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DwellMatch: An AI-Powered Web Application That Matches Furniture to Your Room Using Nearby Local Shops

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Abstract - Have you ever tried buying a new couch and ended up completely overwhelmed? Most of us have been there. You walk into a store, see something you like, but then immediately a doubt pops up. Will this actually fit in my living room? Does the color match my walls? It's a frustrating, time-consuming process. You end up looking around three different physical showrooms, wasting your entire weekend just trying to find the right piece. And while we struggle as customers, independent local furniture shop owners are struggling just as much. They find it hard to reach nearby customers.

That's why I created DwellMatch—it's a simple app I put together to make all this less confusing. All you do is snap a picture of your room, and the app gets a sense of your space, the light, and your colors—basically, it tries to see your room the way you do. Instead of just dumping a bunch of random listings on you, it actually suggests stuff from shops nearby that would fit your space and style. You can easily check prices, see what things are made of, and compare a few favorites without running all over town. When you find something you like, just tap to buy—it's all super straightforward. We'll bring it over and even set it up for you, so you don't have to lift a finger.

That's just the beginning. I'm hoping soon you'll be able to use your phone to drop a 3D couch right into your living room, just to see how it looks, before you decide. At the end of the day, I just want to make furniture shopping a whole lot less of a headache. I also hope this helps out local stores who could use a little extra support and maybe some new customers.

Keywords: DwellMatch, Artificial Intelligence, Computer Vision, Machine Learning, Augmented Reality (AR), Smart Home, Local Retail, E-Commerce, Spatial Visualization

1. INTRODUCTION

1.1 Market Need

Most everyday purchases have become easier. Groceries arrive within an hour and clothes can be returned for free. Furniture is the exception. A sofa or bed is large, costly and hard to return, and its value depends on how it sits inside one particular room with its own light and colours. A product photo on a white background cannot answer these questions, so buyers still visit shop after shop, carry measurements on scraps of paper, and often discover a wrong size or clashing colour only after delivery.

Online shopping removes the travel but adds a new doubt: how will this look at home? Studies show that buyers feel far more confident when they can see an item in their own space [2], [3], and that AI can read a room photo and judge what suits it [6]–[9]. These two strengths are usually built separately and rarely reach small shops.

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Local furniture shops face the other half of the problem. Their products are often well made, yet they stay invisible at the moment a customer is standing in the living room deciding what to buy. Large marketplaces have the advertising budget, the apps and the delivery network; a small shop has none of these. A service that connects a buyer's room to the stock of shops a few streets away creates value for both sides.

1.2 The DwellMatch Solution

DwellMatch is built around one simple action: upload one photo of your room. The system works out the room type, free space, colours and lighting, searches the stock of registered local shops, and shows only the items that really fit, ranked from best to least suitable. The customer compares favourites, pays, and asks the shop to deliver and install the item. Because it runs in the browser, nothing needs to be downloaded.

In simple words: *You show the website your room. It tells you which sofas, beds or tables from nearby shops will fit and look good there, and the shop brings and sets it up for you.*

1.3 Objectives and Contributions

1. Design a web application that turns a room photo into a short room profile (type, free space, colours, light).
2. Match the profile with real stock from nearby local shops and rank items by suitability.
3. Give customers one place to compare, pay and book delivery and set-up, and give shops an easy dashboard.
4. Present a clear business model and a practical plan to test the idea with real users.

The main contributions are an end-to-end design from room photo to delivered item, a set of twelve clear modules, a simple and explainable matching score, and a focus on local independent shops as the supply side.

2. RELATED WORK

Research on technology-assisted furniture shopping follows two tracks. The first is visualisation: letting people see a product in their own room before paying. The second is understanding: software that reads a room photo and decides what would suit it.

On the visualisation track, IKEA Place (2017) let users place true-to-scale 3D furniture through a phone camera [1]. More et al. [2] found that AR raises buyer confidence about fit and lowers the felt risk of a purchase. Franco et al. [3] built a cross-platform prototype with ARCore, ARKit and Three.js and reported higher satisfaction, while further prototypes use WebXR [4] and Unity with ARCore [5]. The shared finding is that people decide faster and with less doubt when they can see the item in place.

