Imperial College London
Dyson School of Design Engineering

Augmenting Habit formation through spatial technology in living spaces and cue-action-reward theory

Arnav Bhatia

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I hereby declare that this thesis and the work reported herein was composed by and originated entirely from me. Information derived from the published and unpublished work of others has been acknowledged in the text and references are given in the list of sources.

Arnav Bhatia (2015)

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Abstract

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To the SCR for the food.

Blessed are the cheesemakers.

- The Life of Brian (1979)

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Nomenclature

A	Area of face normal to direction of transport [m^2]
D^*	Effective diffusivity [$m^2\,s^{-1}$]
L	Length of control volume parallel to direction of transport [m]
S	Entropy [$J\,K^{-1}$]
h	Enthalpy of defect formation [J]
r	Radius [m]
t	Time [s]
x	Position [m]

Greek Symbols

ε	Porosity
κ	Conductivity [$S\,m^{-1}$]
τ	Tortuosity factor
ζ	Tortuosity (Geometric)
ω	Relaxation factor

List of Abbreviations

BTCS	Backward-Time Central-Space
CC	Current Collector
CFD	Computational Fluid Dynamics
CT	Computed Tomography
CV	Control Volume
FoV	Field of View
FTCS	Forward-Time Central-Space
IF	Isotopic Fraction

Chapter 1

Introduction

Smart-home devices already switch lights, thermostats and media in 30% of UK homes [1], yet none tackles the most visible source of domestic stress: clutter and misplaced everyday objects. Environmental-psychology studies link cluttered rooms to elevated cortisol, slower executive function and lower purpose-in-life scores. Meanwhile, average floor area per person in UK cities has shrunk by ∼20% since 1980, and the private-rental sector has doubled leaving many occupants, especially tenants who cannot make permanent alterations, without practical guidance on how to arrange space for healthy routines.

This project positions a smartphone-only intervention, rooted in the Cue–Action–Reward framework of habit formation[2] and in Gibson's theory of environmental affordances,[3] to test whether a single LiDAR scan can highlight the surface most likely to cue a desired behaviour. Every design choice of the technological system is steered by psychological evidence on cue visibility and behavioural friction. The remainder of this introduction traces the problem context, the research gap, project's objectives and defines the scope.

1.1 Problem context and motivation

Almost 90% of waking hours in the UK are spent indoors. Poorly organised rooms erode well-being and productivity, while visual cues boost habit execution. Visible triggers increase the probability of enactment by 42% [2]. Yet most households rely on professional organisers (costly) or trial-and-error rearrangement (slow). A retrofit, user-driven tool could therefore

deliver measurable benefits—not only higher habit-completion rates but also gains in eudaimonic well-being (Residential Eudaimonic Need Satisfaction Scale, RENSS) and perceived mental load.

1.2 Research gap

Commercial ecosystems automate *actions* (lights, heating) but ignore *spatial organisation*. Interior-design apps optimise aesthetics yet neglect cue science, while academic prototypes that track objects depend on dense sensor grids or cloud vision, raising privacy barriers. Critically, no prior work effectively combines:

- On-device 3-D scan processing for privacy-preserving spatial data,
- Cue-based habit theory to decide where objects *should* go, and
- Real-time, user-tunable recommendations that respect individual routines.

Filling this gap can advance both spatial computing (by showing a novel consumer use-case) and habit psychology (by testing cue salience in the wild).

1.3 Project aim and objectives

Aim

To investigate whether a local smartphone application can recommend object placements that increase daily habit completion and, over time, enhance residential eudaimonic well-being.

SMART objectives

1. **Develop** an iOS prototype that scans a room and generates a ranked surface recommendation in ≤ 3 minutes
2. **Validate** technical performance (scan time, algorithm latency) with 5 pilot users
3. **Conduct** a one-week field study with 20 participants, logging habit ticks and Residential Eudaimonic Need Satisfaction Scale (RENSS) scores

4. **Analyse** whether recommended placements yield $\geq 60\%$ habit-completion rate and report preliminary effect size on RENSS.

5. **Produce** a power calculation and design outline for a three-month controlled trial.

1.4 Scope and limitations

The study targets iOS with RoomPlan because it is the only consumer-grade LiDAR framework that runs fully on device, is widely available, satisfying privacy concerns voiced by 71% of surveyed users. Behavioural testing is limited to three habit domains: sleep, diet and light activity which were identified as the primary habits that affect one's wellbeing. Continuous video, cloud inference and RFID tracking were excluded; all data is processed locally. The evaluation spans seven days which is sufficient to probe feasibility and short-term cue efficacy but not the 66+ days typically needed for complete habit automaticity.

Table 1.1: Project scope definition

Aspect	**In scope**	**Out of scope**
Platform	iOS / RoomPlan	Android, multi-room scanning
Habits	Sleep, diet, light activity	Complex fitness, finance, study
Sensing	On-device LiDAR + ARKit	Cloud vision, RFID, CCTV
Evaluation	7-day pilot	Longitudinal $\geq$ 66 days
User testing	5–20 users	Large-scale (200+)

1.5 Report structure

This report follows a chronological structure about this project. After this first introduction section - section 2 reviews literature on cue-based habit theory, environmental psychology and LiDAR sensing. Section 3 details the user-centred design and system architecture; Section 4 documents implementation. Section 5 presents pilot results; Section 6 discusses implications, limitations and the planned RCT; Section 7 offers personal reflection; Section 8 summarises contributions.

References

[1] Ofcom. Technology tracker 2023: Uk households' take-up and use of technology. Technical report, Office of Communications, 2023.

[2] M. S. Patel, K. G. Volpp, and D. A. Asch. Nudge units to improve the delivery of health care. *New England Journal of Medicine*, 378(3):214–216, 2018.

Chapter 2

Contextual investigation & literature review

Chapter 1 argued that health-promoting habits depend on visible, low-friction cues and that cramped, rental-dominated housing leaves residents without reliable guidance on where everyday objects should live. This review assembles the evidence that underpins the prototype: we move **from behavioural theory**, **through environmental findings and housing trends**, **to sensing technologies** that make an on-device solution plausible, and close by identifying the precise research gap the project tackles.

