, src, vis, auth, rail) whose user-facing fields F_u = {cp, amt, cur, src, vis} state what is paid, to whom and from which account, and whose procedural fields F_p = {auth, rail} state how the platform executes it (step-up authentication level and payment rail). The platform executes a only if $a \vDash_\sigma R$.

Definition 1 (Anchoring). For each $f \in F_u$ an evidence function $E_f(u, \sigma) \subseteq D_f$ returns the values of f that are literally supported by u. Given a parsed AST a, field f is *locked* if $a_f \in E_f$, *free* if $E_f = \emptyset$ (the value is a platform default) and *flagged* otherwise. The anchored intent is $I(a) = \{(f, a_f) \mid f$ locked$\}$.

Definition 2 (Intent-preserving repair). An AST a' is an intent-preserving repair of a if (i) $a' \vDash_\sigma R$, (ii) $a'_f = a_f$ for every locked f, and (iii) $a'_f \in D_f$ for every free or procedural f. Among these repairs Rep(a), IPR selects

$$\hat{a} = arg\ lexmin \langle |\Delta(a, a')|, \varphi(a') \rangle, \quad a' \in Rep(a) \quad (1)$$

where Δ is the set of changed fields and $\varphi(a') = 2\cdot$[auth = mfa] + [auth = otp] + [rail = standard] measures procedural friction for the customer.

Definition 3 (Repair-induced intent drift). A repair procedure drifts on u if the initial parse a_0 agrees with the user's intent, the procedure executes $a' \neq a_0$, and a' differs from a_0 in a user-stated field.

Proposition 1 (Soundness and intent preservation). Every transaction executed by IPR satisfies all rules of R and agrees with $I(a)$ on every locked field. *Proof sketch:* rules enter the repair program as integrity constraints and locked fields as facts, so every answer set, and in particular the optimal one, satisfies both; the verifier's soundness argument for integrity constraints under the stable model semantics applies unchanged.

Proposition 2 (Necessary escalation). If IPR escalates a request whose parse has no flagged field on rule grounds, then no assignment of the free and procedural fields within their domains satisfies R, and the returned relaxation set is a minimum-cardinality set of rules that every intent-preserving completion violates. *Proof sketch:* the ground repair program is finite and clingo's optimisation is exhaustive; an optimum with $k > 0$ relaxed rules excludes all models with fewer relaxed rules, in particular all compliant ones.

4. Intent-Preserving Repair

4.1. Architecture and Adopted Components

Fig. 1 shows the pipeline. We build on the Verifier–Actor

architecture of VA-NSF [7] and adopt three of its components: grammar-constrained parsing into a typed AST, an ASP verifier whose rules follow the C1–C5 taxonomy (threshold approval, account validity, KYC, duplicate detection, currency), and structured violation reports of the form (rule, field path, observed value, hint). Table I lists the nine rules. C1–C5 adapt the VA-NSF taxonomy to consumer payments, where the approver of C1 becomes a step-up authentication level and the account hierarchy of C2 becomes the customer's set of active funding accounts; C6–C9 add balance, instant-rail, 24-hour aggregation and privacy rules. The rules fall into two repair classes: procedural rules can be satisfied by changing procedural or defaulted fields, whereas conflict rules can only be satisfied by changing what the user asked for.

