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GK - Keerthana Govindarazan

Research Projects

1-1-2026

Projects inside:

1. Synthetic Participants for qualitative interview study
2. AI on Phone vs PC
3. Photo Memory Suggestions
4. VR behavioral evaluation

LLM-Generated “**Synthetic Users**” for Qualitative Research — A Validation Protocol

Keerthana Govindarazan* (Ideation, Lit Review, Protocol Development, Coding)

Hui Min Lee* (Lit Review, Protocol Development, Coding)

Temilade Adeeko* (Literature Review)

*PhD Student, Penn State, USA

UX and market research teams are starting to use LLM "synthetic users" for interview studies to derive product-related insights

<u>But there is need to evaluate systematically:</u>

1. which LLM configuration settings affect interview response quality

2. how personas should be created

3. when LLM-generated interview data is useful vs misleading

Research Questions

RQ1 — Configuration & Response Quality

How do differences in LLM configuration settings (model, temperature, API vs consumer platform, zero-shot vs few-shot memory) and interview method (LLM-moderated interviewing vs human interviewing vs LLM-generated themes and quotes) affect the depth, coherence, and realism of synthetic interview responses?

RQ2 — Persona Design

How does the level and type of persona detail (explicit demographic traits vs context-rich backstory) influence contextual nuance, bias, and stereotyping in interview responses?

RQ3 — Research Use-Cases

Under what conditions are LLM-generated interview transcripts useful for exploratory or ideation-focused research—and when do they become misleading or unsuitable as substitutes for human participants?

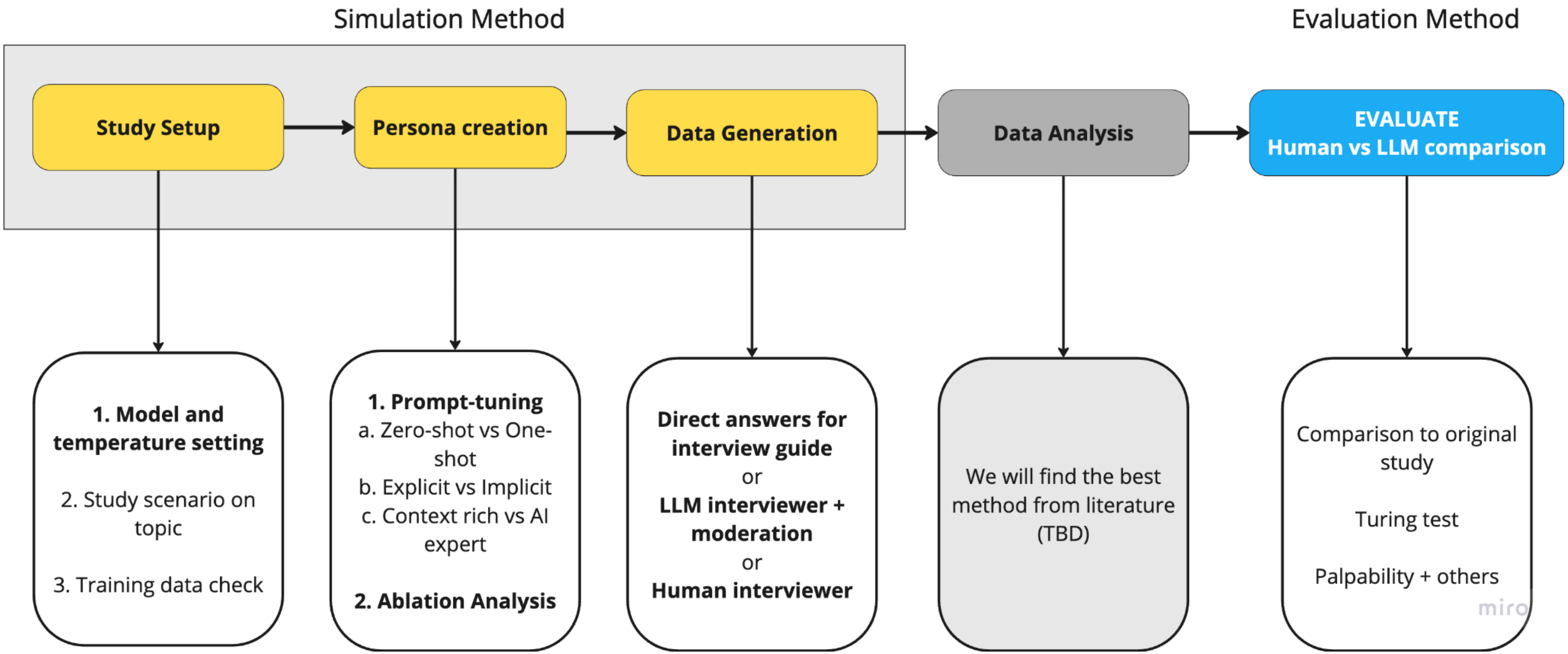
Method (in-progress)

I replicate published HCI qualitative interview studies

Generate LLM interview transcripts by systematically varying LLM settings & persona conditions and benchmark against human interview results

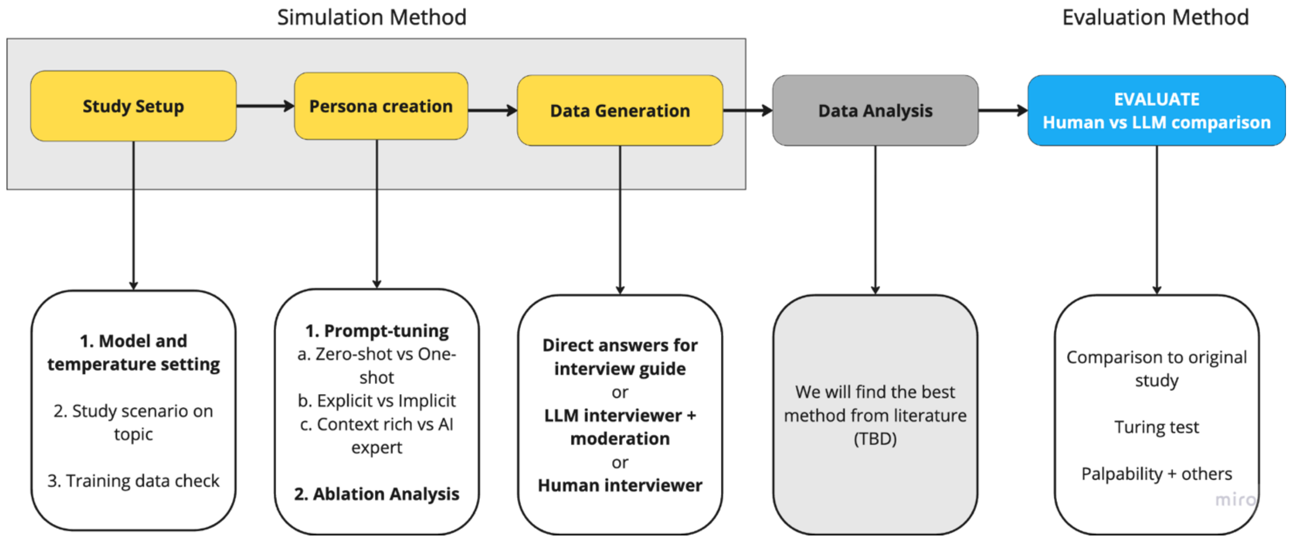
Goal: To understand how each configuration changes the quality of insights produced.

