Self-Actualization

Will systems replace users' decision practices?

How can we balance automation and control?

Your Long-Term Goals?

Recommenders reinforce behaviors that fulfill our **immediate desires**

- They create "filter bubbles" that isolate us from viewpoints and experiences that may be relevant to our longer-term goals

Recommenders are **traps** (Seaver 2019)

- Users are prone to follow a recommender's advice
- This creates a positive feedback loop: Users unknowingly make themselves "fit in" with the system better

Prediction: recommenders turn us into **cat video zombies**

Self-Actualization

Knijnenburg et al.: "Recommender Systems for Self-Actualization", RecSys 2016

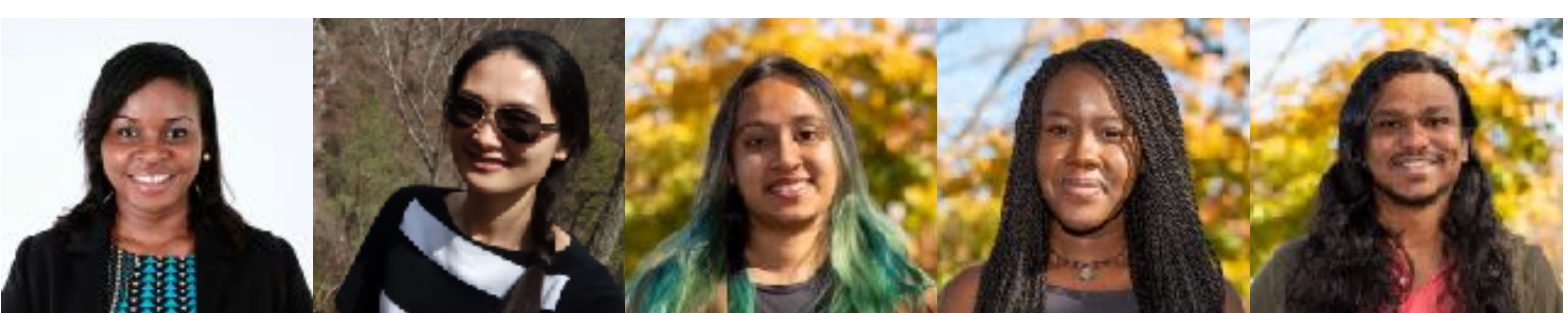
- Support rather than replace decision-making
- Exploration rather than consumption
- Cover users' tastes, plural

Goal: support users in developing, exploring, and understanding their unique personal tastes

- This will help them cater more to the user's longer-term goals

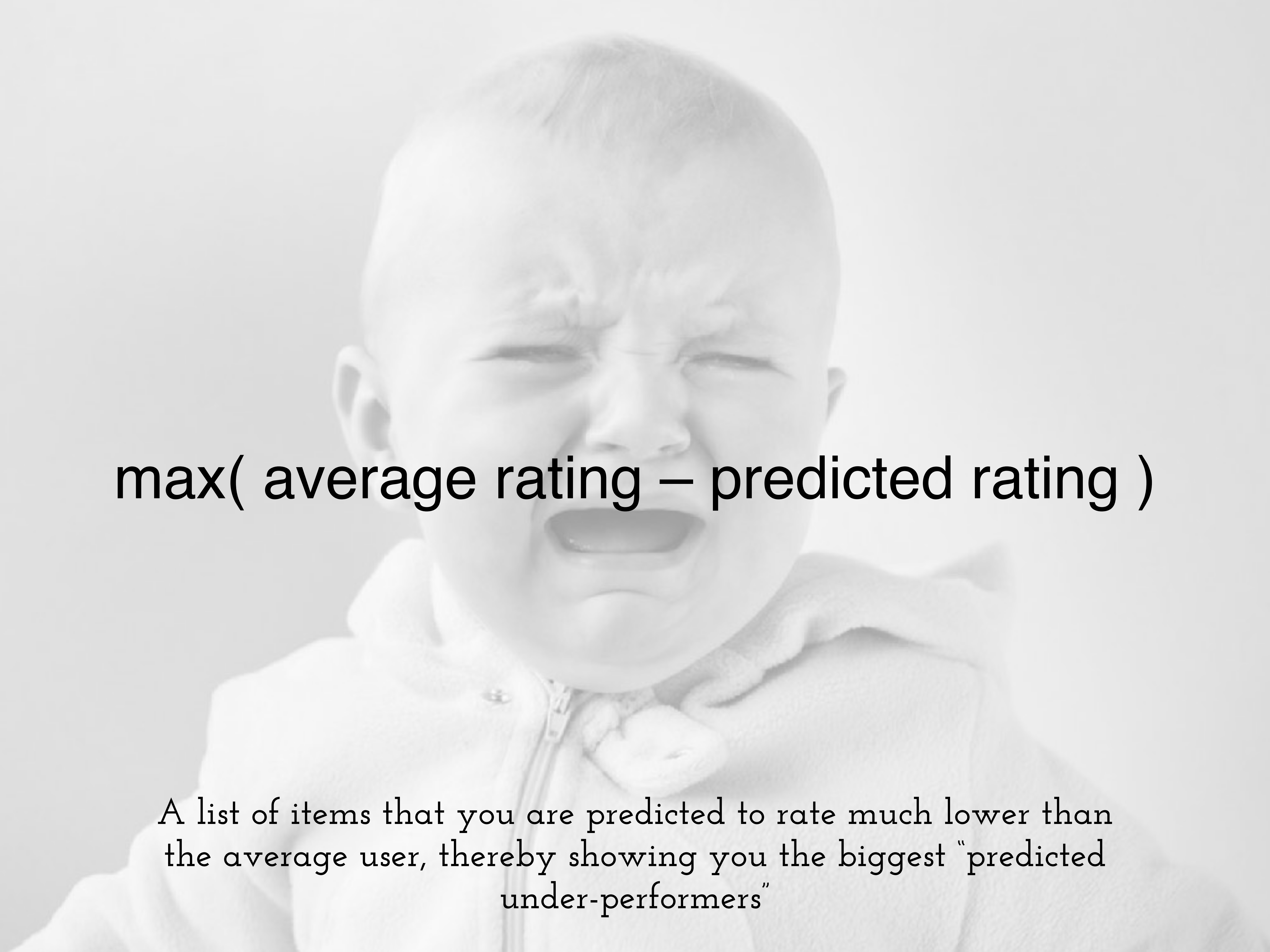
Beyond the "Things We Think You'll Like"

Build a recommender system that shows two lists…



Things We Think You'll Hate

You normally don't get to see these predictions, but showing them to you allows you to correct potential mistakes.



max(average rating – predicted rating)

A list of items that you are predicted to rate much lower than the average user, thereby showing you the biggest "predicted under-performers"

Things We Have No Clue About

Recommenders often try to "cash in" on good predictions as soon as possible. By showing you highly uncertain items the system can learn about your other preferences as well.

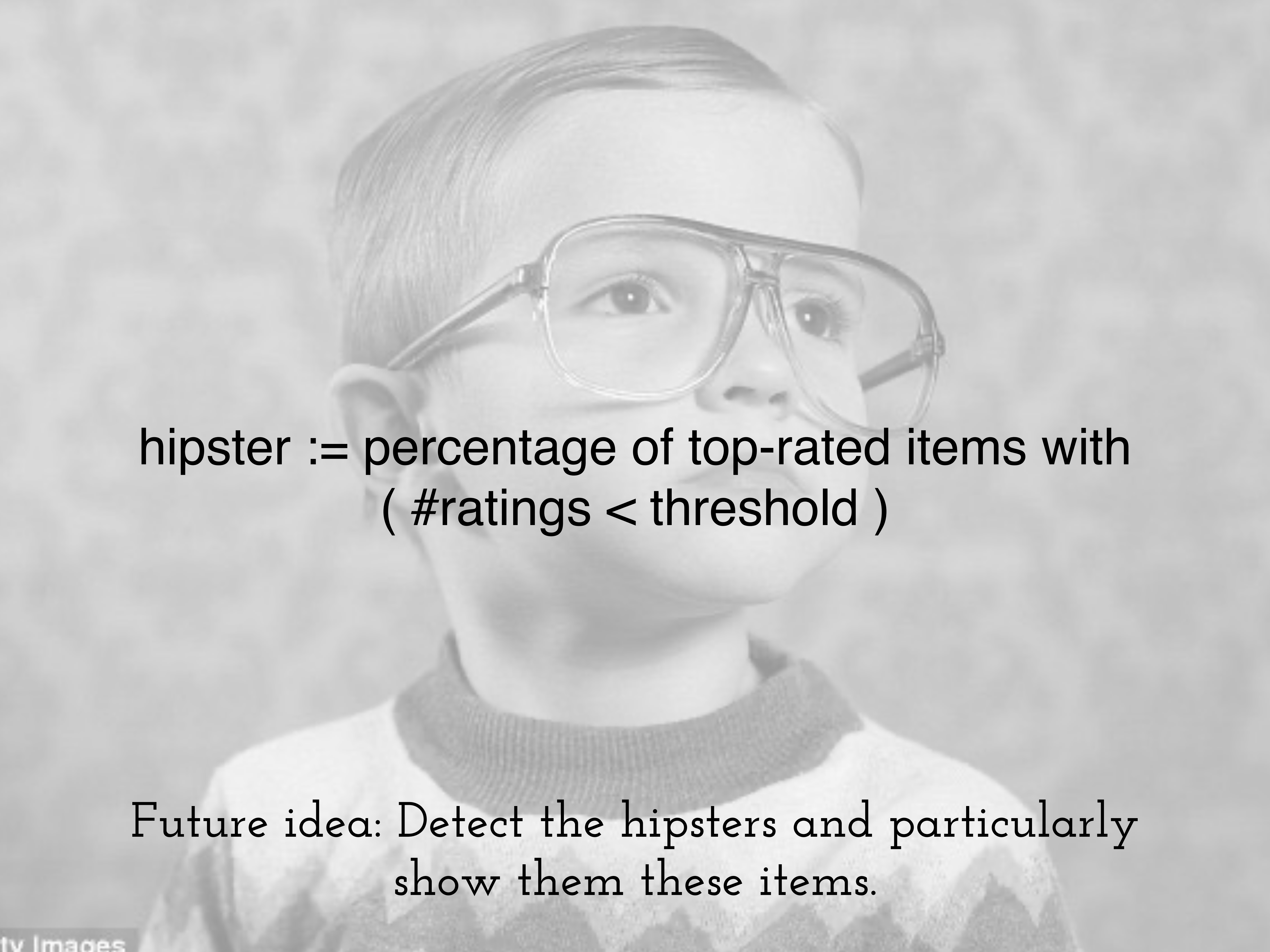
Predictions:

