Choice Overload

Advanced Decision Support Systems

Choice overload

Iyengar & Lepper (2000): a tasting booth with jams…

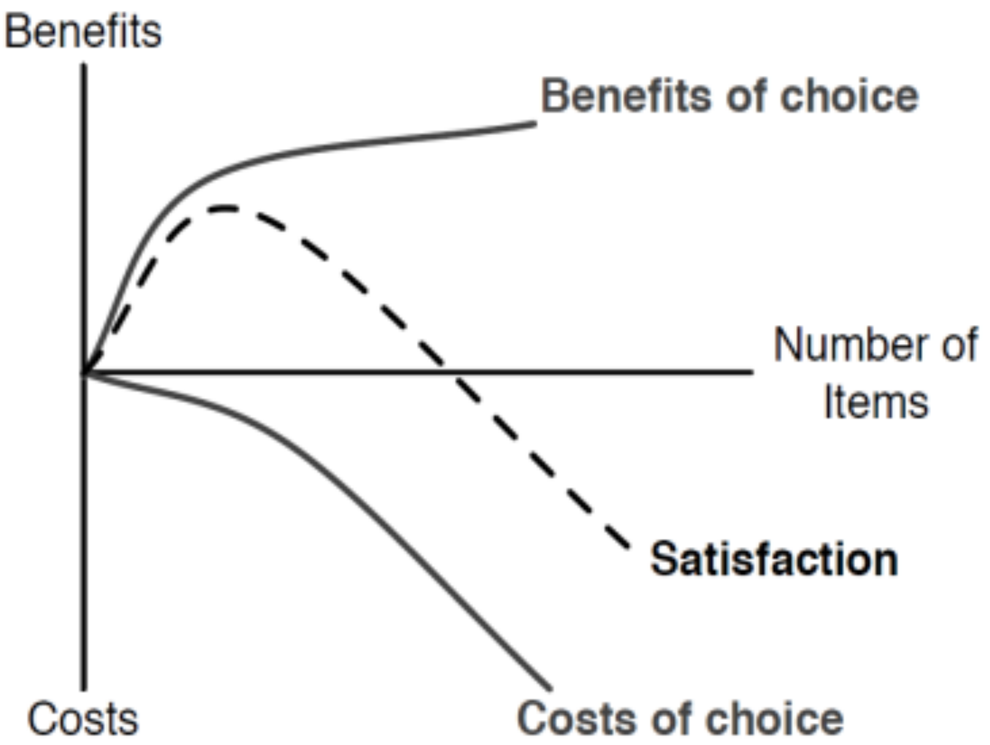
Less attractive
30% sales
Higher choice satisfaction

More attractive
3% sales
Lower choice satisfaction

Choice overload

Satisfaction = benefit – cost

- Benefit of more options: easier to find the right option
- Cost of more options: more comparisons, higher potential regret



Is this also true for recommendations?

What can we do about it?

Experiment 1

Demonstrating choice overload

Experiment 1

Bollen et al.: "Understanding Choice Overload in Recommender Systems", RecSys 2010

What is the effect of the number of recommendations?

What about the composition of the recommendation list?

Tested with 3 conditions:

- Top 5 (recs: 1 2 3 4 5)
- Top 20 (recs: 1 2 3 4 5 6 7 8 9 ... 20)
- Lin 20 (recs: 1 2 3 4 5 99 199 299 399 ... 1499)

Top5

Item1
Item2
Item3
Item4
Item5

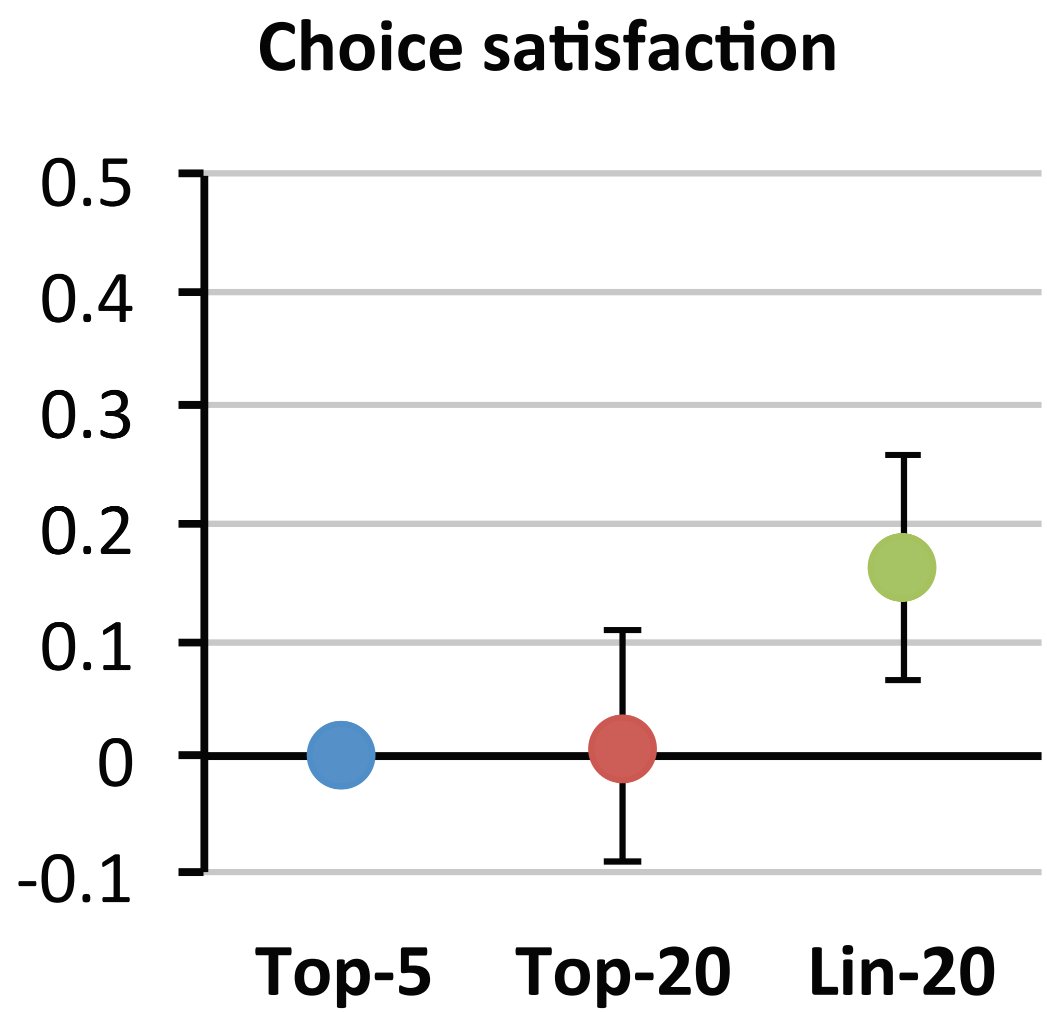
Top20

Item1
Item2
Item3
Item4
Item5
Item6
Item7
Item8
Item9
Item10
Item11
Item12
Item13
Item14
Item15
Item16
Item17
Item18
Item19
Item20