Protocol to be tested



Key LLM Configuration Factors

- **Zero-Shot vs Few-Shot vs Platform Memory**
  - whether transcript history shapes persona consistency
- **Explicit vs Implicit Personas**
  - demographic traits vs context-rich identity cues
- **Human Interviewer vs LLM Interviewer + Moderator**
  - probe behavior & response adaptation
- **LLM-as-Subject vs LLM-as-Expert**
  - simulate respondent vs summarize themes
- **API vs Consumer Platform**
  - accessibility trade-offs for non-technical researchers



UX Research Impact

This protocol will help teams:

- decide when LLM interview data is appropriate
- understand what different LLM setups are good for
  - ideation & early exploration
  - scenario prototyping
  - rapid hypothesis testing
- identify risk points:
  - stereotyping
  - loss of contextual depth
  - persona drift
  - saturation concerns and non-meaningful insights
- choose LLM configurations based on intended research purpose

```python
# ==============================
# 1) CONFIG OBJECTS & TYPES
# ==============================
PersonaStrategy = Literal["zero_shot_explicit","few_shot_explicit","implicit_context_rich"]
RoleMode = Literal["llm_as_subject","llm_as_expert"]
InterviewerMode = Literal["human_interviewer","llm_interviewer","llm_interviewer_with_moderation"]
FewShotMemoryMode = Literal["summary","full"]

@dataclass
class ModelConfig:
    model: str = "gpt-4o-mini"  # EDIT model
    temperature: float = 1.0    # EDIT temperature
    seed: Optional[int] = 42    # EDIT - helps reproducibility when supported

#study and method setup
@dataclass
class StudyConfig:
    project_name: str = "llm_interview_study1"              # EDIT project name
    today_str: str = datetime.now().strftime("%B %d, %Y")
    threshold: int = 80                                      # EDIT threshold to activate probe question
    max_probes_per_question: int = 1                         # EDIT number of probes
    persona_strategy: PersonaStrategy = "zero_shot_explicit" # EDIT study method
    role_mode: RoleMode = "llm_as_subject"                   # EDIT study method
    interviewer_mode: InterviewerMode = "llm_interviewer"    # EDIT study method
    few_shot_memory_mode: FewShotMemoryMode = "summary"      # EDIT study method. summary/full.
    out_dir: str = "./runs"                                  # EDIT where the output is stored - filepat
    run_notes: str = "Pilot test with zero-shot persona"     # EDIT put in any notes about the run to be

#persona variables
@dataclass
class Persona:
    name: Optional[str]
    demographics: Dict[str, Any]
    implicit_context: Optional[str] = None

#interview topic
@dataclass
class InterviewGuide:
    topic: str
    questions: List[str]
    # note: probes are now DYNAMIC (no templates); keeping type for compatibility
    probes_library: Dict[str, List[str]] = None

# cost per response
# Optional: token->cost estimates (fill with your real prices per 1K tokens)
PRICE_USD_PER_1K = {
    "gpt-4o-mini": {"prompt": 0.00015, "completion": 0.00060},  # EDIT with actual pricing if desired
}
```

One AI, Two Contexts — Rethinking AI-UX Across Phone and PC

Keerthana Govindarazan* (Ideation, Data Collection, Data Analysis)

Chaehyeon Lim** (Ideation, Data Collection, Data Analysis)

Jungwoo Jang** (Data Collection, Data Analysis)

*PhD Student, Penn State, USA
** PhD Student, Interaction Science Dept, Sungkyunkwan University, Seoul, South Korea

Gen AI chatbots often use the same interface across phone and desktop

But device context may change:

- task type
- trust & verification behavior
- perceived AI persona

Do users relate to and use the same AI differently on phone vs PC?

How should cross-device UI design reflect those differences?

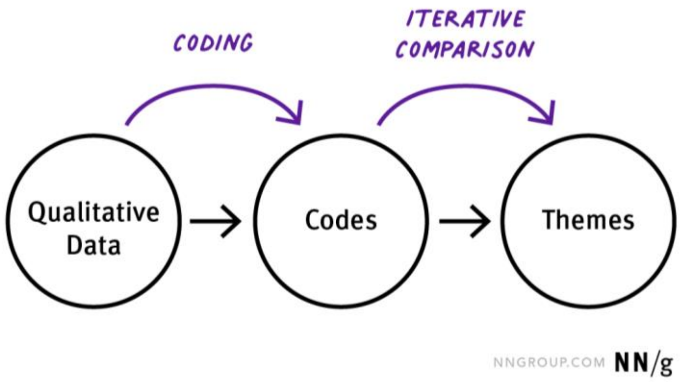
Background

LLM-powered chatbots like ChatGPT are used on both desktops & smartphones.

(Bröhl et al., 2018)	**Users use phones primarily for social connection but PCs for work**
(Vincent, 2013)	**Users perceive phones as personalized social robots or emotional companions.**
(Tang & Hew, 2022)	**Users experience greater social connectedness using phone apps than PC apps.**
(Liao et al., 2023)	**Additionally, users pay lesser attention to information on their phones and show lower skepticism toward misinformation compared to PC use.**

Method

Thematic Analysis



Interview study (n=10)

Participant recruitment via Cloud Research Connect. Interview conducted on Zoom. Interviews conducted till we reached saturation.

Inclusion criteria: Have experience using platforms like ChatGPT, Claude on phone and PC.

Thematic analysis

Participant Recruitment

CloudResearch®

Thematic Analysis

Phone → personal, lightweight, in-the-moment tasks
"On my phone it feels like messaging a nerdy friend."

Laptop → structured, professional, analytical work
"On the computer it's more like a teacher or co-worker."

Phones = skimming, fewer checks
"I don't double-check unless it's serious — on my phone it's casual."

Laptops = deeper reading & source checking
"On my computer I click sources — on my phone I just read and move on."

Mobile personas suggest social proximity but **emotional attachment was not explicit** in the data
→ possible **intimacy–skepticism gap.** A survey study is planned as the next step.

Design Takeaways

Support task migration across devices

– "continue on desktop" feature, bookmarks, and resume-task reminders.

Acknowledge device-shaped personas

– AI chatbot on phones = conversational & personal

– AI chatbot on desktops = analytical & task-oriented

→ opportunity for context-aware UX and task-support rather than uniform designs.

Design for trust on mobile

– lighter-weight source previews, citation pop-outs, & verify-later reminders

– reduce friction without burdening quick tasks.

– Support skimming on phones without losing accuracy (key-points, expand-for-details, clearer formatting)

Exploratory Survey study - RQs (in-progress)

RQ1

Uses and Persona

How does user interaction with LLM-based chatbots differ between mobile phones and desktop PCs, in terms of **use cases and perception of chatbot persona?**

RQ2

Emotional Attachment

Are users more **emotionally attached** to their chatbots on their phones compared to PCs?

RQ3

Susceptibility to AI Hallucinations

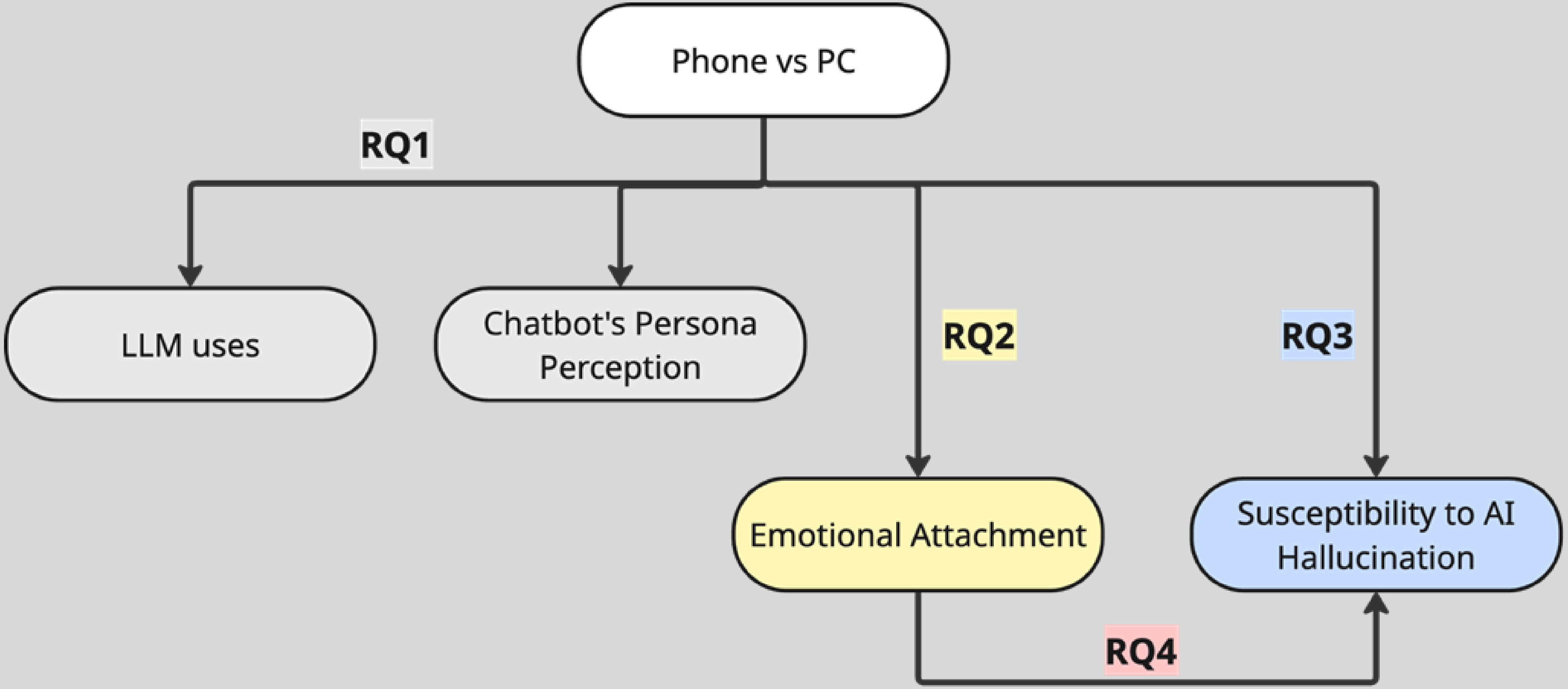
Are users more **susceptible to AI hallucinations** when interacting with LLMs on P vs PC?

