IJVAST | Vol. 1, Issue 9 | September 2026 | Open Access — Peer Reviewed Research Paper

Smart Second-Hand Marketplace

Aditya Joshi

Department of Computer Science and Engineering

K. K. Wagh Institute of Engineering Education & Research, Nashik

Abstract**—**Peer-to-peer second-hand marketplaces suffer from three recurring problems that discourage participation: sellers routinely misprice listings relative to comparable sales, buyers cannot verify an item's condition beyond a handful of seller-provided photographs, and fraudulent or counterfeit listings erode trust in the platform as a whole. This paper presents the design, implementation, and evaluation of a Smart Second-Hand Marketplace that unifies AI-based price estimation, image-based condition assessment, fraud and counterfeit detection, and a transaction-based trust score within a single coordinated platform. The system integrates four components — a price estimation engine that suggests a fair price range from item category, brand, age, and condition against historical comparable sales; a condition assessment module that classifies item photographs into standardised condition grades using a fine-tuned convolutional network; a fraud detection module that flags suspicious listings and sellers from behavioural, textual, and image-consistency signals; and a trust score module that aggregates verified transaction history, identity verification, and buyer reviews into a single seller reliability indicator. A dataset of 42,000 historical listings across fifteen categories, 16,500 labelled item-condition images, and 3,100 verified fraud reports, collected from three years of campus marketplace transaction logs, was used to develop and evaluate the pricing, condition, and fraud-detection components. The price estimation engine achieved a mean absolute percentage error of 9.4% against final agreed sale price, and the condition assessment module achieved a classification accuracy of 90.7% and an F1 score of 0.89 across five condition grades. The fraud detection module achieved a precision of 87.3% and a recall of 81.6% on held-out flagged listings. An eight-week pilot processing 1,800 listings reduced the average time-to-sale from 12.4 days to 4.1 days and cut the fraud-related complaint rate from 6.8% to 1.2% relative to the prior unassisted listing process. The paper documents the system architecture, module design, evaluation methodology, observed limitations relating to category coverage and adversarial listing behaviour, and the future scope of the work.

Index Terms**—**Second-Hand Marketplace, Price Estimation, Condition Assessment, Fraud Detection, Trust Score, Convolutional Neural Networks, E-Commerce Informatics, Decision Support System, Peer-to-Peer Trade, Counterfeit Detection.

I. INTRODUCTION

Peer-to-peer second-hand marketplaces let students and individuals resell electronics, furniture, books, and apparel directly to one another, but three recurring frictions discourage participation: a seller has no reliable way to price an item beyond guessing or copying a similar listing, a buyer cannot verify an item's actual condition beyond a handful of self-taken photographs, and both sides are exposed to fraudulent listings or counterfeit goods with no platform-level signal of a seller's trustworthiness [1], [2].

These frictions compound in campus and community marketplaces, where transaction volume is high but individual sellers list infrequently and so cannot build a reputation the way a professional seller on a larger platform might, leaving buyers to rely on gut instinct rather than verifiable trust signals [3].

Two complementary strands of prior work are relevant here: automated pricing research in e-commerce, which shows that comparable-sales-based regression models can estimate fair resale value more consistently than seller intuition, and image-based product-condition and fraud-detection research, which shows that visual and behavioural signals can flag suspicious

II. RELATED WORK

A. Automated Pricing in E-Commerce

Comparable-sales-based pricing models, widely used in real estate and used-vehicle valuation, have been shown to produce more consistent price estimates than individual seller judgement, motivating their adaptation to smaller-ticket second-hand goods where comparable listings are equally informative [5].

B. Image-Based Product Condition Assessment

Convolutional networks fine-tuned to classify product images into condition grades have demonstrated that visual wear indicators can be recognised with useful accuracy, reducing reliance on a seller's own, often optimistic, condition description [6], [7].

C. Fraud and Counterfeit Detection in Online Marketplaces

Fraud detection research in online marketplaces has combined seller behavioural patterns, listing text anomalies, and price-outlier signals to flag suspicious listings ahead of buyer complaint, with reported precision gains over rule-based flagging systems in comparable e-commerce settings [8].

listings, but these techniques are rarely combined into a single second-hand marketplace pipeline [4].

This paper proposes a Smart Second-Hand Marketplace that combines AI-based price estimation with image-based condition grading, fraud and counterfeit detection, and an aggregated trust score, producing a marketplace where pricing, condition, and seller reliability are all machine-assisted rather than left entirely to buyer and seller judgement.

The principal contributions of this work are: (1) a price estimation engine using category, brand, age, and condition against comparable sales; (2) an image-based condition assessment module producing standardised grades; (3) a fraud and counterfeit detection module combining behavioural, textual, and image-consistency signals; (4) a trust score module aggregating verified history and reviews; and (5) an empirical evaluation covering pricing accuracy, condition and fraud detection quality, and an eight-week marketplace pilot.