	Recommender 1	Recommender 2	Recommender 3	var(x)
Item A	**3.7**	**3.6**	**3.8**	**0.01**
Item B	**3.9**	**4.9**	**2.3**	**1.72**

An ensemble of algorithms, where we pick items with the most disagreement.

Things You'll Be Among **The First** To Try

Show the least-rated items that are predicted to be reasonably good.



hipster := percentage of top-rated items with
(#ratings < threshold)

Future idea: Detect the hipsters and particularly show them these items.

Things That Are Polarizing

What if your nearest neighbors are divided about certain controversial items?


Yay! The Matrix!
your nearest neighbors
MATRIX
You
(likes Sci-Fi)


Yay! Firefly!
Booh! Firefly!
your nearest neighbors
firefly
You
(likes Sci-Fi)

Self-Actualization

Exploring items **outside** the traditional recommendations**…**

…may give recommender systems a better idea of your tastes (prevents overspecialization)

…may help users to better understand their own unique tastes (avoids creating mindless zombies)

…may turn us towards the fulfillment of our longer-term goals (wouldn't that be nice?!)

Go Beyond the Top-N: Alternative Recommendations to Support Self-Actualization

Motivation

Recommender Systems for Self-Actualization (RSSA) aims to:

Support rather than replace decision making

Focus on *exploration* rather than consumption

Attempt to cover users' *various* tastes

How can we help users explore their preferences?

Four alternative recommendation lists (**RSSA features**) that go beyond the top-N

- *Things we think you'll hate*
- *Things you'll be among the first to try*
- *Things we have no clue about*
- *Things that are controversial*

Algorithms

Things we think you'll hate

Algorithm 1: Hate items

Input: Predicted ratings $\{\hat{R}_{ui}\}$ set
Get mean predicted rating $\bar{R}_i$ over all observed ratings
For $u \epsilon U$:
    Sort $\bar{R}_i - \hat{R}_{ui}$ for unrated items in ascending order
    Get the last 10 items

Algorithms

Things you'll be among the first to try

Algorithm 2: Hipster items
Input: Predicted ratings $\{\hat{R}_{ui}\}$ set
For $u \epsilon U$:
Sort $\hat{R}_{ui}$ for unrated items in descending order
Get the top 200 items
Get the numbers of observed ratings for those top 200 items
Get 10 items with lowest number of observed ratings
Sort them in descending order based on predicted ratings

Algorithms

Things we have no clue about

Algorithm 3: Item-based CF

Input: Observed ratings $\{R_{ui}\}$ set

Get general mean of observed ratings μ

For $u \epsilon U$:

  Get mean ratings $\bar{R}_u$ over all rated items

  Get user bias by $b_u = \bar{R}_u - \mu$

For $i \epsilon I$:

  Get mean ratings $\bar{R}_i$ over all observed ratings

  Get item bias by $b_i = \bar{R}_i - \mu$

For $u \epsilon U$ and $i \epsilon I$:

  Get $b_{ui} = \mu + b_u + b_i$

For $i, j \epsilon I$:

$$S(i,j) = \frac{\sum_{u \epsilon U}((R_{ui}-b_{ui})(R_{uj}-b_{uj}))}{\sqrt{\sum_{u \epsilon U}(R_{ui}-b_{ui})^2}\sqrt{\sum_{u \epsilon U}(R_{uj}-b_{uj})^2}}$$

For $i \epsilon I$:

  Get nearest neighbors $N_{s(i)}$ set

  For $u \epsilon U$:

$$\hat{R}_{ui} = \frac{\sum_{n \epsilon N_{s(i)}}(S(i,n)(R_{un}-b_{un}))}{\sum_{n \epsilon N_{s(i)}}|S(i,n)|}, n = |N_{s(i)}|$$

Algorithms

Things we have no clue about

Algorithm 4: Re-sampling
Input: Observed ratings $\{R_{ui}\}$ set m - number of repetitions α - portion of R_{ui} to be re-sampled each time Get N - the number of observed ratings in $\{R_{ui}\}$ Get $n = \alpha \times N$ - sample size For $j = 1 : m$: Randomly select n observed ratings $\{R_{ui}^{(j)}\} \subset \{R_{ui}\}$ Execute Item-based CF on $\{R_{ui}^{(j)}\}$ to get $\{\hat{R}_{ui}^{(j)}\}$ Get $C_{ui} = \frac{1}{sd(\hat{R}_{ui}^{(j)})}$, confidence of $\hat{R}_{ui}$ For $u \epsilon U$: Sort C_{ui} in descending order Get the last 10 items

Algorithms

Things that are controversial

Algorithm 5: Controversial items
Input: $\{R_{ui}\}$ set and $\{\hat{R}_{ui}\}$ set
Get the same μ, b_u, b_i, b_{ui} with Item-based CF
For $u, v \epsilon U$:
$\quad S(u,v) = \frac{\sum_{i \epsilon I}((R_{ui}-b_{ui})(R_{vi}-b_{vi}))}{\sqrt{\sum_{i \epsilon I}(R_{ui}-b_{ui})^2}\sqrt{\sum_{i \epsilon I}(R_{vi}-b_{vi})^2}}$
For $u \epsilon U$:
$\quad$ Get nearest neighbors $N_{s(u)}$ set
$\quad$ For i in unrated items by the user:
$\quad\quad$ Sort $var(\hat{R}_{vi}), v \epsilon N_{s(u)}$ in ascending order
$\quad$ Get the last 10 items

How do these alternative algorithms perform?

Built these algorithms into a recommender system for an online user study

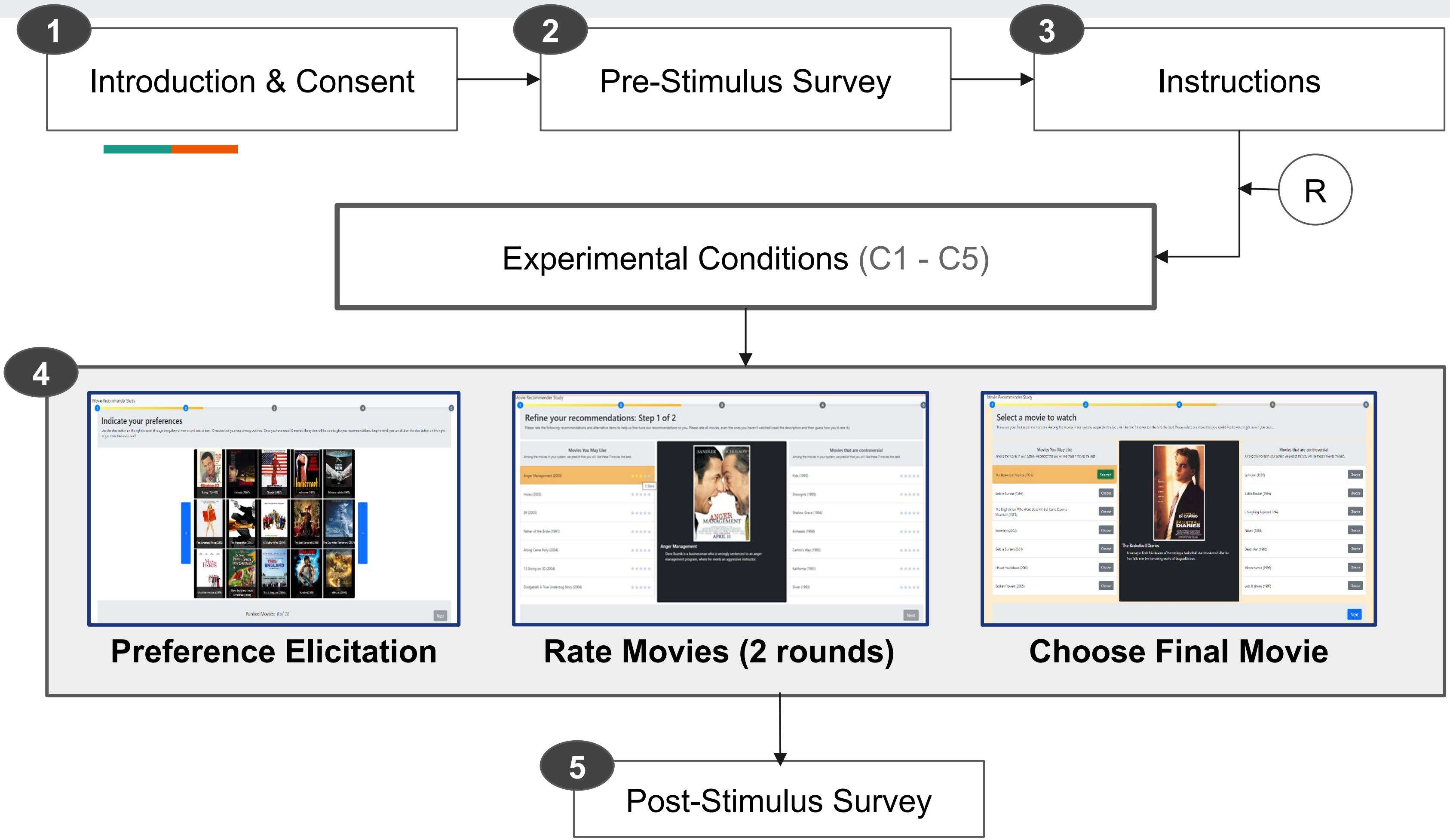
- *Things we think you'll hate*
- *Things you'll be among the first to try*
- *Things we have no clue about*
- *Things that are controversial*