RQ4

Emotional Attachment -> Sus. to AI Hallucinations

Does this **emotional attachment make users less vigilant** toward AI response?

Visual RQs for Exploratory Survey study (in-progress)



UX of Photo Memory Feature

Keerthana Govindarazan* (Ideation, Study design, Data collection, Analysis)

Kumari Davis* (Study design, Data collection, Analysis)

Soumika Mukerjee* (Data collection, Analysis)

*PhD Student, Penn State, USA

You have a new memory!

Problem: Algorithms tell us when to remember the past and what to remember!

How are users experiencing these memory recalls?

Goal: Identify design opportunities for more supportive memory experiences.

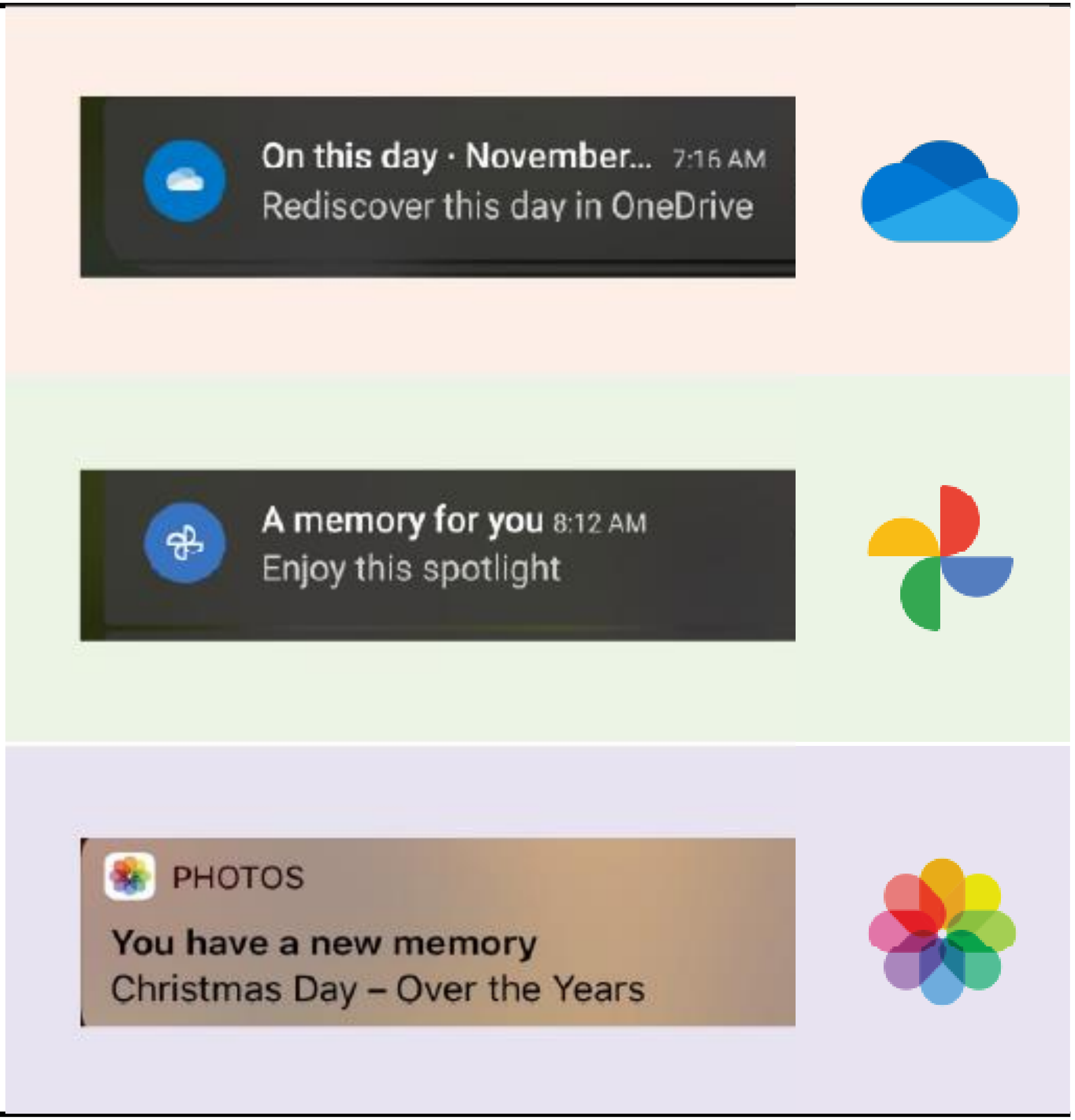
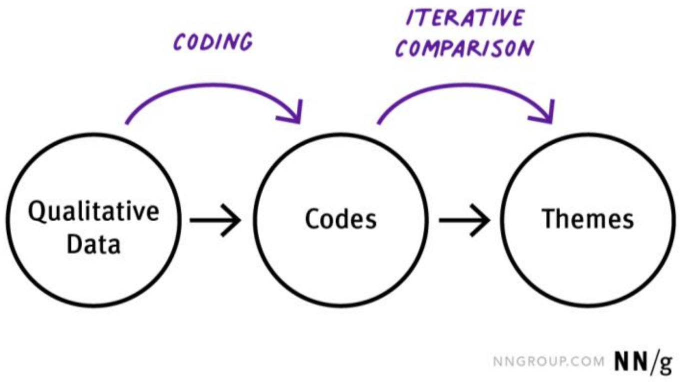


Image generated with GPT-5.1

Research Questions

1. Why do people **engage** with these photo-memory notifications?
2. What **gratifications** do they experience?
3. How do these memories influence **behavior** (photo taking, sharing, planning social events etc.)?
4. How does these memories affect users' psychological **well-being**?

Thematic Analysis



Mixed-Method Study

1. **7 in-depth interviews** (female 6, mean age = 28.66 yrs) → snowball Sampling
2. **Thematic Analysis** → Identified user experience/gratifications and common uses cases
3. **82-participant surve**y (female = 40, mean age = 35.5 yrs) → validated patterns & behavioral outcomes
4. **Multiple Linear Regression analysis** → identified predictors of engagement.

Survey design

qualtrics XM

Participant Recruitment

CloudResearch

Statistical Analysis

jmp STATISTICAL DISCOVERY

Interview Study - Results

Gratifications

Nostalgia
Convenience in organizing 10k photos
Social Interaction gratifications
Entertainment benefits
Escapism
Reflection on the past