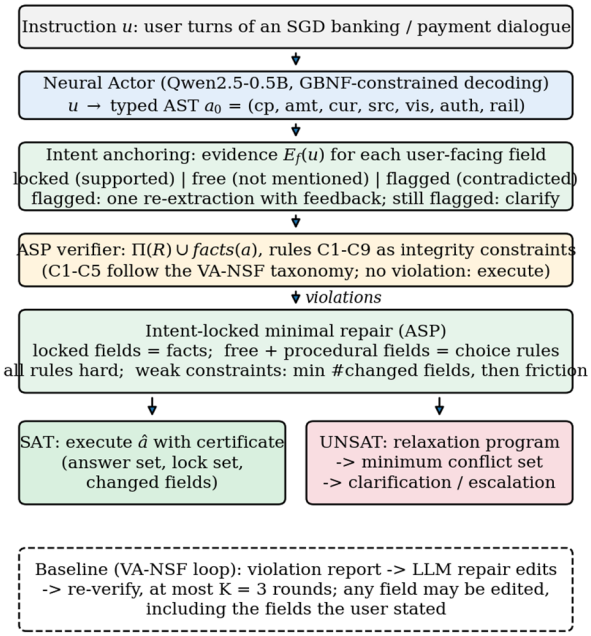


Fig. 1 IPR pipeline. The dashed box marks the LLM repair loop of the VA-NSF baseline; IPR replaces it with intent anchoring and an intent-locked ASP repair whose unsatisfiable case yields a minimum conflict explanation.

Table I. Business Rules of SGD-Fin

ID	Condition that must hold	Class	Origin
C1	amount above step-up threshold ⇒ auth = mfa	procedural	VA-NSF C1
C2	source is an active account of the customer	conflict	VA-NSF C2
C3	counterparty is a KYC-verified payee	conflict	VA-NSF C3
C4	no identical payment to the payee within 24 h	conflict	VA-NSF C4
C5	currency is accepted by the payee	conflict	VA-NSF C5
C6	amount ≤ balance of the source account	conflict*	new
C7	instant rail only up to the instant cap	procedural	new
C8	24-h total to a payee above threshold ⇒ mfa	procedural	new
C9	P2P payment above privacy limit is private	procedural†	new

Procedural if the customer did not name the source; †conflict if the customer explicitly asked for a public payment

4.2. Neural Actor

The Actor is Qwen2.5-0.5B-Instruct [26] (Q4_K_M GGUF weights served by llama.cpp) prompted with four parsing demonstrations and one repair demonstration that share a single prompt prefix. Decoding is constrained by a GBNF grammar with a fixed key order, enumerated categorical values and bounded strings. The generated language is regular, so the constraint is exact, as with finite-state token masking [18]. The parse emits the five user-facing fields; auth and rail start at the platform defaults none and instant.

4.3. Intent Anchoring

Evidence extraction is deliberately simple and auditable. Payee names are matched against the payee directory, amounts against numerals (including comma-grouped figures and English number words), currencies against symbols and words, and accounts and visibility against a small lexicon (e.g., 'visa' → credit card, 'check card' → debit card). On SGD-Fin the evidence sets contain the annotated counterparty, amount and funding account of all 607 instances. A flagged field triggers one re-extraction in which the Actor receives the grounding feedback together with the candidate values found in the utterance; a field that is still flagged ends the request with a clarification question naming that field. Locked fields form the anchored intent; free fields join the procedural fields as repairable.

4.4. Verification

Facts derived from the AST and the master data are grounded together with the rule program. Each rule is an integrity constraint whose body is reified as `viol/1` for reporting, for example:

```
viol(c1) :- val(amount,A), threshold(T), A > T,
            not val(auth,mfa).
viol(c3) :- val(cp,P), not kyc(P).
viol(c8) :- prior(P,S), S > 0, val(amount,A),
            threshold(T), S+A > T, not val(auth,mfa).
```

A plain-Python policy oracle written independently of the ASP program agreed with the verifier on all 5,463 (AST, state) pairs of a randomised cross-check, and with gold intents as input IPR reproduced all 607 gold outcomes of SGD-Fin.

4.5. Intent-Locked Minimal Repair

When verification fails, IPR solves the following repair program together with the rules and the master data:

```
val(F,V) :- locked(F), actor(F,V).
1 { val(F,V) : dom(F,V) } 1 :- mutable(F).
:- viol(R).
changed(F) :- val(F,V), actor(F,V0), V != V0.
:~ changed(F), weight(F,W). [W@2, F]
:~ val(auth,mfa). [2@1]    :~ val(auth,otp). [1@1]
:~ val(rail,standard). [1@1]
```

Locked fields are facts; mutable fields (free user fields together with auth and rail) are chosen from finite domains, namely the customer's accounts, the visibility values, the authentication levels and the rails; the rules are hard constraints; and the two weak-constraint levels implement objective (1). If the program is unsatisfiable, IPR solves a relaxation variant that adds `{ relax(R) } :- rule(R).`, replaces the hard constraint by `:- viol(R), not relax(R).` and minimises `:~ relax(R). [1@3, R]` at the highest priority. The optimal relaxed

set is a minimum-cardinality conflict explanation, and each conflicting rule is mapped to a clarification template; for C3, for instance, the customer is told that the named payee is not verified and is asked to confirm a verified recipient.