On the understanding track, Boppana et al. [6] used YOLOv3 to find furniture in a room photo and suggest items matched to dimensions. Vegesna [7] scored lighting, colour saturation and décor harmony with YOLO. Sunitha et al. [8] combined a CNN for style recognition with a generative model, and Shreya et al. [9] used Stable Diffusion with depth estimation to turn empty rooms into furnished images.

The gap. Visualisation tools assume the buyer has already chosen an item. Recommendation tools suggest items but rarely link them to a real shop where the buyer can order today, and almost none consider local independent retailers. Marketplaces sell and deliver but do not look at the buyer's room. To the best of our knowledge, a single product that reads the room, matches real local stock and completes the purchase has not been built for local retail. Fig. 1 summarises this gap.

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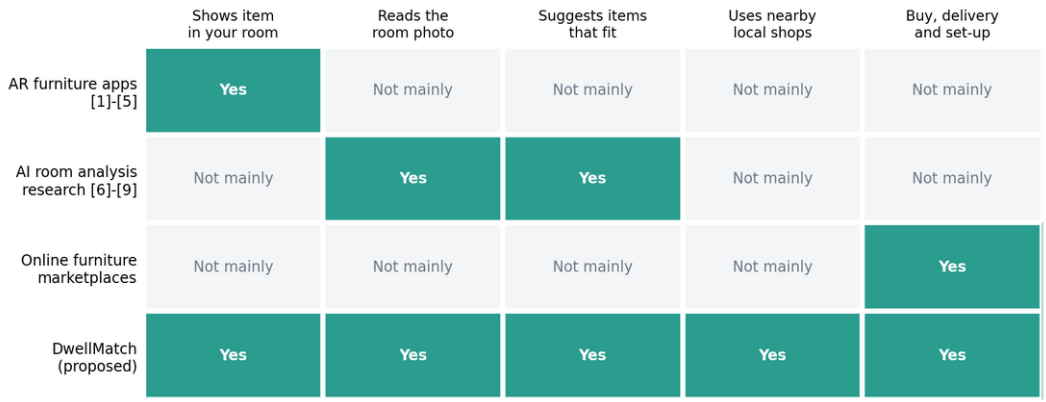


Fig. 1. Coverage of key features by existing work and by the proposed DwellMatch system.

3. PROBLEM STATEMENT AND REQUIREMENTS

Customers face three repeated costs when buying furniture: the time spent visiting many showrooms, the effort of remembering room size, colours and prices, and the money risk of a wrong purchase that is hard to return. Local shops face the mirror image: fewer visitors, weak online presence and no affordable channel to reach nearby buyers when they are ready to decide. Existing tools solve only fragments. What is missing is a complete path from a room photo to a delivered, installed item from a local shop.

The system has four types of users: customers, shop owners, delivery partners and administrators. Table I lists the main functions it must provide.

TABLE I MAIN FUNCTIONAL REQUIREMENTS

ID	The system shall…
FR1	let customers and shop owners register, log in and manage a profile
FR2	let a customer upload or capture a room photo and confirm room type and free wall width
FR3	analyse the photo and create a room profile (room type, free space, colours, light, style)
FR4	let shops add and edit products with photos, size, material, colour, style, price and stock
FR5	match the room profile with nearby products and rank them by a match score
FR6	support search and filters (budget, colour, material, style, distance) and comparison of up to four items
FR7	provide cart, secure online payment (with cash on delivery) and delivery-slot booking with live status
FR8	support reviews, shop dashboards and administrator approval of shops

Beyond these functions, the system must be easy to use (first suggestions within about three steps), fast enough that users do not lose interest, responsive on phones and laptops, and secure and private (HTTPS, hashed passwords, consent for photos and a delete-my-data option). Ranking must also be fair to shops: it depends on fit and relevance, not on advertising spend.

4. SYSTEM DESIGN AND BUSINESS MODEL

4.1 Architecture

DwellMatch uses a layered design in which each layer has one clear job. The web front end is what users see in the browser. The back-end server holds the business rules and offers a secure REST API. The AI services read the room

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photo and calculate match scores. The data and outside services layer holds the database, image storage, maps, payments and message services (Fig. 2).