Behavioral and Psychological Outcomes

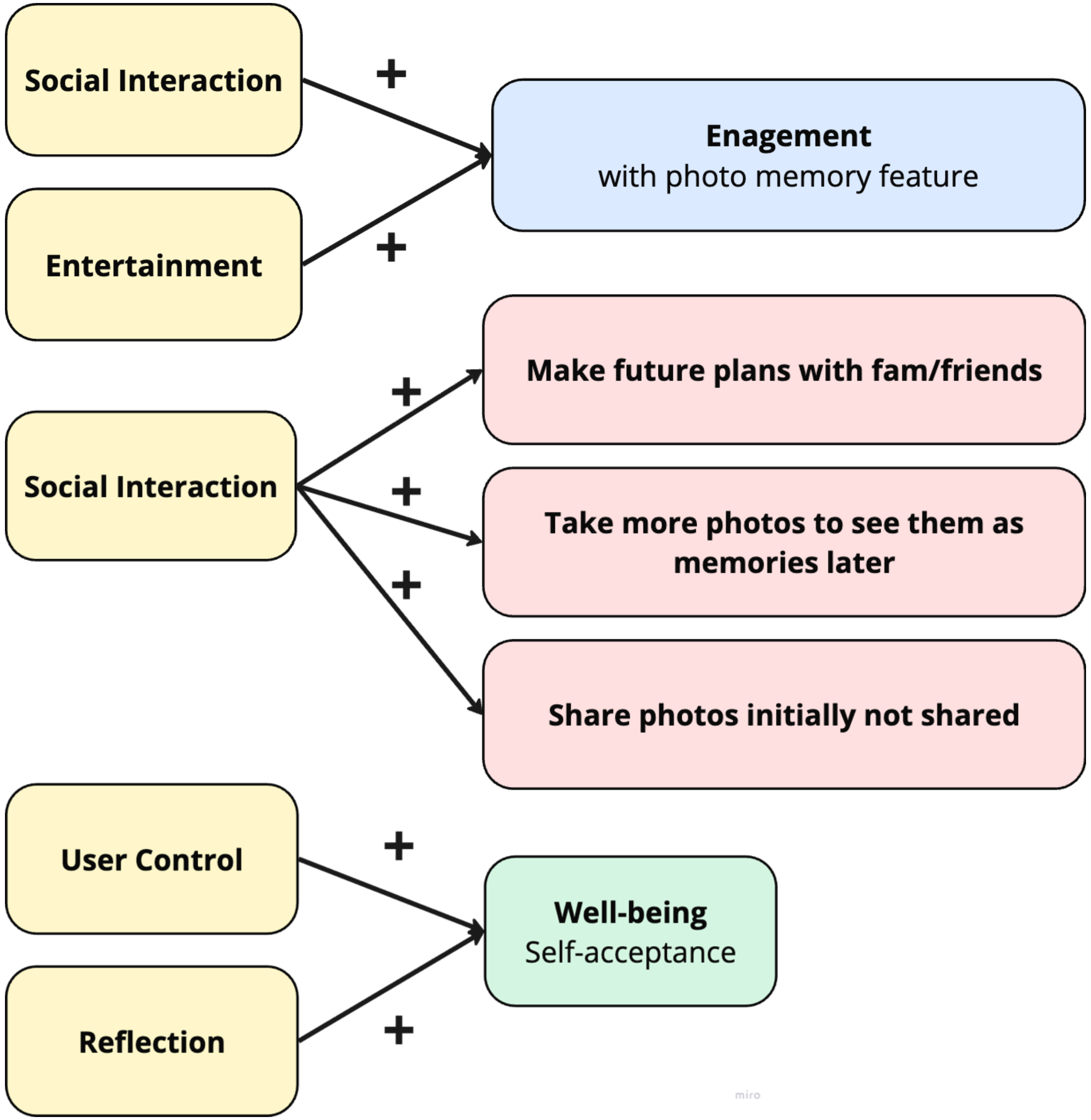
Intention to capture more photos
Intention to share unshared photos
Make plans with friends and family
Self-acceptance

Survey Results

Engagement with this photo memory feature is predicted by the gratifications of social interaction and entertainment.

Social interaction is the responsible for downstream behavioral outcomes.

Having control over the timing and content of this feature and self-reflection overall leads to user well-being.



Design Takeaways

Memory features should balance reflection, autonomy, and social connection — supporting both engagement and user well-being.

Design for social connection to drive engagement

1. Surface socially meaningful clusters (people, relationships, shared events)
2. Enable co-memory features where users can invite friends to comment on memories.
3. Make sharing easy and provide new forms of content for entertainment and more social engagement.

Support emotional well-being through control

1. Let users choose when and what resurfaces
2. Provide “not now / hide similar memories / mute themes” options more clearly visible and not hidden away

Interview study

Sample Questions:

1. What 5 words describe what you enjoy about viewing/using photo memories notified by your phone?
2. Are there any specific benefits you receive from receiving memory notifications?
3. What uses of photo memory notifications are most important to you?
4. How do you think your phone's memory notifications influence your behaviors? Behavior we mean photo sharing, photo curating, photo taking)

Thematic Analysis of Participant responses

"I quickly open it. It will be first thing in the morning." P1

"Thematic arrangement of photo by the AI interests me." P6

"Zoom into faces- see changes over time." P4

"I am reminded that life goes fast when I look at the photo memories in the photo memory suggestions." **P7**

"I have lot of friends from a lot of countries. I sends these photos and talk to them" **P2**

"Photo memory notifications are a new form of entertainment for me." P2

"I like it when the photo memory suggestions curates a new album that I would not think of doing myself." P3

"Only negative memories make me feel bad for split second." P5

"Casual and non serious photo curation and titles are enjoyable for me" P8

"I don't have control over when I receive the notifications. Sometimes photo memories are pushed at the wrong time. I want control over when I receive my memory notifications." **P1**

"Sometimes I ignore the notifications. I open the notifications based on my mood." P9

"I am teaching the app to recognize faces and people and force it to create collages for them." P5

***"I share the photo memories to my friends.
I make plans for future with my friends/family to recreate the moments in my photo memories.
I correct how I take photos after looking at my old photos from photo memories.
Some photos seem insta worthy when I look back on it through the photo memory notifications.
I share of the photos I did not share when I took the photo." P2***

"Encourages me to take more photos to see more funny TITLES." **P8**

Online Survey Study

Sample Measures - Likert type questions

Engagement: I would quickly open the suggested memory.

Social Interaction: Photo memory suggestions allow me to stay in touch with my family/friends.

Entertainment: Algorithmically generated titles of notification entertain me. g) I enjoy the thematic arrangement of the photos.

Reflection: The memory notifications/photo memories make it easy to see how much I have changed.

User Control: I can customize the feature to fit my needs (e.g., disable memories of a specific person.

Behavioral Outcomes: a) The memory suggestions lead me to make plans for the future with my friends/family to recreate past moments. d) I improve how I take photos after looking at my old photos from photo memories. e) I find myself taking more photos because of these memory suggestions. f) I share the photos I did not share when I initially took the photo.

Analysis: Regression analysis controlling for age, gender and general tendency to interact with photos (n = 82).

Restaurant Design with VR Behavior Testing

Keerthana Govindarazan*

*PhD Student, Penn State, USA

Restaurant Design using VR Behavior Testing

Problem:
The built environment shapes our emotions and behavior.

Given this, can we design restaurants to foster healthy eating behaviors?

Goals:
To test how design affects emotions and behavior.

To test if VR usability for eating behavior testing.

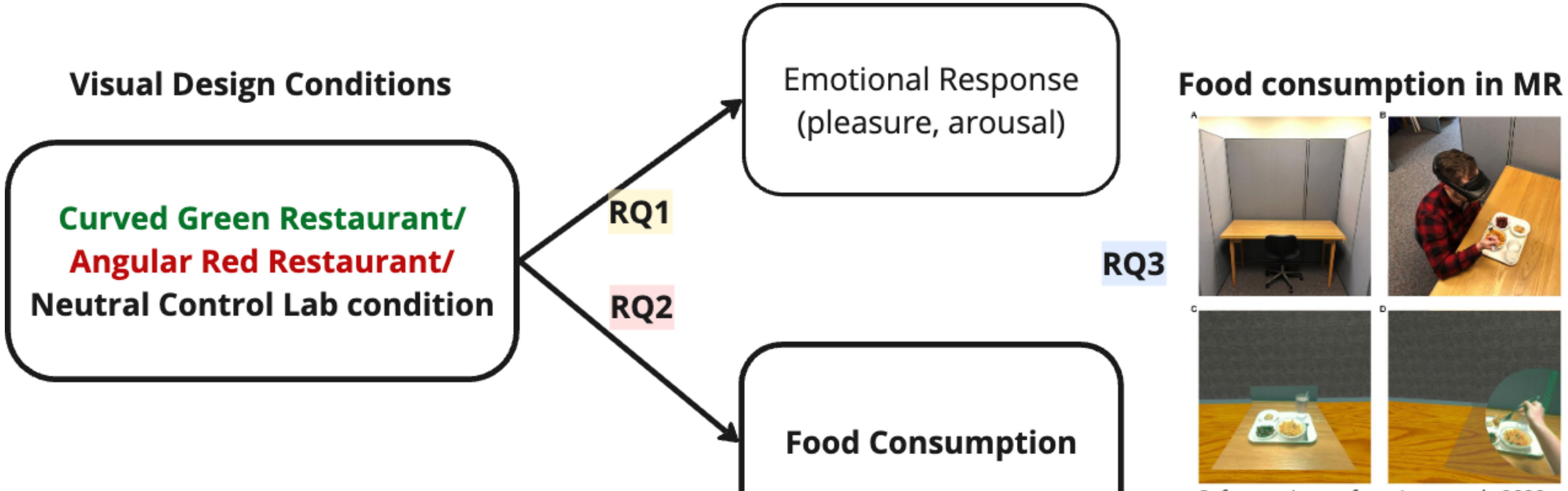
Image generated with GPT-5.1

Research Questions

RQ1 — Design Impact on Emotion: How does restaurant visual design affect emotional responses?

