From Code to Consequence:

Applied AI, Industry Impact, and Building Your Career

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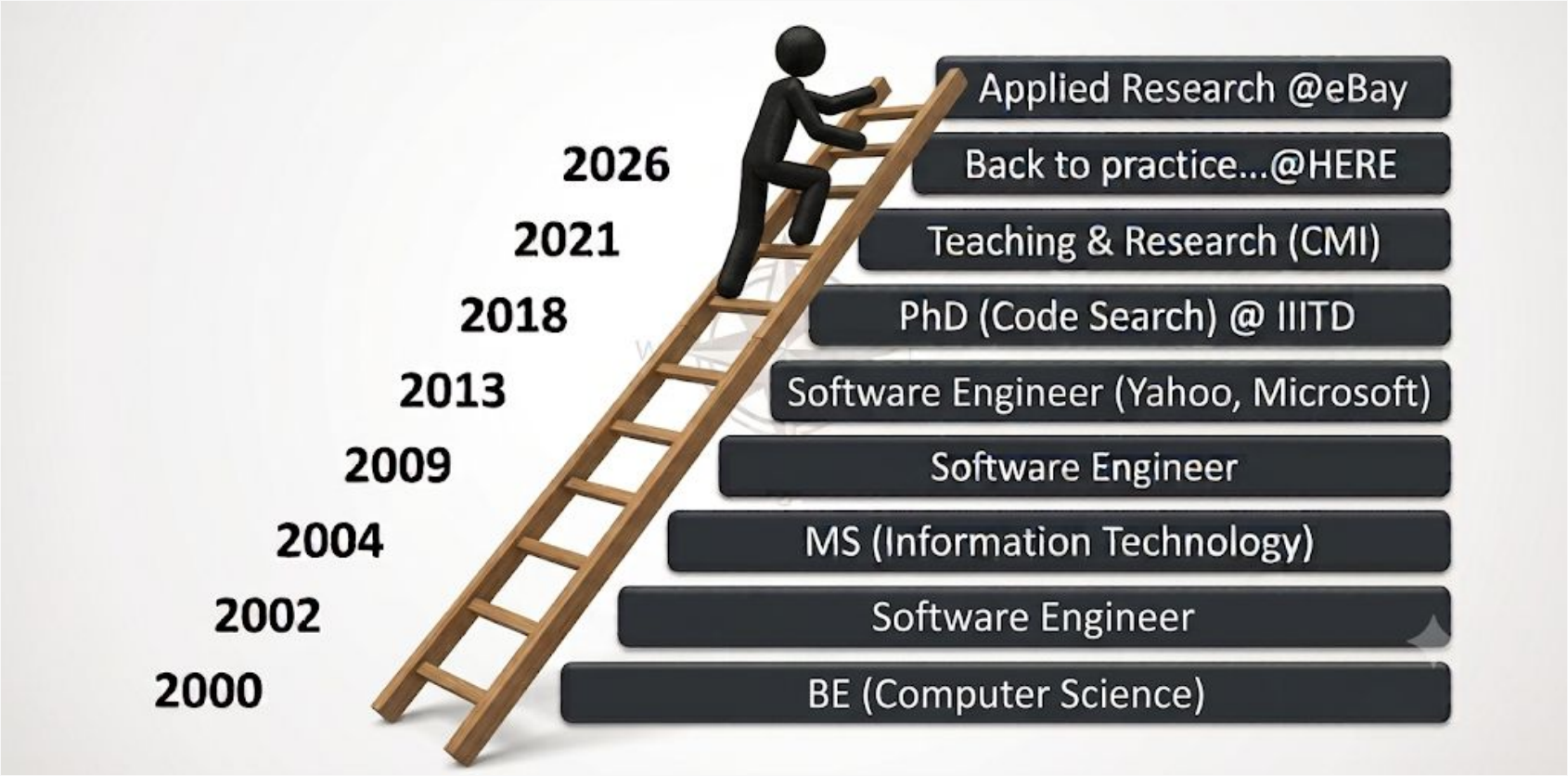
Disclaimer

All views and opinions discussed in this presentation/talk belong solely to me and do not reflect the views/opinions of eBay.

About Me



Standalone Models To Core Products

...
Xgboost
Gemini
GPT
LLaMa
RoBERTa
VisionTransformer
...

...
Search Engines
Ride Sharing Apps
Ecommerce
Banking
Social Media
Job Portals
...