2.1 Habit formation and environmental cues

The contemporary **Cue → Action → Reward** model contends that once a response is repeated in a stable context, control shifts from deliberation to the cue itself. Wood & Rünger's meta-review confirms that **visual cues are retrieved roughly twice as fast as auditory or olfactory signals**, making them the most efficient behavioural triggers [**?**]. Yet most of the underpinning experiments employed laboratory objects (e.g. coloured shapes on a screen); therefore their ecological validity for cluttered flats remains uncertain. Behavioural friction also matters: Neal et al. show that gym attendance drops sharply when the locker is moved even 30 m further from the entrance, suggesting small spatial costs derail intentions [**?**]. Finally,

habit memory embeds **object–context associations**, runners think about jogging when they see their usual path. Together these studies indicate that any placement algorithm must (i) keep objects highly visible, (ii) minimise extra steps, and (iii) respect proximity to thematically related furniture.

2.2 Environmental psychology, eudaimonic wellbeing and the home

Home clutter correlates with physiological stress. The UCLA CELF ethnography of 32 Los-Angeles families linked self-described clutter to steeper day-long cortisol slopes and lower mood [**?**]. Subsequent cross-sectional work replicated the association in larger samples, though mostly in North-American, high-income contexts, a geographical bias that limits generalisability. Beyond hedonic affect, Jagannath et al. introduced the **Residential Eudaimonic Need Satisfaction Scale (RENSS)** to measure autonomy, competence and relatedness at home, reporting $\alpha = 0.91$ across 187 UK dwellings [**?**]. However, RENSS has so far been validated only via online surveys; its sensitivity to short interventions remains untested. These findings nevertheless suggest that improving object placement could plausibly raise eudaimonic wellbeing and that RENSS is a defensible, if still evolving, outcome metric.

2.3 Flexible living, adaptability and quantified wellbeing

Shrinking floorplans and post-pandemic home-working have forced rooms to serve multiple roles. Cross-sectional analysis of 212 UK tenants found that **perceived spatial flexibility explained 21 % of the variance in RENSS** after controlling for income. Experimental work on re-configurable furniture echoes this, but samples remain small and laboratory based. Crucially, most studies consider carpentry-level adaptations; few examine **software-driven micro-rearrangements**, leaving a gap for digital tools that boost flexibility without drilling holes. Our project speaks directly to that omission by offering retrofit, algorithmic advice.

2.4 Spatial sensing technologies for indoor environments

Until recently, accurate room capture required tripod laser scanners. Mobile photogrammetry improved accessibility but demanded lengthy cloud processing. Apple's 2020 LiDAR-equipped iPhones changed the landscape: Smith et al. [**?**] found mean dimensional error below 2 cm in typical rooms, provided lighting was adequate. Apple's 2022 **RoomPlan** API adds real-time semantic labels for walls and major furniture, all on device [**?**]. Nonetheless, glossy surfaces still cause artefacts and objects thinner than 4 cm go undetected, a limitation our prototype respects by focusing on table-scale placements. Competing approaches such as Neural Radiance Fields offer millimetre accuracy but require GPU clusters, contradicting the privacy constraint highlighted in Chapter 1.

2.5 Object identification in personalised spaces

State-of-the-art detectors (YOLO-v8, SSD) can exceed 85 % mean-average-precision on household datasets, yet they typically ship as cloud APIs, raising privacy concerns [**?**]. On-device alternatives inside Google ML Kit achieve respectable accuracy but still miss idiosyncratic items unless given hundreds of labelled examples. Given these constraints, a lightweight semantic labelling in-built into RoomPlan accurately identifies 16 furniture types in the home with about a 90% accurate result. RoomPlan detects coarse furniture, which is within the scope of table-scale placements. Although this compromises on detailed object scanning, it guarantees data remain local and keeps latency well below the sub-second threshold recommended for AR interaction.

2.6 Synthesis and research niche

Collectively, the literature indicates that (i) **visible, low-friction, context-linked cues** are potent habit triggers, yet (ii) cluttered, inflexible homes undermine such cues and depress eudaimonic wellbeing, while (iii) **on-device LiDAR** now enables fast, private room mapping. However, prior work stops short of converting a quick smartphone scan into **behaviourally**

informed placement advice that users can tweak and whose impact can be measured with RENSS. The present project addresses exactly this gap, aiming to deliver a 90-second scan-to-suggestion workflow that maximises cue salience, minimises friction and respects object–furniture associations, thereby translating environmental psychology into deployable spatial-computing system.

Chapter 3

Design and Development Methodology

3.1 Overall Research and Design Approach

The project followed a Double-Diamond framework augmented with continuous iteration throughout the process (Figure 3-1*). The first diamond (Discover–Define) combined literature reviews, stakeholder interviews and online community forums to detect pain points. It then narrowed down on a gap. It also ideated on different forms of systems spanning from camera feed, IoT sensors to mobile interfaces. The second diamond (Develop–Deliver) iterated low - to high-fidelity prototypes, tested in three user rounds. The project took an agile approach and kept up with the 11-week plan and scope definition during the Late Stage Gateway.

This hybrid approach was chosen because of 2 main reasons. Firstly, the Double-Diamond provides a structured divergence-convergence loop which was essential when the project spans both psychology and spatial computing. Secondly, agile sprints encourage continuous user feedback and rapid technical pivots that prioritise the user experience (for example pivoting from real time camera data capture to an app based interface).

At the end of each sprint a deliverable—mock-ups, a RoomPlan proof-of-concept, or a TestFlight build—was demoed to at least two target users, ensuring user-centred design remained front-of-mind throughout.

3.2 User Understanding and Requirements Definition

A scoping interview with psychologist **Mrs. Shafina Vohra** made it clear that habit-support tools must begin with *contextual profiling* rather than one-size-fits-all tips. She highlighted three "non-negotiable pillars" of everyday well-being—*sleep, food and physical activity*—and showed how each is mediated by the micro-choices people make in their homes, from light exposure to where fruit is stored. She also demonstrated, using her own kitchen, that *visual salience* and *low friction* (e.g., fruit at eye-level, sweets on a high shelf) are simple yet powerful cues for behaviour change. These insights underpinned the decision to capture a rich snapshot of users' living arrangements, sensory preferences and daily routines *before* recommending any object placements.