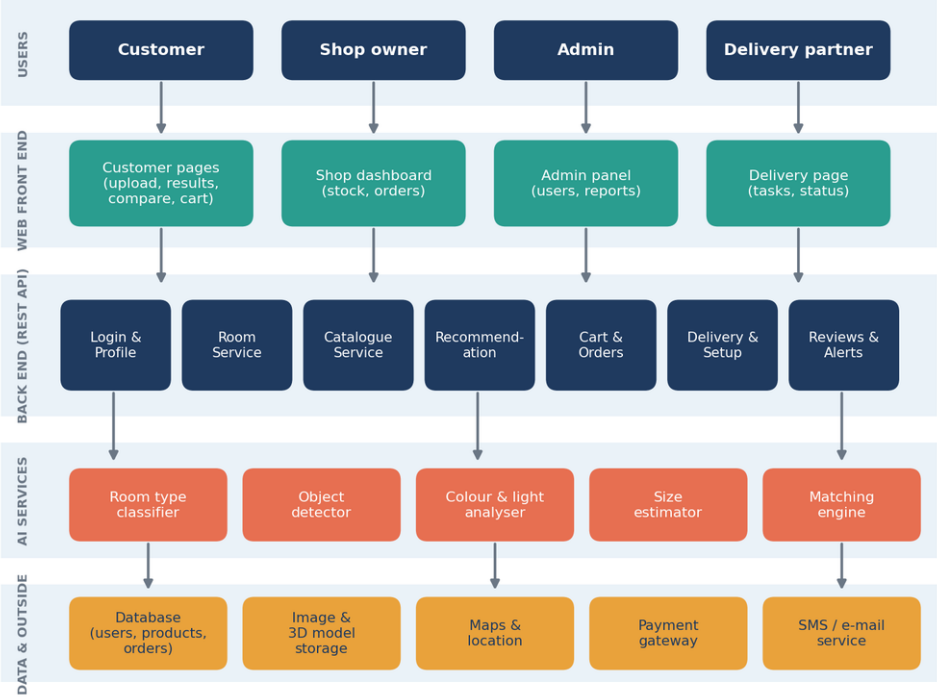


Fig. 2. Layered architecture of the DwellMatch web application.

Table II lists the proposed tools. They are widely used and free to start with, which suits a student project; equivalent tools can be swapped in without changing the design.

TABLE II PROPOSED TECHNOLOGY STACK

Layer	Proposed tools	Why
Front end	React with HTML, CSS and JavaScript; browser camera upload	One responsive site, no app install
Back end	Python (Flask or Django) with a REST API	Same language as the AI code
Room analysis	OpenCV, YOLO detector [10], scene classifier [14], k-means colours [13]	Proven open-source methods
Data	PostgreSQL or MySQL; cloud storage for photos and 3D models	Reliable and scalable
Services	Maps for distance, payment gateway, SMS and e-mail alerts	Needed for local delivery and trust
AR (future)	WebXR with glTF 3D models	AR directly in the browser [4]

4.2 Customer Journey

The customer path is deliberately short (Fig. 3). The heavy work—steps 3 and 4—is done by the system. The customer uploads a photo, looks at the results, and confirms the order. If nothing fits, the customer can relax the filters and run matching again.

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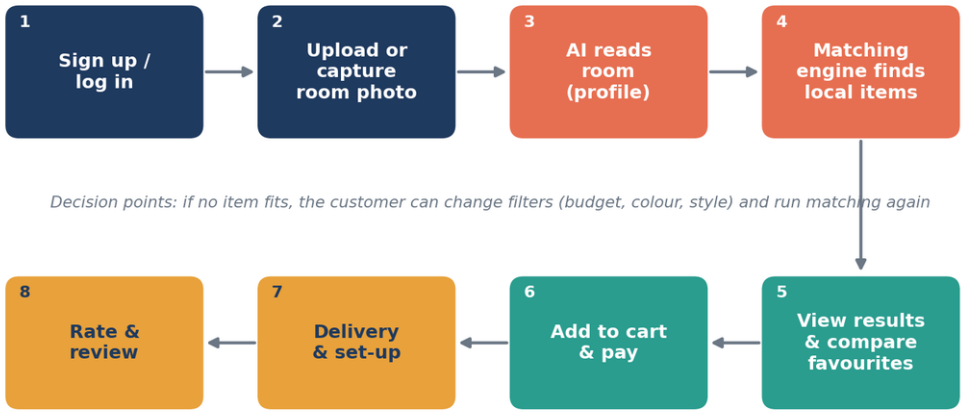


Fig. 3. Customer journey from sign-up to review.

