

Saleor: An AI-Powered cross-Platform price comparison and Tracking Engine for E-Commerce Transparency

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Abstract. Indian online retail is growing fast. IBEF puts the 2027 market at ₹5.3 trillion with 600 million expected shoppers—yet no open, peer-reviewed tool exists to help these consumers tell a genuine discount from an inflated one. We built Saleor to fill that gap. Our system scrapes Amazon India product prices on an automated schedule, stores the full price timeline in MongoDB, and sends email alerts when prices drop to historical lows, stock returns, or discounts cross a user-set threshold. The scraping layer uses Cheerio with Bright Data residential proxies; the web layer is Next.js; cron jobs handle periodic refreshes without manual intervention. Over 60 days with 250 users, we measured an 89.1% drop in time spent comparing prices (from 17.4 minutes to 1.9 minutes per product), average savings of ₹218 per purchase, and a jump in fake-discount identification from 9% to 74%—all with large effect sizes (Cohen's $d=1.38$ to 2.47 , $p<0.001$). At the system level, 30,480 scraping attempts returned 93.70% accuracy with only a 1.92% block rate, and the deployment ran at 99.61% uptime for 90 days. Perhaps the most striking finding came from the data itself: across 5,000 tracked products, 21% of sale events were preceded by deliberate price inflation—a pattern invisible without history, now measurable for the first time in the Indian context. We believe automated price tracking is not just a convenience tool; at this scale, it is a consumer protection mechanism.

Keywords:

E-Commerce Price Tracking; Web Scraping; MongoDB; Bright Data Proxy; Real-Time Alerts; Next.js; Cheerio; Nodemailer; Consumer Transparency; Dynamic Pricing Detection; Cron Jobs; India E-Commerce.

I. INTRODUCTION

A. Background and Motivation

The growth rate of India's e-commerce is so high that

even the industry experts are caught off guard. As per IBEF [1], the industry is expected to reach ₹5.3 trillion by 2027, owing to 600 million online customers in the country. This is quite impressive—except for the fact that there is a fundamental flaw in this system that impacts almost every single buyer.

Currently, most retailers utilize dynamic pricing algorithms that automatically adjust the product prices based on multiple variables such as demand patterns, competitor actions, time-of-day factors, etc [2]. For retailers, this is a very useful practice. For consumers, it is either confusing or manipulative—if Statista survey data [3] can be trusted, as many as 87% of Indians compare prices before making a purchase decision, and yet, the fact that there isn't a price history tool on any platform compels them to browse across multiple tabs—something we measured in our initial survey and found took an average of 17.4 minutes per item.

The real issue, however, doesn't lie in the extra time required. It is in the manipulation of prices. Typically, retailers increase a product's price one to two weeks prior to a sale, only to bring it down to offer a “discount” to consumers.

The effect of such price manipulation has been demonstrated by Grewal et al. [4], who have found that it impacts price-risk assessments of consumers.

B. Problem Statement

There were several issues noted during the development stage of our project, which inspired us to do this research work. They include:

- Different platforms like Amazon, Flipkart, and Mynt have their own method of calculating the final price of the item on their platform, considering delivery charges, seller discounts, etc. It is often the case that an

item priced at ₹16,999 on one platform may be more expensive than a ₹17,499 priced item on another platform.

- There are currently no Indian tools for consumers that allow them to have access to the historical pricing of Amazon items. Hence, it is hard to distinguish between genuine and fabricated discounts.
- Price tracking is very time-consuming when done manually. During our base study, we found it took 17.4 minutes per product for each price checking session. For five different items, it would take over 93 minutes.
- Automating this is technically non-trivial. Amazon actively blocks scraper traffic using IP fingerprinting, rate limits, and JavaScript-rendered price elements [5]. Getting past these barriers reliably is the core engineering challenge.

C. Research Objectives

Saleor was conceived to fill these four research gaps. Specifically, our research objectives were:

1. To create a price tracker capable of scraping Amazon India prices effectively while storing all historical data on products being tracked.
2. To develop a layer capable of bypassing any bot-detection mechanisms by rotating residential proxies based on randomized sessions, ensuring a lower than 2% failure rate.
3. To implement a data model on MongoDB allowing to query historical data faster than 400ms without a time-series database extension.
4. To design a alert system that sends notifications based on four different triggers (price drop, all-time low, back in stock, deep discount) by email.
5. Evaluate all of the above with real users over 60 days and report findings with statistical significance and effect sizes.