Conditions

Things we think you'll hate (*hate* condition)
Things you'll be among the first to try (*hipster* condition)
Things we have no clue about (*noClue* condition)
Things that are controversial (*controversial* condition)

VS.

Baseline: More things you might like (*nest-N* condition)
Baseline: Single list


1
Introduction & Consent
2
Pre-Stimulus Survey
3
Instructions
R
Experimental Conditions (C1 - C5)
4
Indicate your preferences
Refine your recommendations: Step 1 of 2
Select a movie to watch
Preference Elicitation
Rate Movies (2 rounds)
Choose Final Movie
5
Post-Stimulus Survey

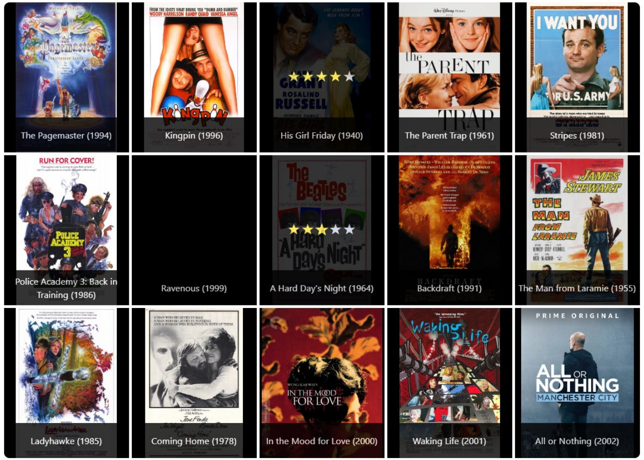
Movie Recommender Study

1 2 3 4 5

Indicate your preferences

Use the blue button on the right to scroll through the gallery of movies and rate at least 10 movies that you have already watched. Once you have rated 10 movies, the system will be able to give you recommendations. Keep in mind, you can click on the blue button on the right to get more movies to rate!

<



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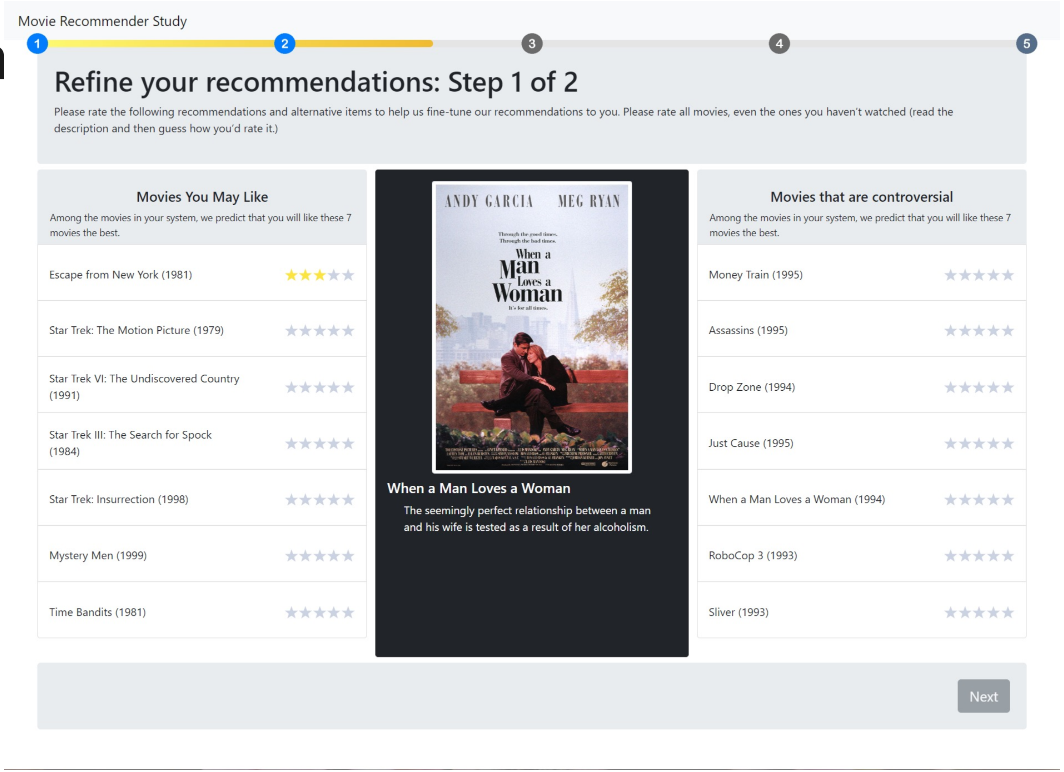
Ranked Movies: *1 of 10*

Next

Please hang on while we find the recommendations for you.

Recomm


Movie Recommender Study
1
2
3
4
5
Refine your recommendations: Step 1 of 2
Please rate the following recommendations and alternative items to help us fine-tune our recommendations to you. Please rate all movies, even the ones you haven't watched (read the description and then guess how you'd rate it.)
Movies You May Like
Among the movies in your system, we predict that you will like these 7 movies the best.
Escape from New York (1981)
Star Trek: The Motion Picture (1979)
Star Trek VI: The Undiscovered Country (1991)
Star Trek III: The Search for Spock (1984)
Star Trek: Insurrection (1998)
Mystery Men (1999)
Time Bandits (1981)
ANDY GARCIA
MEG RYAN
When a Man Loves a Woman
When a Man Loves a Woman
The seemingly perfect relationship between a man and his wife is tested as a result of her alcoholism.
Movies that are controversial
Among the movies in your system, we predict that you will like these 7 movies the best.
Money Train (1995)
Assassins (1995)
Drop Zone (1994)
Just Cause (1995)
When a Man Loves a Woman (1994)
RoboCop 3 (1993)
Sliver (1993)
Next

Movie Recommender Study

1 2 3 4 5

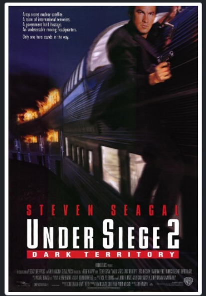
Refine your recommendations: Step 2 of 2

Please rate the following recommendations and alternative items to help us finalize our recommendations to you. Please rate all movies, even the ones you haven't watched (read the description and then guess how you'd rate it.)

Movies You May Like

Among the movies in your system, we predict that you will like these 7 movies the best.

- Hackers (1995)
- Showgirls (1995)
- Mary Shelley's Frankenstein (1994)
- The Quick and the Dead (1995)
- Tank Girl (1995)
- Heavy Metal (1981)
- The Lawnmower Man (1992)



Under Siege 2: Dark Territory

Casey Ryback hops on a Colorado to LA train to start a vacation with his niece. Early into the trip, terrorists board the train and use it as a mobile HQ to hijack a top secret destructive US satellite.

Movies that are controversial

Among the movies in your system, we predict that you will like these 7 movies the best.

- Showgirls (1995)
- Under Siege 2: Dark Territory (1995)
- Tommy Boy (1995)
- Airheads (1994)
- Carlito's Way (1993)
- The Englishman Who Went Up a Hill But Came Down a Mountain (1995)
- The Brady Bunch Movie (1995)

Next

Movie Recommender Study

1 2 3 4 5

Select a movie to watch

These are your final recommendations. Among the movies in our system, we predict that you will like the 7 movies (on the left) the best. Please select one movie that you would like to watch right now if you could.

Movies You May Like

Among the movies in your system, we predict that you will like these 7 movies the best.