4.3 Data Design

The system remembers users, rooms, shops, products, recommendations, orders, deliveries and reviews. Fig. 4 shows how these tables are linked. A "|" mark means one and a fork mark means many, so one shop sells many products and one order contains many order items. PK is the unique key of a table and FK links it to another table.

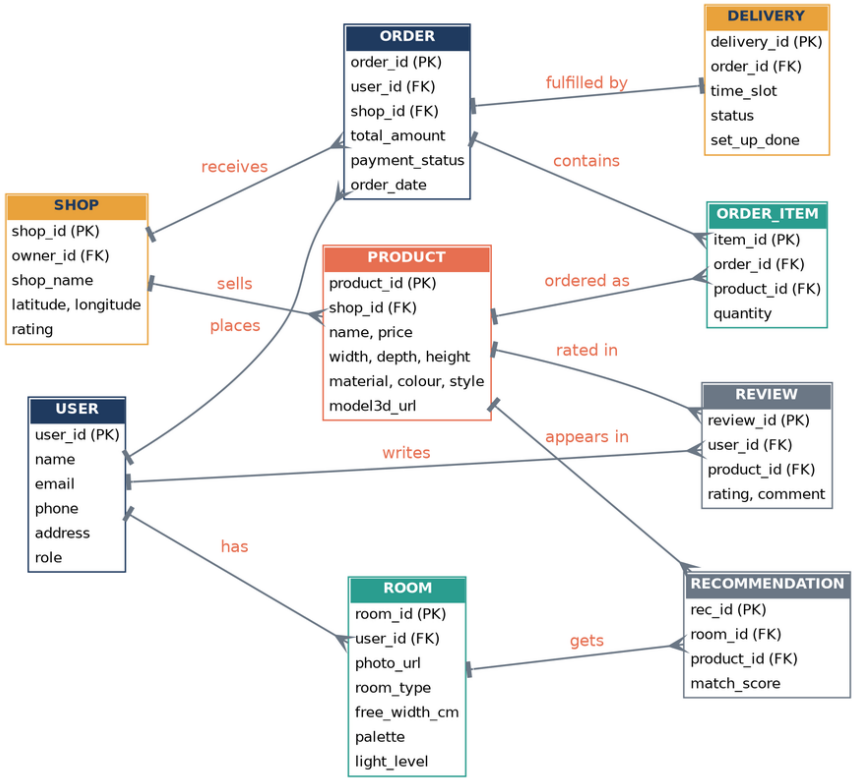


Fig. 4. Entity-relationship diagram of the DwellMatch database.

4.4 Business Model

DwellMatch is designed so that every party gains something and the platform can earn a fair return. The revenue ideas below are proposals to be tested; in the first phase shops join free so that the platform can build a useful catalogue.

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TABLE III VALUE FOR EACH PARTY AND PROPOSED EARNING MODEL

Party	Value received	How DwellMatch can earn
Customers	Saves time, lowers the risk of a wrong purchase, one place for compare, pay and delivery	Free to use; small delivery and set-up service fee
Local shops	New nearby customers, a digital shop window, simple order tools	Small commission on each completed order
Delivery partners	Steady local delivery and installation work	Share of the service fee
Platform	Fair, trusted marketplace for local furniture	Commission, service fees, later optional shop subscriptions for analytics

5. MODULES AND USER INTERFACE

The web application is split into twelve modules. A module is a self-contained part of the software with one clear job, which makes the system easier to build in stages, test, and improve without breaking other parts. Fig. 5 shows the modules; M12 has a dashed border because it belongs to the next phase.