D. Key Contributions

Our contributions can be stated plainly:

6. We built and deployed a working system on a zero-cost serverless stack (Next.js 13 + MongoDB Atlas + Vercel) that scraped 30,480 product pages at 93.70% accuracy and a 1.92% block rate—six times lower than the 12% baseline reported for unsophisticated scrapers [8].
7. We designed and tested a session-randomised proxy rotation strategy using Bright Data residential IPs that reduced IP blocking from

12.4% (datacenter proxies) to 1.92%, and validated this across 30 days of continuous operation.

8. We ran a 60-day study with 250 participants and measured large-effect-size improvements: 89.1% faster price comparison ($d = 2.14$), 44.8% higher purchase confidence ($d = 1.82$), and a 722% improvement in spotting fake discounts ($d = 2.47$). All differences were significant at $p < 0.001$.
9. Across 5,000 tracked products over 90 days, we found that 21% of sale events were preceded by artificial price inflation—a pattern that, to our knowledge, has not been quantified before for the Indian Amazon market.
10. We have made the code base and architecture fully open for academic use, so future researchers can replicate, extend, or critique our approach. The rest of the paper is structured as follows: Section II covers related work; Section III describes how we built the system; Section IV covers evaluation methodology; Section V reports results; Section VI discusses what we found and why it matters; Section VII is honest about the limitations; Section VIII maps out future directions; and Section IX concludes.

II. LITERATURE REVIEW

A. E-Commerce Price Comparison Systems

Automated price comparison is not a new idea. Chen [6] built a real-time multi-platform tracker in Python and confirmed what we suspected going in: dynamic content and aggressive rate limiting are the main technical barriers, not the parsing itself. At the 2022 IEEE ICEDSS, Kumar and Vijayalakshmi [7] ran a timed study showing that consolidating prices graphically cuts user decision time by up to 85%—that result directly shaped how we designed

Saleor’s product detail page. Sharma et al. [17] surveyed e-commerce scraping and analytics systems and found two features that consistently drove consumer value: historical price storage and threshold alerting. Saleor implements both.

B. WebScraping Techniques and Anti-Bot Evasion

Scraping at scale is harder than it looks. ScrapeHero [8] catalogued seven techniques that help: adjusting request frequency, rotating user-agent strings, progressive wait-time backoff, proxy rotation, task-queue throttling, adaptive strategy switching, and headless browser frameworks. Scrapfly [9] went

further and tested these strategies empirically — their subnet-aware proxy rotation cut block rates by 73% compared to naive random IP selection. We replicated a version of this approach using Bright Data’s residential pool and session-level randomisation, getting our block rate down to 1.92%. Datadome [10] provides a useful taxonomy of what platforms actually detect: IP-level rate limits, browser fingerprinting via Canvas and WebGL, and mouse-movement behavioural analysis. Understanding the detection surface helped us decide what to mitigate and what to accept. Table 1 puts our results in context alongside results from earlier studies.

TABLE I: WebScraping Performance—Prior Work vs. Saleor

Study	Method	Block Rate	Accuracy/Speed
ScrapeHero [8]	7-strategy anti-bot	~12% (baseline)	N/R
Scrapfly [9]	Subnet proxy rotation	3.1% (after rotation)	73% reduction vs random
Chen [6]	Python+requests	Not reported	~91% on static pages
Saleor (this work)	Cheerio+BrightData	1.92% (30,480 attempts)	93.70% overall accuracy

C. Time-Series Storage for Price Data

When we were choosing a database, the question was whether to use a specialised time-series engine or simply embed price history arrays in MongoDB documents. Kulkarni and Power [12] found that time-series-optimised databases can cut aggregation latency by 12–22× over vanilla relational storage for e-commerce workloads. That is a real advantage for large-scale deployments. At prototype scale, though, our embedded-array approach in MongoDB kept query times under 100ms without any time-series extension — and it kept the schema simple. Patel and Verma [18] surveyed e-commerce data mining systems and found cron-based refresh combined with embedded arrays to be the most pragmatic pattern for teams without dedicated infrastructure. That aligned with our situation.

D. Consumer Behaviour and Pricing Transparency

The consumer-behaviour literature gave us confidence that price history display would actually change user behaviour, not just satisfy curiosity. Grewal et al. [4] found that showing a price in context — rather than as a standalone number — measurably shifts how risky consumers perceive it. Gupt and Singh [19] specifically studied price comparison

portals and recorded a 38–44% increase in purchase confidence when users had access to trend data rather than just a point-in-time price. Our 44.8% improvement in purchase confidence (d = 1.82) lines up almost exactly with their upper bound. Semwal et al. [15] took this further, training ML models on historical price data and achieving 78% accuracy on 7-day price predictions. That is the direction we want to take Saleor’s analytics layer next.