Lin20

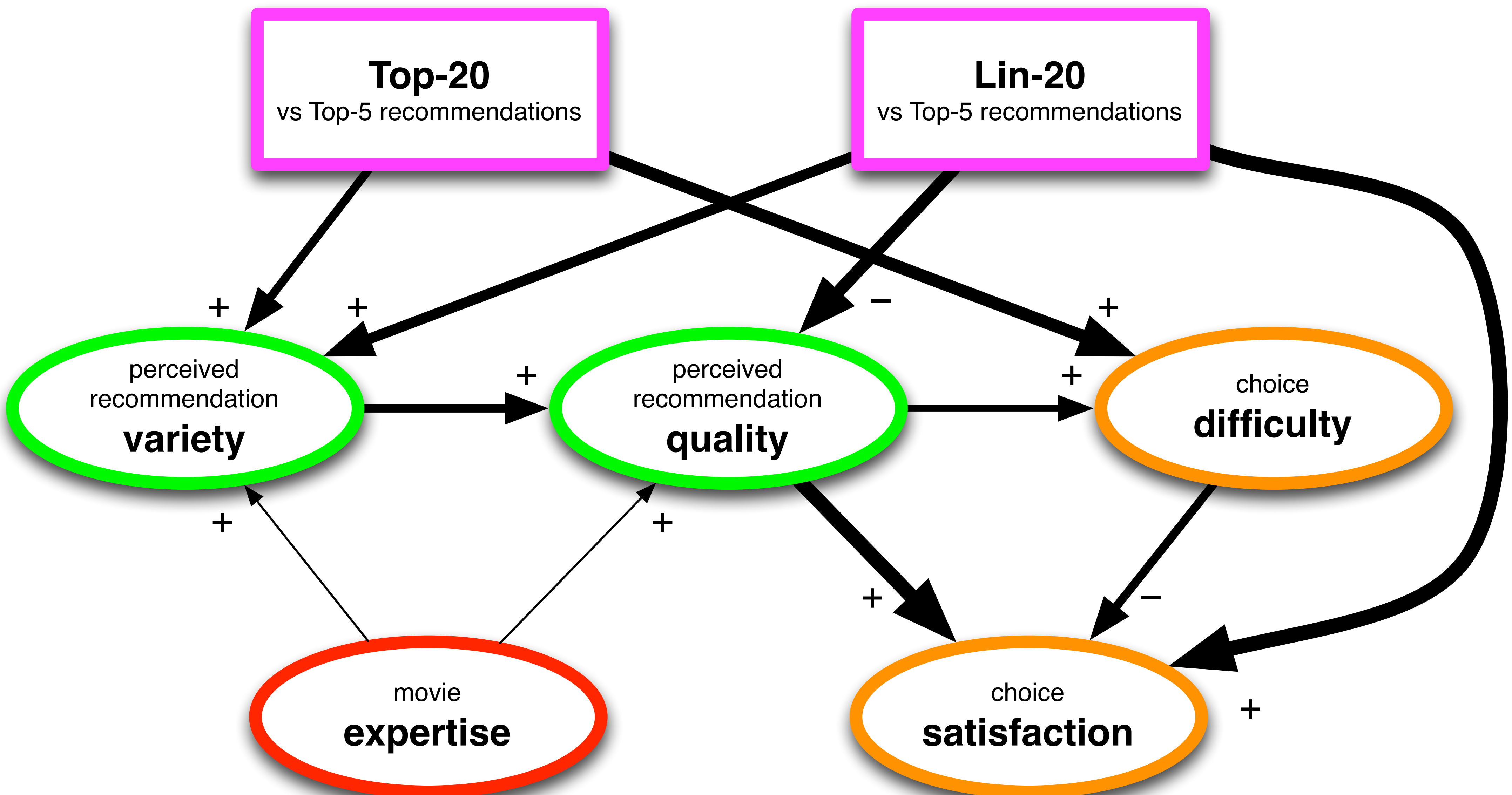
Item1
Item2
Item3
Item4
Item5
Item99
Item199
Item299
Item399
Item499
Item599
Item699
Item799
Item899
Item999
Item1099
Item1199
Item1299
Item1399
Item1499

Analysis



Bollen et al.: "Understanding Choice Overload in Recommender Systems", RecSys 2010

Structural model



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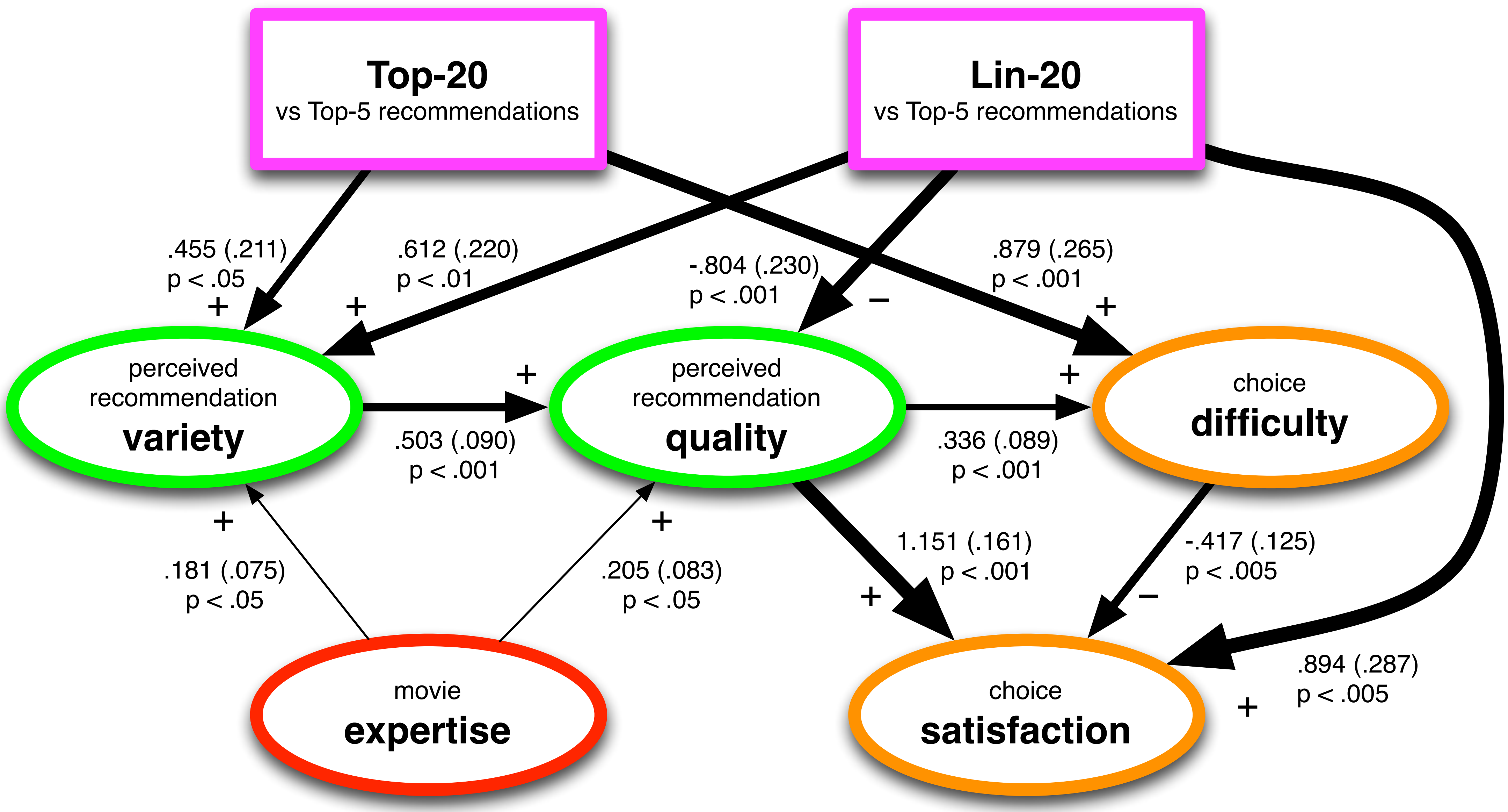