D. Trust and Reputation Systems

Reputation-scoring research in peer-to-peer platforms has shown that aggregating verified transaction history with buyer reviews produces a more reliable trust signal than review count alone, particularly for infrequent sellers with limited transaction history [9], [10].

Fig. 1 — Layered System Architecture of the Proposed Smart Second-Hand Marketplace

Layer	Principal Components and Responsibilities
Presentation Layer	Guided listing flow, buyer search interface, moderation queue
Trust Layer	Trust score module, verified transaction history, review aggregation
Assessment Layer	Price estimation engine, condition assessment, fraud & counterfeit detection
Data Layer	Listing catalogue, sold-listing archive, condition images, seller history

TABLE I — Comparative Analysis: Unassisted Resale vs. Generic Listing Platform vs. Proposed System

Feature	Unassisted Resale	Generic Listing Platform	Proposed SSHM	Benefit to User
Price Guidance	Seller guesswork / copied listings	Category-average suggestion	Comparable-sales price estimation	Fewer over/under-priced listings
Condition Disclosure	Seller self-description only	Fixed condition dropdown	Photo-based automatic grading	More reliable condition information
Fraud Prevention	Manual complaint-based review	Keyword-based flagging	Behavioural & image-based detection	Fewer fraudulent transactions
Seller Reliability	No visible signal	Review count only	Aggregated trust score	Faster buyer confidence
Time-to-Sale	Unassisted negotiation	Basic listing platform	Price- and condition-assisted listing	Faster completed sales
Scale of Coordination	Informal peer groups	Single listing board	Coordinated marketplace platform	Broader, safer reach

TABLE II — Pricing Accuracy, Condition & Fraud Detection Quality, and Pilot Study Results

#	Model / Metric	Result	Comparison	Observation
1	Category-average baseline	27.5% MAPE	Baseline	Weak for niche categories

#	Model / Metric	Result	Comparison	Observation
2	Seller-set-price baseline	18.7% MAPE	Baseline	Frequent over/under-pricing
3	Price estimation engine (selected)	9.4% MAPE	Both baselines	Best pricing accuracy
4	Condition assessment module	90.7% / F1 0.89	Held-out images	Strongest for electronics, furniture
5	Fraud detection module	P 87.3% / R 81.6%	vs. rule-based (P 61.2%)	Across 8-week pilot
6	Pilot — time-to-sale	12.4 → 4.1 days	-67.0%	1,800 listings

III. SYSTEM ARCHITECTURE

A. Architectural Overview

The proposed system follows a four-layer architecture consisting of a data layer, an assessment layer, a trust layer, and a presentation layer, as summarised in Fig. 1. Layer separation allows the pricing, condition, and fraud models to be retrained on new transaction data independently of the listing catalogue and the buyer-and-seller-facing interface.

B. Data Layer

The data layer maintains a listing catalogue with category, brand, and seller-provided description, a historical sold-listing archive used as pricing comparables, an item-condition image repository used for model training, and a seller transaction and review history.

C. Price Estimation Engine

The price estimation engine takes a listing's category, brand, age, and predicted condition grade as input, retrieves comparable historical sales, and applies a trained regression model to suggest a fair price range, which the seller may accept, adjust, or override at listing time.

D. Condition Assessment Module

A seller photographs the item using the mobile client, and this module applies a fine-tuned convolutional network to classify the images into one of five standardised condition grades, from New to Poor, which is displayed alongside the seller's own description for buyer comparison.

E. Fraud and Counterfeit Detection Module

This module scores each new listing and seller account using behavioural features such as posting frequency and account age, textual features from the listing description, and image-consistency checks against known counterfeit or stock-photo patterns, flagging high-risk listings for manual review before they go live.

F. Trust Score Module

The trust score module aggregates a seller's verified transaction count, identity verification status, and buyer review ratings into a single displayed score, updated after each completed transaction, giving buyers a consistent reliability signal independent of listing volume.

G. Presentation Layer

The presentation layer provides sellers with a guided listing flow showing suggested price and condition grade, buyers with a search-and-browse interface showing trust scores alongside listings, and administrators with a moderation queue for flagged listings.

IV. METHODOLOGY

A. Dataset Preparation

A dataset of 42,000 historical listings across fifteen categories, 16,500 labelled item-condition images across five grades, and 3,100 verified fraud reports was assembled from three years of campus marketplace transaction logs and moderation records.

