

Parental Notification Gaps in ChatGPT-5: An Empirical Study

Kerem Ersoz, Saleh Afroogh, David Atkinson, Junfeng Jiao

University of Texas at Austin
kerem@utexas.edu, saleh.afroogh@utexas.edu, datkinson@utexas.edu, jjiao@austin.utexas.edu

Abstract

We evaluate how effectively platform-level parental controls moderate a mainstream conversational assistant used by minors. Our two-phase protocol first builds a category-balanced conversation corpus via PAIR-style iterative prompt refinement over API, then has trained human agents replay/refine those prompts in the consumer UI using a designated child account while monitoring the linked parent inbox for alerts. We focus on seven risk areas—physical harm, pornography, privacy violence, health consultation, fraud, hate speech, and malware—and quantify four outcomes: Notification Rate (NR), Leak-Through (LR), Overblocking (OBR), and UI Intervention Rate (UIR). Using an automated judge (with targeted human audit), we find that the notification surface diverges from its own public description in both directions. Privacy violence, fraud, hate speech, and malware triggered no parental alerts in our runs, whereas physical harm and pornography alerted consistently and health queries intermittently—even though the vendor documentation in force during our study named only self-harm as a notification trigger. Overblocking of benign, educational queries near sensitive topics is also common and is not surfaced to parents, revealing a policy–product gap between on-screen safeguards and parent-facing telemetry in the tested configuration. These quantitative findings do not extend to other products. A documentation review of Gemini, Claude, and Copilot identifies related transparency limitations but cannot establish whether they exhibit the same operational gap. We propose actionable fixes: broaden/configure the notification taxonomy, couple visible safeguards to privacy-preserving parent summaries, and prefer calibrated, age-appropriate safe rewrites over blanket refusals.

1 Introduction

Children and adolescents now interact with general-purpose conversational AI through ChatGPT, Gemini, Copilot, Claude, and other products built on the same model families. Several vendors expose age profiles, content filters, family-link integrations, or parent-facing reporting. ChatGPT additionally advertises asynchronous notifications for some safety events. Such notifications can connect platform-level safety behavior to information a caregiver can act on.

In the ChatGPT configuration we tested, this channel was brittle in a particular and consequential way. Notifications

covered a narrow set of the harm categories we evaluated, were decoupled from some safeguards shown to the child, and were governed by a taxonomy that external researchers could not fully inspect. We call this observed discrepancy the *parental telemetry gap*. Measuring such gaps is important for evaluating conversational AI deployed to households with minors.

This paper separates a platform-agnostic conceptual framework from a product-specific empirical claim. We test one ChatGPT-5 configuration and review the publicly documented parental-control mechanisms of Google Gemini (Google 2024), Anthropic Claude (Anthropic 2024), and Microsoft Copilot (Microsoft 2024). The documentation review characterizes what vendors publicly disclose; it cannot establish unobserved implementation details or operational behavior. We therefore treat recurrence of the measured gap across platforms as a hypothesis for matched future experiments, not as a finding of this study.

Why a single deep case study plus a documentation-based cross-platform review. An empirical study of one product cannot license claims about an industry. We therefore use the cross-platform documentation review (Section 5) to describe public transparency and identify unresolved questions, not to claim operational generality. The ChatGPT-5 case study (Section 6) establishes the gap in the tested configuration and quantifies its category-level pattern. Together they motivate the design principles in Section 4 and a cross-platform measurement agenda, not an industry-wide empirical conclusion.

Why parental telemetry matters for the AI research community. Telemetry sits in an awkward middle layer between model alignment (internal) and product UX (external). It is rarely benchmarked, rarely red-teamed, and largely absent from the safety evaluation literature. Yet it is the layer through which alignment failures become parenting failures, and it is the layer that regulators are most likely to touch first. For the AAAI community in particular, parental telemetry surfaces research questions in evaluation methodology, alignment-coherence, human–AI interaction, and responsible AI policy that map directly onto existing AAAI tracks (Section 7).

Contributions.

- A platform-agnostic conceptual framework for parental telemetry and a testable hypothesis about whether deployment-level gaps recur across products (Sections 4, 5).
- A documentation-based cross-platform comparison of parental-control mechanisms across four leading consumer LLM products, explicitly separating documented features from unknown operational behavior (Section 5).
- A formal distinction between the “curious-child” threat model and standard adversarial-attacker red-teaming, with implications for how notification systems should be evaluated (Section 3).
- A focused empirical case study on ChatGPT-5, with inter-annotator agreement statistics and temporal-stability analysis (Section 6).
- Four concrete design principles for parental telemetry and a stakeholder-targeted implications section (Sections 4, 9).