Bollen et al.: "Understanding Choice Overload in Recommender Systems", RecSys 2010

Diversification

A potential solution?

Diversification

Ziegler et al. (2015): greedy diversification algorithm:

1. Take the Top-50

2. Add the top ranked item to a list

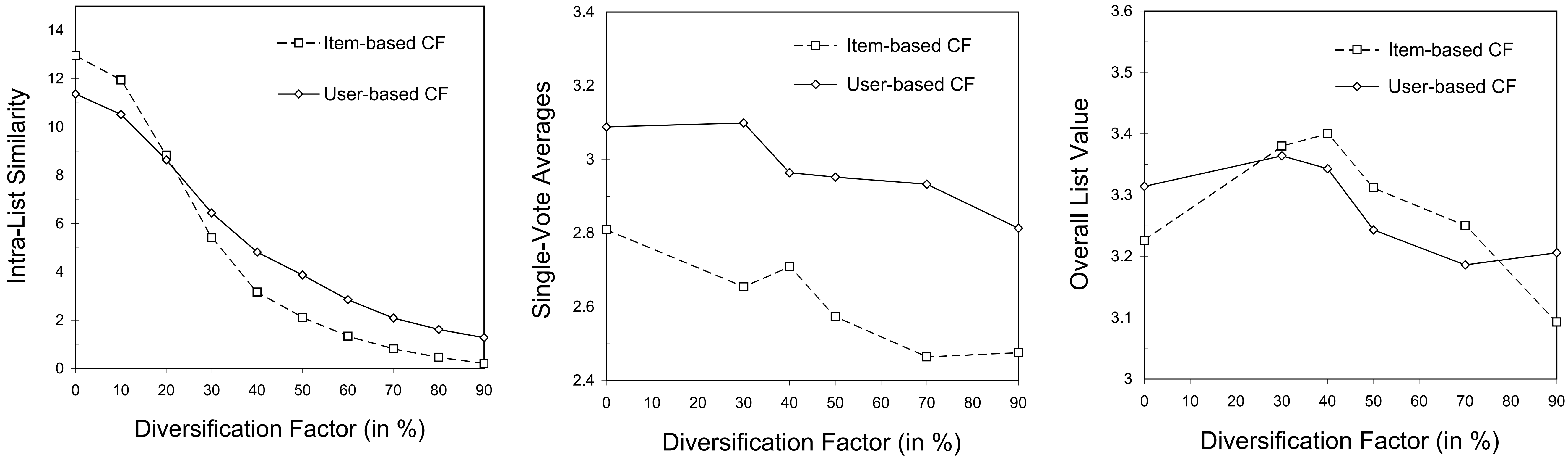
3. Add the item that maximizes a*D + (1-a)*P

    D = difference (in terms of genre*) from items already on the list

    P = predicted rating

4. Repeat step 3 until you have a Top-10

Results



Item-based CF
User-based CF
Intra-List Similarity
Diversification Factor (in %)
Single-Vote Averages
Diversification Factor (in %)
Overall List Value
Diversification Factor (in %)

A solution?

Will diversification reduce choice overload?

- It depends…

Choice difficulty = choosing among many similar options

- Diversification resolves this issue

Trade-off difficulty = comparing options to see which is best

- Diversification actually makes this more difficult

Experiment 2

A first look at diversification

Experiment 2

3 x 3 between-subjects experiment

Three "algorithm" conditions

- Non-personalized most popular (GMP), nearest neighbor CF (kNN), and Matrix Factorization (MF)

Three levels of diversification (Ziegler method)

- Low (Top-N), medium (50/50 diversity), high (10/90 diversity)