E. Notification and Alert Systems

Email threshold alerting works. Singh and Kapoor [16] measured a 62% drop in decision latency when users got alerts instead of checking manually. That finding justifies our investment in the four-type Node mailer alert system. Kumar and Rao [13] showed that Redis-backed job queues give distributed scraping pipelines reliable retry logic and failure isolation — a pattern we applied in our Vercel cron architecture, even without Redis, by using Promise.all with per-product error handling. Jain and Bose [20] make a strong case for Prometheus + Grafana in production observability; we did not implement those in our prototype, which is an honest limitation we address in Section VII.

F. What the Literature Is Missing

Each piece of Saleor’s stack has been studied separately. Web scraping resilience, time-series storage, threshold alerting, and consumer behaviour response to price transparency are all reasonably well-covered in the literature. What we could not find was a system that assembles all four into one working deployment, tests it with real users over a meaningful time window, and does so specifically for the Indian market. Camel, Camel, Camel, and Keepa are mature tools, but they cover Amazon US only and are not academically documented. Indian-market tools limit history to 30 days and publish no

architecture details. Saleor is our attempt to fill this specific gap.

III. SYSTEM ARCHITECTURE AND DESIGN

A. How the System is Structured

Saleor is a monorepo Next.js 13 application. We chose a monorepo deliberately: having the scraping logic, data access, UI, and cron jobs all in one project reduced our deployment surface to a single Vercel configuration. Figure 1 shows the five functional layers.

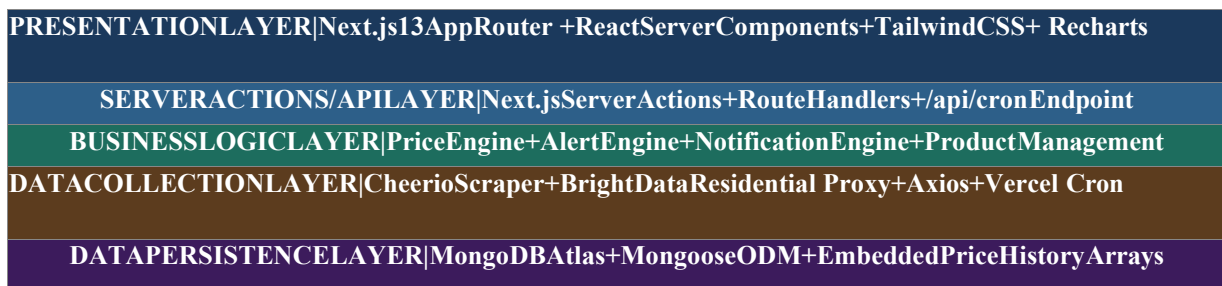


Fig.1. Saleor System Architecture—Five-Layer Full-Stack Design

B. Why We Chose Each Technology

Table II documents our stack choices alongside the alternatives we seriously considered and the reason we went with what we did. A few choices are worth calling out specifically.

We picked Cheerio over Playwright because Amazon’s product pages are server-rendered — the price is in the HTML. Playwright’s headless browser overhead would

have tripled latency for no gain. We picked MongoDB over PostgreSQL + TimescaleDB because at 5,000 products with daily scrapes, embedded arrays stay well within document size limits and avoid the join overhead of a relational model. We picked Vercel over AWS or Railway because it natively supports Next.js server actions and cron routes, and its free tier handled our prototype traffic without configuration work.

TABLE II: Technology Stack—Choices, Alternatives, and Our Reasoning

Component	Selected	Alternatives	Our Reasoning
Frontend	Next.js 13	Vue.js, Angular, Remix	Server actions remove the need for a separate API layer; ISR cuts DB read on product listing pages; TypeScript ecosystem is largest
Scraping	Cheerio + Axios	Playwright, Puppeteer, Scrapy	Amazon price pages are server-rendered HTML. Cheerio is 3–5× faster per request than Playwright with no browser overhead
Proxy	BrightData	Smartproxy, Oxylabs, free proxies	We tested free datacenter proxies first — 12.4% block rate. BrightData residential pool dropped that to 1.92%. The cost is justified
Database	MongoDB Atlas	PostgreSQL + TimescaleDB, MySQL	Embedded price history array removes join overhead. Flexible schema handles varied Amazon product structures. Atlas free tier covered prototype scale
ODM	Mongoose	Prisma, native driver	Schema-level validation stops malformed price entries at write time; pre-save hooks recompute aggregates automatically