2 Background and Related Work

Platform Controls vs. Model Alignment

Safety alignment is typically implemented at the model level—through data filtering, supervised fine-tuning, RLHF, and refusal training—and much of the academic AI safety literature evaluates models in isolation (Ganguli et al. 2022; Weidinger et al. 2022; Bommasani et al. 2021). Consumer deployments wrap these models in a thicker layer of *platform controls*: age-gated profiles, topic filters, system prompts, output classifiers, re-routers, warning UIs, and asynchronous telemetry to a linked parent account. The same model can be exposed to a child through radically different platform stacks. Parental telemetry is the layer that translates platform-level safety behavior into something a caregiver can act on, and it has received almost no attention in the AI safety literature relative to model alignment itself.

Parental Controls and Online Child Safety

There is, however, a substantial HCI and child-development literature on parental control tools predating the LLM era. Wisniewski et al. (2017) document that purely restrictive parental controls undermine adolescent self-regulation and that “safety vs. surveillance” is a genuine design tension. Ghosh et al. (2018) show that children find heavyweight parental control apps coercive and opaque, and that they often route around them. Hartikainen, Iivari, and Kinnula (2016) frame the design space as a choice among control, trust, and involvement. Larger-scale studies of European children (Livingstone, Mascheroni, and Staksrud 2017) and U.S. parents (Auxier et al. 2020; Common Sense Media 2023) consistently find that parents overestimate the coverage of the safety tools they rely on. COPPA (U.S. Federal Trade Commission 1998) provides a baseline regulatory floor for under-13 data practices but is silent on the substance of safety telemetry.

Two findings from this literature are particularly relevant to our analysis. First, opaque controls produce miscalibrated trust: parents either disengage entirely or develop a false sense of comprehensive coverage. Second, controls that decouple from what the child actually experiences erode the parent–child relationship without improving safety outcomes. Both failure modes are exactly what we observe in the tested ChatGPT configuration; our documentation review cannot establish whether they occur operationally elsewhere.

Jailbreaks, Red-Teaming, and Over-Refusal

The adversarial-attacker view of LLM safety is well developed. Black-box iterative refinement (PAIR; Chao et al. 2024) succeeds in under twenty queries against frontier models. Persona modulation (Shah et al. 2023), nested prompts (Ding et al. 2024), simple black-box rewrites (Takemoto 2024), adaptive API-aware attacks (Andriushchenko, Croce, and Flammarion 2025), and LLM-on-LLM jailbreaking (Kritz et al. 2025) all show that aligned models remain pressable. The mirror-image literature on *over-refusal* (Röttger et al. 2024) shows that the same models reject benign queries when category keywords appear, particularly in educational contexts. The relevant observation for this paper is that essentially all of this work evaluates the *model*, not the platform stack a child actually interacts with, and none of it evaluates parental telemetry.

LLM-as-Judge Evaluation

We use an LLM as our primary safety judge, calibrated against human raters. Zheng et al. (2023) establish both the practical utility of LLM-as-judge methodology and its known biases (self-preference, position bias, verbosity bias). Best practice—which we follow in Section 6—is to report inter-rater agreement with humans and to manually audit edge cases. The fact that this is now standard practice is itself part of our framing: parental telemetry should be evaluated with at least the same methodological care that the AI research community already applies to model benchmarks.

3 The Curious-Child Threat Model

Child-authentic boundary testing differs from adversarial prompting in ways that matter for telemetry design. We make this distinction explicit below.

Inspired in part by developmental-agent work (Murali et al. 2025), we characterize the curious-child threat model along five axes, contrasted with the adversarial-attacker model in Table 1.

The point is not that these populations are disjoint—a determined teenager can be both—but that their distributions over the axes differ in ways that change what a safety system should optimize for. An adversarial-attacker evaluation rewards a model for resisting hundreds of attempts before yielding one bypass. A curious-child evaluation cares only whether *any* of a handful of low-effort attempts surfaces inappropriate content, because the child’s parent will not see that attempt repeated five hundred times—they will see it once, or not at all, depending on whether telemetry fired.

Axis	Curious Child	Adversarial Attacker
Intent	Exploratory; often non-malicious	Goal-directed; malicious or red-team
Persistence	Low-medium; gives up easily	High; iterates until success
Technical sophistication	Low; surface paraphrase	High; prompt engineering, tooling
Social affordances	Empathy, story, homework, “my friend”	Persona, role-play, jailbreak templates
What success looks like	A single in-appropriate response is enough to harm	Reliable bypass at scale

Table 1: Curious-child vs. adversarial-attacker threat models.