RQ2 — Design → Eating Behavior: Does restaurant design affect eating behavior (food consumption)?

RQ3 — VR Usability: Is mixed-reality VR a valid and usable method for studying eating behavior?



Reference image from Long et al., 2023

Method

Within-subjects VR experiment.

- 3 conditions – green curved, red angular, neutral lab (control).

VR Pilot lab study (n = 20).

- Convenience sampling.
- 3 visits each = 60 visits.
- SPSS analysis – t-test, Anova, Linear mixed models

Before the VR study:

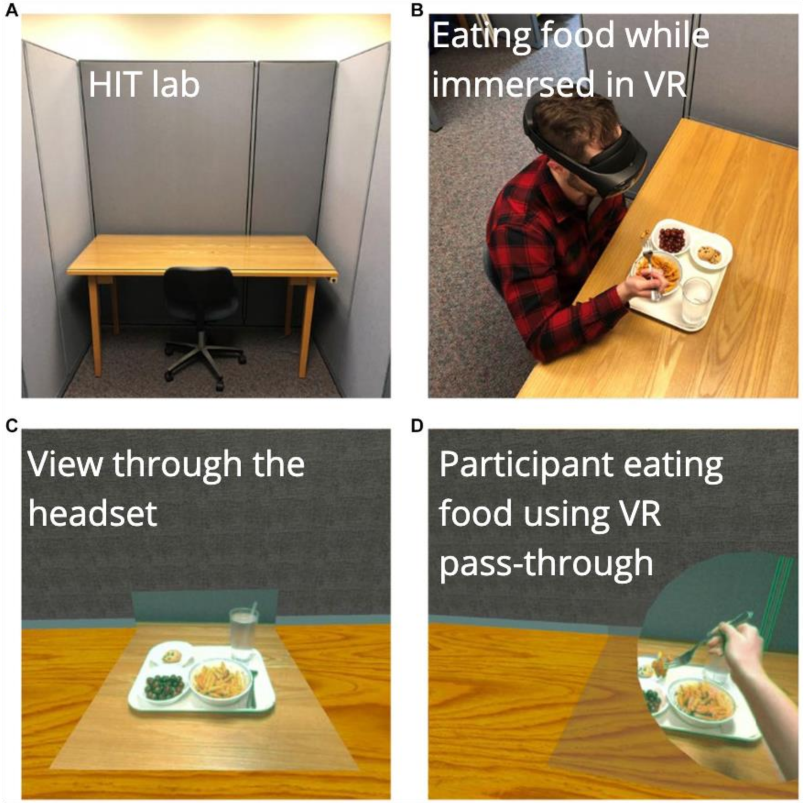
Online pre-test (n=83) → VR visual stimuli validation

Pilot VR Experiment

All three virtual restaurant environments were built in Unity and optimized for Meta Quest Pro. **The spaces were designed for seated, first-person dining to align with participants' real-world posture in the lab (see below).**

Data Collection Setup

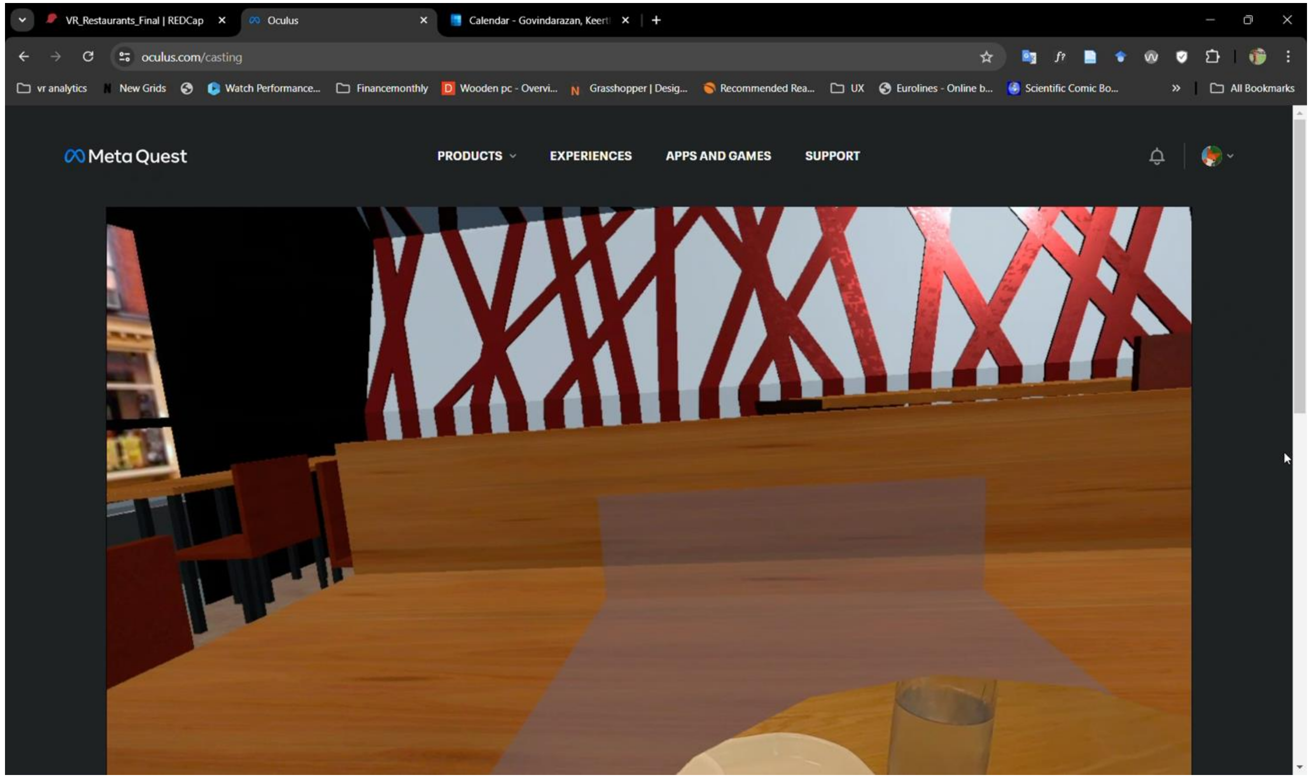
Food consumption in MR



Reference image from Long et al., 2023

miro

Participant POV - Red Angular Environment



Key Takeaways (Results from linear mixed models using SPSS)

RQ1 — Design Impact on Emotion: NEGATIVE EMOTIONS ARE SHAPED BY SPATIAL DESIGN.

Angular red restaurant increased users' negative effect.

Familiarity, not design, predicted positive affect.