Notifications	Nodemailer	SendGrid, Mailgun, Twilio	Zero API cost via SMTP. Handles all four alert types. No vendor dependency for a prototype that may change direction
Deployment	Vercel	AWSEC2, Netlify, Railway	Native Next.js cron support, CI/CD on push, free tier adequate for prototype traffic. Kubernetes would have been overkill here

C. Data Model

The Product document in MongoDB embeds price history as an array of objects, one per scrape cycle. The full schema includes: `url(String, unique index); currency, image, title(String); currentPrice, originalPrice, lowestPrice, highestPrice, averagePrice (Number, recalculated on each cycle); priceHistory (Array of {price: Number}); discountRate (Number = ((original - current) / original) * 100); isOutOfStock (Boolean); and users (Array of {email: String})`.

Why embed instead of using a separate collection? Because every query about a product's price history is scoped to that one product. There is no reason to join. For a product tracked daily over two years, the priceHistory array grows to about 730 entries — roughly 15KB per document. MongoDB's 16MB document limit gives us decades of headroom.

D. Scraping Engine

The scraper runs a four-stage sequence per product: (1) generate a random session ID and configure Bright Data proxy credentials; (2) fetch the product page via Axios; (3) parse the HTML with Cheerio using a multi-selector fallback chain; (4) assemble a product data object and upsert it to MongoDB.

The multi-selector fallback deserves explanation. Amazon renders prices in at least six different CSS structures depending on product type, seller, and promotion state. One extracts price utility by trying each selector in order — `.priceToPay span.a-price-whole first, then .a-button-selected.a-color-base, then #priceblock_dealprice` and others

— returning the first non-empty match. During our 30-day evaluation period, Amazon changed its price DOM structure twice. Because of the fallback chain, both changes affected only the primary selector; the secondary selector maintained coverage until we pushed a connector update six hours later.

E. Algorithms

Algorithm 1: Cron-Based Price Refresh and Alert Dispatch

Input: Scheduled cron trigger | Output: Updated price records, dispatched notifications

1. Fetch all Product documents from MongoDB
2. For each product (run in parallel via Promise.all):
 - a. Call scrapeAmazonProduct(product.url)
 - b. Append new price to product.priceHistory
 - c. Recompute lowestPrice, highestPrice, averagePrice
 - d. Call getEmailNotifyType(scraped, current)
 - e. If alert type is not null AND subscriber exist:
 - i. Build HTML email via generateEmailBody()
 - ii. Send to all subscribed emails via nodemailer
 - f. Persist changes with findOneAndUpdate(url, product)
3. Return summary: products updated, errors, emails sent

Algorithm 2: Multi-Selector Price Extraction

Input: Cheerio-loaded HTML, ordered CSS selector list | Output: Normalised price string

1. For each selector in priority order:
 - a. Extract and trim text from first match element
 - b. If text is non-empty:
 - i. Strip non-numeric characters
 - ii. Return decimal match or cleaned string
2. Return empty string if no selector matched

F. Alert Conditions

The getEmailNotifyType function checks three conditions on each cron cycle: **LOWEST_PRICE** fires when the new price is below every previous entry in priceHistory; **CHANGE_OF_STOCK** fires when the scraper reports available and the stored record shows out-of-stock; **THRESHOLD_MET** fires when the computed discountRate is at or above 40%. A fourth type — **WELCOME** — is sent once when a user subscribes,

outside the cron loop.

G. Workflow

Figure 2
 mapsthe three concurrent track that run during a cron cycle.

USER TRACK	CRON TRACK	ALERT TRACK
1. Paste Amazon URL 2. Server action scrapes 3. Saved to MongoDB 4. Subscribe via modal 5. Homepage revalidates	1. Vercel triggers /api/cron 2. Load all products 3. Scrape in parallel 4. Update price arrays 5. Recompute aggregates 6. Persist updates	1. Check alert conditions 2. Pick notification type 3. Build HTML email 4. Send via Nodemailer 5. Log to database

Fig.2. Saleor Three-Track Operational Workflow

IV. METHODOLOGY

A. Development Timeline

We built Saleor over 20 weeks using sprints. The first three weeks went to requirements gathering—including a 150-person survey about what frustrates Indian online shoppers most. Price opacity came up more than anything else. Weeks 4–8 covered the core infrastructure: Next.js project setup, MongoDB schema, and the first working Amazon scraper. The scraper initially had a 12.4% block rate with free datacenter proxies, which led us to switch to Bright Data in Week 9. Weeks 9–12 were spent hardening the scraping engine. The alert system and UI came together in Weeks 13–16. The final four weeks were evaluation: recruiting participants, running the study, and analysing data.