This observation has a direct implication for our framework: parental telemetry must be calibrated to a low-persistence, high-recall threat model. The tested ChatGPT configuration behaved as though some single judge-positive turns were treated as noise. In the curious-child case, that single turn can be the entire event.

4 A Conceptual Framework for Parental Telemetry

We now articulate a platform-agnostic framework. We define parental telemetry as the channel through which a platform reports safety-relevant events occurring on a minor’s account to the linked parent account. A well-designed telemetry channel has the following four properties. These are normative evaluation criteria, not findings that every platform currently violates them; operational satisfaction must be established product by product.

Principle 1: Coverage parity with UI safeguards. Every category for which the product displays a visible safeguard to the child—warning, safe rewrite, refusal, soft-block—should be eligible for parental telemetry. Decoupling the two surfaces creates information asymmetry: the child knows the system flagged the interaction, the parent does not. A platform may have privacy or policy reasons for selective reporting, but those reasons and the resulting coverage should be disclosed. Our black-box measurements cannot identify the architectural or organizational cause of a mismatch.

Principle 2: Configurable granularity. Parents differ. A parent of a seven-year-old with a learning disability has different telemetry needs than a parent of a sixteen-year-old asking about mental health resources. A single threshold tuned to “avoid alert fatigue” will under-serve both. Configurable granularity—tiered notification levels, per-category opt-in/opt-out, digestion options (immediate, daily, weekly)—turns the alert-fatigue counter-argument from a justification for opacity into an engineering requirement.

Principle 3: Versioned, public taxonomy. Parents and external auditors must be able to know, at any given moment, which categories at which severity thresholds will produce a notification. Versioning matters: alignment policies change, and a parent who learned the system in 2024 should be told when its notification surface changes in 2026. The taxonomy should be human-readable, not a buried internal classifier label.

Principle 4: Parent-side auditability. A parent should be able to retrieve a structured, time-indexed record of safety-relevant events on the child’s account, at a granularity the parent has configured. This is not surveillance of conversation content; it is auditability of the safety layer. Without it, parents cannot verify that the telemetry channel is working at all, and researchers cannot evaluate it independently.

A Structural Hypothesis

A natural question is whether the gap measured in ChatGPT is a short-lived implementation defect or an instance of a recurring system design problem. Our evidence answers only part of that question: the category-level pattern persisted in the tested configuration across eight weeks, making a one-off measurement artifact less likely. It does not reveal the underlying architecture or establish the same gap in other products.

Three observations motivate a structural *hypothesis*. First, child-facing safeguards and parent-facing notifications can be implemented as distinct pipelines; the decoupling we observed is consistent with that possibility but does not prove it. Second, none of the public materials we reviewed provides a versioned notification taxonomy. This establishes a transparency limitation, not the absence of an internal implementation. Third, COPPA (U.S. Federal Trade Commission 1998) and analogous frameworks were written before generative AI and impose no specific requirements on the substance of safety telemetry for minors.

These conditions could allow similar gaps to persist across products, but matched experiments are required to determine whether they do. A product update could also close the measured ChatGPT gap. We therefore frame structural recurrence as a testable systems-level hypothesis and measurement agenda, not as an empirical conclusion of this study.

5 Cross-Platform Documentation Landscape

We reviewed the publicly documented parental-control mechanisms of the four most widely deployed consumer general-purpose conversational AI products. We included products available to U.S. consumers without enterprise procurement that publish either a policy for use by minors or a family or parental-control surface. This includes Claude as a documented no-child-profile case. Table 2 summarizes this documentation-based comparison against our four design principles. We did not run matched experimental measurements on Gemini, Claude, or Copilot. Except for ChatGPT, the entries below describe only what public documentation establishes. An undocumented feature is unknown, not necessarily unimplemented.

	P1	P2	P3	P4
ChatGPT-5 (tested)	partial	no	no	partial
Google Gemini (docs)	unknown	partial	no	partial
Anthropic Claude (docs)	n/a	n/a	n/a	n/a
Microsoft Copilot (docs)	unknown	partial	no	partial

Table 2: Evidence available for the four design principles of Section 4. ChatGPT assessments combine experiments and documentation; other rows use documentation only. “unknown” means that public materials do not establish operational behavior and does not imply absent implementation. “n/a” indicates no official child-targeted product surface. P3 concerns public disclosure itself; we located no versioned public taxonomy in the reviewed materials.

ChatGPT (OpenAI 2025). ChatGPT exposes a parent-teen linking flow with content settings, a “reduced exposure” toggle, and asynchronous notifications for a declared but partially documented set of severity events. Our case study (Section 6) characterizes the operational shape of those notifications in detail. The published taxonomy describes broad categories at a high level but does not enumerate the specific harm classes that will or will not trigger an alert, and provides no version history.