Measurement

Perceived recommendation set diversity

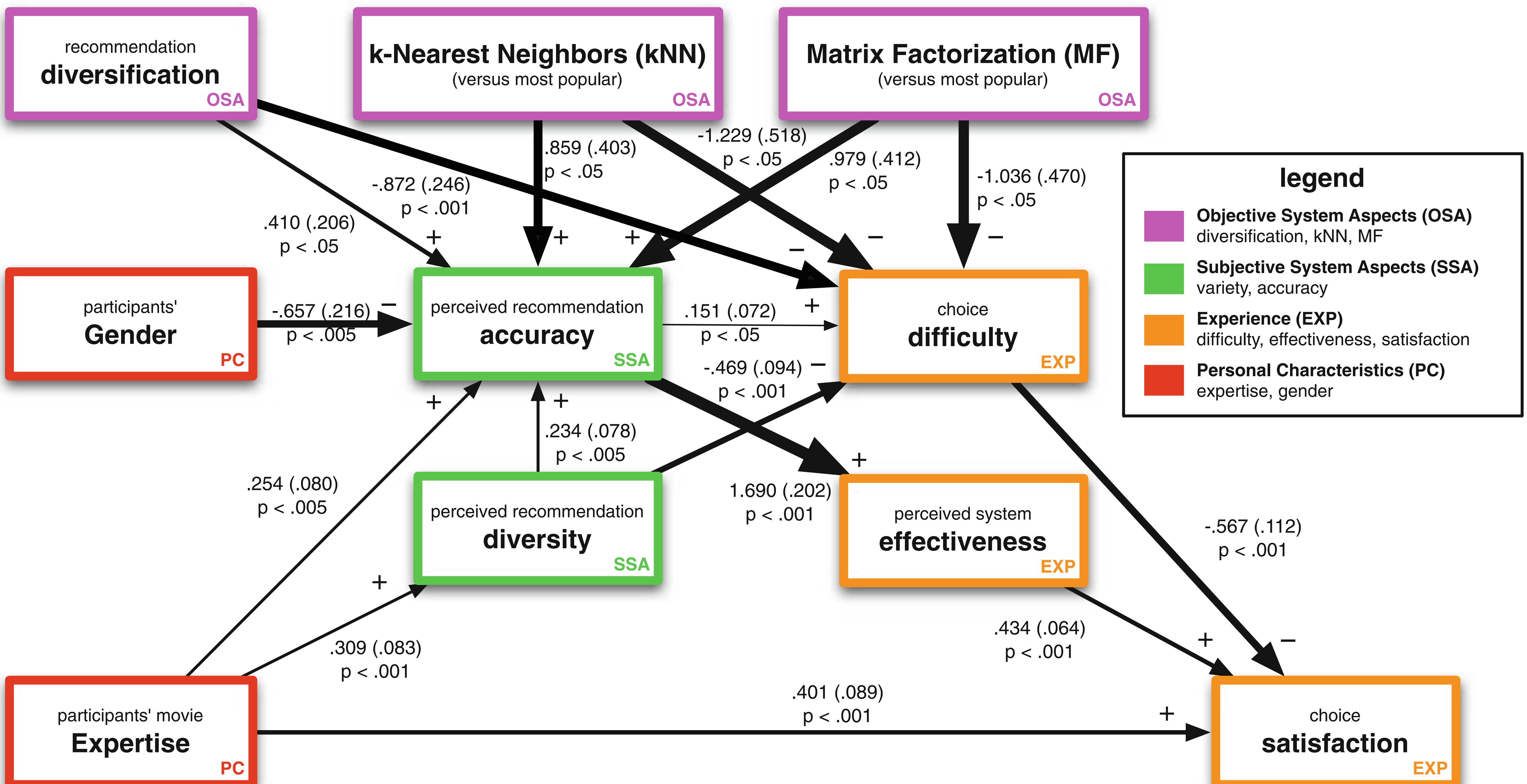
Perceived recommendation set accuracy

Choice difficulty

System effectiveness

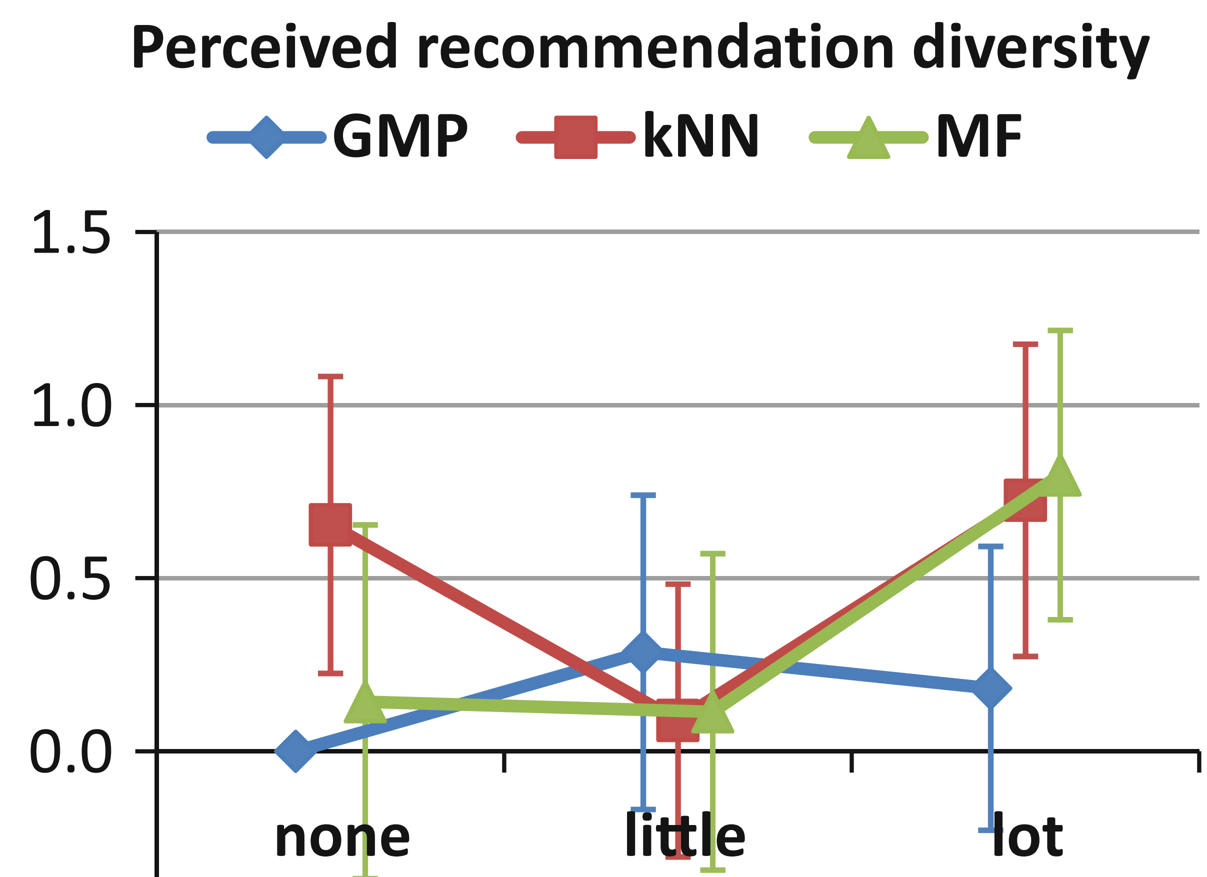
Choice satisfaction