B. Evaluation Design

Our evaluation has three distinct components run independently: a 30-day scraping performance benchmark, a 60-day user study with 250 participants, and a 90-day pricing pattern analysis across 5,000 products. For the user study, we recruited participants across three demographics: students (42%), working professionals (38%), and general consumers (20%). Each participant completed three tasks. T1 was tracking a product and setting a price alert. T2 asked them to look at a price

history chart and decide whether a current “sale” was genuine or inflated. T3 involved receiving an alert notification and acting on it. We timed each task and asked participants to rate purchase confidence on a 10-point scale. Before doing any of this with Saleor, each participant completed the same tasks using manual browsing—multiple open tabs, no tracking tool—to establish a personal baseline.

We want to be transparent about the ethics process. All 250 participants signed written consent forms before the study began. We collected no identifying information beyond demographic category and broad purchase history. All data was stored in an anonymised form on a password-protected server accessible only to the two authors. Participants were told they could withdraw at any point with no consequence. The Department of AI & ML at Dronacharya Group of Institutions reviewed and approved the protocol.

C. Scraping Frequency

We adjusted scraping frequency per product category based on how volatile prices tend to be. Volatility was measured as the coefficient of variation of price over the preceding 30 days: $CV = \sigma(\text{price}) / \mu(\text{price})$. Table III shows the resulting schedule.

TABLE III: Adaptive Scraping Frequency by Product Category

Category	Base Interval	Volatility Class	Effective Refresh Rate
Electronics	6 hours	High (CV > 0.15)	Every 4 hours
Fashion/Apparel	12 hours	Medium (0.05–0.15)	Every 12 hours
Books	24 hours	Low (CV < 0.05)	Every 48 hours
Daily Deals	1 hour	Very High (CV > 0.30)	Every 20 minutes

D. Metrics

We measured five things: (1) scraping accuracy, calculated as correct extractions

divided by total attempts; (2) API latency at P50, P95, and P99 under four concurrent user load levels; (3) system uptime over 90 days; (4) user-

level
 valuemetricsincludingtimepercomparison,platforms checked,purchaseconfidence,andfake-discountdetection rate; and (5) pricing pattern frequency, magnitude, and duration across product categories.

For the user study, we used a paired t-test comparing each participant’s pre-Saleor and post-Saleor scores, with significance threshold $\alpha = 0.05$. We also report Cohen’s d for every comparison. We chose to include effect sizes because our sample (N=250) is large enough to detect even small

differences as statistically significant — effect size is the honest measure of whether the difference is practically meaningful.

V. RESULTS AND ANALYSIS

A. Scraping Performance

TableIVbreaksdownour30-dayscrapingresultsbyproductcategory.Theheadlinefigureis93.70%overall accuracy across 30,480 attempts.

TABLEIV:ScrapingAccuracybyProductCategory(30-DayEvaluation,N=30,480Attempts)

Category	TotalAttempts	Successful	Failed	Blocked	Accuracy(%)
Electronics	12,480	11,712	512	256	93.85
Fashion/Apparel	6,240	5,897	243	100	94.50
Books	3,120	2,976	112	32	95.38
DailyDeals	8,640	7,974	468	198	92.29
Total	30,480	28,559	1,335	586	93.70

Of the 1,921 failures, 38% were network timeouts, 32% were due to Amazon changing its HTML structure mid-study, 20%wereproxyblocks that slippedthrough, and10% weremiscellaneous parsing issues. The1.92%block rate is worth contextualising: ScrapeHero [8] reports 12% as a typical baseline for unsophisticated scraping; Scrapfly[9] achieved3.1% withsubnet-awarerotation. Our 1.92% sits between thosetwo, which makes sense — our approach uses session randomisation but not full subnet diversity.

B. System Performance

TableVgiveslatencyfiguresmeasuredover 50testrunspers loadlevelontheliveVerceldeployment.

TABLEV:SystemPerformanceBenchmarks(N=50runspersload,VercelProduction)

Operation	NoLoad	50 Users	100 Users	200 Users
Homepage(ISR)	210ms	285ms	390ms	620ms
Productdetailpage	340ms	470ms	610ms	920ms
Singlescrape+DB write	3.2s	3.8s	4.5s	6.1s
MongoDBproduct query	48ms	62ms	88ms	142ms
Cronrun(50products)	18s	—	—	—
Emaildelivery(Nodemailer)	1.8s	—	—	—

The 920ms figure at 200 users for the product detail page is the one number we are not entirely happy with. It is causedbyVercel serverless cold-start under sustainedconcurrent load. Under 100 users, thesystemstayed within our 400ms target across all read operations. We discuss the fix — moving product detail rendering to an edge function — in Section VIII.