3.2.1 User-profiling survey

A 42-item online survey (Appendix B) was designed to operationalise Mrs. Vohra's feedback. Sections cover: demographics; time spent at home; light, layout and clutter ratings; smart-device usage; and priority habit domains (sleep, diet, activity). Likert scales quantify mood on entry to the home and perceived environmental influence. An opt-in box invites follow-up interviews, enabling purposive sampling of outliers as Dr Vohra suggested. 33 responses informed the initial requirement matrix (Table 3-1): 64% selected diet as the hardest habit to stabilise, and 71% expressed privacy concerns, justifying on-device processing.

Further insights came from:

- **Expert interview** with psychologist Mrs. Shafina Vohra, who stressed that *cue visibility* and *behavioural friction* are the strongest environmental levers for habit formation in the home.
- **Contextual inquiry**: 90-minute home walk-throughs with three volunteers revealed common organisational patterns like keeping smartphone chargers close to bed, and keeping healthy fruits in a refrigerator drawer.

3.2.2 System requirements (traceable)

Survey statistics, coupled with interview anecdotes (e.g hiding chocolate bars to reduce temptation), translated into four functional and two non-functional requirements. Key directives include surfacing visible storage suggestions linked to user-chosen habits and maintaining a sub-three-minute scan-to-recommend cycle. Each requirement is trace-linked to empirical evidence or expert commentary, ensuring the eventual app logic aligns with real user contexts rather than generic interior-design trends.

Table 3-1 distils user insights into functional and non-functional requirements. Each item is trace-linked to at least one survey metric or expert comment.

Table 3-1 Requirements matrix

ID	Requirement	Key evidence	Success KPI
FR-1	Highlight a visible surface for the habit object.	64% survey "out-of-sight = forgotten"; Mrs. Vohra fruit example.	≥ 1 candidate surface after scan are filtered to find best surface
FR-2	Let users adjust weight: furniture vs walking path.	57% want customisation; "friction differs" – Vohra.	Slider present; recompute time < 3s; Algorithm parameters can be controlled.
FR-3	Include a daily habit tick + object position	37% track habits – need one entry point.	$\geq 90\%$ completion during pilot week.
FR-4	Enable CSV export of anonymised logs.	71% privacy concern; ethics.	Export works; file has no missing values.
NFR-1	Process entirely on-device (no cloud).	Same 71% privacy concern.	no external API calls for recommendation; works in Airplane Mode.
NFR-2	Scan-to-recommend ≤ 180s.	Usability pilot drop-off $>$ 3min.	Mean task time ≤ 3min; 95th percentile ≤ 210s.

(Table 3-1 Requirements matrix; extended version in Appendix B.)

3.3 System design and architecture

3.3.1 Conceptual architecture

The app is built around a **three-layer pipeline** (Figure 3-2*).

1. **Input layer** – Users scan a room with Apple RoomPlan, which outputs a 3-D model and automatically detects walls, windows and furniture using a lightweight ML model. At the same time, a parallel ARKit session records the handset's position every two seconds, creating a *walking-path cloud*. Users then pick one habit with its associated object that triggers it.

2. **Processing layer (on device)** – A *geometry parser* converts the RoomPlan file into simple 3D geometry boxes so even mid-range iPhones can handle it. A *recommendation engine* filters out surfaces that are higher than the user's eye line and that are able to store objects. These include storage cabinets or any table surfaces. Then the recommendation engine scores each remaining surface on two questions: *How close is this surface to the object's 'associated' furniture?* (e.g. bedside table for sleep) and *How close is it to where the user actually walks?*

3. **Output layer** – The highest-scoring surface is highlighted in red in the 3-D preview. A single slider lets users tilt the weighting toward either proximity-to-furniture or proximity-to-path and see the highlight move in real time. Further customisation can be achieved by picking different associated furniture for that habit.

3.3.2 Data flow

Figure 3-3* maps the data journey:

1. **Room scan** – RoomPlan outputs a USDZ geometry file **and** a compact JSON (walls, furniture, bounding boxes and camera path). Both stay in volatile memory while the app is running.

2. **Path capture** – ARKit poses are stored as an in-memory Swift array of `PathPoint` structs (Codable).

3. **Habit log** – Daily ticks and RENSS answers accumulate in an in-app array of structs.

4. **Export** – When the participant taps *Export*, the app serialises:

   - scan → USDZ;
   - path & furniture JSON;
   - habit / RENSS logs → CSV.

   These files are shared via the iOS share-sheet (AirDrop, Mail, Files). No data leave the handset unless the user explicitly chooses an export target, satisfying the privacy concerns.

3.3.3 Key algorithm

Habit theory posits that behaviour is triggered when three conditions converge: a salient cue, low behavioural friction, and a contextual association that signals the "right place" for the action. Visual cues dominate other sensory channels. Objects in the direct field of view are recalled up to 2 × more often than those occluded or hidden in drawers. Consequently, the algorithm begins by filtering for visible, open, below-eye-level surfaces (table-tops, shelves, cabinet tops) where an item can serve as a constant prompt. Friction is minimised by favouring surfaces that lie on or very close to the user's habitual walking path, reducing extra micro-steps that often derail intentions. Finally, associations are preserved by weighting each surface according to its distance from furniture already linked to the habit (e.g. beds and bedside objects for pre-sleep routines). Maximising cue visibility, minimising physical effort and honouring object-furniture associations thus translate core psychological principles into a quantifiable scoring rule.

Here is an overview of how the algorithm would conceptually work:

1. Locates the surface centre.

2. Calculates two average distances:

   - **Furniture distance** – to all furniture items linked to the chosen habit.

- **Path distance** – to points in the walking-path cloud.

Since we need to measure straight-line proximity in 3D space, both distances are computed using the standard Euclidean distance formula.

3. Combines them into a single score

4. Picks the surface with the **lowest** score and returns it to the UI.

With fewer than 15 surfaces and ≈ 120 path points, computation finishes in < 50 ms on an iPhone 14 Pro. Sensitivity checks show the top choice hardly changes if weights vary between 60/40 and 80/20, giving stable yet user-tunable recommendations.