Before: Models were a small part of big products

Now: Products are centered around Models

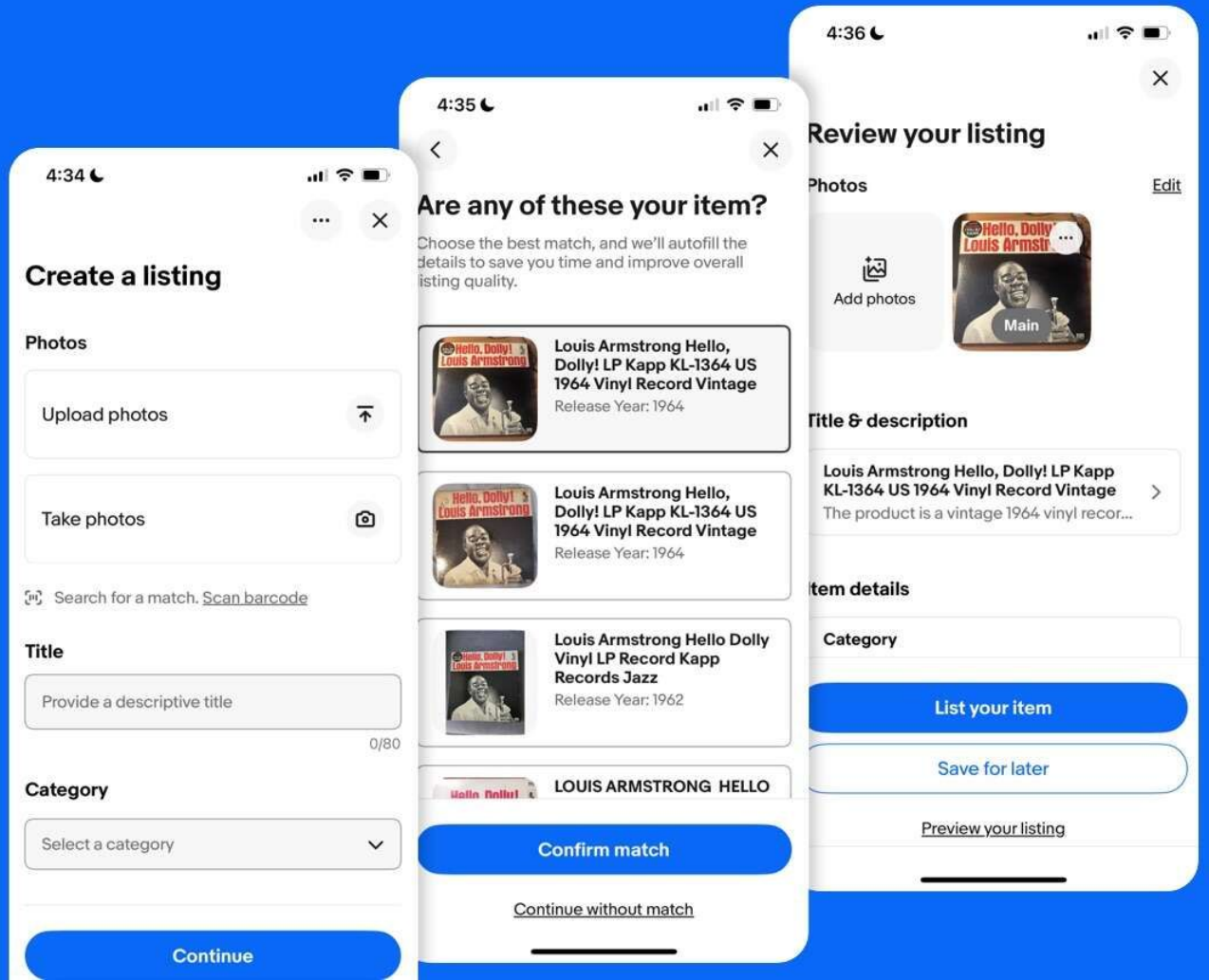
Build That Matters

Identifying high-value use cases

Magical Listings

Faster, easier listing is here.