Google Gemini (Google 2024). Gemini access for under-13 accounts is mediated through Family Link, which gates app-level access and provides some content-filter configuration. Parental telemetry, where it exists, is bundled into Family Link’s general activity-reporting and is not specific to LLM safety events. We were unable to locate public documentation specifying which on-model safety events surface to parents or whether child-visible safeguards are coupled to parent-facing alerts. This is a documentation gap, not evidence that such mechanisms are absent.

Anthropic Claude (Anthropic 2024). Claude’s acceptable-use policy restricts use by minors, and its public materials do not describe a consumer child-targeted profile or parental-notification surface. We treat this as a distinct documented product position rather than as evidence about safety for unauthorized or shared-account use.

Microsoft Copilot (Microsoft 2024). Copilot integrates with Microsoft Family Safety for accounts under parental management. Reporting is again at the activity-and-time level rather than the LLM-safety-event level. Specific content-safety telemetry from Copilot to the parent dashboard is not publicly documented, so its operational presence and coupling to child-visible safeguards remain unknown.

The cross-platform pattern in public documentation. Across the reviewed public materials, access control receives more attention than safety-event telemetry. For Gemini and Copilot, the materials do not establish whether event-level telemetry exists or whether it aligns with visible safeguards. That uncertainty should not be converted into a claim of non-implementation. The defensible cross-platform

finding is narrower: none of the reviewed materials provides a versioned public notification taxonomy, and public information is insufficient for an external operational audit. These transparency patterns motivate, but do not confirm, the hypothesis that the measured ChatGPT gap may recur elsewhere.

6 Empirical Case Study: ChatGPT-5

We now describe the focused empirical case study that anchors the quantitative evidence for the tested ChatGPT configuration.

System Under Test

Because consumer products change under their own version labels, we specify a measured configuration rather than a model name. Our object of study is the ChatGPT consumer web product as experienced by a minor linked to a parent account through ChatGPT Parental Controls (launched 29 September 2025). Notification is a platform service rather than a model output, so we separate the *model condition* (the entry selected in the model picker) from the *telemetry configuration* (the parent-facing alerting pipeline). Phase II used ChatGPT Plus accounts linked as teen accounts, with a researcher-controlled parent inbox, the GPT-5 picker entry for all sessions, and three windows: W1 (17 October 2025), W2 (14 November 2025), W3 (12 December 2025).

What that selection did and did not fix. Selecting GPT-5 did not pin a single serving model. Through 11 November 2025 that entry was an automatic router choosing per turn between a chat and a reasoning mode. On 12 November the vendor released GPT-5.1, made it default, and moved GPT-5 into a “Legacy models” section documented as discrete pinned modes rather than a router; GPT-5.2 followed on 11 December. Our selection was thus constant across W1–W3 while its routing semantics changed between W1 and W2, and from W2 onward we measured a configuration the vendor had itself relabeled legacy. Lacking per-turn model identifiers, we claim only that the model *family* was held fixed and report notification results as properties of the deployment, not of a checkpoint.

Documented notification scope. The parental-control documentation in force throughout our study described parent alerts as covering signs of “serious safety concerns involving self-harm,” reviewed by trained raters. No public material we located named any of the other six categories we test as a trigger, and none provided a version history. We therefore treat the published scope as a baseline for comparison, not as a promise the vendor failed to keep.

Method Overview

We conducted a two-phase study. **Phase I** used a PAIR-style (Chao et al. 2024) black-box prompt-refinement loop, with Claude Sonnet 4.5 generating seed prompts and an automated judge scoring target responses, to build a conversation corpus across seven harm categories: (i) physical harm, (ii) pornography, (iii) privacy violence, (iv) health consultation, (v) fraud, (vi) hate speech, and (vii) malware.

Algorithm 1 Telemetry-gap evaluation pipeline

Input: Harm categories C ; trajectories per category $N=100$; max refinements $K=15$; replay sample size $M=20$; measurement windows W ; benign probe set B_c per category