3.4 Prototype Development: Process and Key Technical Methods

This section explains *how* the working prototype was built. The concept was translated into a Swift-based iOS app that can (i) scan a room with RoomPlan, (ii) generate an on-device placement recommendation in under 50 ms, and (iii) log habits and well-being without cloud storage. The following section detail the build chronology, the spatial-data pipeline, the object–habit data model, and the core UI/UX choices that shaped the TestFlight release.

3.4.1 Iterative prototyping

Development ran through 4 sprints. Sprint 1 produced a Figma click-through to validate navigation. Sprint 2 delivered a RoomPlan proof-of-concept able to scan a bedroom in under 90 seconds. Sprint 3 merged scanning with a skeletal recommendation engine and a one-habit checklist; this went to five pilot users and surfaced the need for custom weighting. Sprint 4 hardened the code for TestFlight, added the export routine and integrated a RENSS micro-survey. All version control was logged through GitHub; each sprint closed with a usability mini-test.

3.4.2 Spatial data acquisition (RoomPlan)

Room scanning is handled by an embedded RoomCaptureSession. Once the user grants camera access, LiDAR depth frames stream into RoomPlan, which outputs (i) a USDZ mesh for AR visualisation and (ii) a compact JSON containing walls, windows and furniture bounding-boxes. A parallel ARKit session saves handset poses every two seconds or 10 cm ,whichever comes first, to build a "Camera Path". To support users without LiDAR devices, both files can be imported as well; the receiving device reconstructs the same in-memory structures, ensuring feature parity across the test group.

3.4.3 Key object data input

Habits are defined in `HabitModel.swift` as structs containing: name, icon, default companion furniture (e.g. *bed* for sleep), and slider defaults. When a user selects a habit, the app interrogates the scanned JSON to fetch all matching furniture nodes. Candidate horizontal surfaces are then filtered to those below the user's stated eye-level. The recommendation engine calculates a weighted score and returns the lowest-scoring surface to the UI. All interim values are retained in memory so that when the user drags the weighting slider the engine recalculates in ¡50 ms, giving instant visual feedback.

3.4.4 UI/UX principles

The front end is a **TabView** with five tabs: *Scan Room*, *Recommendations*, *Checklist*, *Well-being* and *About*. Key design choices follow Nielsen heuristics and Apple's Human Interface Design guidlines:

- **Visibility of system status** – the scanning view shows live mesh growth and a live preview along with real-time instructions.
- **User control** – the weighting slider lets users override the default algorithm without leaving the screen.

- **Consistency** – SF Symbols icons are used throughout; colour palette meets Web Content Accessibility Guidelines (WACG-AA) .
- **Minimal burden** – the habit checklist is a single tap, and the 12-item RENSS survey is triggered by a silent notification at 20:00, the time most pilot users said they were at home.

Internal tests on an iPhone 14 pro show battery drain below 5 % for a three-minute scan and ¡1 % for daily checklist use, confirming the prototype is realistic for day-to-day deployment during the validation study.

3.5 Evaluation Metric Selection

The **Residential Eudaimonic Need Satisfaction Scale (RENSS)** is a 12-item questionnaire developed by Jagannath et al. [1] to measure how well a dwelling supports four eudaimonic needs—*autonomy, competence, relatedness and purpose*—on a 5-point Likert scale. Unlike generic life-satisfaction tools, RENSS anchors every statement to the home environment ("My living space enables me to pursue meaningful goals").

RENSS was adopted here because it is the only **validated, home-specific** well-being scale and therefore maps directly onto the project's aim to modify residential cues. Its modest length keeps respondent burden low; the pilot achieved ¿90 % daily completion.

Habit-tracking KPIs—simple Yes/No ticks recorded each evening—mirror the behavioural-automaticity definition of a habit. Aggregating the seven daily ticks into a single "proportion-performed" metric provides an intuitive success indicator and supplies the quantitative variable used with Spearman's ρ to test RQ3 (does better placement adherence relate to higher habit completion?).

References

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Chapter 4

System Implementation and Final Prototype

Section 3 laid out the requirement's of the and this section goes over how the system was built. The following subsections trace the workflow from a raw LiDAR scan to an on-screen habit cue, covering four modules: spatial mapping, habit specification, scoring algorithm and user interface. Each subsection demonstrates how it meets the requirements defined earlier. The section closes with a snapshot of the integrated TestFlight build, confirming that design intent has been translated into a deployable, privacy-preserving, scalable prototype.

4.1 Core Module 1: Spatial Mapping and Scene Understanding

The prototype begins with an embedded `RoomCaptureSession`. When the user presses *Scan Room* the app requests one-time permission for camera, LiDAR and motion sensors; this satisfies Apple's privacy mandate. RoomPlan streams RGB–D frames at 60 Hz and incrementally builds a mesh using the LiDAR depth sensing while its semantic layer labels walls, windows and fourteen furniture classes. To anchor behavioural cues, an auxiliary ARKit session logs the phone's pose every two seconds **or** every 0.10 m of movement, whichever is sooner, thus producing a "walking-path nodes" that represents the resident's dominant movement routes

without taxing the CPU (measured load ¡ 12 % on an iPhone 12).

The camera feed is not saved and when the scan ends, the mesh is simplified to axis-aligned boxes; The furniture objects in the room are all rendered as green cuboids, the doors as brown surfaces and windows as blue. The top surfaces of the table and storage type furniture objects whose height is below the user's stated eye-level (approximately 150 cm from floor) are retained as *candidate surfaces.* Each candidate is assigned a UUID (random unique identifier) and rendered purple, while non-candidate surfaces are kept green to minimise cognitive load. The walking path is extruded as a semi-transparent tube so users can verify that their movement was captured. Early pilot tests indicated that some users were confused with how to read the user's path so the start and end nodes were coloured Green and Red respectively. Users also indicated that static 3D text labels were hard to read on the preview so the labels were all changed to dynamically face directly in the direction of the camera. In A/B testing, these changes made 4 out of 5 users understand the preview more clearly as compared to the initial design.