4.6. Execution and Certificates

```
Algorithm 1: IPR execution
1: a ← Actor.parse(u)
2: (L, Fr, Fl) ← Anchor(a, u, σ)
3: if Fl ≠ ∅: a ← Actor.parse(u, feedback(Fl, E));
       (L, Fr, Fl) ← Anchor(a, u, σ)
4: if Fl ≠ ∅: return Clarify(Fl)
5: if Verify(a, σ, R) = ∅: return Execute(a, cert)
6: (st, â, Δ, C) ← Repair(a, L, Fr ∪ Fp, σ, R)
7: if st = SAT: return Execute(â, cert(Δ, L))
8: return Escalate(C)      // minimum conflict set
```

Every executed transaction carries a certificate consisting of the answer set, the lock set and the changed fields, and every escalation carries the conflicting rules and the locked fields they involve. IPR calls the LLM at most twice per request.

5. Experimental Setup

5.1. SGD-Fin Benchmark

We use the money-transfer services of the Schema-Guided Dialogue (SGD) corpus [27]: Banks_1 (train split), Banks_2 (dev split) and Payment_1 (test split). Each completed TransferMoney or MakePayment episode becomes one instance. The instruction concatenates the user turns of that service before the system's final confirmation (26.8 words on average), and the gold intent is the annotated dialogue state; slots present before the confirmation turn are marked as user-stated, whereas slots added at confirmation are system defaults. This yields 607 instances (321 Banks_1, 138 Banks_2, 148 Payment_1).

Platform states are synthetic and seeded. For every instance we generate eight payees, the customer's accounts with balances and statuses, per-customer limits and a transaction log, and we assign one of three categories: *clean* (no violation), *procedural* (one or two procedural rules violated by the gold intent) or *conflict* (one conflict rule, optionally combined with a procedural rule). Limits are placed relative to the requested amount so that the intended violations occur. The gold outcome is EXECUTE when at most procedural rules are violated and ESCALATE when the gold intent violates a conflict rule. Because instructions and gold intents come from real annotated dialogues while the states are generated, SGD-Fin measures repair behaviour under realistic language and controlled rule pressure.

Instances are processed in a fixed random order, and we report the first N = 296 completed instances (164 Banks_1, 70 Banks_2, 62 Payment_1; 54 clean, 115 procedural and 127 conflict; 169 EXECUTE and 127 ESCALATE).

5.2. Compared Methods

All methods start from the same Actor parse of an instance, so that differences arise only after parsing. *LLM-only* executes the parse. *Verify-only* executes it if it passes type checking and verification and escalates otherwise. *VA-NSF repair* is our re-implementation of the execution loop of [7] (its Algorithm 2): type check, ASP verification, structured violation report, LLM repair and escalation after at most K = 3 iterations. Following its prompt design, the repair prompt contains the instruction, the current AST and the violation report, instructs the model to modify only the violating fields, and asks for a one-sentence repair strategy before the field edits, which are then applied to the current AST. *VA-NSF + intent guard* adds the anchored intent of IPR as a feedback signal: whenever a repair changes a locked field, the next report contains an `intent_changed` violation for that field. IPR and four ablations complete the comparison: without re-extraction, without grounding (every non-null user field of the parse is locked), without intent lock (classic minimal-change repair over all fields with finite candidate domains) and without minimality (first model of the hard program).