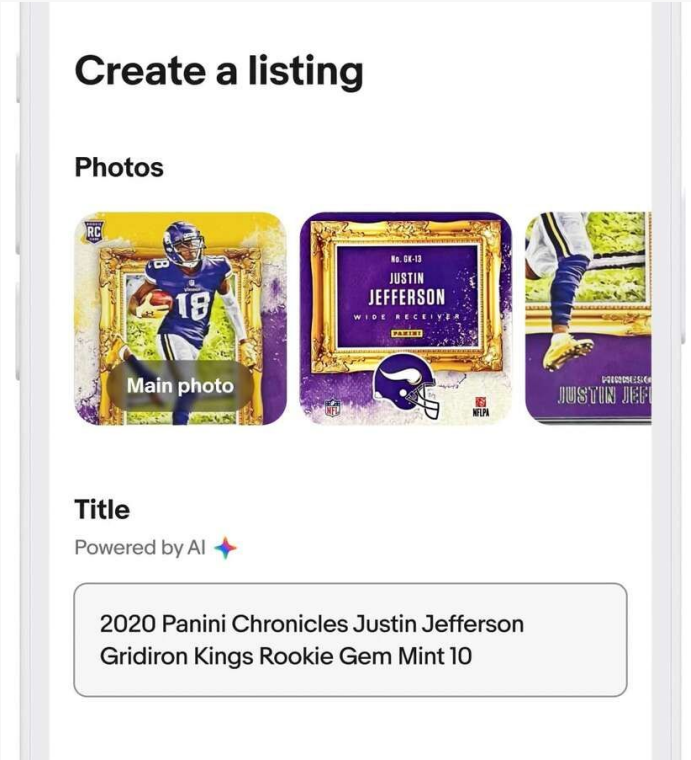
ebay



Magical Listing - Designing Human-Centered Experiences

Just Upload Photos

AI Will Do The Rest



For more information, read this article.

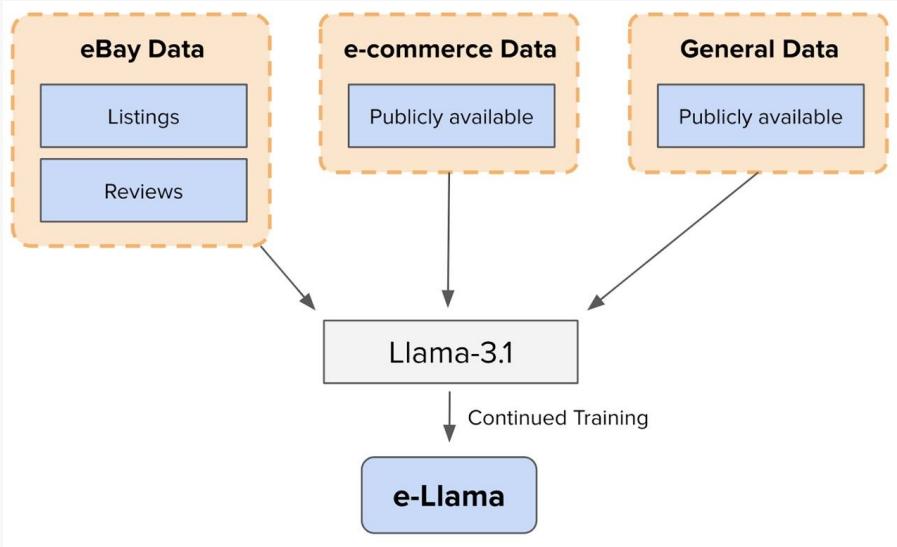
eBay’s - Behind the Scene

- Runs its own data centers, with thousands of GPUs
    - Also uses cloud providers like Azure, and works with suppliers including Nvidia.
- Uses a mix of AI sources: OpenAI models, open-source models such as Meta’s,
    - And its own internally trained models.
- Three decades of buyer/seller and transaction data!

For more information, read this article.

Building LLMs

- **Hybrid LLM strategy:** eBay trains some **models from scratch** (e.g., LiLiuM), while also **adapting open models** such as Llama 3.1 into “e-Llama”
- **How e-Llama was built:** eBay used continued **pretraining** on a balanced mix of e-commerce and general-domain data to add marketplace knowledge while reducing catastrophic forgetting.



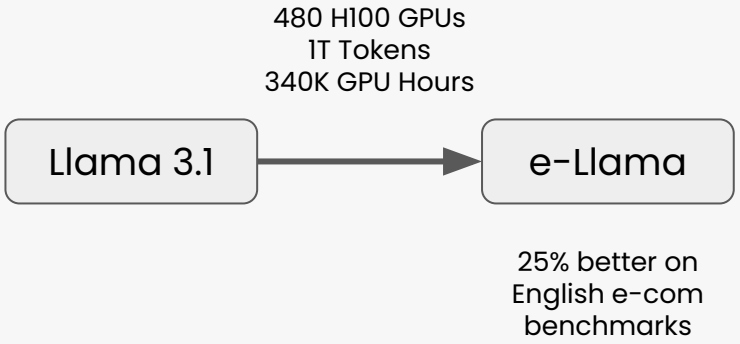
For more information, read this article.