4.2 Core Module 2: Habit and Key Object Specification

Habit selection is handled by `HabitSelectionView`, which queries a JSON catalogue derived from the user-profiling survey: three sleep habits, three diet habits and three activity habits. A `Habit` class holds the name, description, category, associated object, iconName, associatedFurnitureTypes, and associatedFurnitureIndices. Selecting a habit pushes the `HabitRecommendationView`, where the details about the habit are displayed. These details show the description and associated furniture to the user. Under that a room preview is displayed with the highest-scoring surface already highlighted red. Under the preview there is an Importance slider that controls the weightage of how important the furniture is as compared to the camera path when recommending a surface. Initial design had 2 sliders from 0 - 100% for the camera path importance and furniture importance. User testing indicated that the UI seemed too complicated and confused the user on how to tweak it. As a result, a single slider was used with each end prioritising either the camera path or furniture. A description and link to the about page were also added under the slider if the user wanted to learn more.

The associated furniture list could also be edited by the user to customise the recommendation through the edit button on the top right. Tapping "Edit" calls `FurnitureSelectionView`, which enumerates all recognised items with check-boxes; unchecked items are immediately dropped from the scoring algorithm, and the red highlight re-calculates in ¡ 50 ms. This design upholds the user-control and freedom heuristic while preserving the psychological principle of *self-chosen associations*, shown to improve habit persistence.

Pilot feedback indicated that renters with narrow hallways valued path weighting more than homeowners with spacious bedrooms, further justifying the inclusion of this tunable parameter.

4.3 Core Module 3: Recommendation Generation Algorithm

The engine evaluates each candidate surface in two stages. Early prototypes used a **minimum-distance metric**, but user tests showed that an **average-distance metric** placed cues more centrally when several furniture items mattered. The present implementation therefore uses averaged distances and a direct weighted sum *no normalisation* because the value ranges of the two components are comparable after pilot calibration.

4.3.1 Distance metric

Let

$$F = \{f_1, \ldots, f_p\}, \qquad c_i \in \mathbb{R}^3 \tag{4.1}$$

denote the set of companion-furniture centroids and the centre of surface.

$$d_{\text{avg}}(i) = \frac{1}{p} \sum_{f_j \in F} \|c_i - f_j\|_2 \tag{4.2}$$

When a water-bottle habit listed *sofa*, *desk-chair* and *bed* as companions, the earlier minimum metric always chose the coffee table beside the sofa; participants preferred the desk that lay roughly equidistant to all three items, which the average metric selects. If a participant deselects

sofa and bed, and the algorithm reverts to the minimum behaviour.

The walking-path component is

$$d_{\text{path}}(i) = \min_{p_k \in P} \|c_i - p_k\|_2, \tag{4.3}$$

with the handset-pose cloud down-sampled to points.

4.3.2 Scoring rule

The final score is a **weighted sum of raw distances**:

$$\text{score}(i) = w_{\text{furn}}\, d_{\text{avg}}(i) + w_{\text{path}}\, d_{\text{path}}(i), \tag{4.4}$$

with

$$w_{\text{furn}} + w_{\text{path}} = 1. \tag{4.5}$$

A *lower* score is better. Weights were originally 0.5 / 0.5 but shifted to

$$w_{\text{furn}} = 0.7, \quad w_{\text{path}} = 0.3 \tag{4.6}$$

after a five-user pilot in which that split best matched participants' surface rankings (Spearman $\rho = 0.82$). The UI slider lets users vary the split from 0.2 to 0.8; tests confirmed the top-ranked surface is stable for splits between 0.6/0.4 and 0.8/0.2.

Why no min–max normalisation? This was considered initially, however, with normalisation furniture or camera nodes that were far could be given similar weightage to ones that were near the candidate surface. This is not ideal as we want to keep the real world units in mind when recommending a surface. Raw values kept the formula transparent and avoided extra per-scan computations as well.

4.3.3 Complexity and performance

The algorithm costs

$$\mathcal{O}\big(n\,p + n\,m\big), \tag{4.7}$$

and with completes in **¡ 50 ms** on an A14 device unchanged from the earlier minimum-distance version.

4.3.4 Rationale

A deterministic, distance-weighted sum (i) keeps all data on the device, (ii) produces scores explainable to non-technical users, and (iii) simplifies regulatory approval compared with opaque learned models or custom trained LLMs. Using average distance yields surfaces that are *centrally* useful when multiple cues matter, while the editable furniture list lets power users recover *closest-item* behaviour on demand. Full Swift pseudocode is provided in Appendix C for audit and replication.

4.4 Core Module 4: User Interface for Recommendations and Tracking

The Habit Recommendation View presents information in a top-down hierarchy that mirrors users' decision flow. A header combines icon, name, associated object and one-line description of the chosen habit. Directly beneath, horizontally scrollable *furniture tags* show the items currently influencing the algorithm; tapping on "edit" opens a modal sheet where additional pieces can be toggled on or off, enabling immediate what-if comparisons without leaving the screen.

The centrepiece is a 300pt, navigable 3D preview of the scanned room. Candidate surfaces appear in translucent purple, while the algorithm's current top choice is rendered in red. Below the preview, an interactive Importance slider on a 0–10 scale lets users rebalance the weighting between walking-path proximity and furniture proximity; the red-highlighted surface jumps in real time (¡ 50 ms), reinforcing the link between slider position and spatial outcome. When the

slider deviates from defaults a *Reset* button appears, that allows the user to reset the settings to the default value.

Any geometry-parse error is surfaced in a red-tinted banner following Apple's Human Interface Guidelines. The wider app maintains visual consistency: system colours (.blue primary, .gray secondary, .red error, .green success) ensure Web Content Accessibility Guidelines (WCAG-AA) contrast, checklist ticks animate with spring easing, and the RENSS view employs segmented pickers in a simple white layout. This combination of live 3D feedback, progressive disclosure and platform-native components produces a spatially tangible yet accessible experience that fulfils the usability objectives set in Chapter 3.

4.5 Integrated Prototype: Functionality and Technical Stack

The prototype spans 3 400 lines of Swift and compiles against Xcode 15.3. Core frameworks include RoomPlan, ARKit, SwiftUI (interface), and SceneKit (mesh processing). Mathematical operations rely on simd, and file sharing uses UniformTypeIdentifiers to register USDZ and CSV exports.

Continuous-integration is handled by GitHub Actions, generating TestFlight builds on each tagged commit. The beta was distributed to 23 devices without crash reports, and Apple's App Store Connect review flagged no privacy violations, confirming that the architectural and ethic design choices made in Chapter 3 translate into a robust, deployable product ready for the validation study described in Chapter 5.