5.3. Metrics

An executed transaction is *compliant* if the independent oracle finds no violated rule and *intent-faithful* if counterparty, amount, currency and every user-stated source or visibility value match the gold intent. *Safe success* counts faithful, compliant executions on EXECUTE instances and escalations on ESCALATE instances. *Unsafe commits* are executions that are non-compliant or intent-mismatched. *Over-escalation* is the share of EXECUTE instances that were escalated. *Repair-induced drift* is measured on instances whose initial parse is intent-faithful, as the share of repaired commits whose intent differs from the parse. We report 95% bootstrap confidence intervals (2,000 resamples over instances) and exact McNemar tests on paired safe-success outcomes.

5.4. Implementation

The ASP layer uses clingo 5.8.2 through its Python API [25]; the Actor runs in llama.cpp (build b11800) with greedy decoding on a single CPU core with 4 GB of memory. All LLM calls are cached on disk with their prompts, so every reported number can be regenerated from the logged runs. The Actor's initial parse was intent-faithful for 73.6% of the 296 instances; most errors concern the funding account (65 instances), typically when the dialogue mentions both a checking and a savings account.

6. Results

6.1. Main Results

Table II. Main Results on SGD-Fin (N = 296, 95% CIs)

Method	Safe success (%)	Unsafe commits (%)	Over-esc. (%)	LLM calls
LLM-only	14.2 [10.5, 17.9]	85.8 [82.1, 89.5]	0.0	1.00
Verify-only	54.4 [48.6, 60.1]	6.4 [3.7, 9.5]	68.6	1.00
VA-NSF repair	60.5 [54.7, 66.2]	32.1 [26.7, 37.5]	13.0	2.49
VA-NSF + intent guard	75.7 [70.6, 80.4]	16.9 [12.8, 21.3]	13.0	2.74
IPR (ours)	82.4 [78.0, 86.8]	9.8 [6.4, 13.2]	13.6	1.15

Table II summarises the outcomes and Fig. 2 decomposes them. Executing the parse directly is unsafe for 85.8% of the requests, almost entirely because of rule violations (79.4%). Every method that routes the parse through the verifier executes only compliant transactions, so their remaining unsafe commits are intent-mismatched executions. Verify-only is therefore comparatively safe (6.4% unsafe commits,

all caused by parse errors) but refuses 68.6% of the executable requests, because it cannot even add a missing step-up authentication.

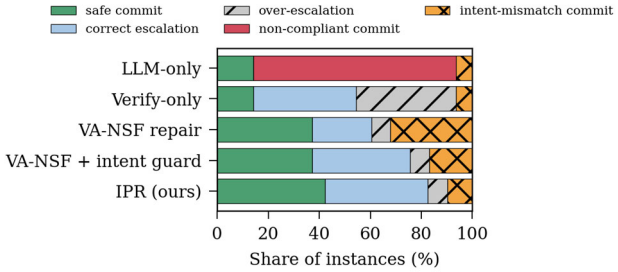


Fig. 2 Outcome composition on SGD-Fin (N = 296). Verifier-based methods never commit non-compliant transactions; their unsafe commits are intent-mismatched executions.

VA-NSF repair recovers most procedural cases and lowers over-escalation to 13.0%, but its unsafe-commit rate rises to 32.1%, and the increase consists entirely of compliant transactions whose intent differs from the request. On the 218 instances with an intent-faithful parse, 36 of the 104 transactions it committed after at least one repair (34.6%) differed from the parse in a user-stated field. Adding the intent guard removes these drifted commits (0 of 68) and raises safe success to 75.7%, at the cost of more LLM calls (2.74 per request); the guarded loop escalated 136 requests after three unsuccessful repair rounds.

IPR attains the highest safe success, 82.4 [78.0, 86.8]%, with 9.8% unsafe commits and 13.6% over-escalation (VA-NSF repair: 13.0%), while calling the LLM 1.15 times per request. Exact McNemar tests confirm the improvement over VA-NSF repair (65 requests improved, 0 worse, $p = 5.4\times10^{-20}$), over the guarded loop (20 vs. 0, $p = 1.9\times10^{-6}$) and over Verify-only (86 vs. 3, $p = 3.8\times10^{-22}$). By category, IPR reaches 72.2% safe success on procedural instances (VA-NSF: 59.1%) and 93.7% on conflict instances (VA-NSF: 54.3%); on clean instances all methods reach 77.8%, the share of intent-faithful parses there. IPR never changed a user-stated field: all 80 of its repaired commits on correctly parsed requests kept the parsed intent, and the fields it changed were auth (72 times), rail (50) and visibility (3). Its residual unsafe commits come from parse errors that are consistent with the utterance: all 29 involve an initial parse that already disagreed with the gold intent, and 27 of them concern the funding account.