Powder (1995)	Choose
Johnny Mnemonic (1995)	Choose
Species (1995)	Choose
The Flintstones (1994)	Choose
Last Action Hero (1993)	Choose
Star Trek V: The Final Frontier (1989)	Choose
Young Guns (1988)	Choose

Kids in the Hall: Brain Candy

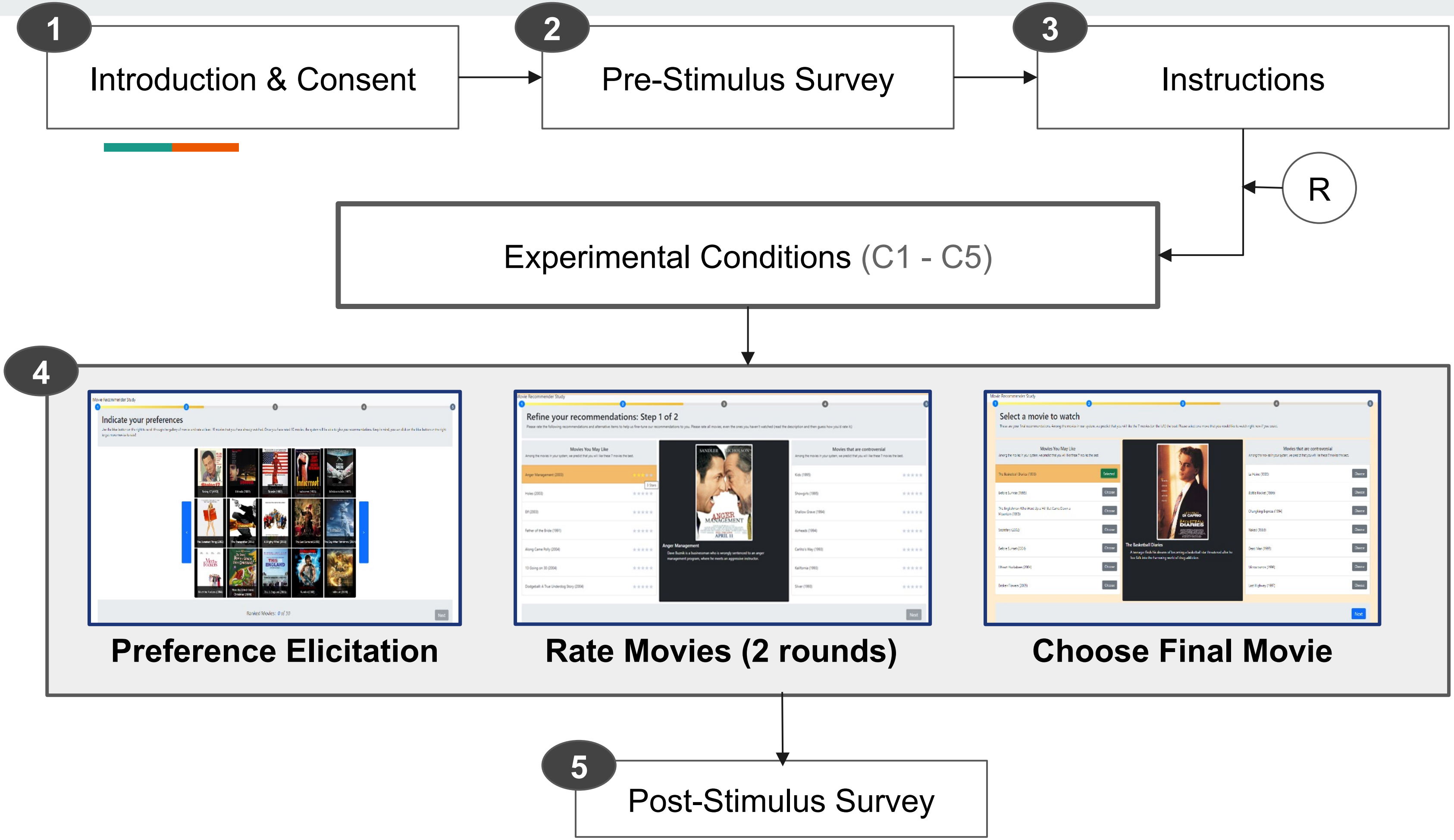
A pharmaceutical scientist creates a pill that makes people remember their happiest memory, and although it's successful, it has unfortunate side effects.

Movies that are controversial

Among the movies in your system, we predict that you will like these 7 movies the best.

La Haine (1995)	Choose
Bottle Rocket (1996)	Choose
Flirting with Disaster (1996)	Choose
Welcome to the Dollhouse (1995)	Choose
The Celluloid Closet (1995)	Choose
Kids in the Hall: Brain Candy (1996)	Choose
Paradise Lost: The Child Murders at Robin Hood Hills (1996)	Choose

Next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Post-Stimulus Survey

Scales

Personal Characteristics (PCs)

- FOMO (Fear of missing things)
- Need for novelty
- Move Expertise
- Maximization tendency

Subjective System Aspects (SSAs)

- Perceived diversity
- Recommendation quality
- Taste coverage
- Recommendation conformity
- Choice difficulty
- System difficulty

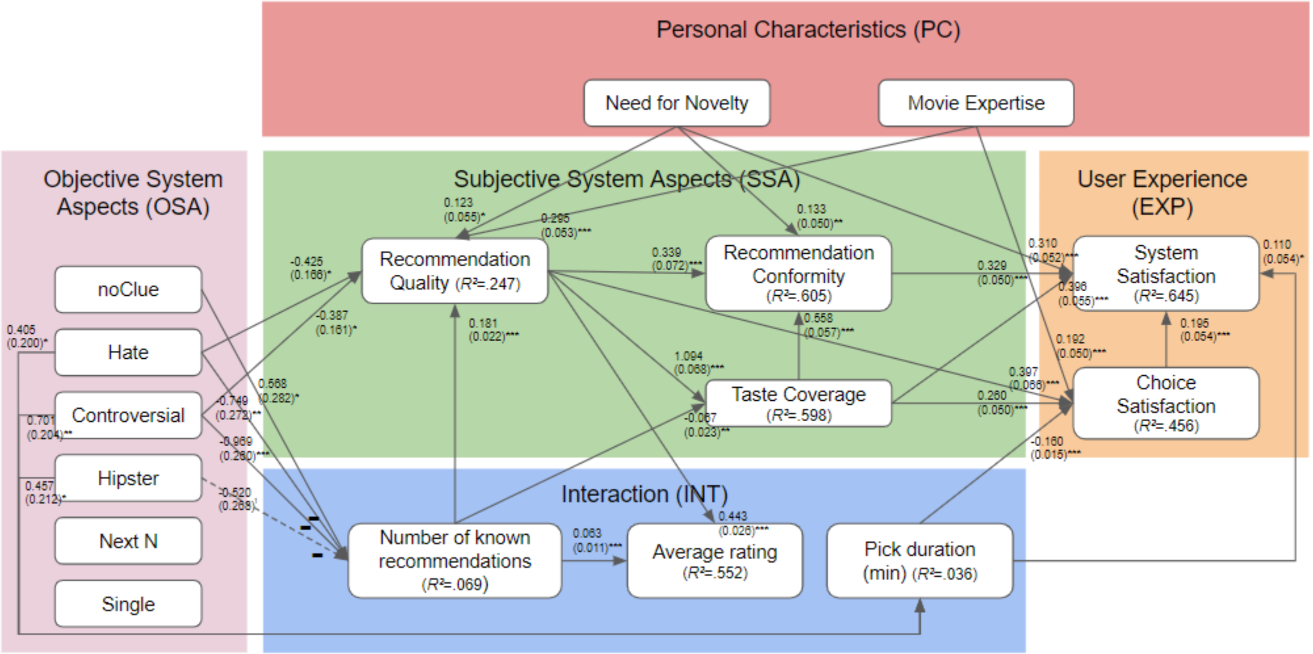
Participants

- Prolific
- 625 participants

Data Analysis

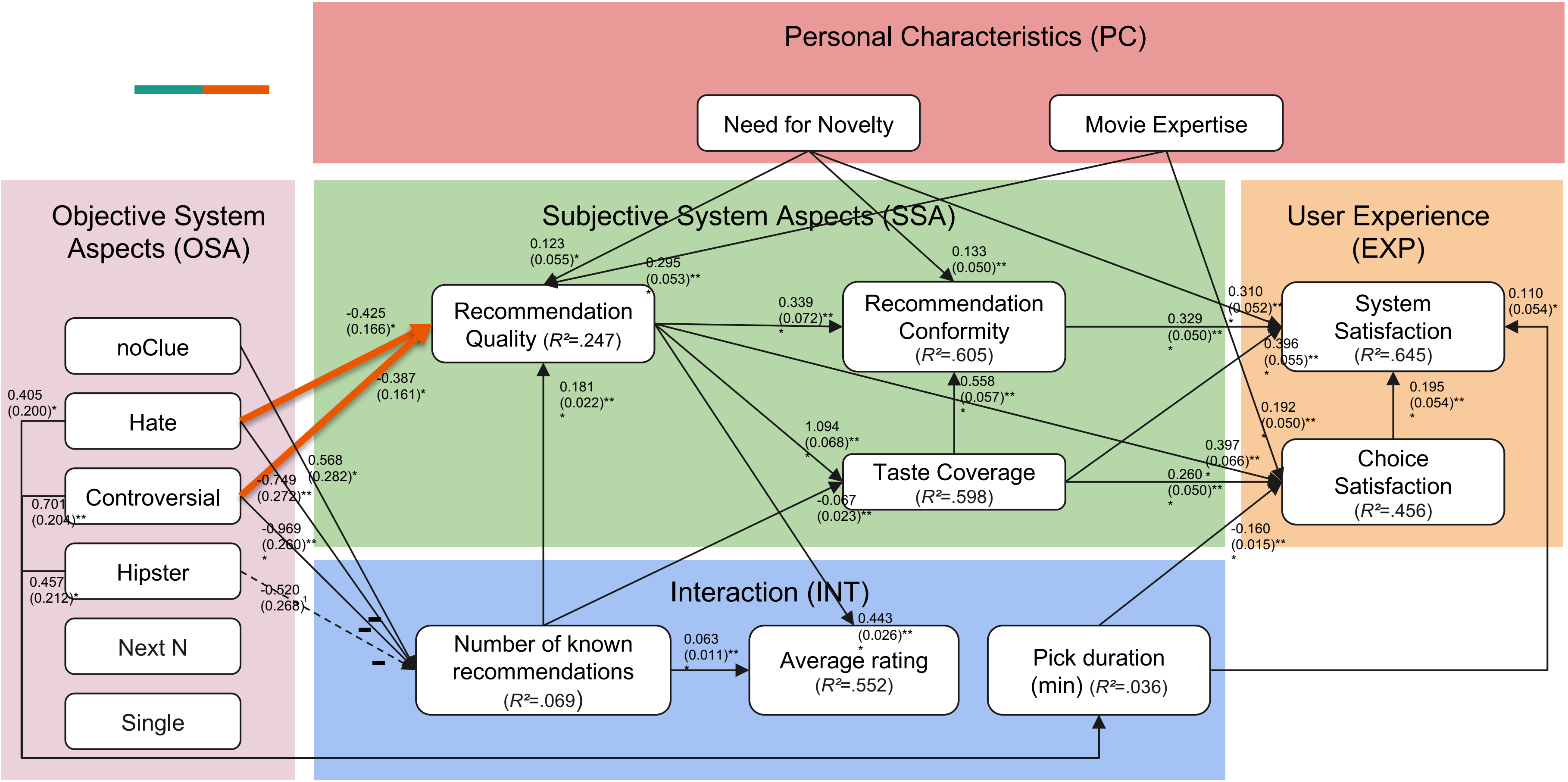
- User-centric Evaluation Framework
- CFA, SEM