Building LLMs

- **Training setup:** Models were trained on 480 H100 GPUs using Megatron-LM and 3D parallelism. The process used 1 trillion tokens, 85k steps, and for the 70B model took about one month, or 340k GPU-hours.

- **Results:** e-Llama improved about 25% on English e-commerce benchmarks and 30% on non-English benchmarks versus base Llama 3.1, with only about 1% decline on general NLU for the 70B model. Instruction tuning then improved safety, guardrails, and usability.

For more information, read this article.



What It Means To You?

- Learn to identify high-value, impactful use cases that solve real-world problems.
- Understand large-scale infrastructure and hardware requirements, such as managing GPU clusters and distributed training systems.
- Appreciate the integration of human-centered design principles in AI-driven product development.
- Have a broad understanding of Computer Science
    - Hardware / Software / Networking
    - Computer Organization and Architecture
    - AI/ML
    - … and others (do not underestimate any subject)
- Mistake
    - Too much focus on (only) coding during college years

Build Breadth and Depth

A Case from Ranking

Hi Venkatesh! Deals Brand Outlet Help & Contact Sell Watchlist My eBay

ebay Shop by category

iphone

Cell Phones & Sm... Search Advanced

Related: ipad iphone 11 iphone 13 samsung iphone 12 macbook iphone 14 iphone unlocked iphone 15 our generation laptop apple watch

Include description

Category

- All
- Cell Phones & Accessories
  - Cell Phone Accessories
  - **Cell Phones & Smartphones**
  - Cell Phone & Smartphone Parts
  - Smart Watch Accessories
  - More +
- Computers/Tablets & Networking
- Consumer Electronics
- Video Games & Consoles
- Home & Garden
- Books & Magazines
- Show More +

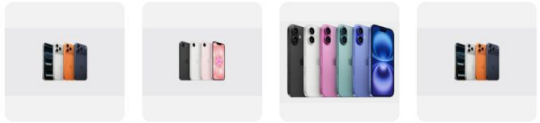
Update your shipping location

Delivery Options

- Free International Shipping

Network

- Unlocked (11,527)
- AT&T (649)
- Verizon (428)
- T-Mobile (506)
- Sprint (205)
- Cricket Wireless (152)
- Boost Mobile (150)
- TracFone (136)

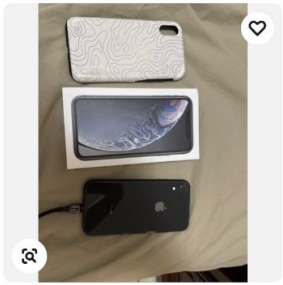


4,100+ results for iphone Save this search

All | Auction | Buy It Now | Condition | Item Location | Sort: Best Match

Popular Filters

Unlocked | AT&T | T-Mobile | 128 GB | 512 GB | 256 GB | Factory Unlocked | Network Unlocked | Network Locked



iPhone XR
Apple iPhone XR · 128 GB · Unlocked
Pre-Owned
★★★★★ 113 product ratings

$90.00
or Best Offer
+$5.00 delivery
Located in Greece
20 watchers

dimmaza_89 0% positive (0)

Apple iPhone 5C UNlocked 8/16/32GB BLUE/GREEN/PINK/WHITE/ YELLOW - New Battery
Pre-Owned
★★★★½ 107 product ratings

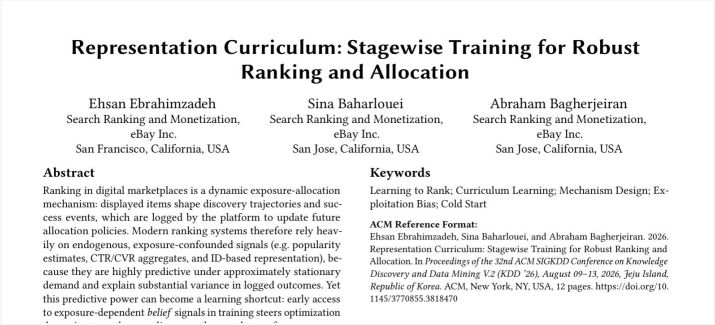
$31.00 to $58.99

mp34phone 99.9% positive (1.7K)