6.2. Where LLM Repair Drifts

Fig. 3 breaks the unsafe commits down by the injected conflict rule. LLM repair is most hazardous when the report points to a field that the user named. For the currency rule C5, VA-NSF committed a payment in another currency than the requested one in 96.7% of the instances, typically by switching from USD to GBP; for the KYC rule C3 it re-routed 55.6% of the payments to a different, verified payee; and for the account rule C2 it debited another account in 54.5% of the cases. Among correctly parsed requests the drifted fields were the currency (19), the counterparty (10) and the funding account (7). Table III reproduces strategies that the model wrote before its edits: the violation is treated as an obstacle to route around rather than as a reason to stop. The duplicate rule C4 is the exception (3.3% unsafe for all verifier-based methods): its report names the amount, which the model rarely altered, so almost all C4 requests were escalated. The guarded loop and IPR committed no drifted repair on correctly parsed requests; their remaining unsafe commits on C2 and C6 stem from parse errors.

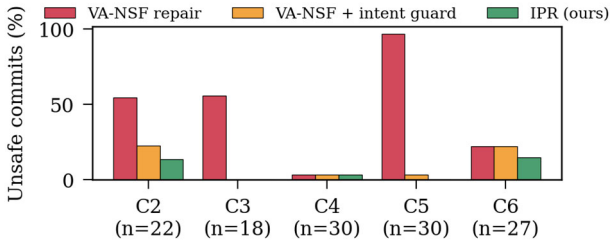


Fig. 3 Unsafe commits by injected conflict rule (C2 account, C3 KYC, C4 duplicate, C5 currency, C6 balance).

Table III. Strategies Written by the LLM Before Drifted Repairs (VA-NSF Loop, Verbatim; Strings End at the 70-Character Grammar Bound)

Rule	Strategy generated by the Actor	Committed change
C3	"Switch the counterparty to 'Wilson' to avoid the rule."	payee Raghav → Wilson
C3	"Switch the counterparty to 'Mom'; the counterparty 'Amir' is not a KYC"	payee Amir → Mom
C5	"Switch the currency to GBP; the currency 'USD' is not allowed."	USD → GBP
C2	"Switch the source to savings; the source account 'checking' is not an "	checking → savings

6.3. Ablation Study

Table IV. Ablation of IPR Components (N = 296)

Variant	Safe success (%)	Unsafe commits (%)	Over-esc. (%)	LLM calls
IPR (ours)	82.4 [78.0, 86.8]	9.8 [6.4, 13.2]	13.6	1.15
IPR w/o re-extraction	81.4 [77.0, 85.8]	9.5 [6.4, 12.8]	16.0	1.00
IPR w/o grounding	80.1 [75.3, 84.5]	18.2 [13.9, 22.6]	3.0	1.00
IPR w/o intent lock	21.6 [16.9, 26.4]	70.6 [65.5, 76.0]	13.6	1.15
IPR w/o minimality	82.4 [78.0, 86.8]	9.8 [6.4, 13.2]	13.6	1.15

Table IV isolates the components. Removing the intent lock turns IPR into classic minimal-change repair: safe success collapses to 21.6% and unsafe commits rise to 70.6%, and 167 of 176 repaired commits on correctly parsed requests (94.9%) altered a user-stated field. Changing the amount to a limit value costs one changed field and no friction, whereas step-up authentication costs one changed field plus friction, so minimality alone prefers to change the request; for conflict rules, changing the request is the only compliant option. Grounding matters for parse errors rather than for repairs: locking every non-null field without evidence checks lowers over-escalation from 13.6% to 3.0% but almost doubles unsafe commits (18.2%), because unsupported values produced by the parser are executed. The single re-extraction call recovers part of the availability lost to clarification (over-escalation 16.0% → 13.6%) at the price of one additional unsafe commit (9.5% → 9.8%). Minimality was not exercised by SGD-Fin: optimised and first-found repairs produced identical outcomes and the same mean number of changed fields (1.23), because every procedural rule of Table I has a

single natural repair field.