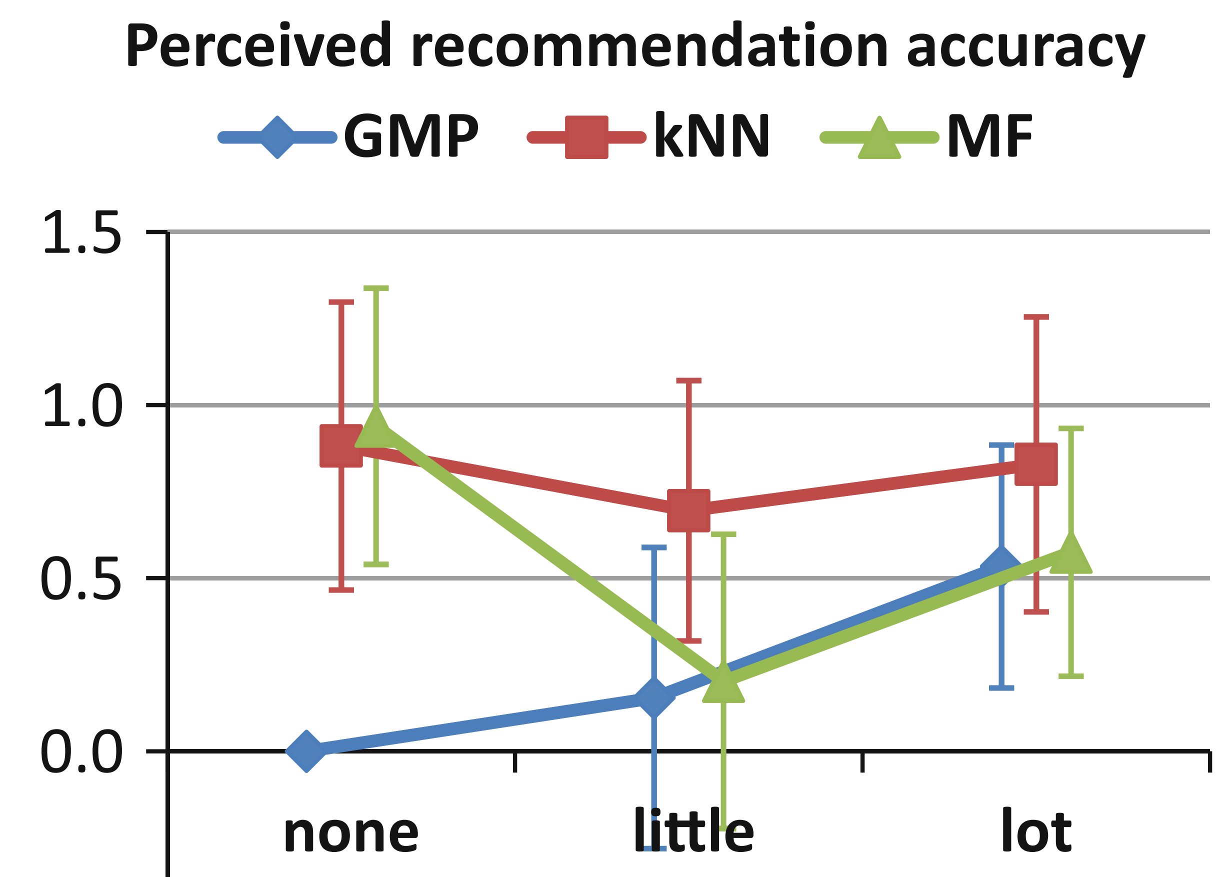
Structural model



Knijnenburg et al.: “Explaining the User-Experience of Recommender Systems”, UMUAI 2012

Differences





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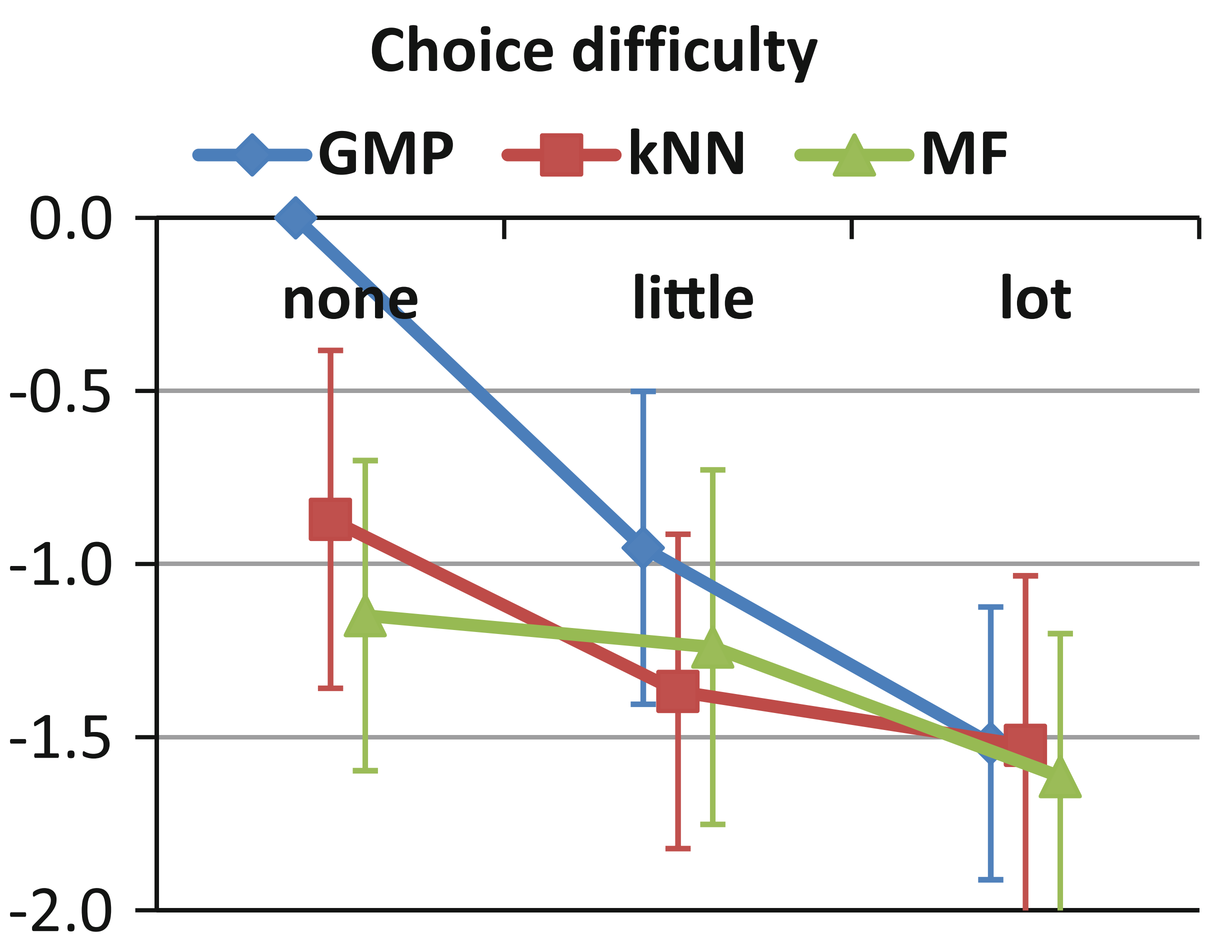