RQ2 — Design → Eating Behavior: NO IMPACT

No significant environmental effect on intake

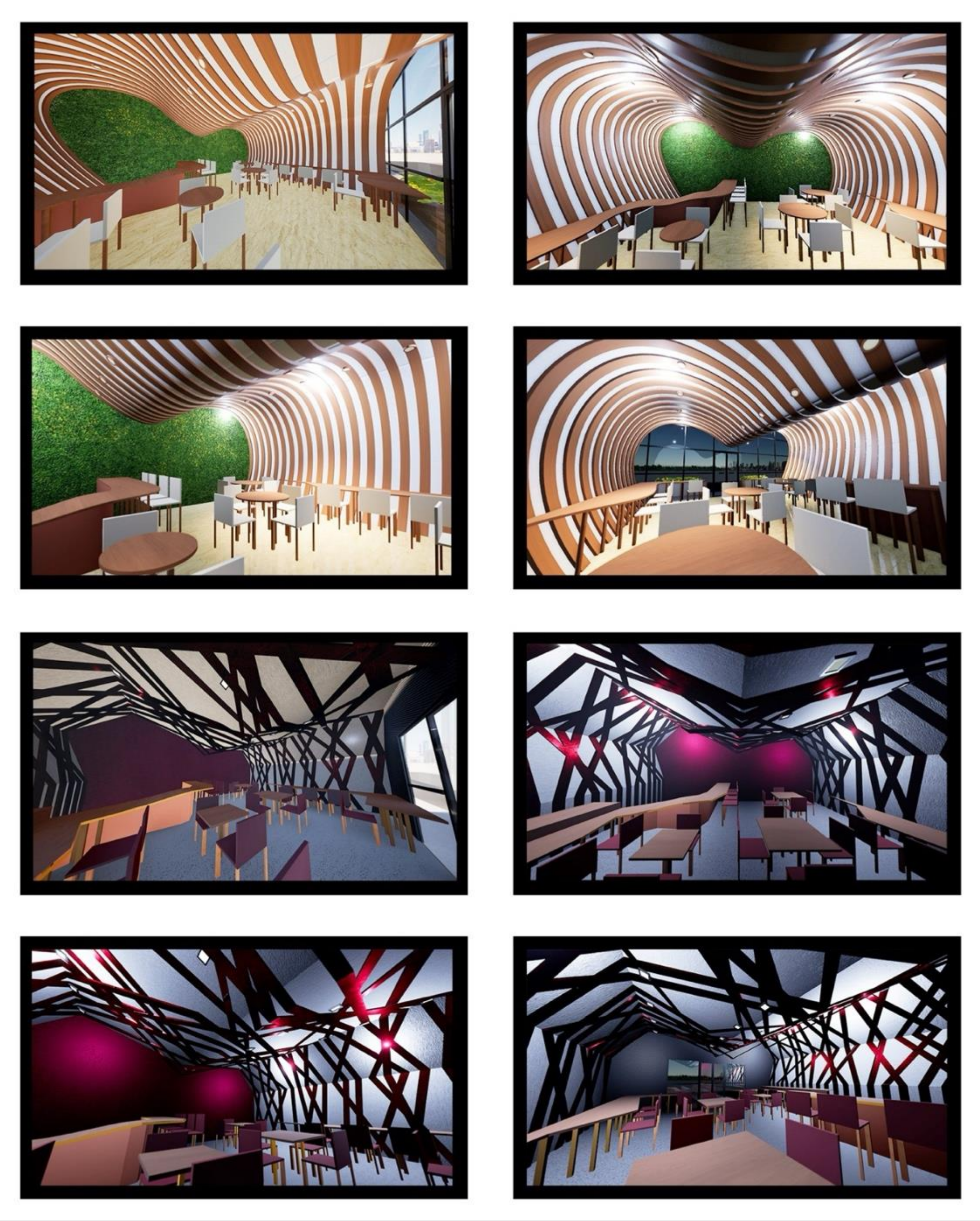
Slight trend: Angular Red > Curved Green > Control

RQ3 — VR Usability: FOOD CONSUMPTION DEPENDS ON VR USABILITY – NEEDS IMPROVEMENT

High Realism ratings reflected - VR restaurant felt believable, and realistic – Supports tool Usability

Natural Interaction scores (a usability measure) predicted food intake. High variability in this score.

⇒ Technical friction (hand-tracking, lag, headset comfort) disrupted the eating experience – Needs refinement.



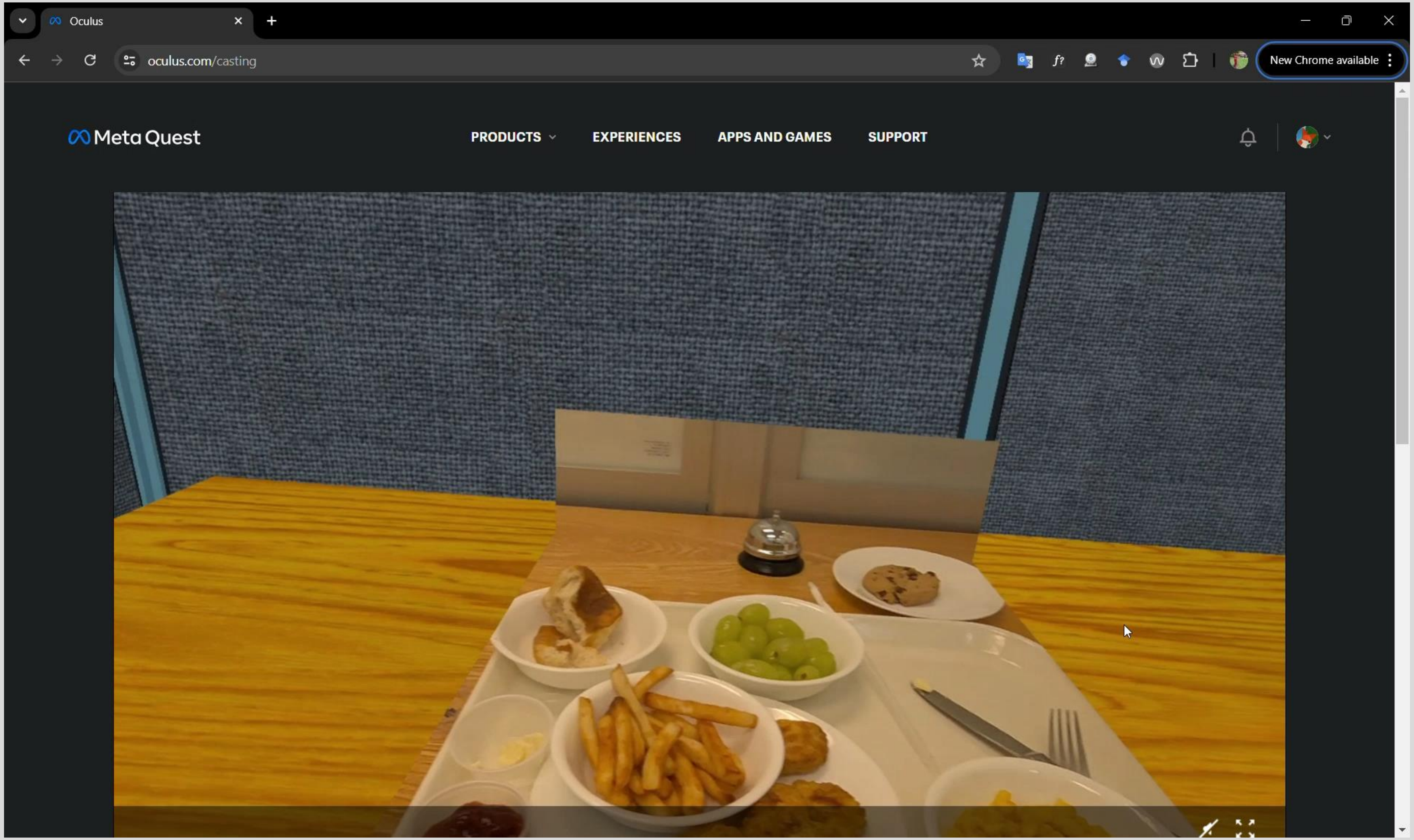
Pre-test

Online study (n=83); Cloud Research Connect

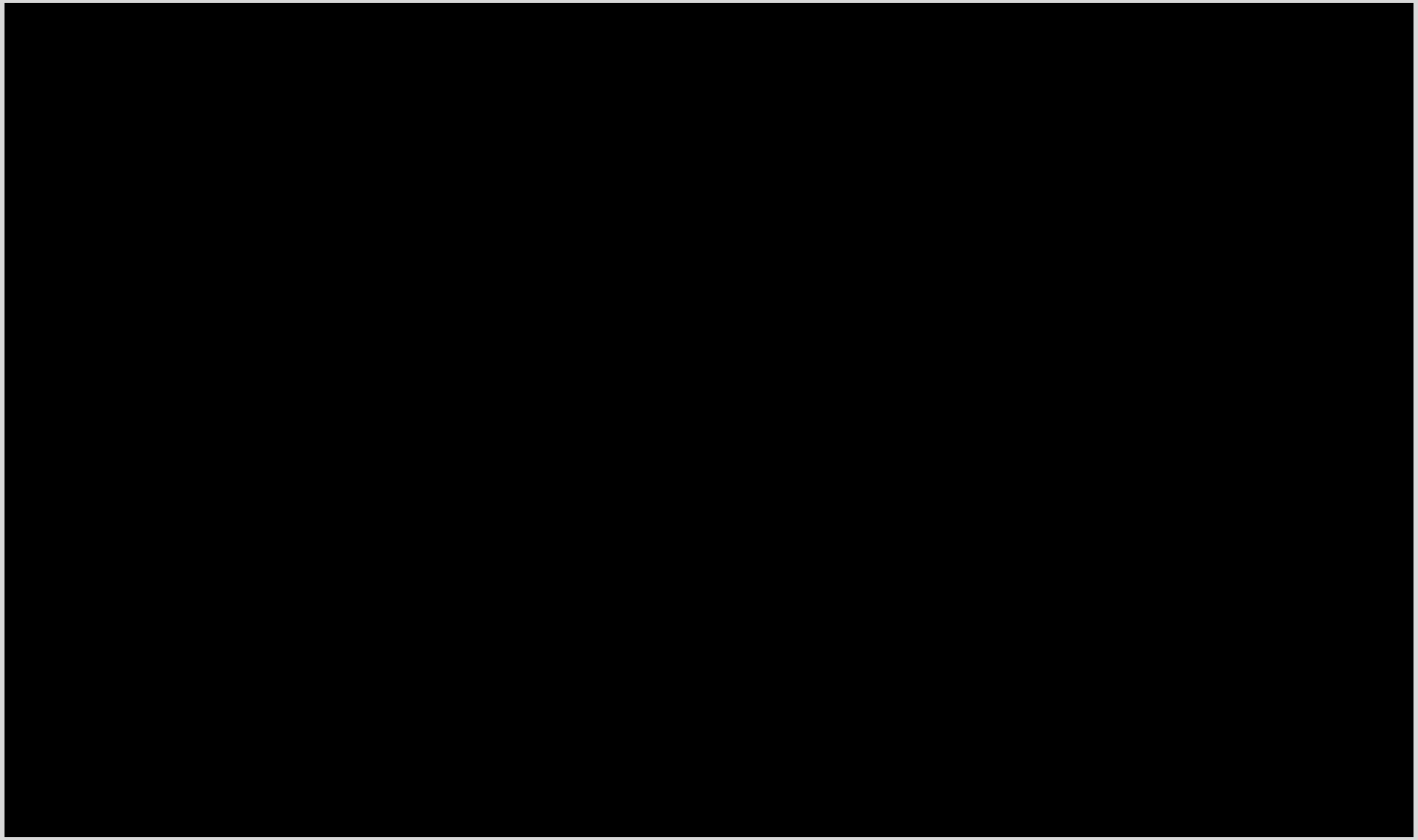
Roof form, colour, and spatial quality differed significantly across Green and Red environments.