6.4. Escalation Quality and Cost

IPR escalated 142 requests, 106 because the locked intent conflicted with the rules and 36 with a clarification question about a flagged field. All 23 over-escalations of IPR are clarification requests, so it never escalated an executable request on rule grounds, as Proposition 2 predicts for grounded parses. Each of the 106 rule-based escalations returned a minimum conflict set containing the injected conflict rule, which gives the reviewer or the customer the exact reason for the refusal. VA-NSF escalations carry the last violation report, which contained the conflicting rule in 66 of its 69 correct escalations, but the loop escalated only 54.3% of the conflict instances, against 93.7% for IPR. The symbolic stages are cheap: grounding, verification and repair take a median of 7.0 ms per request (measured on the variant without re-extraction, which runs the same symbolic code without the optional LLM call), so the cost of IPR is dominated by the single parse. Fig. 4 places all configurations in the safety–availability plane: only IPR, and its minimality ablation that coincides with it on SGD-Fin, stay below both 10% unsafe commits and 15% over-escalation.

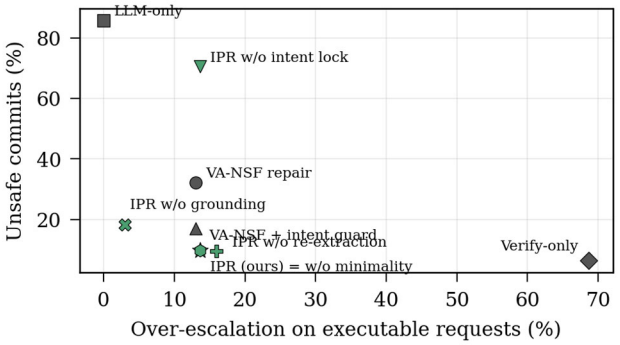


Fig. 4 Safety–availability trade-off of all methods and ablations (lower left is better).

7. Discussion and Limitations

Intent preservation is relative to the anchor. IPR guarantees that a repair never changes an anchored field, but it cannot recover from a parse that picks the wrong one of two mentioned accounts, because both values are supported by the utterance; such cases account for nearly all of its unsafe commits. A stronger Actor, or anchoring that also models argument roles (from my checking to her savings), would reduce them without changing the repair layer. The same logic covers payment splitting: our AST has no batch node, so splitting could not be observed, but the aggregation rule C8 already sums payments to the same payee within 24 hours and therefore removes the arithmetic incentive of structuring.

The evaluation has four further limits. First, the platform states are synthetic: instructions and gold intents are real, but the frequency of rule pressure is set by our generator. Second, the Actor is a 0.5B-parameter model chosen to run on a single CPU core; larger models may follow violation reports more conservatively, although the guard experiment indicates that intent feedback reduces but does not remove the tendency to edit the reported field, while costing additional LLM calls and escalations. Third, the evidence lexicon is domain-specific and English-only. Fourth, as for any formal approach, the guarantees are relative to the encoded rules, and errors in translating policies into ASP are outside the scope of this study.

8. Conclusion

We identified repair-induced intent drift as a failure mode of verifier-guided LLM transaction agents and proposed IPR, which anchors the parsed command in the user's words and confines repair to an intent-locked, minimal-change ASP search with conflict explanations. On SGD-Fin, IPR improved safe task success from 60.5% to 82.4% over a VA-NSF-style repair loop, produced no drifted repair and needed less than half of the LLM calls. Future work will learn role-aware evidence extraction, evaluate larger Actors and extend the AST to batch payments.