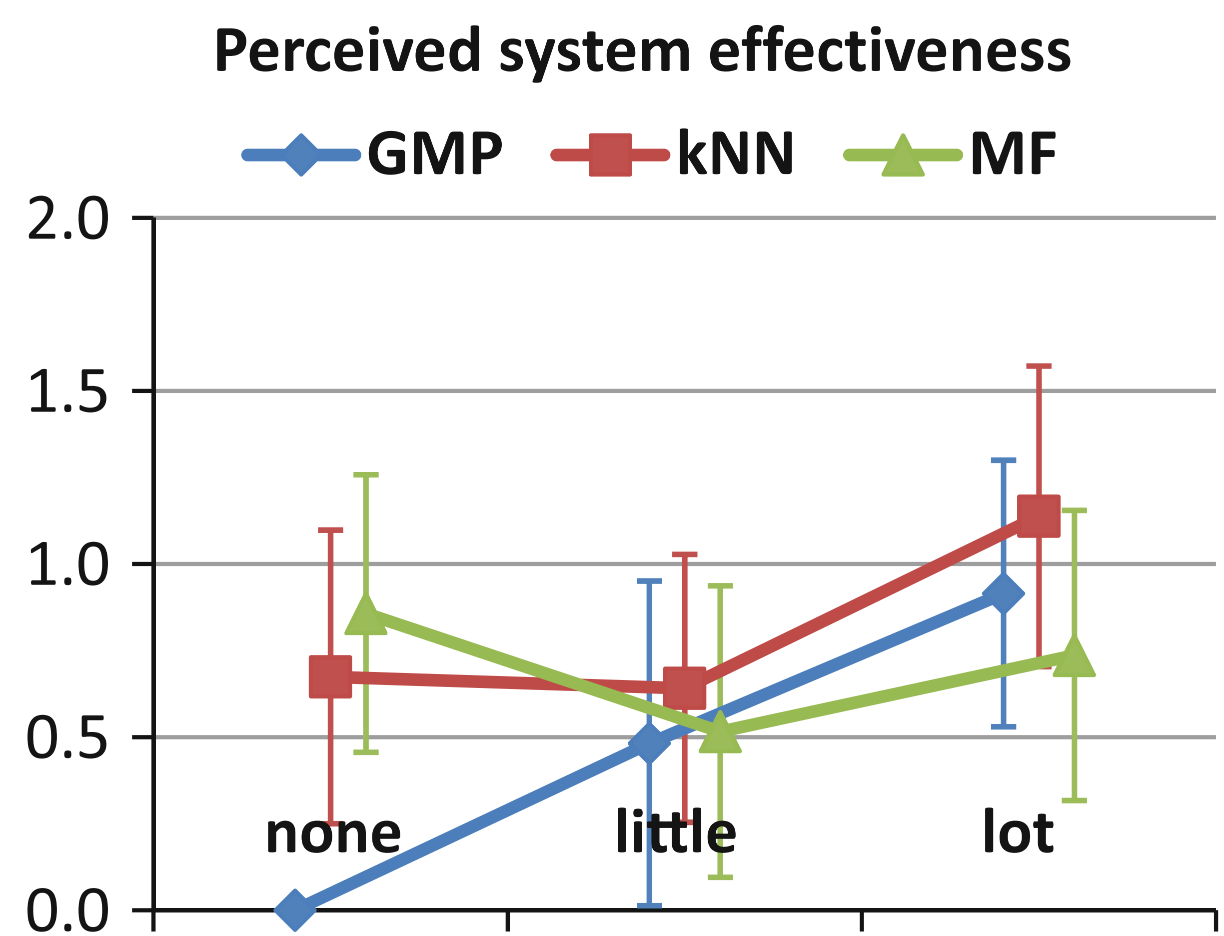

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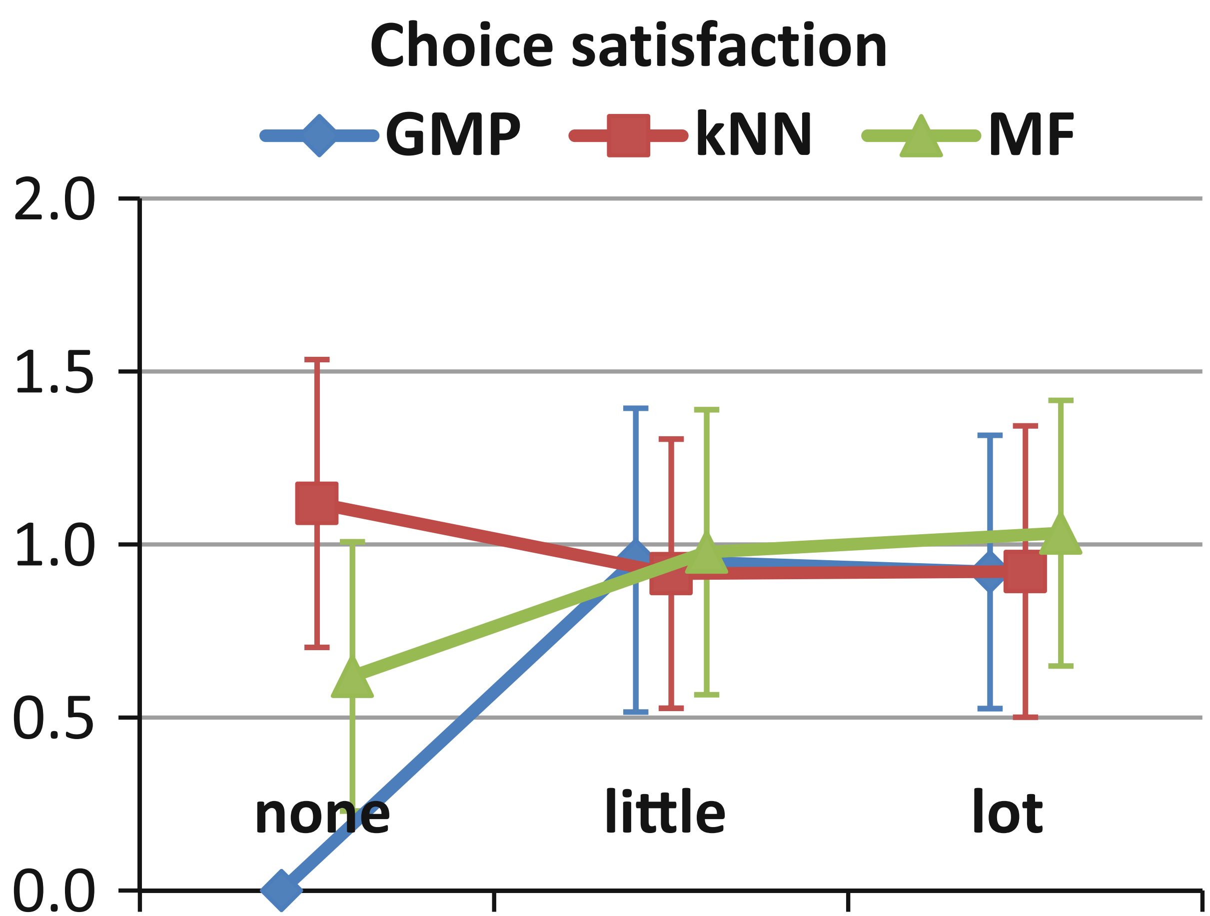


Latent diversification

Thoroughly testing the effect of diversification

Latent diversification

Can we diversify recommendation lists without the use of genres?

Solution: use the latent factors of a Matrix Factorization algorithm!