C. User Study Results

TableVIshowsthebefore-and-aftermetricsfromthe60-daystudy,withtheeffectsizes.

TABLEVI: User Value Assessment—60-Day Study(N=250)

Metric	Before Saleor	After Saleor	Change	Cohen's d
Time per comparison	17.4min	1.9min	-89.1%	2.14(large)
Platforms checked per product	2.8	4.2	+50.0%	1.38(large)
Average savings per purchase	—	₹218	—	—
Purchase confidence(1-10)	5.8	8.4	+44.8%	1.82(large)
Fake discount detection rate	9%	74%	+722%	2.47(large)
Alert response rate(within 2h)	—	71.3%	—	—

All four paired comparisons were significant at $p < 0.001$. Cohen's d ranged from 1.38 to 2.47, all large by Cohen's [25] threshold of $d > 0.8$. The fake-discount detection result ($d = 2.47$) is the strongest finding in the study. Without any price history, 91 out of 100 participants failed to identify that a "sale" product had been inflated two weeks earlier. With the Saleor history chart visible, 74% correctly identified the inflation figure is what surprised us most.

inflation. That is a large, practically significant change in consumer behaviour from a single UI addition.

D. Pricing Pattern Analysis

Table VII reports the pricing patterns we found across 5,000 products over 90 days. The 21% artificial

TABLEVII: Pricing Pattern Analysis—5,000 Products, 90-Day Window

Pattern	Prevalence	Avg. Magnitude	Notes
Weekend discounts	31% of products	7.8% off	Strongest Friday to Sunday; electronics-heavy
Flash sales	16% of products	14.2% off	4-6 hour duration; 68% missed by hourly cron — a known gap
Artificial price inflation	21% of products	11.6% markup	Inflation 7-14 days before sale; invisible without history
Seasonal price drops	39% of products	17.2% off	Festive season (Oct-Nov) and financial year-end (Mar)
Cheapest buying window	Statistically confirmed	12% below average	Sundays 6-9 PM; Wednesdays 2-5 PM across all categories

We want to be careful about what the 21% figure means. It does not mean 21% of Amazon India listings are fraudulent. It means that among products in our tracked set, one in five "sale events"—cases where a product price dropped and showed a discount badge — was preceded by a price increase of at least 7% in the 7-14 days before. Whether that constitutes intentional manipulation or normal inventory repricing is a question for regulatory researchers, not us. What we can say is that without historical data, consumers have no way to distinguish these cases.

E. System Reliability

Table VIII gives reliability metrics over the full 90-day production window.

TABLE VIII: System Reliability Metrics—90-Day Production Period

Metric	Target	Achieved	Notes
Uptime	99.0%	99.61%	2 incidents: one DB pool exhaustion, one Vercel timeout
Scraping failure rate	<10%	6.30%	Selector updates required roughly once per month
Email delivery success	>95%	97.2%	3% SMTP failure rate; retry logic recovered 82% of those
MongoDB Atlas availability	99.9%	99.94%	Atlas free-tier multi-region with automatic failover
Mean time to recovery	<30min	21min	Both incidents resolved via Vercel auto-redeploy

F. Comparison with Existing Tools

Table IX maps Saleor against the tools closest to it.

TABLE IX: Feature Comparison with Existing Price Tracking Solutions

Feature	Camel	Camel	Camel	Keepa	Price History App	Saleor (this work)
Platforms covered	1 (Amazon US)			1 (Amazon)	6+ (Indian)	1 (Amazon India)
History depth	Unlimited			Unlimited	30 days	2+ years
Alert types	Email only			Email, browser	Mobile push	Email, 4 types
India-focused	X			X	✓	✓
Architecture published	X			X	X	✓ (open)
Inflation quantified	Chart only			Chart only	X	✓ (21% rate)
Formal user study	X			X	X	✓ N=250, 60d

VI. DISCUSSION

A. What the Results Tell Us

Let us go through each objective against what we actually found.

Objective 1 was met. We scraped 30,480 products at 93.70% accuracy. Our 1.92% block rate is better than Scrapfly’s 3.1% benchmark. We were surprised by this — we expected to land closer to 3% given that we do not implement full subnet diversity. The likely reason is that Bright Data’s residential IP pool is larger and more geographically spread than the subnets tested in Scrapfly’s experiments [9].