SEM model



Personal Characteristics (PC)
Need for Novelty
Movie Expertise
Objective System Aspects (OSA)
noClue
Hate
Controversial
Hipster
Next N
Single
Subjective System Aspects (SSA)
Recommendation Quality (R²=.247)
Recommendation Conformity (R²=.605)
Taste Coverage (R²=.598)
User Experience (EXP)
System Satisfaction (R²=.645)
Choice Satisfaction (R²=.456)
Interaction (INT)
Number of known recommendations (R²=.069)
Average rating (R²=.552)
Pick duration (min) (R²=.036)

The structural equation model for the data of the experiment. Significance levels:solid arrows: p < .05, dashed arrows: p < 0.1.
R^2 is the proportion of variance explained by the model. Minus symbol beside the arrows represent negative effects



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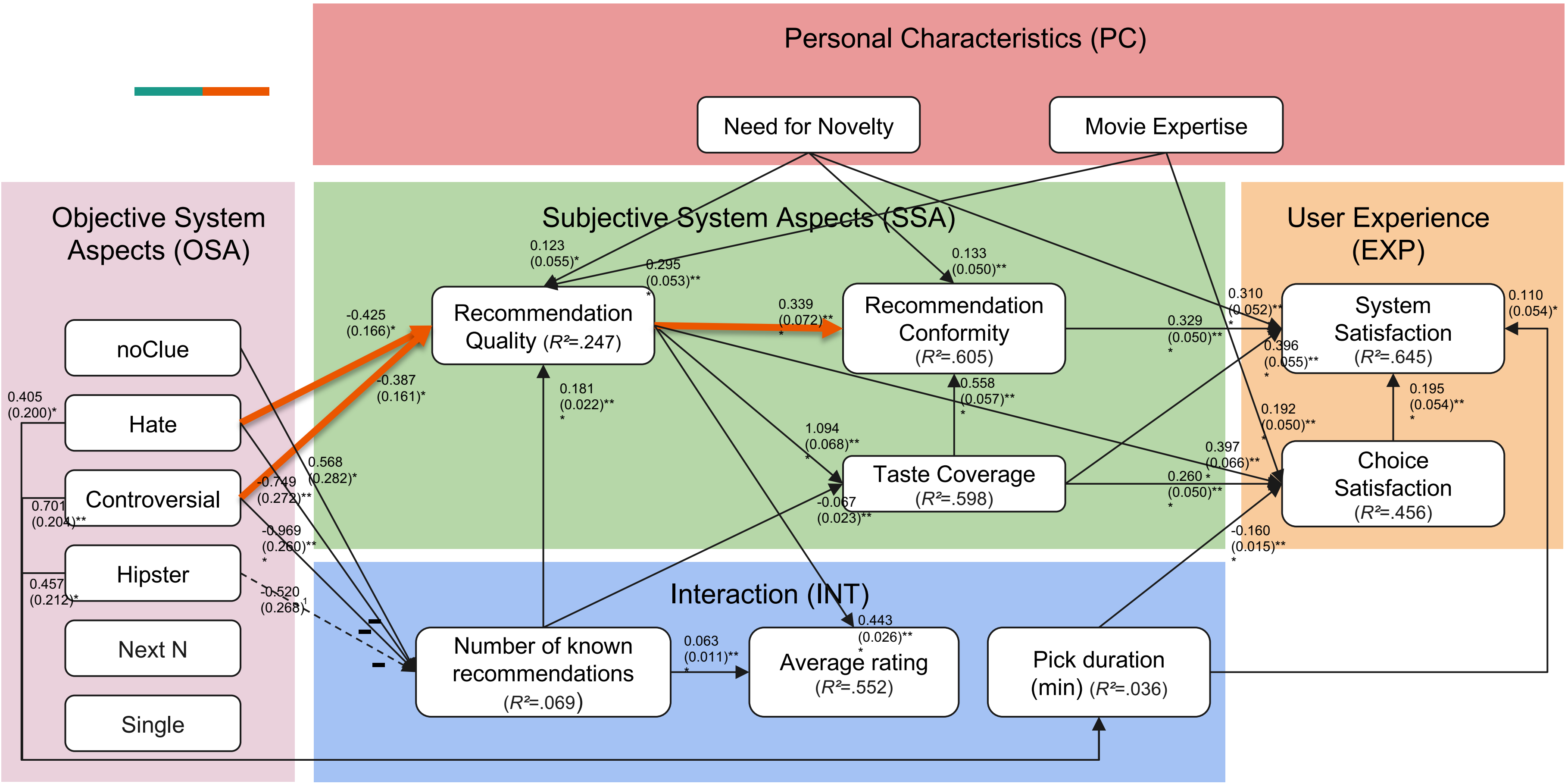

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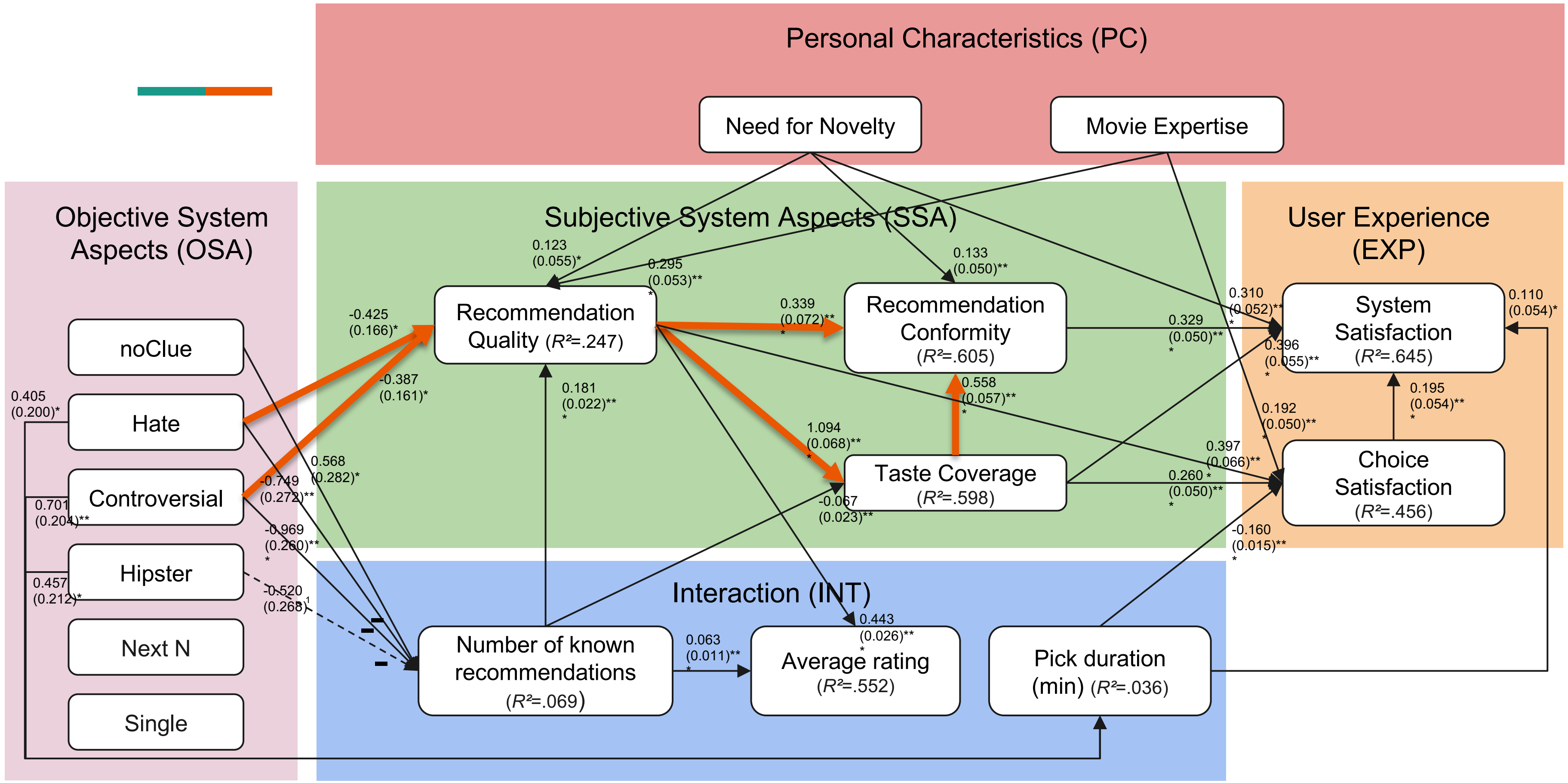