References

[1] Liu, X., Yu, H., Zhang, H., Xu, Y., Lei, X., Lai, H., Gu, Y., Ding, H., Men, K., Yang, K., Zhang, S., Deng, X., Zeng, A., Du, Z., Zhang, C., Shen, S., Zhang, T., Su, Y., Sun, H., … & Tang, J. (2024). AgentBench: Evaluating LLMs as agents. In Proceedings of the International Conference on Learning Representations (ICLR).

[2] Schick, T., Dwivedi-Yu, J., Dessì, R., Raileanu, R., Lomeli, M., Zettlemoyer, L., Cancedda, N., & Scialom, T. (2023). Toolformer: Language models can teach themselves to use tools. Advances in Neural Information Processing Systems, 36, 68539-68551.

[3] Qin, Y., Liang, S., Ye, Y., Zhu, K., Yan, L., Lu, Y., Lin, Y., Cong, X., Tang, X., Qian, B., Zhao, S., Hong, L., Tian, R., Xie, R., Zhou, J., Gerstein, M., Li, D., Liu, Z., & Sun, M. (2024). ToolLLM: Facilitating large language models to master 16000+ real-world APIs. In Proceedings of the International Conference on Learning Representations (ICLR).

[4] Wang, J., Liu, J., Ge, Y., & Jiang, B. (2023). Risk-aware ensemble learning for credit default prediction under economic uncertainty. World Journal of Economics and Business Research, 1(1), 18-32.

[5] Yang, H., Liu, X.-Y., & Wang, C. D. (2023). FinGPT: Open-source financial large language models. arXiv, arXiv:2306.06031. https://doi.org/10.48550/arXiv.2306.06031

[6] Ruan, Y., Dong, H., Wang, A., Pitis, S., Zhou, Y., Ba, J., Dubois, Y., Maddison, C. J., & Hashimoto, T. (2024). Identifying the risks of LM agents with an LM-emulated sandbox. In Proceedings of the International Conference on Learning Representations (ICLR).

[7] Qin, Y., Rhee, M., Teng, D., Zhang, C., & Zi, B. (2026). Neuro-symbolic constraint verification for LLM-driven internet finance transaction execution. Scientific Reports, 16, Article 65233. https://doi.org/10.1038/s41598-026-65233-w

[8] Structuring transactions to evade reporting requirement prohibited, 31 U.S.C. § 5324.

[9] Smith, E. K., Barr, E. T., Le Goues, C., & Brun, Y. (2015). Is the cure worse than the disease? Overfitting in automated program repair. In Proceedings of the 10th Joint Meeting on Foundations of Software Engineering (ESEC/FSE) (pp. 532-543). ACM. https://doi.org/10.1145/2786805.2786825

[10] Madaan, A., Tandon, N., Gupta, P., Hallinan, S., Gao, L., Wiegreffe, S., Alon, U., Dziri, N., Prabhumoye, S., Yang, Y., Gupta, S., Majumder, B. P., Hermann, K., Welleck, S., Yazdanbakhsh, A., & Clark, P. (2023). Self-Refine: Iterative refinement with self-feedback. Advances in Neural Information Processing Systems, 36, 46534-46594.

[11] Huang, J., Chen, X., Mishra, S., Zheng, H. S., Yu, A. W., Song, X., & Zhou, D. (2024). Large language models cannot self-

correct reasoning yet. In Proceedings of the International Conference on Learning Representations (ICLR).

[12] Kamoi, R., Zhang, Y., Zhang, N., Han, J., & Zhang, R. (2024). When can LLMs actually correct their own mistakes? A critical survey of self-correction of LLMs. Transactions of the Association for Computational Linguistics, 12, 1417-1440. https://doi.org/10.1162/tacl_a_00713

[13] Teng, D. (2025). RSRBench: Reproducibility and performance benchmarking for regional seismic risk workflows. Academic Journal of Architecture and Civil Engineering, 3(1), 40-52.