Measure	Curved Green (M)	Angular Red (M)	Statistic
Roof form (Curved vs. Angular)	8.35	2.54	$t(82) = 20.37$, $p < .001$
Spacious vs. Narrow	6.02	4.49	$t(82) = 5.11$, $p < .001$
Familiar vs. Unfamiliar	5.02	3.92	$t(82) = 3.32$, $p = .001$
Simple vs. Complex	4.75	3.54	$t(82) = 3.82$, $p < .001$
Ordered vs. Chaotic	5.86	4.29	$t(82) = 4.46$, $p < .001$
Harmonious vs. Not Harmonious	6.19	4.46	$t(82) = 5.16$, $p < .001$
Symmetrical vs. Asymmetrical	5.04	3.75	$t(82) = 4.11$, $p < .001$

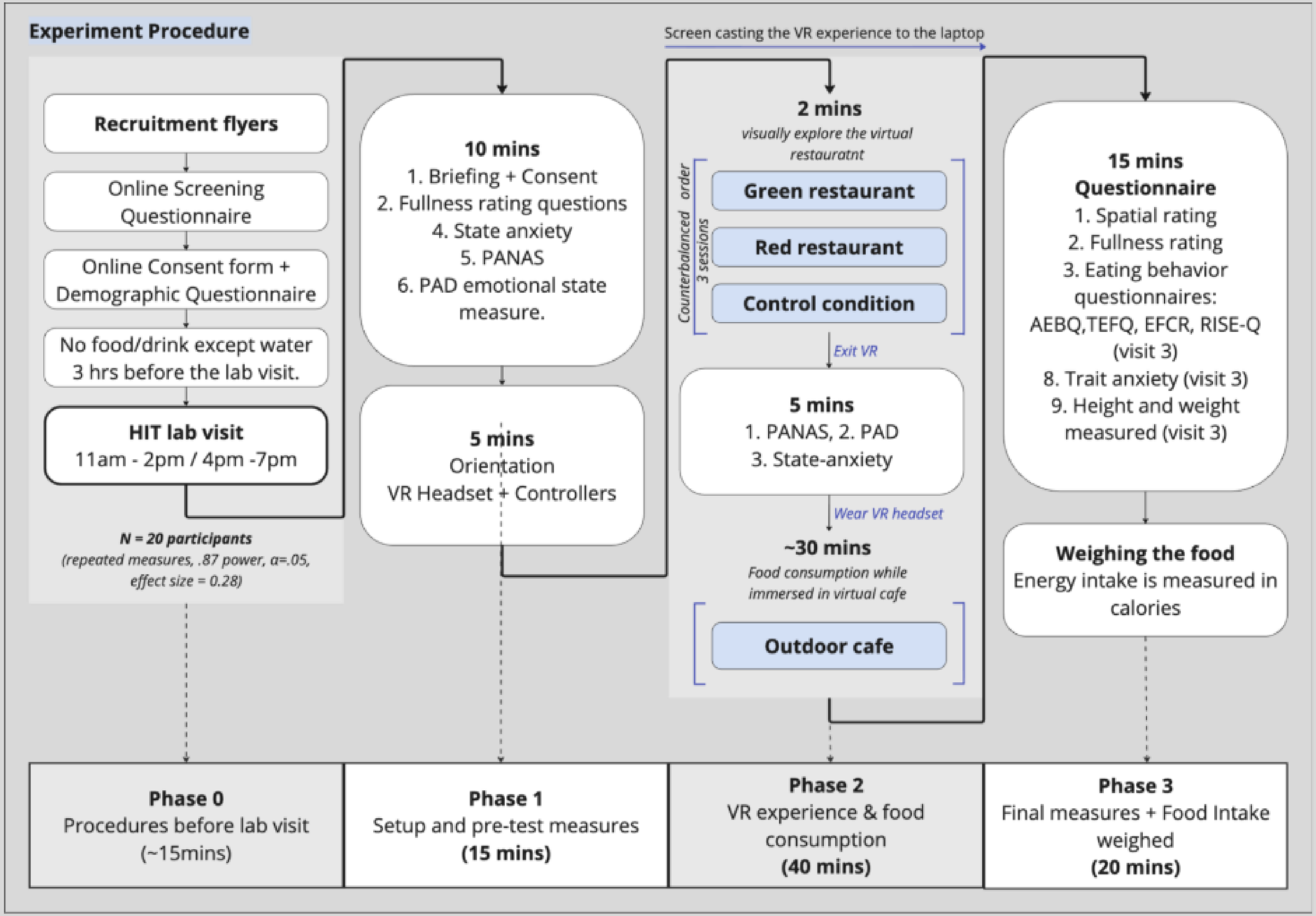
VR LAB STUDY: Participant POV – Neutral Lab Environment



VR LAB STUDY: Participant POV - Green Curved Environment



Additional Information



VR LAB STUDY Procedure

<u>Sample Measures:</u> Emotional and Affective States

Positive and Negative Affect Schedule (PANAS)

20 emotion adjectives (10 positive, 10 negative) rated on a 5-point scale (1–5).

Example items: interested, excited (positive); distressed, upset (negative).

Scores averaged to form Positive Affect and Negative Affect subscales.

Pleasure–Arousal–Dominance (PAD; Mehrabian & Russell, 1974):

18 bipolar adjective pairs on 9-point scales (–4 to +4).

Example pairs: unhappy–happy (pleasure), excited–calm (arousal), controlled–in-control (dominance).