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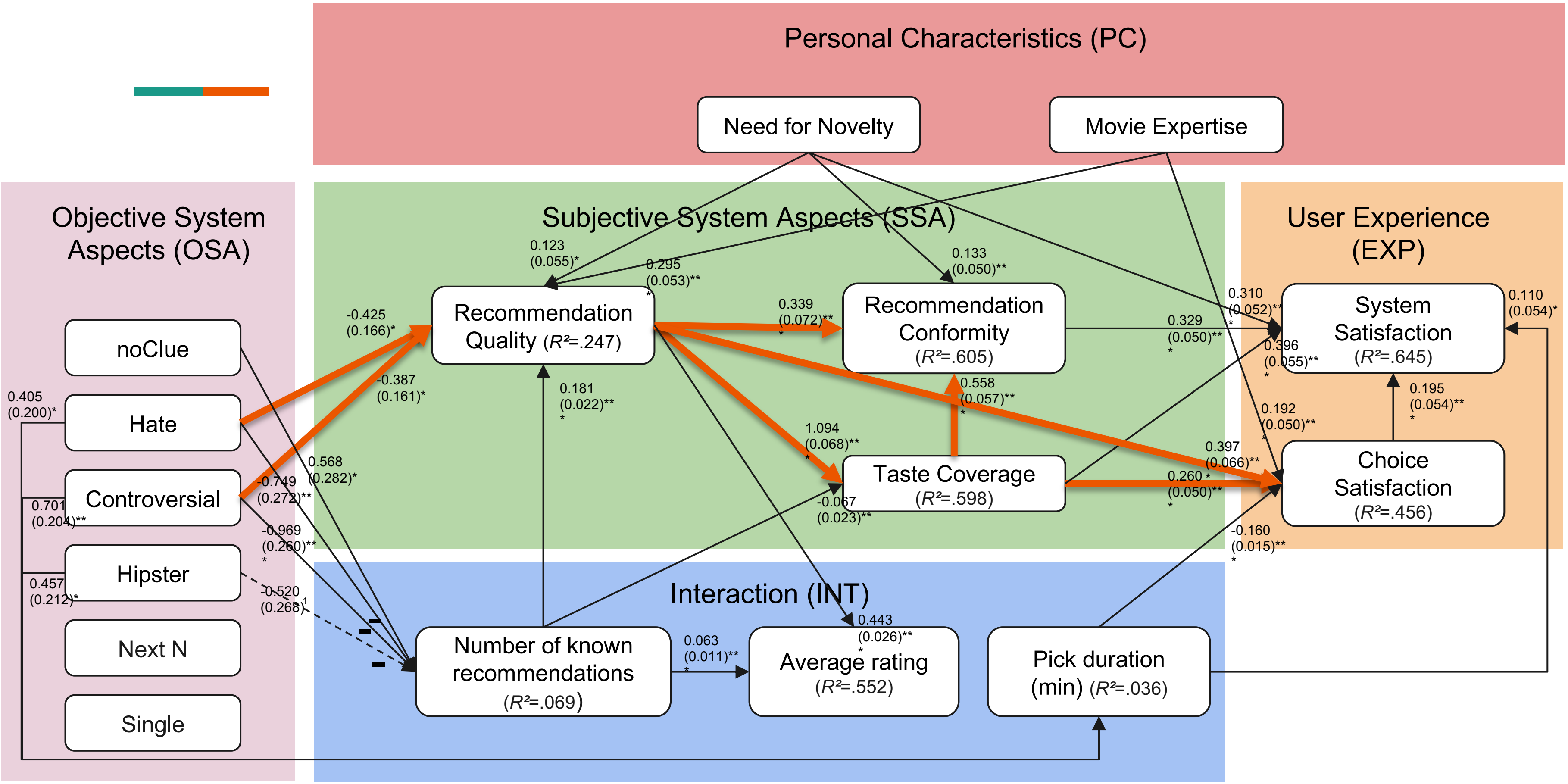

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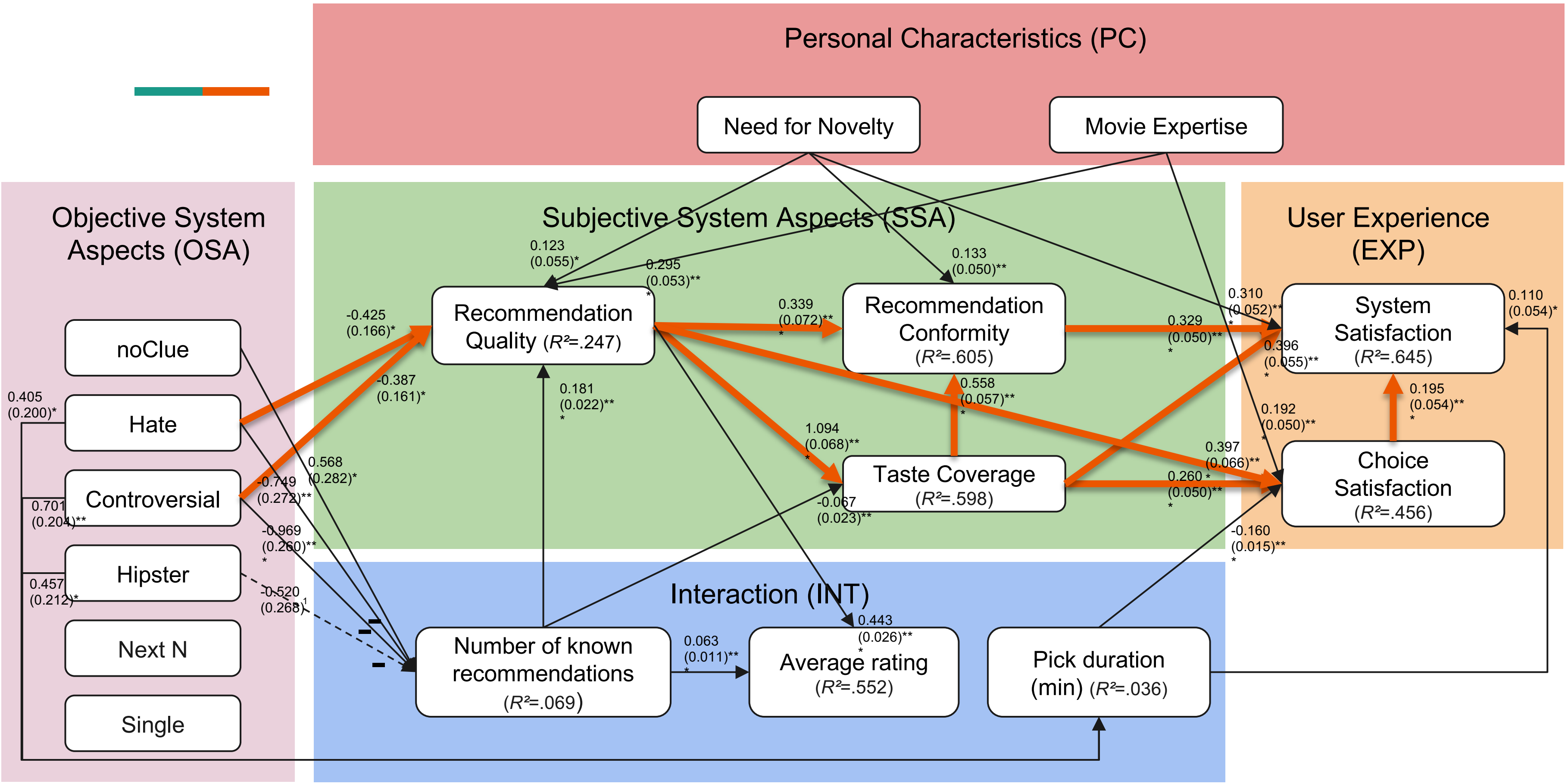
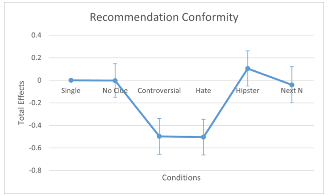
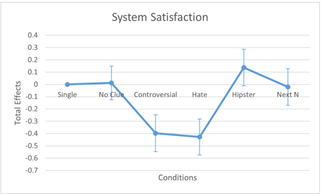
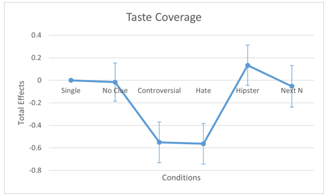