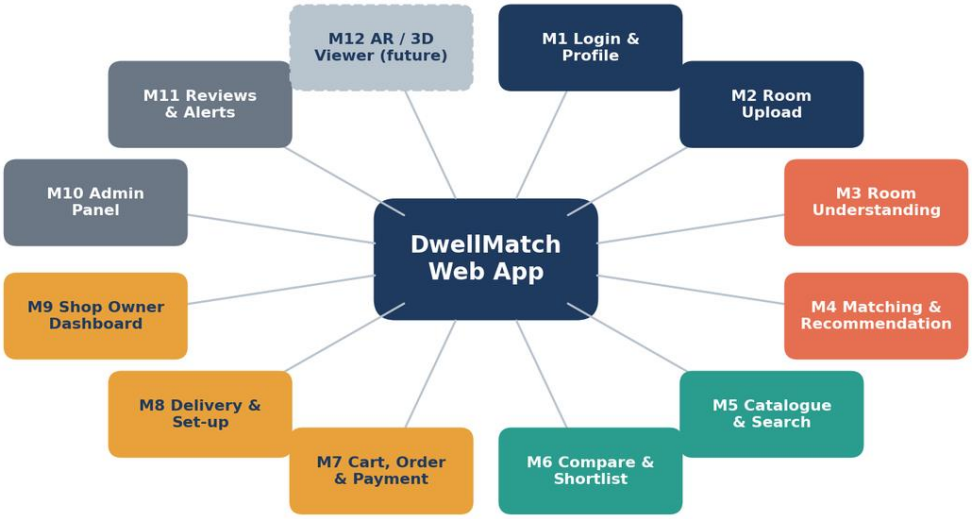


Fig. 5. Module map of the DwellMatch web application (M12 is planned for the next phase).

5.1 M1: Login and Profile (User Interface)

This module creates and protects accounts and gives each user a personal home screen. Passwords are stored only in hashed form, and users can edit their details or delete their account and photos at any time. Shop owners register with shop details and wait for administrator approval. Fig. 6 shows the profile screens of the DwellMatch interface.

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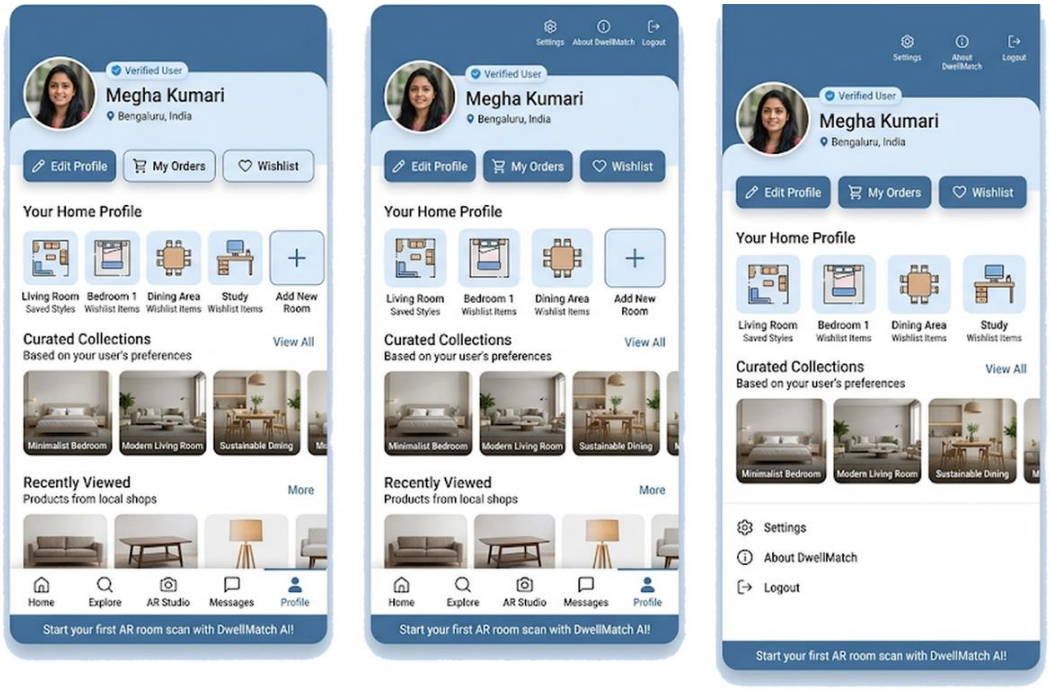


Fig. 6. User interface of the DwellMatch profile screen: (a) profile home, (b) top menu icons, (c) menu opened.