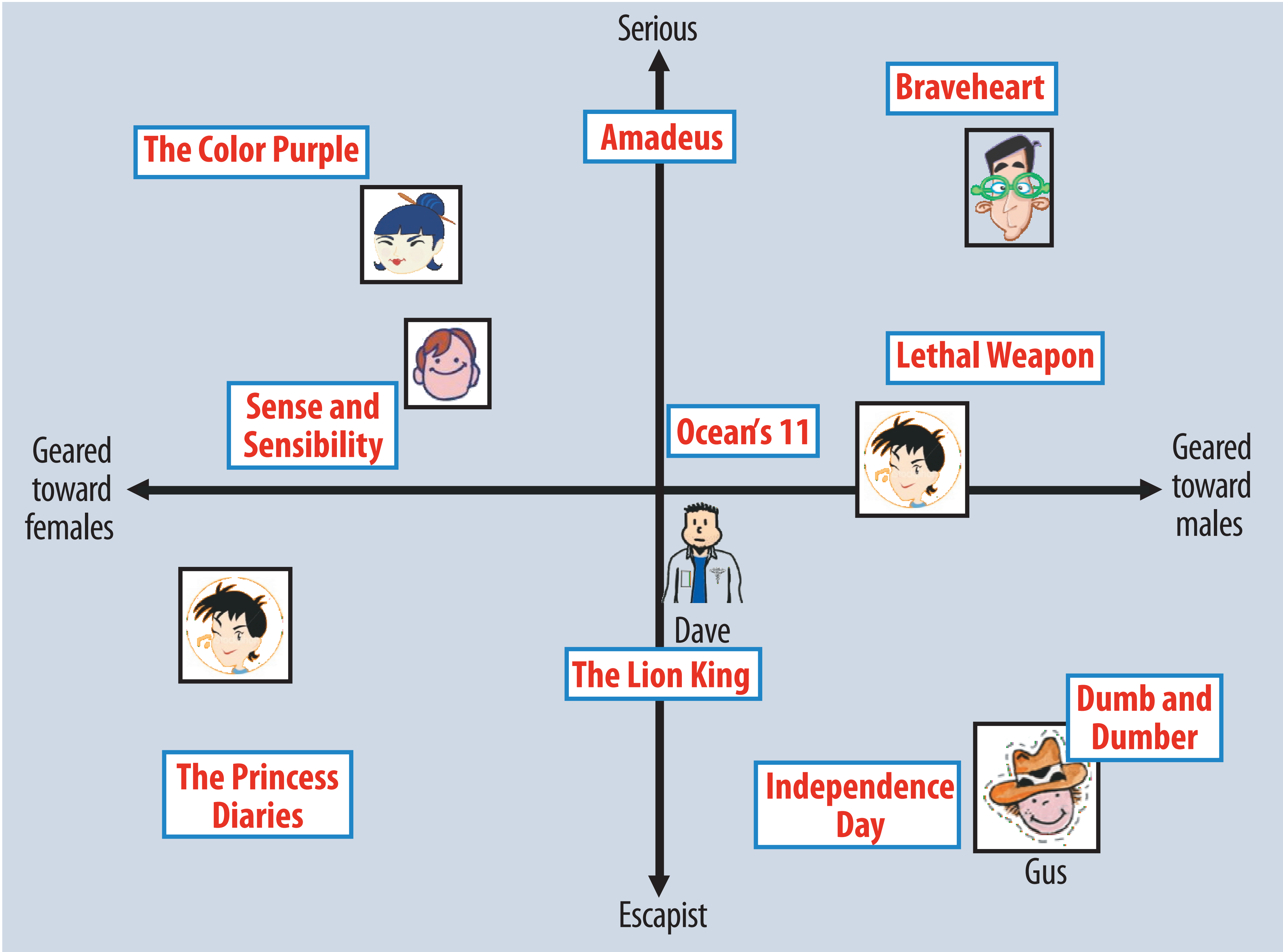
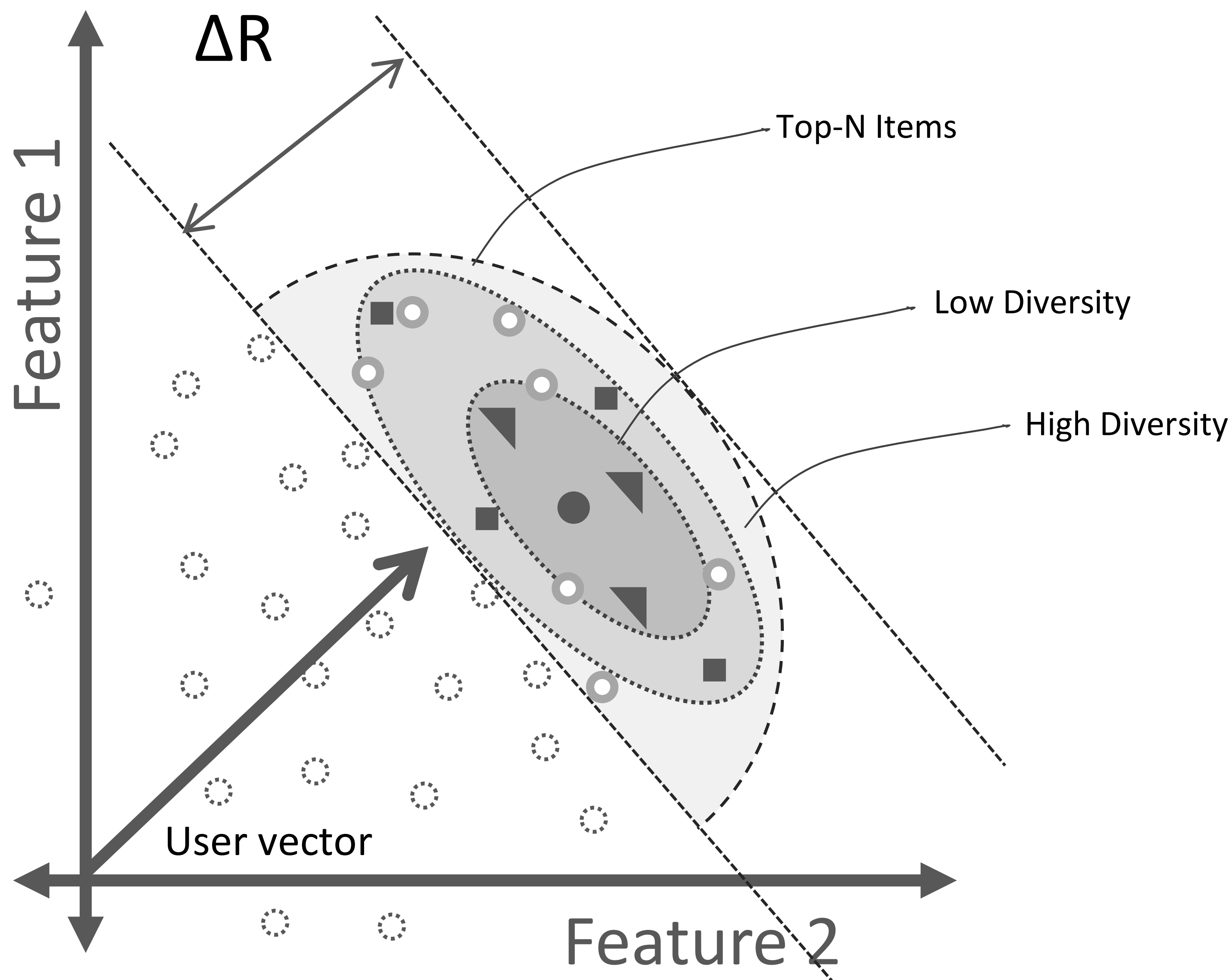


Figure 2. A simplified illustration of the latent factor approach, which characterizes both users and movies using two axes—male versus female and serious versus escapist.