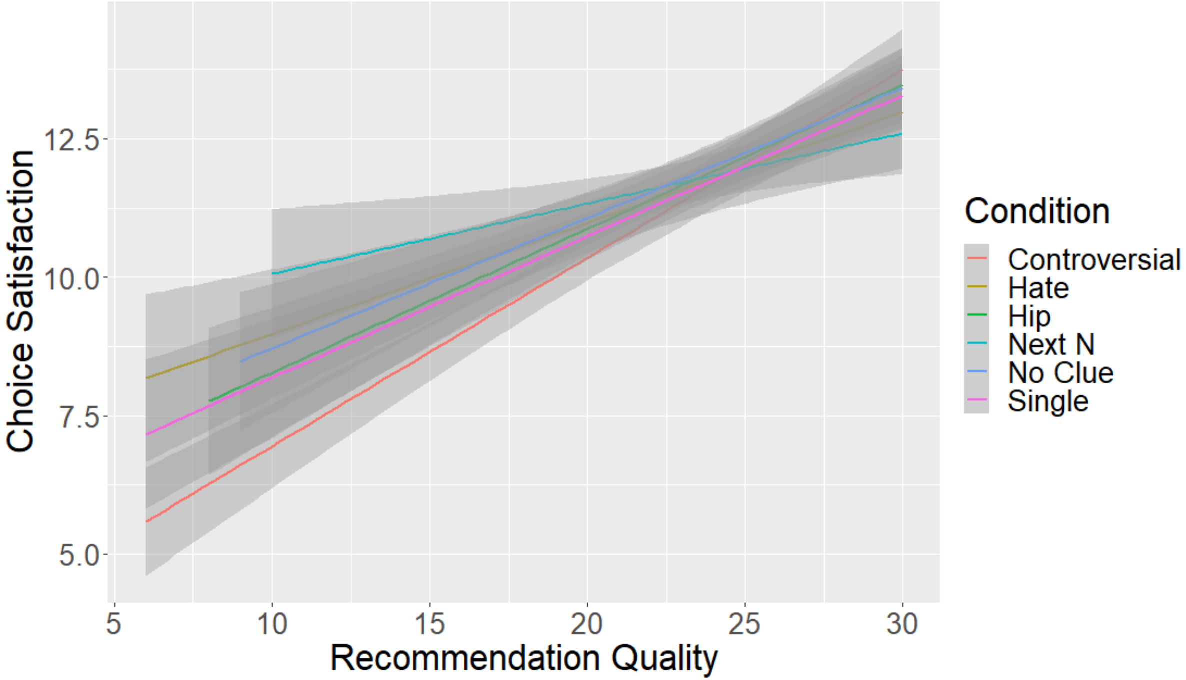
RSSA Features







Interaction effects



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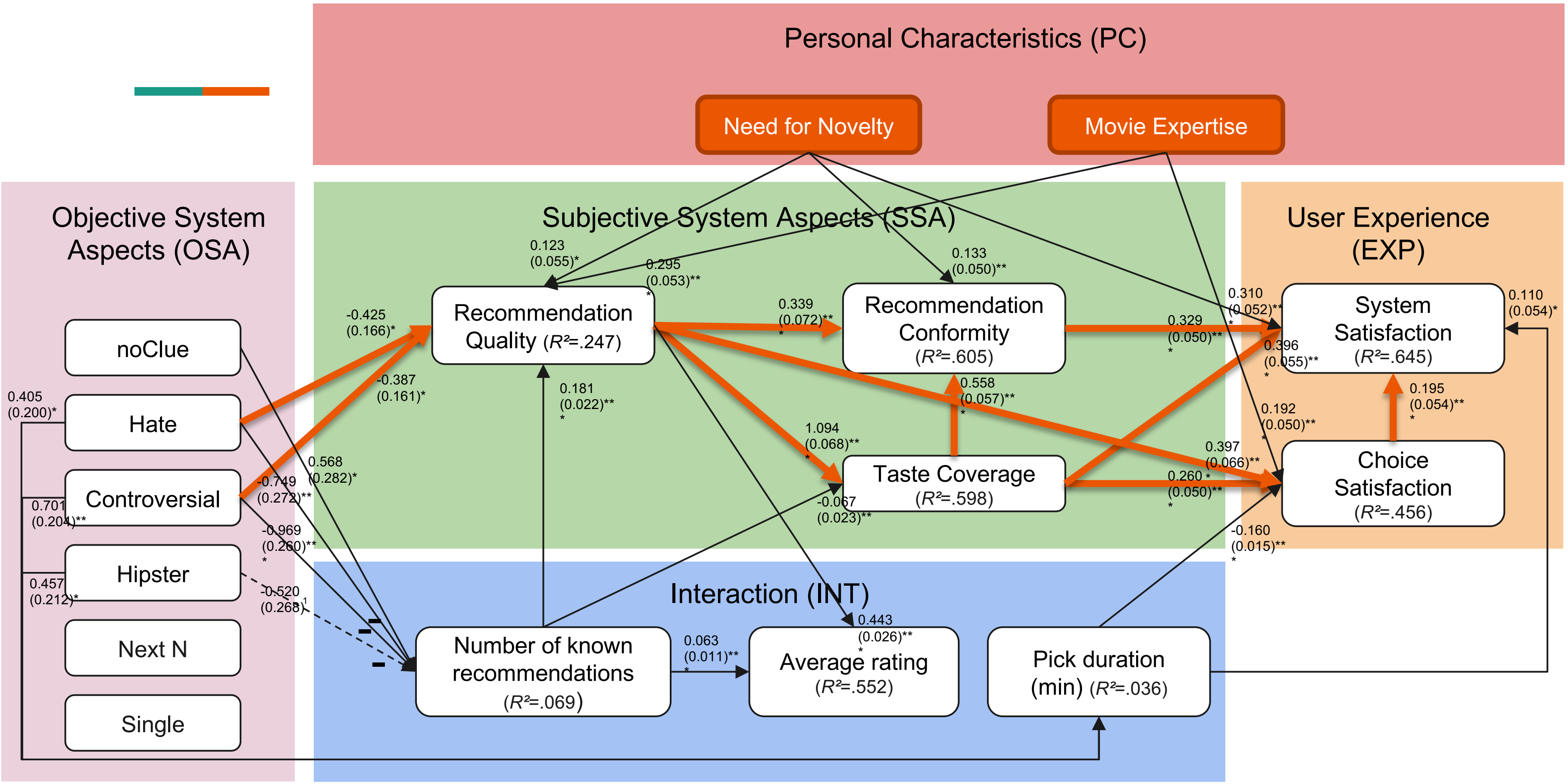

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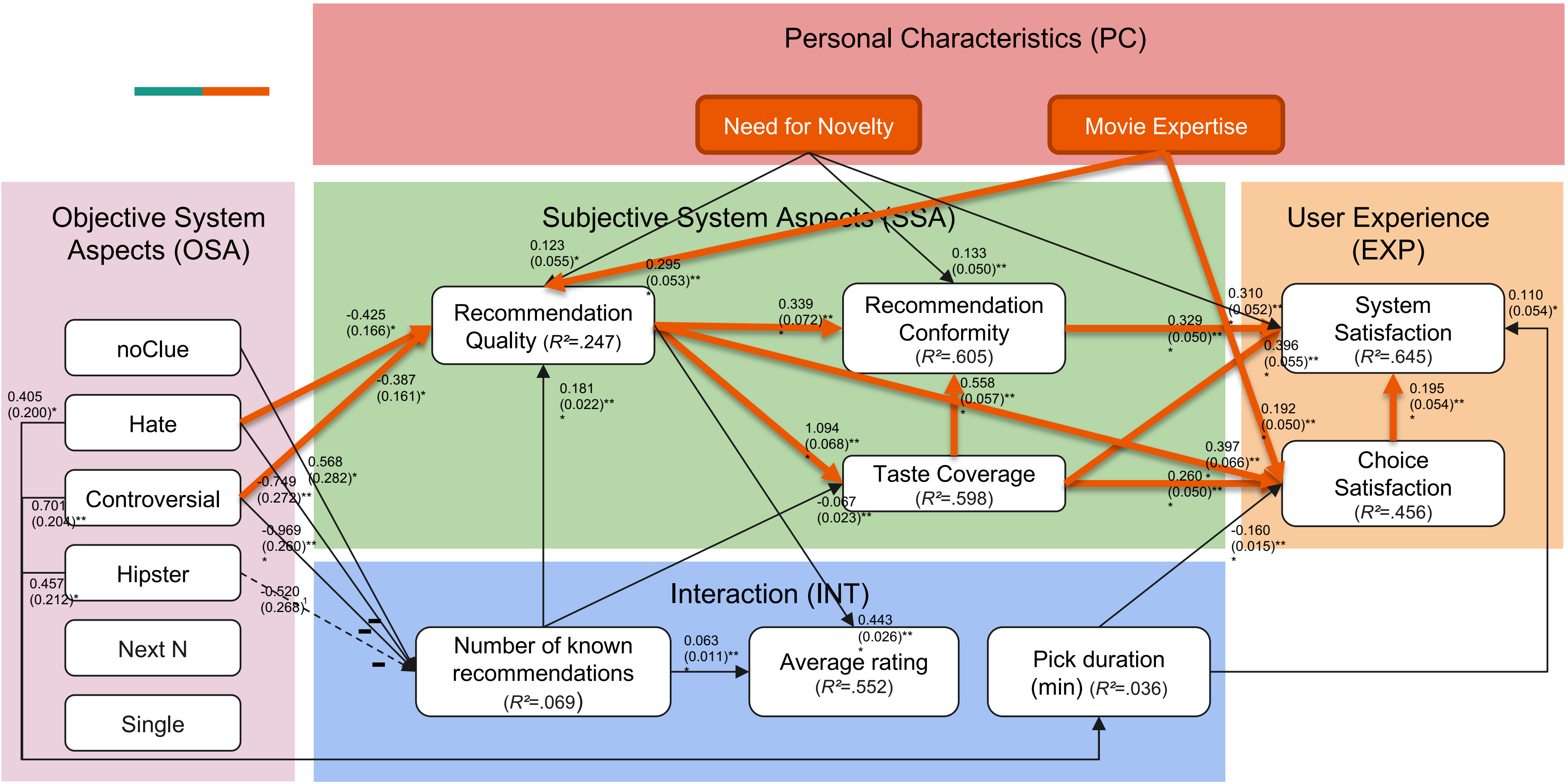