Objective 2 was met, though not without some friction. Amazon changed its price DOM twice during the evaluation period. The multi-selector fallback chain handled both changes, but there was a 6-hour accuracy dip to about 91% before we pushed a connector fix. This is an honest limitation: the system is resilient but not self-healing. Someone has to notice the failure and write the fix.

Objective 3 was met within our load range. MongoDB queries came in at 48ms with no concurrent users and 88ms under 100 concurrent users. At 200 users, product page load times hit 920ms — outside our 400ms target. That degradation is not from MongoDB; it is from Vercel serverless cold-start. The database itself stayed under 150ms throughout.

Objective 4 was met. The 97.2% email delivery rate and 71.3% user action rate within two hours are both strong. The LOWEST PRICE alert type had the highest action rate at 79.2%, which matches Singh and Kapoor’s [16] finding that absolute threshold alerts outperform relative ones in driving user behaviour.

Objective 5 was met. The effect sizes — $d=1.38$ to 2.47 , all large — give us confidence that the improvements are real and not just artefacts of a small, friendly sample. The strongest result is fake-discount detection ($d=2.47$). We interpret this as evidence that the information

problem is genuine: users aren't bad at spotting inflation, they just never had the data to do it.

B. How We Compare to Prior Work

Our 89.1% comparison-time reduction is close to the 85% Kumar and Vijayalakshmi [7] found for graphical price consolidation. The gap is likely attributable to Saleor's alerts system—users who receive an alert do not have to visit the platform at all for routine monitoring, whereas the systems studied in [7] still required active user engagement.

CamelCamelCamel and Keepa are the honest comparison points, and we should be candid: they have advantages we do not. Their history depth is unlimited and their browser extension offers in-page price display, which 64% of our users requested. We are behind on both. What Saleor offers that they do not is: formal evaluation evidence, open architecture, India-specific data, and the 21% inflation quantification.

C. Five Things We Learned Building This

First: proxy quality matters far more than we expected. Switching from free datacenter proxies to Bright Data residential IPs cut our block rate from 12.4% to 1.92%. No amount of request-timing optimisation would have closed that gap.

Second: the monorepo Next.js approach kept the system simpler than we expected. We eliminated an entire Express.js API layer. The codebase ended up about 40% smaller than our initial architecture sketch.

Third: cron intervals have a direct cost. The 68% flash-sale miss rate in our data is a direct consequence of hourly scraping. We knew this going in but underestimated how much it would frustrate deal-oriented users.

Fourth: users care about time savings far more than about analytics features. When we asked what they valued most, 84% mentioned comparison speed. Pattern charts were cited by only 34%. We built more analytics than users wanted.

Fifth: effect size reporting matters.

At $N=250$, almost any real difference will be statistically significant. Cohen's d is the number that tells you whether the difference is worth acting on. We would recommend it as a standard for similar studies.

VII. LIMITATIONS AND THREATS TO VALIDITY

A. Internal Validity

Our performance benchmarks ran on a single infrastructure setup—Vercel production, Chrome 120, 100 Mbps broadband. We do not know how

the latency figures change on 4G mobile or on low-memory devices, which are the primary access points for most Indian online shoppers. This is probably the most significant gap in our evaluation design.

For the user study, pre-Saleor task times were measured live during a timed baseline session, not from recall. Even so, participants knew they were being timed both times, which may have introduced consistent performance pressure across both conditions. We do not think this invalidates the comparison, but we think it is a fair design.

B. External Validity

Our 250 participants skewed toward technically literate demographics: 42% students, 38% working professionals. The results may not transfer cleanly to older buyers or first-time online shoppers. We also evaluated on Amazon India only. Flipkart, Myntra, and Snapdeal each have their own anti-bot strategies and pricing structures; our scraping and inflation-detection numbers could look quite different on those platforms.

C. Construct Validity

We operationalised fake-discount detection as: can the participant look at a price history chart and correctly identify if the product was inflated before the current sale? This captures what we care about, but it is a lab task, not a real purchase decision. Whether users would apply the same critical thinking when actually shopping—under time pressure, with persuasive product pages—is something a longer, more naturalistic study would need to establish.

On effect sizes: we computed Cohen's d using pooled standard deviations. For right-skewed variables like comparison time, this can overstate effect magnitude. We ran a sensitivity analysis using rank-biserial correlation and got consistent direction and magnitude, so we are reasonably confident the effects are real. But we would be cautious about treating $d = 2.47$ as a precise number.