The interface is built for quick use with one hand on a phone. At the top, the user sees a Verified User badge and three shortcuts: Edit Profile, My Orders and Wishlist. Below it, Your Home Profile stores each room the user has added with saved styles and wishlist items. Curated Collections shows style ideas based on the user's preferences, and Recently Viewed lists products from local shops. A bottom bar gives one-tap access to Home, Explore, AR Studio, Messages and Profile. These screens are design prototypes; the AR Studio tab hosts the room scan today and the 3D preview in the next phase.

5.2 M2: Room Upload

The user takes a photo with the phone camera or uploads one from the gallery. The module checks that the photo is clear and well lit, shows a short tip card on how to photograph the room, and asks for two quick details that improve accuracy: the room type and the width of the space where the furniture will go.

5.3 M3: Room Understanding

This is the "eyes" of the system. It turns the photo into a short room profile using four small analysers (Fig. 7): a room type classifier (living room, bedroom, study) as shown in [8]; an object detector that finds existing furniture, windows and doors [6], [7], [10]; a colour analyser that groups wall and floor colours into a small palette using k-means [13]; and a light analyser that labels the room bright, medium or dim. Because size from one photo is never exact, the module combines its own estimate with the width the user confirms in M2.

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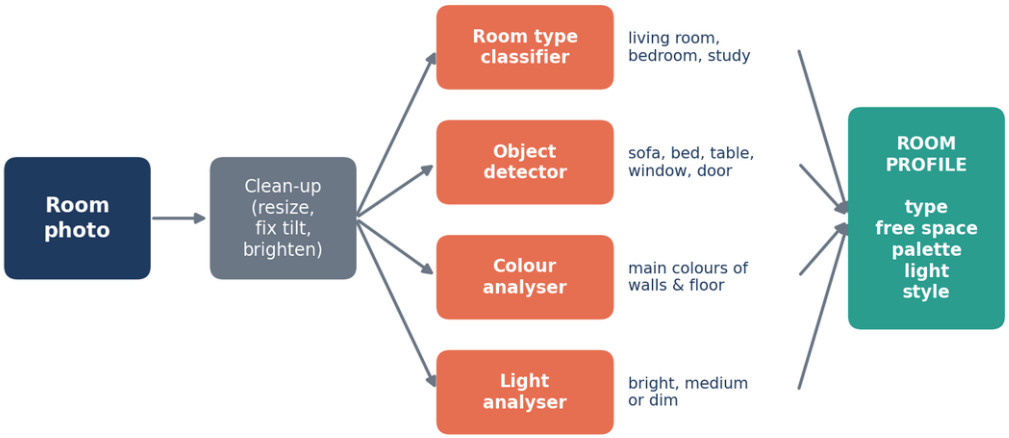


Fig. 7. Pipeline of the room understanding module.

5.4 M4: Matching and Recommendation

This is the "brain". It scores every nearby product between 0 and 1 in two steps. Step 1 removes items that cannot fit. If the free width is W_free, the item width is W_item and m is a small safety gap (for example 10 cm each side), the item is kept only if

$$W_item + 2m \leq W_free \qquad (1)$$

Step 2 scores the rest on five things: fit in the space (F), colour match with the room palette (C), style match (St), nearness of the shop (Dn) and price against budget (P). Colour closeness uses the standard ΔE difference in CIELAB colour space, and nearness and price scores fall as distance or cost grows. The final score is a weighted sum:

$$Score = w1 \cdot F + w2 \cdot C + w3 \cdot St + w4 \cdot Dn + w5 \cdot P \qquad (2)$$

The starting weights are 0.30, 0.25, 0.20, 0.15 and 0.10, so fit counts most because a wrong size is the costliest mistake. They are only a starting point and will be tuned with user feedback. Table IV gives a worked example with sample values chosen only to explain the method, not experimental results. A living room has 220 cm of free wall width; three sofas pass the size rule and an L-shaped 260 cm sofa is removed.