[14] Pan, L., Albalak, A., Wang, X., & Wang, W. Y. (2023). Logic-LM: Empowering large language models with symbolic solvers for faithful logical reasoning. In Findings of the Association for Computational Linguistics: EMNLP 2023 (pp. 3806-3824). Association for Computational Linguistics. https://doi.org/10.18653/v1/2023.findings-emnlp.248

[15] Olausson, T. X., Gu, A., Lipkin, B., Zhang, C., Solar-Lezama, A., Tenenbaum, J. B., & Levy, O. (2023). LINC: A neurosymbolic approach for logical reasoning by combining language models with first-order logic provers. In Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing (EMNLP) (pp. 5153-5176). Association for Computational Linguistics.

[16] Yang, Z., Ishay, A., & Lee, J. (2020). NeurASP: Embracing neural networks into answer set programming. In Proceedings of the 29th International Joint Conference on Artificial Intelligence (IJCAI) (pp. 1755-1762). https://doi.org/10.24963/ijcai.2020/243

[17] Ishay, A., Yang, Z., & Lee, J. (2023). Leveraging large language models to generate answer set programs. In Proceedings of the 20th International Conference on Principles of Knowledge Representation and Reasoning (KR) (pp. 374-383). https://doi.org/10.24963/kr.2023/37

[18] Willard, B. T., & Louf, R. (2023). Efficient guided generation for large language models. arXiv, arXiv:2307.09702. https://doi.org/10.48550/arXiv.2307.09702

[19] Geng, S., Josifoski, M., Peyrard, M., & West, R. (2023). Grammar-constrained decoding for structured NLP tasks without finetuning. In Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing (EMNLP) (pp. 10932-10952). Association for Computational Linguistics. https://doi.org/10.18653/v1/2023.emnlp-main.674

[20] Zhou, F. (2026). Moment-constrained side-force allocation for wind-assisted merchant ships: Hydrodynamic performance of retractable anti-leeway fins and flap rudders. Innovation and Technology Studies, 3(1), 27-41.

[21] Arenas, M., Bertossi, L., & Chomicki, J. (1999). Consistent query answers in inconsistent databases. In Proceedings of the 18th ACM SIGMOD-SIGACT-SIGART Symposium on Principles of Database Systems (PODS) (pp. 68-79). ACM. https://doi.org/10.1145/303976.303983

[22] Wijsen, J. (2005). Database repairing using updates. ACM Transactions on Database Systems, 30(3), 722-768.

[23] Gelfond, M., & Lifschitz, V. (1988). The stable model semantics for logic programming. In Proceedings of the 5th International Conference and Symposium on Logic Programming (pp. 1070-1080).

[24] Brewka, G., Eiter, T., & Truszczyński, M. (2011). Answer set programming at a glance. Communications of the ACM, 54(12), 92-103. https://doi.org/10.1145/2043174.2043195

[25] Gebser, M., Kaminski, R., Kaufmann, B., & Schaub, T. (2019). Multi-shot ASP solving with clingo. Theory and Practice of Logic Programming, 19(1), 27-82. https://doi.org/10.1017/S1471068418000054

[26] Qwen Team, Yang, A., Yang, B., Zhang, B., Hui, B., Zheng, B., Yu, B., Li, C., Liu, D., Huang, F., Dong, G., Wei, H., Lin, H., Tang, J., Wang, J., Yang, J., Tu, J., Zhang, J., Ma, J., … & Zhou, Z. (2024). Qwen2.5 technical report. arXiv, arXiv:2412.15115. https://doi.org/10.48550/arXiv.2412.15115

[27] Wang, J., Ge, Y., Liu, J., & Jiang, B. (2024). Early warning of liquidity stress in U.S. banks with seasonally aligned frailty hazards and delayed-feedback conformal alarms. Journal of Trends in Finance and Economics, 1(1), 85-100.

[28] Yue, X., Yang, J., & Liu, W. (2026). FRAUDDEBATE-AGENT: A multi-agent LLM framework with an evidence-based debate mechanism for financial statement fraud detection. Mathematics, 14(15), Article 2695. https://doi.org/10.3390/math14152695

[29] Yang, J.-S., Zeng, Z., & Shen, Z. (2025). Neural-symbolic dual-indexing architectures for scalable retrieval-augmented generation. IEEE Access, 13, 1-15. https://doi.org/10.1109/ACCESS.2025.3638761