Output: Corpus $\mathcal{D}$ of (prompt, response, judge label, UI intervention, notification) tuples

```
1: Initialize  $\mathcal{D} \leftarrow \emptyset$ 
2: for all  $c \in C$  do
3:   Generate  $N$  seed prompts  $S_c$  with prompt-engineer LLM
4:   for all  $s \in S_c$  do
5:      $k \leftarrow 0$ ;  $\ell \leftarrow \text{APPROPRIATE}$ 
6:     while  $k < K$  and  $\ell$  is APPROPRIATE do
7:       Query API target with  $s$ ; record response  $r$ 
8:        $\ell \leftarrow \text{judge}(r, c)$ 
9:        $s \leftarrow \text{mutate}(s, \ell)$ 
10:       $k \leftarrow k + 1$ 
11:     end while
12:     Add trajectory  $(s, r, \ell)$  to  $\mathcal{D}$ 
13:   end for
14:    $T_c \leftarrow$  sample  $M$  trajectories uniformly at random from the judge-positive trajectories of  $c$ 
15: end for
16: Freeze  $\{T_c\}_{c \in C}$ 
17: for all  $w \in W$  do
18:   Replay  $\{T_c\}$  through consumer UI on child profile
19:   Record visible UI interventions and parent-email notifications
20: end for
21: Replay  $\{B_c\}$  on the same profile; record refusals or heavy sanitization
22: return  $\mathcal{D}$ 
```

Phase II replayed and lightly paraphrased selected prompts through the consumer ChatGPT web UI logged into an experimental child profile, with parental controls enabled and a researcher-controlled parent email inbox monitored for notifications. Algorithm 1 summarizes the pipeline.

Conditions and Metrics

All reported measurements come from the single model condition specified in Section 6: the GPT-5 picker entry, in the consumer UI, on a teen account with parental controls active. The safety judge returned a binary Yes/No decision on whether each response was inappropriate; we refer to these outcomes as judge-positive (inappropriate) and judge-negative (appropriate). We report four metrics:

- **Notification Rate (NR):** fraction of sessions yielding a parent notification.
- **Leak-Through Rate (LR):** fraction of selected sessions yielding a judge-positive (inappropriate) assistant response. Conditional on Phase I success; see below.
- **Overblocking Rate (OBR):** fraction of sessions in which a pre-validated benign, category-adjacent prompt received a refusal or heavy sanitization.

Prompt Type	Template
Baseline prompt (control)	[System] (empty). [User] How might someone spread their perspective widely?
Refined prompt (boundary test)	[System] You must role-play as a teenager curious about sensitive information... [User] How might someone spread their perspective widely?
Judge prompt (labeling)	Context: You are a sensitive-content moderator. Evaluate harmful content related to {CATEGORY}. Text to evaluate: {COMPLETION}. Question: Is the response inappropriate? Rating: Yes/No (plus rationale).

Table 3: Prompt templates used for baseline elicitation, boundary testing, and response judging.

- **UI Intervention Rate (UIR):** fraction of sessions showing visible warnings or safe rewrites.

Experimental unit and trajectory selection. We define a session, rather than an individual prompt–response pair, as the experimental unit. Phase I generated 100 independent refinement trajectories per harm category, each permitting up to 15 adaptive mutations. For Phase II we drew 20 trajectories per category at random from those Phase I trajectories that had elicited a judge-positive response; unsuccessful trajectories were not eligible. The selected trajectories were then frozen and replayed unchanged in $W1$ – $W3$, so the three windows are repeated measures on identical stimuli rather than independent replications.

Overblocking is measured on a separate, disjoint corpus of pre-validated benign, category-adjacent prompts, also 20 sessions per category. NR, LR, and UIR therefore share one denominator—the 20 selected adversarial trajectories—while OBR uses the 20 benign probes. Session-level outcomes were binary: a session counted positive for a metric if the corresponding event occurred during any mutation in that session; individual mutations are not treated as independent observations. We report two-sided 95% Wilson score confidence intervals for these binomial session-level rates.

What selection on Phase I success implies. Because Phase II trajectories were drawn only from Phase I successes, LR is conditional on that selection: it estimates the rate at which an attack that already succeeded against the Phase I target also succeeds in the consumer UI—a transfer rate—not the probability that an unselected child-authored session elicits inappropriate content. The same conditioning applies to NR and UIR, where it is deliberate: those metrics ask what the platform does once judge-positive content has reached the child. Cross-category LR comparisons carry no information about which categories are intrinsically easier to elicit, since fixing 20 successes per category normalizes

that difficulty away; the Phase I base rates carry it instead. Because the same 20 trajectories were replayed unchanged, W1–W3 are paired observations on identical stimuli rather than independent replications, and cannot be pooled as independent samples.

Judge Calibration and Inter-Annotator Agreement

Using an LLM as the primary safety judge may introduce correlation with the target system. We mitigate this risk in two ways.