TABLE IV WORKED EXAMPLE OF THE MATCHING SCORE (ILLUSTRATIVE)

Item	Fit	Colour	Style	Near	Price	Final score
Sofa A (3-seater, grey)	0.95	0.85	0.90	0.90	0.80	0.89 (rank 1)
Sofa B (3-seater, brown)	0.75	0.90	0.70	0.60	0.90	0.77 (rank 2)
Sofa D (2-seater, teal)	0.70	0.55	0.75	0.50	0.95	0.67 (rank 3)
Sofa C (L-shaped, 260 cm)	–	–	–	–	–	Removed: too wide

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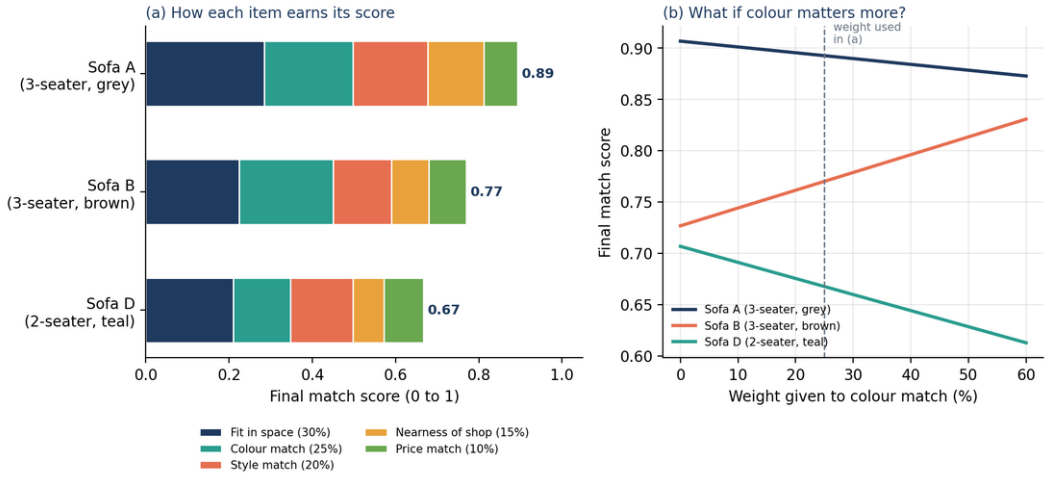


Fig. 8. Matching model: (a) how each sample item earns its score; (b) how scores change if colour is given more weight.

Fig. 8(a) shows how each part adds to the final score. Fig. 8(b) is a sensitivity check: Sofa A stays first at every colour weight from 0% to 60%, while Sofa B rises and Sofa D falls. Such checks help tune the weights and explain to users why an item ranked high.

In simple words: *First remove anything that will not fit. Then give each remaining item marks for fit, colour, style, distance and price, and show the highest total first.*

5.5 M5 to M8: Catalogue, Comparison, Orders and Delivery

M5 Catalogue and Search stores every shop's products and supports search and filters by price, colour, material, style and distance; a product added by a shop is available for matching immediately. M6 Compare and Shortlist lets the customer save favourites and compare up to four items side by side on price, size, material, shop, distance and match score, with a short reason such as "fits your 220 cm wall and matches the beige walls". M7 Cart, Order and Payment handles buying: orders are split by shop, payment is online or cash on delivery, and card details stay with the payment gateway and are never stored by DwellMatch. M8 Delivery and Set-up moves each order through Accepted, Packed, Out for delivery, Delivered and Set-up done, with a time slot chosen by the customer, live status and a complaint option. This full-service ending removes the last practical objection to buying furniture online [2].

5.6 M9 to M11: Shop Dashboard, Admin Panel, Reviews and Alerts

M9 Shop Owner Dashboard lets a shop add products from a phone, update stock and prices, accept or reject orders and see a simple sales report; a spreadsheet upload is offered for shops that already keep stock lists. M10 Admin Panel lets the administrator approve shops, check listings, handle complaints, watch system health and monitor that ranking stays fair. M11 Reviews and Alerts collects ratings and reviews after delivery and sends SMS or e-mail alerts for order, delivery and review reminders.

5.7 M12: AR / 3D Viewer (Next Phase)

Shops will upload simple 3D models of selected products, and the customer will see the sofa placed at true size in the live camera view of the room, walk around it, and check scale and colour against the real walls before confirming the order. As a web application, this can be built with WebXR [4] without any install. Studies suggest this feature lowers the felt risk of purchase [2], [3], so it is a core part of the roadmap, while the rest of the application stays fully usable on phones without AR.