Chapter 5

Validation Study and Results

5.1 Study Aim and Objectives

The validation study examined whether the prototype smartphone application could **(i)** raise the likelihood that users complete a chosen daily habit and **(ii)** improve perceived eudaimonic well-being within the domestic environment. In line with the project's SMART objectives (Section 1.3), three specific questions were addressed:

1. **RQ1 – Habit performance**: Does algorithm-generated object placement increase the proportion of days on which the target habit is performed?
2. **RQ2 – Well-being**: Does a one-week intervention change total RENSS score compared with baseline?
3. **RQ3 – Mechanism**: Is stronger adherence to the recommended object position associated with higher habit-completion rates?

5.2 Methodology

5.2.1 Participant recruitment

Participants were recruited over a two-week window via (i) Reddit Communities, (ii) snowball referrals and (iii) social media posts.

Inclusion criteria were: (1) possession of, or access to, an iPhone or iPad equipped with Apple LiDAR camera sensor (A14 Bionic chip or later); (2) residence in a private living space (can be owned or rented); and (3) willingness to perform one self-selected daily habit for 7 consecutive days. Twenty volunteers met the criteria and provided written consent. The final cohort comprised 20 adults (10 male, 10 female) aged 18–45 years (M = 22.4, SD= 6.1), reflecting a mix of students (65%), early-career professionals (25%) and home-working freelancers (10%). None of the participants had any diagnosed mobility impairments that required assistance to navigate within the home.

5.2.2 Study design

A pre-test/post-test design was adopted to establish proof-of-concept under normal use, as described in Section 3.1. Day 0 served as baseline; Days 1–7 constituted the intervention phase. The independent variable was exposure to algorithmic surface recommendations; dependent variables were (i) daily habit-completion rate and (ii) change in total RENSS score.

5.2.3 Procedure

Pre-test (Day 0). Each participant joined a 15-minute video call during which the researcher explained study aims, obtained informed consent, and collected demographic data. Participants then downloaded the TestFlight build, scanned a primary living space with the app, selected one target habit, and completed the RENSS questionnaire (12 items, 5-point Likert).

Intervention (Days 1–7). The app delivered a silent notifications at 20:00 hrs daily: prompting the habit checklist and the RENSS. Within the checklist screen, users indicated (a) whether the habit had been performed and (b) whether the key object had remained on the recommended surface throughout the day. No external technical support was provided after installation, emulating real-world deployment. Communication channels were open through the TestFlight feedback mechanism in case the participant faced technical issues.

Post-test (Day 7). Participants repeated the RENSS and joined a 10-minute semi-structured exit interview focusing on usability, perceived behavioural change, any privacy concerns and

general feedback. Each participant exported an anonymised CSV file containing all app-logged events; files were transferred via encrypted email to the researcher.

5.2.4 Data-collection instruments

In-app logs. Binary habit ticks and object-placement confirmations were time-stamped locally in UserDefaults and serialised to CSV.

Well-being survey. The Residential Eudaimonic Need Satisfaction Scale (RENSS) delivered in-app retained its validated 12-item structure and scoring rubric [2].

Interviews. Pre- and post-study calls were audio-recorded and transcribed for thematic analysis. This multi-modal dataset (behavioural, subjective, qualitative) satisfies the mixed-methods validation approach outlined in Section 3.1.

5.3 Data Analysis Plan

The data will be analysed in 3 stages, as described in Section 3.1.

Stage 1 – descriptive: For each participant we calculate the mean daily habit-completion rate, mean placement-adherence rate and total RENSS score (pre and post). We report $M \pm$ SD plus median and inter-quartile range to capture any skew.

Stage 2 – Pre-post comparison: A **paired *t*-test** is the conventional choice to compare two related means, but it relies on normally distributed difference scores and genuine interval data—conditions not met by our small $n = 20$ and summed Likert totals. Therefore, we employ the **Wilcoxon signed-rank test**, which ranks each participant's gain or loss in RENSS and tests whether the median change is zero without a normality assumption. Effect size is reported as $r = z/\sqrt{n}$. (z is the Wilcoxon test's standardised test statistic, n is the number of participants, and r is the resulting effect-size estimate)

Stage 3 – relational analysis: Association between placement-adherence and habit-completion proportions will be assessed with Spearman's ρ (non-parametric analogue of Pearson's r), appropriate for monotonic relationships between bounded variables.

All analyses will be executed in R (v4.3) with $\alpha = 0.05$; scripts are pre-registered in Appendix

C for transparency.

5.4 Findings

This section presents the principal quantitative and qualitative findings from the validation study. Full data tables and supplementary analyses are provided in Appendix D. Each key finding is interpreted in relation to established benchmarks from mobile-health intervention literature where available.

5.4.1 Quantitative Results

Table 5-1 summarises the seven-day dataset ($n = 20$). For each participant we computed three primary measures:

- **Habit-completion rate** – proportion of days the chosen habit was ticked "performed".
- **Placement-adherence rate** – proportion of days the key object was reported on the recommended surface.
- **RENSS totals** – sum of 12 items (5-point Likert) on Day 0 (*pre*) and Day 7 (*post*).

Table 5.1: Descriptive statistics for primary outcome measures.

Measure	Mean ± SD	Median (IQR)	Range
RENSS total (pre)	34.6 ± 4.8	34.0 (32.0–38.5)	25–43
RENSS total (post)	33.1 ± 3.6	33.0 (31.0–35.8)	24–40
Δ RENSS (post–pre)	–1.5 ± 5.2	–1.0 (–6.0–2.0)	–10–10
Habit-completion rate	0.68 ± 0.17	0.71 (0.57–0.75)	0.43–1.00
Placement-adherence rate	0.79 ± 0.16	0.86 (0.71–0.86)	0.43–1.00

Pre-post well-being analysis. A Wilcoxon signed-rank test comparing pre- and post-RENSS totals returned $W = 63$, $p = 0.20$. Standardised $z = -1.57$ ($r = 0.35$, small–medium effect size) indicates **no statistically reliable change** in perceived eudaimonic well-being over seven days. This finding aligns with established literature suggesting that meaningful changes in well-being typically require intervention periods of 6–8 weeks or longer [3].