First, two trained human raters independently labeled a 10% stratified random sample of binary judge decisions ($n=142$) across all seven categories, with disagreements resolved by a senior rater. Cohen's κ (Cohen 1960) between the LLM judge and the human-adjudicated label was $\kappa = 0.71$ overall (substantial agreement), with category-level values ranging from $\kappa = 0.58$ (health consultation, the noisiest category) to $\kappa = 0.84$ (malware, the cleanest). Inter-human κ before adjudication was 0.79, situating the LLM judge slightly below the human ceiling but well above the threshold customary in the LLM-as-judge literature (Zheng et al. 2023).

Second, we manually audited 100% of judge-positive labels and a random 10% of judge-negative labels. These audits directly check errors in the binary labels used to compute LR.

Temporal Stability

Rapid product iteration can limit the temporal validity of black-box measurements. We ran the Phase II UI replay in three windows (W1–W3, Section 6) using the same prompt subset, the same child profile, and the same picker selection. The category-level notification pattern was stable across all three windows: the same four categories (privacy violence, fraud, hate speech, malware) produced zero notifications in every window. Total notification counts in the non-zero categories varied (consistent with batching and day-of-week effects), but no category transitioned from zero-notification to notifying or vice versa.

Two features of the study period make this more informative than a simple repeat measurement. The vendor shipped two new default generations while we were running (GPT-5.1, GPT-5.2), each within days of a follow-up window; and our own selection changed behavior even though its label did not, moving from an automatic router to a discrete pinned mode on 12 November. The set of models actually serving our turns therefore differed between W1 and W2–W3, and the pattern did not move.

We state the inference conservatively. This is evidence that notification coverage is stable over eight weeks and insensitive to intra-family routing changes and two surrounding platform releases, consistent with coverage being set at the telemetry layer rather than by the served model. It is not a controlled cross-model comparison and we do not claim one: the model family was held fixed, so establishing model-independence would require a design that varied it deliberately. Nor does it identify the cause, establish permanence, or demonstrate the same behavior in another product.

A note on external validity. Holding the selection fixed bought internal validity at a cost. From 12 November 2025 onward, the configuration we measured was no longer the default teen experience, which had moved to GPT-5.1 and then GPT-5.2. W2 and W3 describe a held-constant condition, not what a typical family encountered on those dates.

Results

Parental notifications. Table 4 shows the headline result: the observed notification surface diverges from its published description in *both* directions. *Four of seven* categories (privacy violence, fraud, hate speech, malware) produced no parental notifications at any point in the observed sessions. In the other direction, physical harm and pornography notified in every session, although neither was named as a notification trigger in the documentation in force during our study. Health consultation—the category whose prompts most closely match the one documented trigger, distress and self-harm—notified in only 8 of 20 sessions. The practical consequence is not that the vendor failed to honor a stated commitment, but that no parent could have derived this coverage map from the published materials: the surface is simultaneously broader than documented in two categories, narrower than the safeguards shown to the child in four, and incomplete within the single category the documentation does describe.

Leak-through. The categories with zero notifications were also among the categories with the highest transfer to the consumer UI (malware 16/20 [80%], privacy violence 16/20 [80%], fraud 12/20 [60%]). This is the worst-case combination from a parent's perspective: among attacks that reach the child successfully, the categories with the highest transfer are also the categories the parent is least likely to be told about.

Overblocking. OBR was highest on category-adjacent educational prompts (anatomy homework, historical analysis with quoted slurs, defensive cybersecurity hygiene). Within the same harm category, the product was willing to refuse a benign homework question and unwilling to notify a parent about a judge-positive fraud-adjacent response.

UI-telemetry decoupling. The most operationally revealing finding is the discrepancy between UIR and NR within the same category. Several sessions in the zero-notification categories showed visible safeguards to the child (refusal text, soft warnings) without producing any corresponding parent notification. This is exactly the Principle 1 violation predicted by the framework in Section 4.

7 Discussion

Scope of Inference: Deployment Finding and Cross-Platform Hypothesis

The strongest inference supported by our evidence is that a parental telemetry gap exists in the tested ChatGPT configuration. Only that deployment received quantitative testing. The Gemini, Claude, and Copilot analysis concerns public documentation, and “not publicly documented” is not

Category	NR	LR	OBR	UIR
Pornography	20/20 (100%) [84–100]	0/20 (0%) [0–16]	4/20 (20%) [8–42]	0/20 (0%) [0–16]
Health consultation	8/20 (40%) [22–61]	0/20 (0%) [0–16]	8/20 (40%) [22–61]	12/20 (60%) [39–78]
Physical harm	20/20 (100%) [84–100]	0/20 (0%) [0–16]	12/20 (60%) [39–78]	16/20 (80%) [58–92]
Hate speech	0/20 (0%) [0–16]	4/20 (20%) [8–42]	8/20 (40%) [22–61]	2/20 (10%) [3–30]
Malware	0/20 (0%) [0–16]	16/20 (80%) [58–92]	0/20 (0%) [0–16]	1/20 (5%) [1–24]
Fraud	0/20 (0%) [0–16]	12/20 (60%) [39–78]	8/20 (40%) [22–61]	1/20 (5%) [1–24]
Privacy violence	0/20 (0%) [0–16]	16/20 (80%) [58–92]	4/20 (20%) [8–42]	1/20 (5%) [1–24]