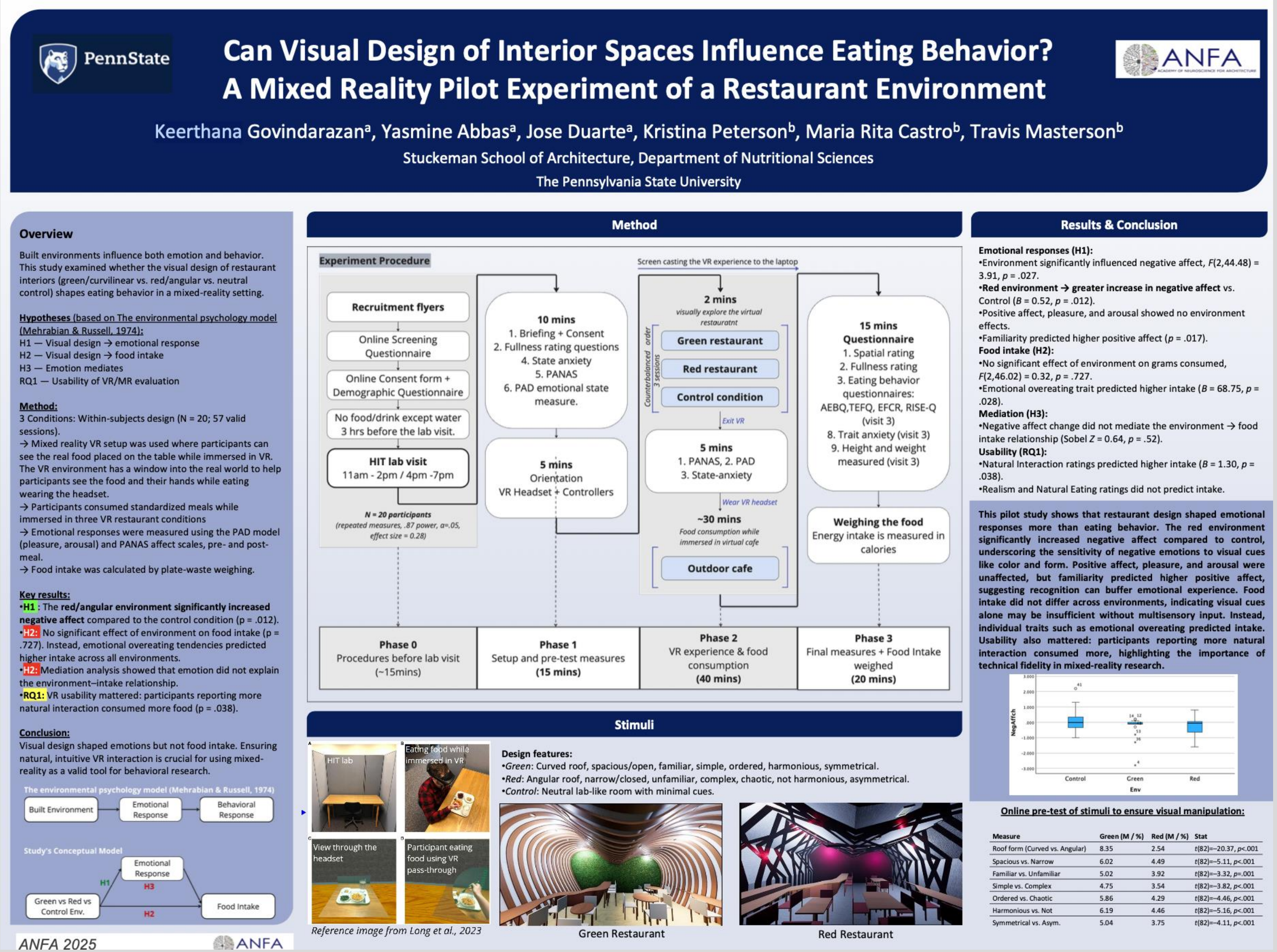
Six items per dimension averaged to yield Pleasure, Arousal, and Dominance scores.

Additional Information

Presented at

ANFA 2025

Academy of Neuroscience For Architecture



Can Visual Design of Interior Spaces Influence Eating Behavior? A Mixed Reality Pilot Experiment of a Restaurant Environment

Keerthana Govindarazan[a], Yasmine Abbas[a], Jose Duarte[a], Kristina Peterson[b], Maria Rita Castro[b], Travis Masterson[b]
Stuckeman School of Architecture, Department of Nutritional Sciences
The Pennsylvania State University

Overview

Built environments influence both emotion and behavior. This study examined whether the visual design of restaurant interiors (green/curvilinear vs. red/angular vs. neutral control) shapes eating behavior in a mixed-reality setting.

Hypotheses (based on The environmental psychology model (Mehrabian & Russell, 1974):
H1 — Visual design → emotional response
H2 — Visual design → food intake
H3 — Emotion mediates
RQ1 — Usability of VR/MR evaluation

Method:
3 Conditions: Within-subjects design (N = 20; 57 valid sessions).
→ Mixed reality VR setup was used where participants can see the real food placed on the table while immersed in VR. The VR environment has a window into the real world to help participants see the food and their hands while eating wearing the headset.
→ Participants consumed standardized meals while immersed in three VR restaurant conditions
→ Emotional responses were measured using the PAD model (pleasure, arousal) and PANAS affect scales, pre- and post-meal.
→ Food intake was calculated by plate-waste weighing.

Key results:
•**H1** : The **red/angular environment significantly increased negative affect** compared to the control condition (p = .012).
•H2: No significant effect of environment on food intake (p = .727). Instead, emotional overeating tendencies predicted higher intake across all environments.
•H2: Mediation analysis showed that emotion did not explain the environment–intake relationship.
•**RQ1:** VR usability mattered: participants reporting more natural interaction consumed more food (p = .038).

Conclusion:
Visual design shaped emotions but not food intake. Ensuring natural, intuitive VR interaction is crucial for using mixed-reality as a valid tool for behavioral research.

The environmental psychology model (Mehrabian & Russell, 1974)
Built Environment → Emotional Response → Behavioral Response

Study's Conceptual Model
Green vs Red vs Control Env.
H1
Emotional Response
H3
H2
Food Intake

ANFA 2025 ANFA

Method

Experiment Procedure
Screen casting the VR experience to the laptop

Recruitment flyers
Online Screening Questionnaire
Online Consent form + Demographic Questionnaire
No food/drink except water 3 hrs before the lab visit.
HIT lab visit 11am - 2pm / 4pm -7pm
N = 20 participants (repeated measures, .87 power, α=.05, effect size = 0.28)

10 mins
1. Briefing + Consent
2. Fullness rating questions
4. State anxiety
5. PANAS
6. PAD emotional state measure.

5 mins
Orientation
VR Headset + Controllers

2 mins
visually explore the virtual restauratnt
Counterbalanced order 3 sessions
Green restaurant
Red restaurant
Control condition
Exit VR
5 mins
1. PANAS, 2. PAD
3. State-anxiety
Wear VR headset
~30 mins
Food consumption while immersed in virtual cafe
Outdoor cafe

15 mins
Questionnaire
1. Spatial rating
2. Fullness rating
3. Eating behavior questionnaires: AEBQ,TEFQ, EFCR, RISE-Q (visit 3)
8. Trait anxiety (visit 3)
9. Height and weight measured (visit 3)

Weighing the food
Energy intake is measured in calories

Phase 0
Procedures before lab visit (~15mins)
Phase 1
Setup and pre-test measures (15 mins)
Phase 2
VR experience & food consumption (40 mins)
Phase 3
Final measures + Food Intake weighed (20 mins)

Stimuli

HIT lab
Eating food while immersed in VR
View through the headset
Participant eating food using VR pass-through
Reference image from Long et al., 2023

Design features:
•*Green*: Curved roof, spacious/open, familiar, simple, ordered, harmonious, symmetrical.
•*Red*: Angular roof, narrow/closed, unfamiliar, complex, chaotic, not harmonious, asymmetrical.
•*Control*: Neutral lab-like room with minimal cues.

Green Restaurant
Red Restaurant

Results & Conclusion

Emotional responses (H1):
•Environment significantly influenced negative affect, $F(2,44.48) = 3.91$, $p = .027$.
•**Red environment → greater increase in negative affect** vs. Control ($B = 0.52$, $p = .012$).
•Positive affect, pleasure, and arousal showed no environment effects.
•Familiarity predicted higher positive affect ($p = .017$).
Food intake (H2):
•No significant effect of environment on grams consumed, $F(2,46.02) = 0.32$, $p = .727$.
•Emotional overeating trait predicted higher intake ($B = 68.75$, $p = .028$).
Mediation (H3):
•Negative affect change did not mediate the environment → food intake relationship (Sobel $Z = 0.64$, $p = .52$).
Usability (RQ1):
•Natural Interaction ratings predicted higher intake ($B = 1.30$, $p = .038$).
•Realism and Natural Eating ratings did not predict intake.

This pilot study shows that restaurant design shaped emotional responses more than eating behavior. The red environment significantly increased negative affect compared to control, underscoring the sensitivity of negative emotions to visual cues like color and form. Positive affect, pleasure, and arousal were unaffected, but familiarity predicted higher positive affect, suggesting recognition can buffer emotional experience. Food intake did not differ across environments, indicating visual cues alone may be insufficient without multisensory input. Instead, individual traits such as emotional overeating predicted intake. Usability also mattered: participants reporting more natural interaction consumed more, highlighting the importance of technical fidelity in mixed-reality research.

NegAffch
Control Green Red
Env

Online pre-test of stimuli to ensure visual manipulation:

Measure	Green (M / %)	Red (M / %)	Stat
Roof form (Curved vs. Angular)	8.35	2.54	$t(82)=-20.37$, $p<.001$
Spacious vs. Narrow	6.02	4.49	$t(82)=-5.11$, $p<.001$
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Symmetrical vs. Asym.	5.04	3.75	$t(82)=-4.11$, $p<.001$

The End.

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Portfolio: www.govindarazan.com