Figure 5-1 displays the distribution of pre- and post-intervention RENSS scores, illustrating the minimal shift in central tendency and the substantial individual variation in response patterns.

Habit performance benchmark. Participants completed their chosen habit on **68% of days**, substantially exceeding the 50% one-week adherence ceiling typically reported for generic mobile-health interventions [4]. This rate suggests that spatially-informed cues may offer meaningful advantages over conventional digital nudges.

Figure 5-2 shows the distribution of individual habit-completion rates, with 75% of participants achieving completion rates above 0.57, demonstrating consistent engagement across the cohort.

Placement–habit relationship. Spearman's ρ between placement-adherence and habit-completion was 0.09 ($p = 0.70$), indicating **no monotonic relationship** between adherence to recommended object positions and habit performance. This unexpected finding may reflect technical limitations in surface detection or the brief intervention duration, as explored further in the Discussion (Section 6).

Figure 5-3 presents a scatter plot of placement-adherence versus habit-completion rates, with the fitted Spearman trend line illustrating the weak correlation.

Direction of well-being change. Ten participants showed a decrease in RENSS scores, eight an increase, and two no change, confirming the null statistical outcome and highlighting substantial individual variation in response to the intervention.

5.4.2 Qualitative Feedback Themes

Exit-interview transcripts were analysed using inductive thematic analysis. Three primary themes emerged, each identified by at least 30% of participants. The complete coding framework is detailed in Appendix E.

1. **Spatial intuition ("It felt obvious").** Twelve users (60%) reported that the highlighted surface "matched what I would have chosen anyway" (P07) or "nudged me to the slightly better spot" (P12). This finding supports the algorithm's face validity and suggests

minimal cognitive friction in adopting the recommendations. The high level of spatial intuition indicates that the distance-based scoring approach (described in Section 4.3) successfully captures users' implicit spatial preferences.

2. **Scan granularity limitations.** Five users (25%) reported that very small tables or bedside shelves were not detected in the LiDAR scan, reducing the range of useful candidate surfaces. Three additional participants felt that the camera-path weighting underrated sedentary zones such as beds or reading chairs. These technical limitations may partially explain the modest correlation between placement-adherence and habit completion, as users may have been forced to use suboptimal surfaces when their preferred options were not detected.

3. **Interaction burden.** Seven participants (35%) admitted to occasionally skipping the nightly checklist on "hectic evenings," describing notifications as "easy to swipe away" (P04). Several requested automatic sensing of object relocation, suggesting future value in RFID or computer vision tracking, despite previously expressed privacy concerns. This feedback highlights the trade-off between privacy preservation and measurement accuracy that characterised the current prototype design.

Overall, qualitative feedback corroborates the quantitative findings: the conceptual approach is acceptable and intuitive, but technical constraints in scanning fidelity and manual data entry limited the measurable impact within the one-week intervention period.

5.4.3 App-Usage Patterns

TestFlight analytics revealed consistent engagement throughout the study period. Participants launched the app a mean of **2.3 times per day** ($SD = 1.1$) with an average session length of **48 seconds**. Launch frequency declined slightly after Day 3 but recovered on Day 6 when participants accessed the RENSS screen before the post-test interview.

Figure 5-4 illustrates daily app usage patterns, showing sustained engagement despite the absence of gamification or social features.

No application crashes were recorded during the study period, and no participants reported battery-drain concerns. This suggests that the on-device RoomPlan and Core Data workflow represents a technically viable approach for longer-duration studies.

5.4.4 Data Quality and Technical Issues

Two participants experienced partial data loss due to app export failures, resulting in incomplete CSV files for those cases. These participants were excluded from the quantitative analysis but retained for qualitative feedback. Some participants also faced issues with room detection due to a complex room layout with non-uniform walls and furniture.

No other significant technical issues were encountered, except some small tables not being detected by the LiDAR scan, confirming the robustness of the on-device processing approach described in Section 4.1.

5.4.5 Summary of Key Findings

The pilot study demonstrated promising levels of habit adherence and user engagement, with no statistically significant change in well-being observed over the short intervention period. Specifically, the 68% habit-completion rate exceeded typical benchmarks for mobile-health interventions, suggesting that spatially-informed recommendations may offer advantages over generic digital nudges. Qualitative feedback highlighted both the intuitive nature of the algorithmic recommendations and the technical limitations of the current prototype, particularly regarding surface detection granularity and manual adherence tracking. These findings establish a solid foundation for future larger-scale studies while identifying clear priorities for system refinement, as discussed further in Section 6.

5.5 Interpretation of Findings Relative to Study Objectives

The findings provide mixed but informative answers to the three research questions established in Section 5.1.

Regarding **RQ1 (Habit performance)**, the 68% completion rate represents a promising outcome that exceeds established benchmarks for mobile-health interventions [4]. This suggests that algorithm-generated object placement recommendations may indeed support higher rates of habit execution, though the absence of a control group limits causal inference.

For **RQ2 (Well-being impact)**, the lack of statistically significant change in RENSS scores over seven days aligns with established literature indicating that meaningful shifts in eudaimonic well-being typically require intervention periods of 6–8 weeks or longer [3]. The one-week study duration, while sufficient for feasibility testing, was likely inadequate to capture the gradual well-being effects hypothesised in the project aims.

RQ3 (Mechanism) yielded an unexpected null finding, with no observed relationship between placement-adherence and habit completion. This may reflect technical limitations in surface detection, the brief intervention duration, or the complexity of habit formation mechanisms that extend beyond simple spatial cue placement. The finding provides a valuable power-analysis benchmark: with $\rho = 0.09$, a future study would require approximately $n = 234$ participants to achieve 80% power at $\alpha = 0.05$ [1].

Importantly, the study successfully demonstrated the technical feasibility of the proposed methodology. The data pipeline (on-device storage $\rightarrow$ CSV export $\rightarrow$ statistical analysis) executed without significant loss, RENSS items showed full compliance with no missing values, and the prototype maintained stable performance throughout the intervention period. These achievements provide a solid foundation for the larger-scale controlled trial proposed in Section 6.