Representation Curriculum

- Modern Rankers need to incentivize
  a. Suppliers (exposure to their products)
  b. Consumers (discoverability of inventory)
  c. Platform (evolution of marketplace)
- We apply Curriculum Learning
  a. Learn easy concepts first
  b. Then go to the harder concepts (leads to smoother convergence)
- Proposes **Representation Curriculum** (RC),
  a. Stage 1 learns a model trained only on content-based signals.
  b. Stage 2 introduces historic signals but anchors the optimization so that content-based competence is preserved.

Avoids shortcut learning!



Representation Curriculum: Stagewise Training for Robust Ranking and Allocation

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Abstract

Ranking in digital marketplaces is a dynamic exposure-allocation mechanism: displayed items shape discovery trajectories and success events, which are logged by the platform to update future allocation policies. Modern ranking systems therefore rely heavily on endogenous, exposure-confounded signals (e.g. popularity estimates, CTR/CVR aggregates, and ID-based representation), because they are highly predictive under approximately stationary demand and explain substantial variance in logged outcomes. Yet this predictive power can become a learning shortcut: early access to exposure-dependent *belief* signals in training steers optimization

Keywords

Learning to Rank; Curriculum Learning; Mechanism Design; Exploitation Bias; Cold Start

ACM Reference Format:

Ehsan Ebrahimzadeh, Sina Baharlouei, and Abraham Bagherjeiran. 2026. Representation Curriculum: Stagewise Training for Robust Ranking and Allocation. In *Proceedings of the 32nd ACM SIGKDD Conference on Knowledge Discovery and Data Mining V.2 (KDD '26), August 09–13, 2026, Jeju Island, Republic of Korea.* ACM, New York, NY, USA, 12 pages. https://doi.org/10.1145/3770855.3818470

Hard Problems; Novel Solutions

Representation Curriculum: Stagewise Training for Robust Ranking and Allocation

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For more information, read this research paper.

What It Means To You?

- Pick an area/topic of interest and go deep
  - Attend Summer Schools
  - Collaborate with faculty and seniors to publish papers
  - Take up high-quality internships
  - Network actively with industry professionals and alumni to gain mentorship, guidance, and a broader perspective on the industry.
  - Strive to become a problem-solver (a deep thinker)
  - Build things outside the classroom through personal projects, open-source contributions, or hackathons to apply theoretical knowledge.
- Mistake
  - Optimizing your time for gaining high grades
  - Doing low quality internships
  - Just increasing the internship count (and not quality)

Attend Summer (winter/autumn) Schools

ASIRF, Germany

Use Internship Opportunities

Microsoft Research, Cambridge

The AI Trend

Trust at Scale and Delivering the Right Context

AI Trend

Trust at Scale

With AI verifying identity, intent, product integrity, and regulatory fit.

Deception at Scale

How LLMs spontaneously generate deceptive UI designs—commonly known as "dark patterns"—when asked to generate front-end e-commerce web code?

Key Findings at a Glance

- **Widespread Deception:** Over half (**55.8%**) of all generated web components contained at least one deceptive design element, and **30.6%** contained two or more.
- **Mitigation Success:** Mitigating deceptive designs requires value-centered prompting interventions rather than standard instructions.

What are Values-Centered Prompts?

Explicitly guiding the model to respect user autonomy, transparency, and ethical UX standards.

Goal: Avoid Dark Patterns

Dark Patterns - Examples

1. **Interface Interference:**
   a. Pre-selecting expensive options by default,
   b. using low-contrast text for critical opt-out disclaimers, or
   c. placing "Decline" buttons in hard-to-find locations.
2. **False Urgency & Scarcity:**
   a. Generating fake countdown timers or
   b. artificially limited stock counters without real underlying logic.
3. **Misdirection:** Using prominent, vibrant colors for the higher-priced or recurring option while making neutral options visually unappealing or obscured.

Seeing the Reasoning

Key Question

How presenting LLM step-by-step reasoning rationales influences user trust, confidence, and advice adoption?