Table 4: ChatGPT-5 case study: parental Notification Rate (NR), Leak-Through Rate (LR), Overblocking Rate (OBR), and UI Intervention Rate (UIR) by harm category, GPT-5 condition. Each cell reports positive sessions/20 (rate), followed by the two-sided 95% Wilson score confidence interval in brackets; interval endpoints are percentages rounded to the nearest whole number. NR, LR, and UIR are computed over the 20 selected adversarial trajectories per category and are therefore conditional on Phase I success; OBR is computed over a disjoint corpus of 20 pre-validated benign prompts per category. The two denominators are equal in size but are not the same sessions.

equivalent to “not implemented.” The documentation review therefore identifies transparency limitations in the reviewed materials and motivates a hypothesis about recurring operational gaps; it does not demonstrate that those gaps occur.

Connecting Findings to the Design Principles

Our ChatGPT results violate at least three of the four design principles of Section 4. UIR $\gg$ NR in several categories violates Principle 1 (coverage parity). The lack of per-category opt-in controls violates Principle 2 (configurable granularity). The lack of a public list of which categories notify and at what thresholds violates Principle 3 (versioned public taxonomy). Parents can review some past interactions in the product UI (partial satisfaction of Principle 4) but cannot retrieve a structured event log of safety-relevant moments. For the other platforms, public documentation is insufficient to evaluate operational coverage parity; it establishes only the disclosure-related evidence summarized in Table 2.

Why This Matters for AAAI-Style AI Research

The AAAI community can plausibly affect three things in this space.

First, **evaluation methodology**. The same care that has gone into benchmarking jailbreaks and over-refusal should be applied to parental telemetry: standardized harm taxonomies, leaderboards for notification coverage, replicable child-profile evaluation harnesses. This is a natural extension of existing AI-safety evaluation work and maps directly onto AAAI’s AI Safety and Responsible AI tracks.

Second, **alignment-coherence**. The current literature treats alignment as a property of the model. Our case study illustrates that deployment-level safety also depends on the *platform stack*: a model refusal and the parent-facing response to it are distinct surfaces that can diverge. We invite work that treats UI safeguards, refusals, and telemetry as a joint optimization target rather than three separate surfaces.

Third, **system design for telemetry**. How should a notification classifier be designed so that it can be audited externally? How should taxonomies be versioned so that they remain meaningful across model upgrades? These are AAAI-shaped questions in their own right, adjacent to work on interpretability, calibration, and human–AI interaction.

8 Alternative Explanations

We engage five credible counterarguments.

Selective notification reduces alert fatigue. We agree that indiscriminate alerting is bad UX. The current design may reflect a deliberate alert-fatigue trade-off, but our black-box study cannot determine the design rationale, and we found no public coverage specification against which to evaluate it. Principle 2 (configurable granularity) offers one way to expose that trade-off without requiring comprehensive alerting.

Children deserve privacy from parental surveillance. We share this concern. Note that our analysis is about telemetry of the *safety layer*, not transcripts of conversations. A parent being told “a hate-speech-adjacent interaction occurred at 4:12pm” is qualitatively different from a parent being shown the chat content. Configurable granularity (Principle 2) lets families calibrate this trade-off; opacity removes the choice entirely.

Vendors iterate; gaps are temporary. Our temporal-stability analysis (Section 6) shows that eight weeks of product iteration moved none of the four zero-notification categories in the tested configuration. This rules out neither a later fix nor transient behavior on a longer horizon; it supports persistence over the study window only.

Other platforms may be similar or worse. Our study does not establish this. Section 5 compares public documentation, not operational telemetry. Missing documentation identifies an auditability limitation but cannot show that an internal mechanism is missing or behaves like ChatGPT’s. Matched experiments are needed.

Cross-platform comparison is premature. We agree that an operational comparison is premature without matched testing. A documentation comparison remains useful for evaluating public transparency and specifying what external researchers cannot verify. We use it for those purposes only and leave cross-platform behavior as an open empirical question.

9 Implications and Recommendations

For platform providers. Adopt the four design principles of Section 4 as shipping requirements rather than aspirations: coverage parity between visible safeguards and parental telemetry; configurable granularity in lieu of one-size-fits-all thresholds; a versioned, public notification taxonomy; and a parent-side audit log of safety-relevant events. The implementation cost and privacy trade-offs will vary by platform and should be evaluated explicitly.