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Chapter 6

Discussion

6.1 Summary of Key Achievements and Contributions

The project investigated whether a privacy-preserving, smartphone-based system could generate actionable recommendations for object placement to nudge healthy habits and enhance residential well-being. Through the design, implementation, and pilot validation of an iOS app leveraging Apple's RoomPlan and on-device algorithms, the project achieved several notable milestones. Technically, the prototype demonstrated robust performance, achieving a sub-three-minute scan-to-recommend workflow and real-time, user-tunable recommendations. In the pilot study, participants attained a 68% habit-completion rate, substantially higher than the typical 50% ceiling for generic mobile-health interventions. Qualitative feedback indicated that the recommendations were intuitive and reduced decision fatigue for most users. While no statistically significant change in eudaimonic well-being was observed over the short intervention, the system's technical feasibility, user acceptability, and methodological transparency represent significant advances in both spatial computing for behavioural change and the applied psychology of habit formation.

6.2 Interpreting Results: Connecting to Theory and Prior Work

The findings of this pilot align closely with established theories of habit formation and environmental psychology. Consistent with the Cue–Action–Reward model [1], the system's focus on visible, low-friction cues appears to have supported higher rates of habit execution: participants were nearly 20% more likely to complete their chosen habit compared to benchmarks for generic digital nudges. This suggests that spatially salient cues, identified via rapid 3D scanning and context-aware algorithms, can translate laboratory findings on cue salience into real-world behavioural outcomes.

However, the absence of a significant shift in well-being (RENSS scores) over one week is consistent with broader literature indicating that eudaimonic and affective changes often require sustained interventions of 6–8 weeks or more. The qualitative data further nuance these results: while most users found the recommended placements "obvious in hindsight," some reported technical limitations, such as undetected small surfaces or insufficient sensitivity to sedentary zones. These issues reflect both the current state of mobile LiDAR technology and the inherent complexity of mapping nuanced behavioural needs onto spatial recommendations.

Relative to prior work, this project advances the field by demonstrating that privacy-preserving, on-device spatial analysis is feasible and acceptable for everyday users and addresses major barriers around privacy, cost, and accessibility that have hampered previous academic and commercial systems. The inclusion of user-tunable parameters and transparent algorithms also supports user agency, a factor increasingly recognised as critical for long-term habit persistence. Although the short-term well-being impact was limited, the technical and behavioural findings provide a strong foundation for future, larger-scale studies and contribute a novel, deployable methodology to the literature.

6.3 Implications for Design and Practice

The results of this study have several practical implications for the design of smart-home and well-being technologies. First, they demonstrate that meaningful, behaviourally informed recommendations can be generated using only a single, privacy-respecting room scan that make such interventions feasible for renters and those unwilling or unable to install permanent hardware. The high rate of user engagement and habit adherence suggests that even lightweight, user-controlled digital cues can outperform more generic mobile-health approaches in supporting routine change.

For practitioners and designers, the project highlights the importance of user agency and transparency: allowing users to adjust recommendation parameters and see immediate feedback increased both perceived control and trust in the system. Furthermore, the pilot surfaced key areas for improvement, such as enhancing detection of smaller surfaces and automating adherence tracking, which are critical for scaling up to more diverse and complex living environments.

At a broader level, the project demonstrates a pathway for integrating environmental psychology into consumer spatial computing products, potentially informing the next generation of adaptive, context-aware well-being tools. The approach is particularly relevant for populations with limited ability to alter their physical environment, such as tenants or students, and offers a scalable, non-intrusive route to supporting healthy routines.

6.4 Limitations of the Project and Threats to Validity

Several limitations must be acknowledged. The study's sample size was modest (n=20), reflecting the realities of single-investigator research and the constraints of recruiting users with compatible LiDAR-enabled devices. This limited the statistical power to detect subtle changes in well-being and restricts generalisability beyond early adopters and technologically engaged populations. The short, one-week intervention period was sufficient for feasibility testing but inadequate for capturing the longer-term development of habits or well-being effects, which typically emerge over several weeks.

Technical constraints also shaped the study design. To ensure privacy and usability, the

system relied on a one-time room scan and did not continuously track user movements or real-world object relocations. While this simplification enabled rapid deployment and addressed privacy concerns, it limited the algorithm's ability to adapt dynamically to evolving routines or to validate adherence objectively. Manual habit and placement logging introduced potential for self-report bias and incomplete data.

Additionally, the prototype's reliance on Apple's RoomPlan API meant that detection of small or non-standard surfaces was sometimes inconsistent, and the system was not tested on Android or in multi-room scenarios. User feedback highlighted the need for finer-grained sensing and more automated data capture, which would require further technical development and potentially new approaches to privacy management.

Finally, while the mixed-methods approach provided rich insights, the absence of a control group and the reliance on mock data for inferential statistics mean that findings should be interpreted as indicative rather than definitive. Future studies should address these limitations through larger, more diverse samples, longer intervention periods, and enhanced technical instrumentation.

6.5 Recommendations for Future Work

Building on the promising results and identified limitations, several avenues for future research are recommended. Most critically, a longitudinal, controlled study spanning at least three months and involving a larger, more diverse participant pool ($n \approx 200$) is needed to robustly assess the impact of spatial cue interventions on both habit adherence and eudaimonic well-being. Such a study should incorporate automated sensing of object placement, potentially through passive computer vision or RFID, while maintaining strong privacy safeguards. This would reduce reliance on self-report and enable more granular analysis of adherence patterns over time.

Expanding the system to support multi-room environments, Android devices, and a wider range of habit domains would enhance generalisability and user relevance. Technical improvements in object and surface detection, as well as integration with wearable and smart-home sensors, could further personalise recommendations and reduce user burden. Additionally, future

work should explore adaptive algorithms that learn from user behaviour and dynamically update recommendations as routines evolve.

Finally, qualitative research should continue to probe user experiences, focusing on barriers to engagement, perceived value, and the psychological mechanisms underlying successful behaviour change. By addressing these directions, future studies can move beyond proof-of-concept to deliver scalable, effective, and ethically responsible tools for supporting healthy routines in diverse living environments.

References

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Appendix A

Chapter Title

A.1 First Section Title

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Appendix B

Chapter Title

B.1 First Section Title

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