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6. METHODOLOGY AND EVALUATION

The project follows a design-and-evaluate approach in small stages, each producing something that can be checked before the next begins.

1. Study and design: review related work, talk to a few buyers and shop owners, and finalise requirements, architecture and database.

2. Room understanding (M2, M3): build photo upload and analysers, train and tune them on public interior datasets, and measure accuracy on labelled test images.

3. Matching engine (M4): connect it to a simulated catalogue of local stock and check that every suggestion passes the size rule and also looks right in colour and style.

4. Web front end, shop dashboard, orders and delivery (M1, M5 to M11): build the pages and test them on phones and laptops.

5. User study: a small group completes a furniture-finding task with and without DwellMatch, using real stock from partner shops. Feedback then guides the next phase and the AR viewer (M12).

The first phase is deliberately focused on one category (sofas and seating) in one city. A small, finished product is more useful than a large, unfinished one. Table V lists what will be measured.

TABLE V EVALUATION MEASURES

What is checked	How it is measured	Why it matters
Room and object recognition	Accuracy on labelled test images; detection quality (mAP)	Wrong reading gives wrong suggestions
Colour analysis	Colour difference (ΔE) from the true palette	Colour match depends on it
Size rule	Share of suggestions that pass the fit check (target: all)	Prevents wrong-size purchases
Suggestion quality	User rating of top suggestions (1 to 5); top-k hit rate	Shows if suggestions feel right
Time saved	Time to decide and showroom visits avoided, with and without the app	Main customer benefit
Usability and acceptance	System Usability Scale [12]; usefulness and ease-of-use questions [11]	Shows if people would adopt it
Shop owner view	Short interviews on effort, new customers and trust	Local shops must gain too

Room photos can show private details of a home, so DwellMatch asks for clear consent, stores photos securely, never shares them with shops, and lets users delete them at any time. Study participants join voluntarily and only the data needed for the study is kept.

7. EXPECTED OUTCOMES, RISKS AND LIMITATIONS

This paper presents a design and an evaluation plan, so it does not claim measured results. If the prototype performs as intended, the following outcomes are expected and will be tested in the user study.

- For customers: less time, because one photo replaces several showroom visits; more confidence, because size and colour are checked before payment, echoing the gains reported for AR [2], [3]; and less effort, because payment, delivery and set-up are in one place.

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- For local shops: a low-cost digital shop window that reaches nearby buyers at the moment of intent, fair visibility based on fit rather than advertising, and simple tools to manage orders from a phone.
- For the business: a repeatable local marketplace model that can grow city by city and category by category.

The main risks and planned responses are as follows. Room size from one photo may be inaccurate, so a safety margin is used and key widths are confirmed by the user. Colours look different on different cameras and screens, so colours are shown as a guide with a simple correction step. Too few shops may register, so the launch starts with a small group of partner shops and very simple onboarding. Not all phones support AR, so the application stays useful without it. Photo privacy is protected by consent, secure storage and a delete option.

The study also has limits. The first phase covers one category in one city, size from a single photo is never perfect, suggestion quality depends on how many shops share stock, the matching weights are a starting guess, and the user study will be small, so it will show a direction rather than final proof.

8. FUTURE SCOPE

- AR in the browser (M12), so buyers can see 3D furniture in their own room before paying.
- Better measurement and learning: use phone depth sensors where available and improve weights from clicks, purchases and ratings.
- Whole-room planning that suggests a matching set (sofa, table, rug, lights), and more categories and cities.
- Local languages such as Kannada and Hindi, so more shop owners and buyers can use the service comfortably.

9. CONCLUSION

Furniture shopping has stayed slow and stressful because earlier fixes solved only parts of the problem. DwellMatch brings the parts together in one web application: a room photo becomes a room profile, the profile becomes a ranked shortlist of real items from nearby shops, and the shortlist ends with payment, delivery and set-up. The twelve-module design, the simple and explainable matching score, the practical user interface and the shared-value business model make the idea realistic to build and test. The planned AR viewer will later let buyers see the item in their own room before paying. The aim is to leave both sides better off: customers who spend their weekend on life instead of touring showrooms, and local furniture businesses that finally get a fair chance with the customers living a few streets away.

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