Drivers of Trust

1. **Rationale Correctness (Factual Accuracy):** Whether the step-by-step logic and underlying evidence provided in the explanation are factually correct or flawed.
2. **Certainty Framing (Linguistic Confidence):** The tone and explicit certainty cues used in the rationale (e.g., confident assertions vs. hedges indicating uncertainty).
3. **Presentation Format (UI Exposure):** How the rationale is physically revealed to the user—whether shown immediately (**instant**), after a short pause (**delayed**), or hidden behind a toggle (**on-demand**)

Seeing the Reasoning

Example Scenario: Fact-Checking a Science Claim

Task: A user asks an LLM to verify: *"Did Albert Einstein win the Nobel Prize in Physics for his Theory of Relativity?"*

Ground Truth: False (He won it for his discovery of the law of the photoelectric effect).

Certain Framing: *"It is well-documented and verified that Einstein won for the photoelectric effect..."*

Effect: High-certainty language boosts user confidence and likelihood to adopt the answer.

Uncertain Framing: *"I am not entirely certain, but available records suggest Einstein may have received it..*

Effect: Hedging or uncertainty cues reduce user trust, decision confidence, and reliance on the AI.

AI Trend


Progressive Refinement of E-commerce Search Ranking Based on Short-Term Activities of the Buyer

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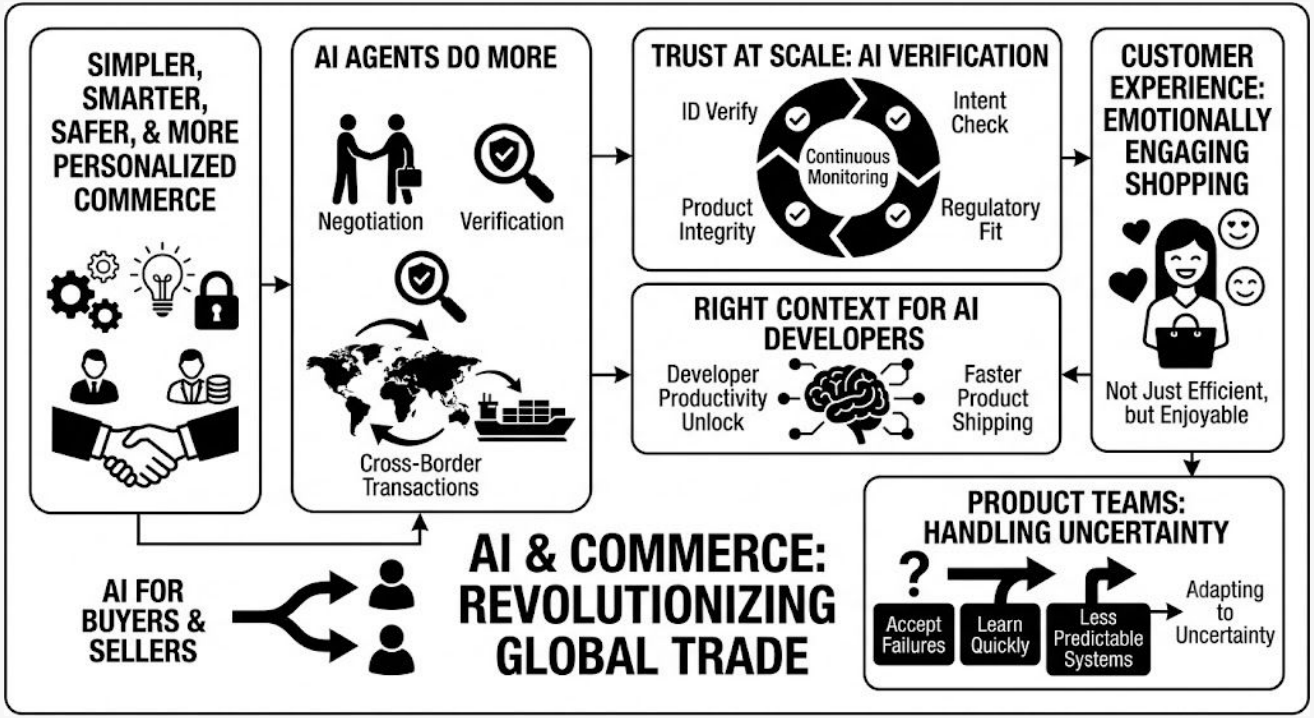
Delivering the right context to AI systems will be the biggest unlock for developer productivity and faster product shipping.