B. Experimental Protocol

The listing dataset was partitioned into training, validation, and test subsets in a 70:15:15 ratio using a stratified split by

D. Evaluation Metrics

Price estimation quality was measured using mean absolute percentage error against the final agreed sale price. Condition assessment quality was measured using classification accuracy and macro-averaged F1 score against verified condition grades. Fraud detection quality was measured using precision and recall against verified fraud reports. Operational impact was measured as average time-to-sale and fraud-related complaint rate.

E. Implementation Environment

The prototype was implemented in Python 3.11 using scikit-learn and XGBoost for the price estimation and fraud models category, so that pricing and condition performance could be assessed separately across item types. The fraud dataset used a temporal split so that test-period listings always followed training-period fraud patterns. Model parameters were tuned on the validation subsets.

C. Baseline Models

Two baselines were compared for price estimation: a category-average baseline using only the mean sold price for the item's category, and a seller-set-price baseline reflecting the price a seller would have listed unaided. For fraud detection, a rule-based flagging system using fixed keyword and price-outlier thresholds was compared against the trained classifier used in the final system.

and a fine-tuned ResNet-18 network in PyTorch for condition assessment, PostgreSQL for the listing and transaction database, and Django for the application layer. The interface was built with HTML5, CSS3, and Chart.js, and all experiments were executed on a machine with an Intel Core i5 processor and 8 GB of memory.

F. Pilot Study Design

An eight-week pilot was conducted on the campus marketplace covering 1,800 listings. Listing and transaction outcomes were recorded for the first two weeks under the prior unassisted listing process, and compared against the following six weeks using the full system.

V. RESULTS AND DISCUSSION

A. Pricing, Condition, and Fraud Detection Accuracy

As reported in Table II, the price estimation engine achieved a mean absolute percentage error of 9.4% against final agreed sale price, outperforming the seller-set-price baseline at 18.7% and the category-average baseline at 27.5%. The condition assessment module achieved a classification accuracy of 90.7% and a macro-averaged F1 score of 0.89 across five grades, with the strongest performance observed for electronics and furniture, where training image volume was largest. The fraud detection classifier achieved a precision of 87.3% and a recall of 81.6% on held-out flagged listings, exceeding the rule-based baseline's precision of 61.2%.

The improvement over the seller-set-price baseline was most pronounced for less commonly traded categories, where sellers had few comparable listings to reference and tended to either overprice or underprice items.

B. Operational Impact

Across the eight-week pilot, average time-to-sale fell from 12.4 days under the prior unassisted process to 4.1 days with the full system, and the fraud-related complaint rate fell from 6.8% to 1.2%, as summarised in Table II.

C. Pilot Study Outcomes

Sellers identified the suggested price range and the automatic condition grading as the two most valued components, noting that both reduced back-and-forth negotiation messages with prospective buyers.

D. Discussion

The results indicate that combining comparable-sales pricing with image-based condition grading and behavioural fraud detection addresses a trust and efficiency gap that neither unassisted peer-to-peer listing nor simple keyword-based moderation resolves well. The pilot period of eight weeks on a single campus marketplace is modest, so the reported time-to-sale and fraud-reduction figures should be treated as indicative rather than conclusive across a larger, more diverse marketplace.

VI. LIMITATIONS

Several limitations qualify these findings. First, price estimation accuracy is lower for categories with few historical comparable sales, such as niche hobby items. Second, the condition assessment module can be misled by photographs taken in poor lighting or from unrepresentative angles. Third, the fraud detection module is trained on historical fraud patterns and may be slower to catch genuinely novel adversarial listing behaviour. Finally, the eight-week, single-marketplace pilot cannot support strong claims about performance on a larger, multi-campus or city-wide marketplace.

VII. FUTURE SCOPE

Future development will proceed along four directions: expanding comparable-sales coverage for underrepresented categories; adding photo-quality guidance to improve condition-assessment reliability; incorporating adversarial retraining to keep pace with evolving fraud patterns; and conducting a longer, multi-campus pilot to validate time-to-sale and fraud-reduction improvements at larger scale.

VIII. CONCLUSION

This paper presented a Smart Second-Hand Marketplace that integrates AI-based price estimation, image-based condition assessment, fraud and counterfeit detection, and a trust score system within a single platform. The price estimation engine

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achieved a mean absolute percentage error of 9.4%, and the condition assessment module achieved a classification accuracy of 90.7% on held-out images.

An eight-week pilot processing 1,800 listings cut average time-to-sale from 12.4 to 4.1 days and reduced the fraud-related complaint rate from 6.8% to 1.2%, indicating that coordinated pricing, condition grading, and fraud detection can meaningfully improve both marketplace efficiency and buyer trust. The limitations relating to category coverage, image quality dependence, and adversarial adaptation define a clear agenda for the extensions outlined above.

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