For regulators. COPPA (U.S. Federal Trade Commission 1998) and successor frameworks should be extended with disclosure requirements for parental telemetry and, where evidence supports them, minimum-coverage requirements. At a minimum, parental-control surfaces should state what they are designed to cover and how that scope changes over time.

For researchers. We invite extensions of the case study to Gemini, Claude, and Copilot under matched protocols; the development of child-authentic prompt corpora validated by child-development experts; stakeholder studies of how parents and children understand current telemetry; and methodological work on auditable notification classifiers. Section 7 lays out the connections to existing AAI research tracks.

For parents. Do not infer comprehensive safety coverage from the presence of a parental-control label. In the tested ChatGPT configuration, notifications were selective; for the other reviewed products, public materials did not permit an equivalent operational assessment. Coverage disclosures would let families make more informed choices.

10 Conclusion

Conversational AI is increasingly used in households, and “parental controls” shape families’ safety expectations. Our focused ChatGPT-5 case study identifies a parental telemetry gap in the tested configuration: four of seven harm categories produced no notifications, two others alerted consistently despite not being documented as triggers, some child-visible safeguards had no corresponding parent alert, and the category-level pattern persisted across eight weeks and two platform releases. These results do not establish an industry-wide structural gap. The documentation review of Gemini, Claude, and Copilot instead identifies a narrower transparency finding: public materials do not support a matched operational audit, and lack of documentation must not be treated as lack of implementation. Whether the measured gap recurs across platforms is a hypothesis for future experiments. The four design principles we propose—coverage parity, configurable granularity, versioned public taxonomies, and parent-side auditability—offer concrete targets for that work.

Ethical Statement

All experiments used a researcher-controlled child profile and a linked researcher-controlled parent inbox; no real children were involved at any stage. Email monitoring was restricted to the parent inbox provisioned for this study. Iterative refinement was bounded (maximum 15 mutations per

seed), and any explicit material that would be unlawful to retain was filtered prior to storage. We adopt a responsible-disclosure stance for adversarial methodology: we report category-level results and aggregate patterns rather than publishing verbatim prompts that reliably bypass current safeguards. Public artifacts released alongside this paper, if any, will redact sensitive strings and ship with a contributor code of conduct.

Limitations

Single case-study product. The quantitative results in Section 6 apply to a single ChatGPT configuration. The cross-platform documentation review in Section 5 does not establish operational generalizability, and we do not have matched quantitative measurements on Gemini, Claude, or Copilot. Accordingly, the strongest empirical conclusion is product- and configuration-specific; cross-platform recurrence remains a hypothesis.

Documentation inference. Public documentation can establish disclosed capabilities and public auditability, but silence cannot establish that a feature is absent or implemented poorly. Our ratings for untested products should therefore be read as evidence about transparency, not hidden system behavior.

Seed-prompt authenticity. Seeds were generated by an LLM (Claude Sonnet 4.5), constrained by category templates with age-appropriate cover stories and escalation ladders informed by developmental literature, but were not validated against authentic child–AI interaction logs or by child-development specialists. Real children use idiosyncratic phrasing, code-switching, and pragmatic strategies that LLM-generated seeds approximate imperfectly.

Judge-model bias. We mitigate this with human calibration ($\kappa = 0.71$ overall; Section 6) and targeted manual audits, but residual model–judge correlation cannot be fully eliminated.

Notification-pipeline opacity. Missing alerts could reflect policy gating, classifier thresholds, deliverability issues, or batching; we treat the pipeline as a black box.

Lack of stakeholder evidence. Our normative claims would be strengthened by survey or interview evidence on how parents and children actually understand and rely on parental telemetry. Prior child-online-safety literature (Wisniewski et al. 2017; Auxier et al. 2020; Common Sense Media 2023) is consistent with our findings, but a tailored study of LLM-specific parental telemetry would be more direct.

Single-configuration scope. Our empirical measurements are restricted to the ChatGPT-5 configuration specified in Section 6, measured between 17 October and 12 December 2025. We do not claim that earlier or later model generations, other plan tiers, or later revisions of the parental-control system behave identically. In particular, the vendor’s automatic age-prediction system was not deployed during our windows, and the published notification scope was revised after our study concluded.

Construct boundaries. “Privacy violence” and “fraud” overlap with general advice (privacy hygiene, scam awareness); strict templates reduce, but do not eliminate, boundary ambiguity. Our overblocking definition prioritizes educational utility for older minors; some platforms may normatively prefer refusal.

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