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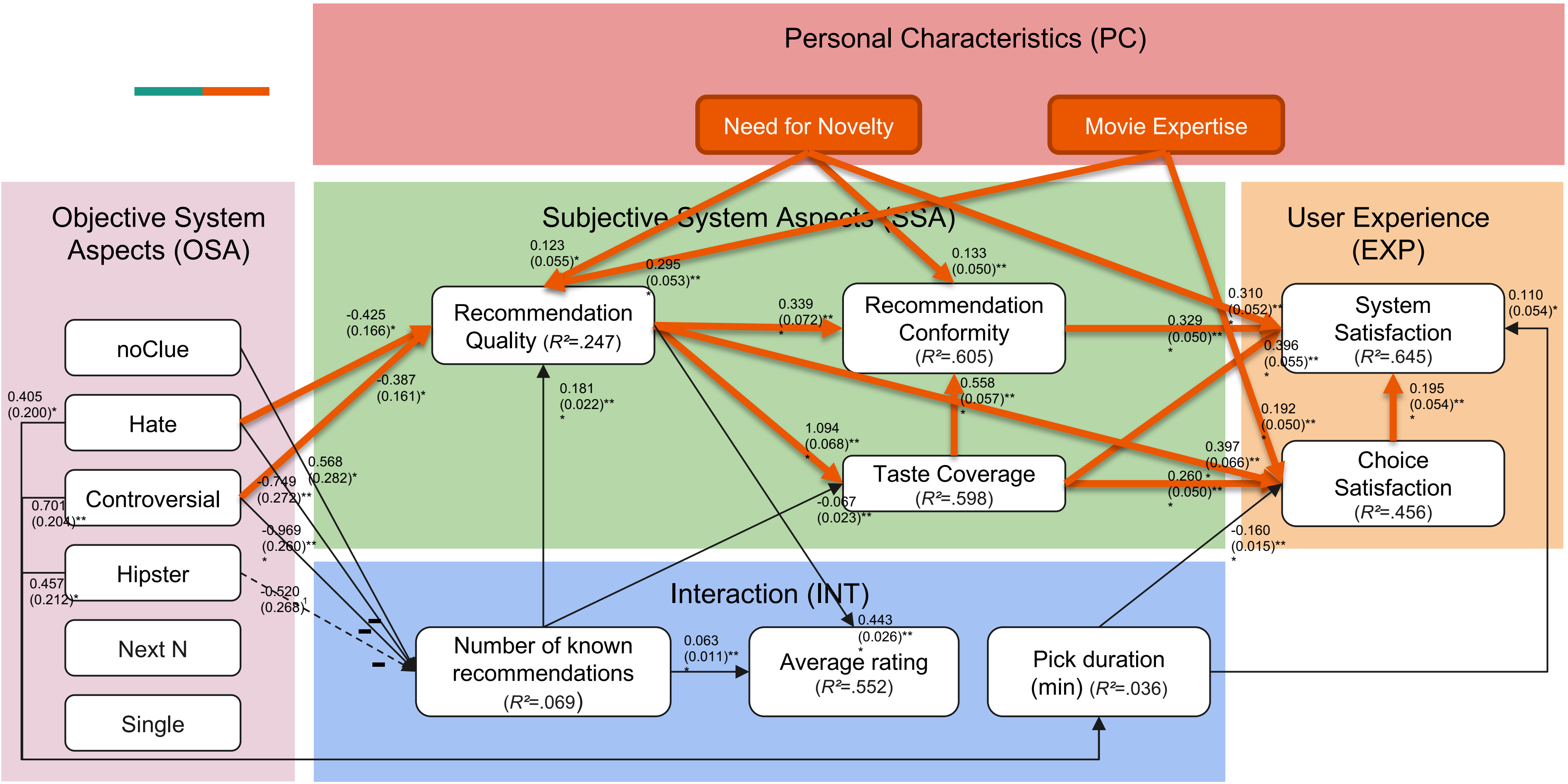
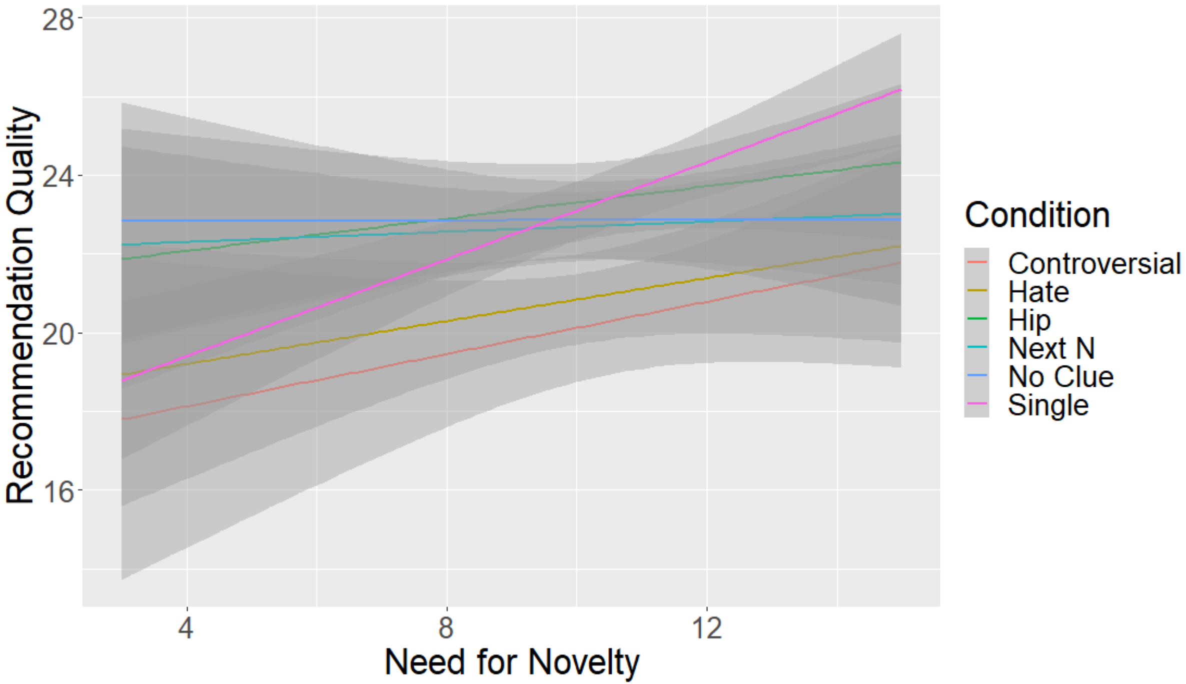
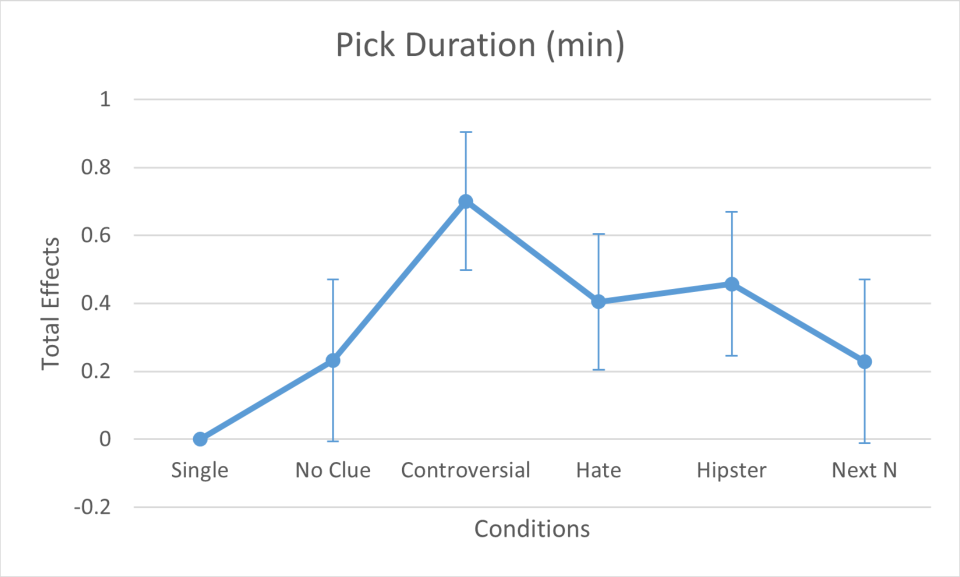


Interaction effects




Pick Duration (min)
Total Effects
1
0.8
0.6
0.4
0.2
0
-0.2
Single
No Clue
Controversial
Hate
Hipster
Next N
Conditions

Scales to be Measured

- Taste Exploration Scales:
    - **Taste clarification potential**
        - participants’ perception of how well the recommender helps users understand their preferences
    - **Taste development potential**
        - participants’ perception of the ability that the recommender helps users develop their unique taste
    - **Self-actualization**
        - participants' perception of the extent to which the recommendations are attuned to help them meaningfully improve their own lives