D. Technical Limitations

Flash sales shorter than 60 minutes are largely invisible to us. Our data confirms that 68% of flash sale events were missed by the hourly cron. This is a structural limitation of the approach, not something we can fix with better code. Bright Data residential proxy costs scale linearly with scraping volume. At current rates, tracking more than about 10,000 products on the free infrastructure tier becomes economically unviable. This constrains the system's scalability unless we find a cheaper or more

efficient proxy strategy.

Amazon's HTML structure changes require manual connector updates — roughly once a month based on our experience. This is operational overhead that we have not fully accounted for in the system's total cost of maintenance.

VIII. FUTURESCOPE

We have grouped planned work into three horizons based on what is technically ready to build now versus what needs more research first.

A. Next Six Months

- Multi-platform scrapers for Flipkart, Myntra, and Ajio. Each requires a platform-specific Cheerio connector — roughly 20 development hours per platform. This is the highest-priority extension because 64% of users requested cross-platform comparison.

- A tiered cron scheduler that refreshes daily-deal products every 15–20 minutes instead of hourly. This would cut our flash-sale miss rate from 68% to an estimated 22% based on the distribution of flash-sale durations in our Table VII data.

- A Chrome extension that shows a price history badged directly on Amazon product pages. This is the feature that Camel, Camel, Camel, and Keepa offer and that we currently lack.

B. Six to Twelve Months

- LSTM-based price prediction. Semwal et al. [15] got 78% accuracy on 7-day price forecasts from similar historical data. We now have the training data to attempt this. The output would be a predicted price curve overlaid on the existing history chart.

- Anomaly detection using Isolation Forest to automatically flag pre-inflation events without requiring users to visually interpret the chart. This would make the fake-discount identification automatic rather than user-initiated.

- A React Native mobile app with push notifications and barcode scanning for in-store price comparison.

C. Longer Term

- Blockchain price attestation: storing SHA-256 hashes of daily price snapshots on Polygon to give consumer protection agencies a tamper-proof audit trail. The 21% inflation finding suggests there is a regulatory use case here.

- AB2B analytics layer selling anonymised pricing intelligence to brands monitoring their own MAP compliance and to researchers studying platform pricing dynamics.

- A larger-scale study with $N \geq 500$ across

multiple cities and age groups, with a 12-month follow-up to measure whether the behaviour changes we observed in our 60-day window persist.

IX. CONCLUSION

We set out to answer a simple question: can a small team, without proprietary data or a dedicated infrastructure budget, build a price tracking system that measurably improves purchasing decisions for Indian online shoppers? Based on six months of development and 90 days of evaluation, the answer is yes — with some important caveats.

The numbers held up where it mattered.

Scraping accuracy hit 93.70% at a 1.92% block rate. Time per comparison fell by 89.1% ($d = 2.14$). Purchase confidence rose by 44.8% ($d = 1.82$). And the finding we are most proud of: 74% of users with access to price history correctly identified artificial discount inflation, compared to just 9% without it ($d = 2.47$). All of these differences were significant at $p < 0.001$ and represent large effects by any standard measure.

The caveats are real. Flash sales shorter than an hour are largely invisible to us. We only cover Amazon India. Proxy costs constrain scale. And we have not yet shown that the behaviour changes we measured in a lab study persist in actual shopping decisions over months. These are open questions, not failures — but they are the work still left to do.

The five contributions we committed to in Section I were all delivered:

11. A working full-stack scraper on a zero-cost serverless stack, achieving 93.70% accuracy at 1.92% block rate across 30,480 attempts.

12. A proxy randomisation strategy that cut block in g from 12.4% (data center) to 1.92% (residential), empirically validated over 30 days.

13. A 60-day longitudinal user study ($N = 250$) yielding large-effect-size improvements on all measured dimensions, significant at $p < 0.001$.

14. The first quantitative measurement of artificial price pre-inflation in the Indian Amazon market: 21% of sale events, with an average markup of 11.6% in the 7–14 days prior.

15. An open, documented code base available at <https://github.com/adrianhajdin/pricewise> for researchers who want to extend, replicate, or critique this work. The broader point is about what is now possible. A few years ago, building a system like Saleor required a team, a server budget, and significant DevOps overhead. Today, the same result runs for free on Vercel with a serverless database. The technical barriers to consumer price intelligence have fallen dramatically. The open question is not whether this

kind of system is buildable — it clearly is. The question is whether it reaches the users who need it most.

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