Progressive Refinement

1. User interests (intent) changes during the search process.
2. Context vs. Static Memory:
    - **Without Context (Static Model):** A traditional e-commerce search ranker relies heavily on global query relevance or a user's static historical profile (**long-term preferences**).
    - **With Context** (The Paper's Core Focus)**:** The paper addresses how a buyer's immediate session intent shifts (e.g., switching from browsing broad product categories to searching for a specific item). The system continuously captures **short-term signals**—such as the last 1 to 5 clicks, active query shifts, and recent session interactions—as dynamic **contextual features**.

AI Trends

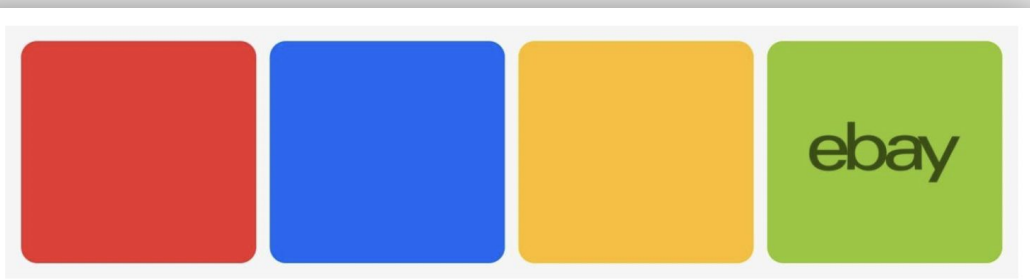


For more information, read this article.

What It Means To You?

- Find hard problems; Build innovative solutions
- Be fearless with facing challenges
- Understand the industry priorities
- Improve Communication and Networking Skills
- Prioritize integrity and ethical responsibility in everything you build
- Stay adaptable and embrace continuous learning, allowing your strategies to evolve dynamically as new situations unfold.
- Mistake
    - Not believing in yourself.

eRUPT Program at eBay



2027 eRUPT Academic Research Grants

eBay is trying to solve the most complex problems facing our industry. Strong relationships and collaborations with universities and academic faculty around the world can be a game changer.

eRUPT - eBay's Research and University Partnership for Technology - is excited to offer support and funding for proposals for academic research collaboration projects for 2027. Typical grants provide funds for one year of sponsored research of gift funding, or can be structured as no-fee research projects.

Key Dates

- **Submissions due: September 21, 2026**

Challenges

For eBay to succeed at scale, it must execute seamlessly across three core technical pillars:

- **Hardware & Infrastructure Engineering:** Designing resilient data centers and managing compute capacity (including GPU clusters) to maintain sub-second latency and high availability.
- **Software Engineering:** Building intuitive user interfaces and scalable seller tools that minimize friction during the product listing process.
- **AI & Applied Research:** Developing advanced search, ranking, and recommendation algorithms to match buyers with the right products efficiently.
- And perhaps more.

And therefore, we need you!

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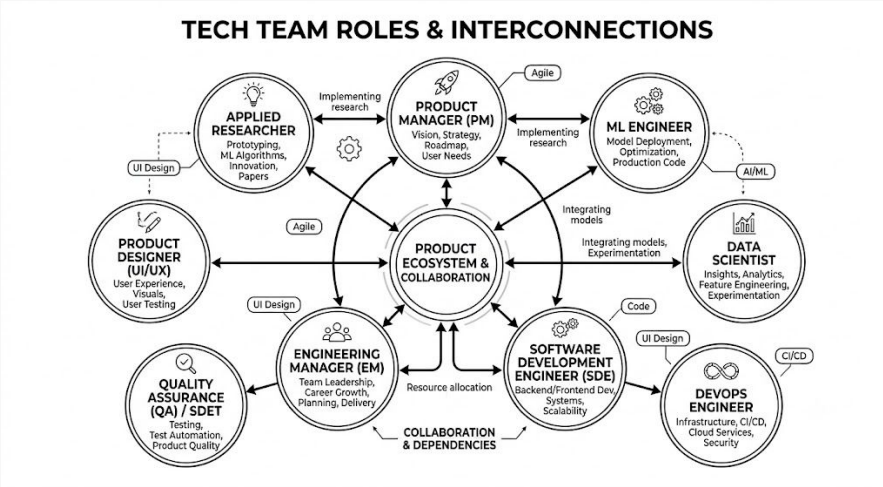
5. Magical Listing
6. Inside eBay's Quest to Become an AI Leader
7. Scaling Large Language Models for e-Commerce

Thank You



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Annexure

Roles