ΔR
Top-N Items
Low Diversity
High Diversity
Feature 1
User vector
Feature 2

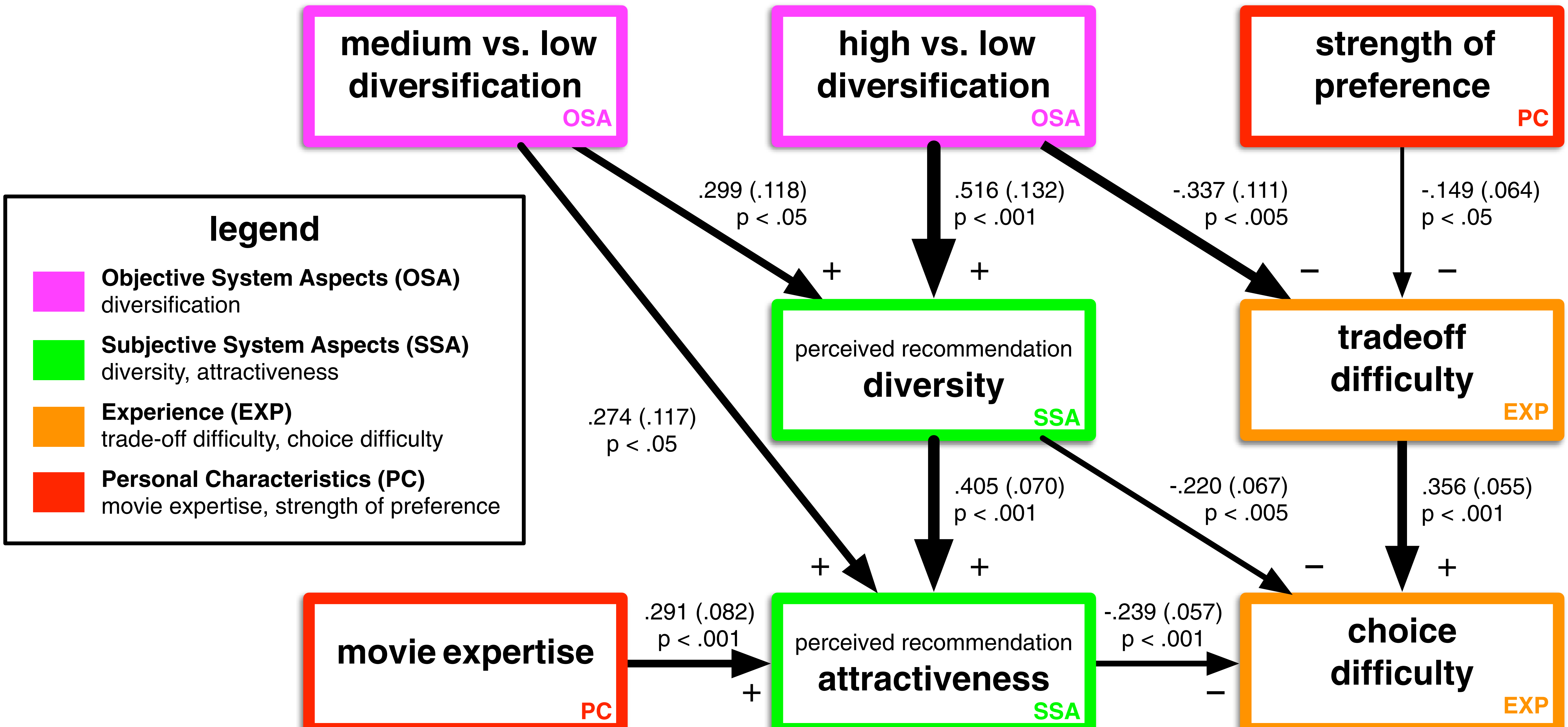
Experiment 3

Within-subjects study: show people lists with low, medium, and high diversification (but same accuracy)

Measure for each list:

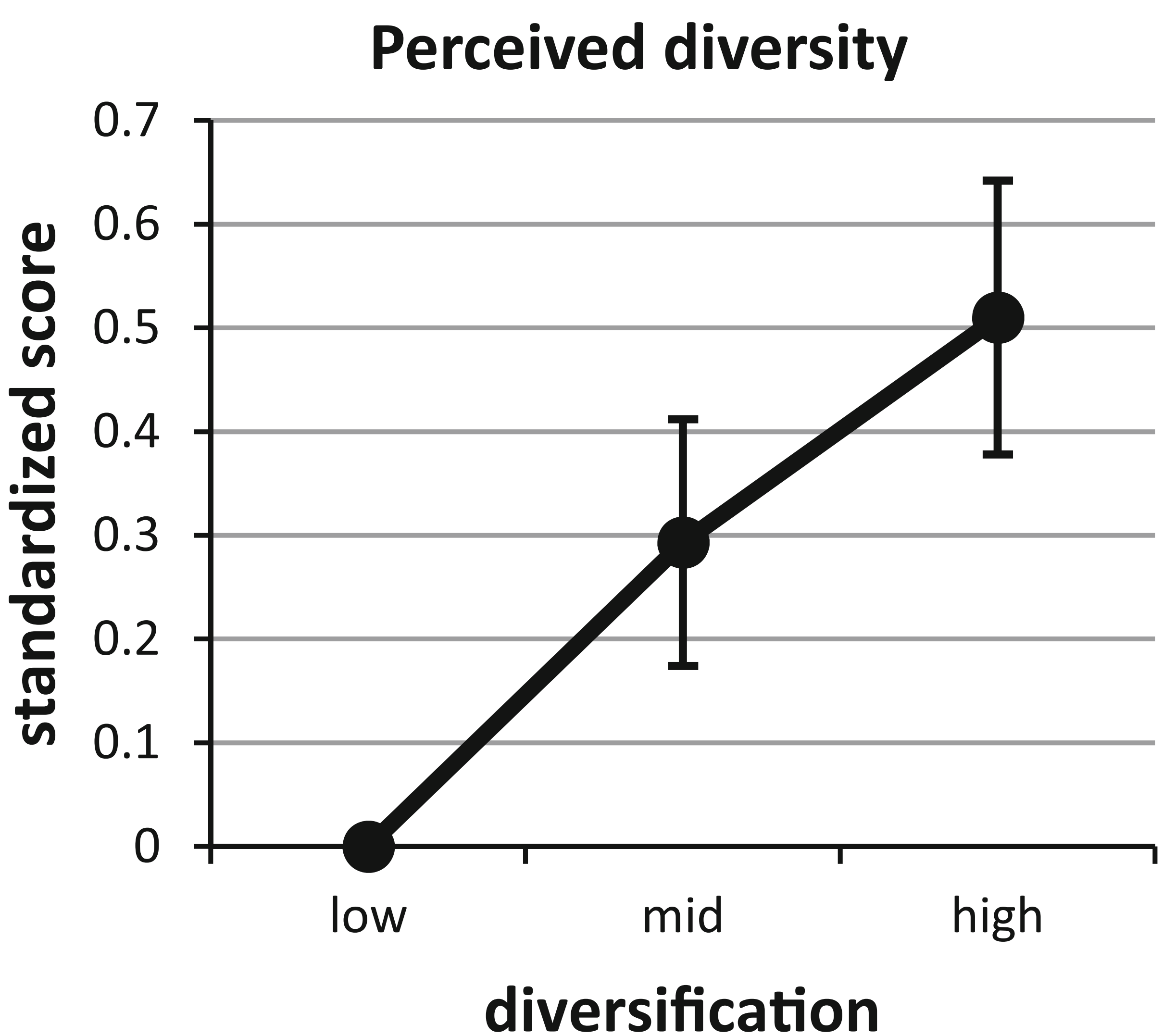
- Perceived list diversity (should increase with diversification)
- List attractiveness (should be somewhat similar)
- Tradeoff difficulty (should increase with diversification)
- Choice difficulty (should decrease with diversification)

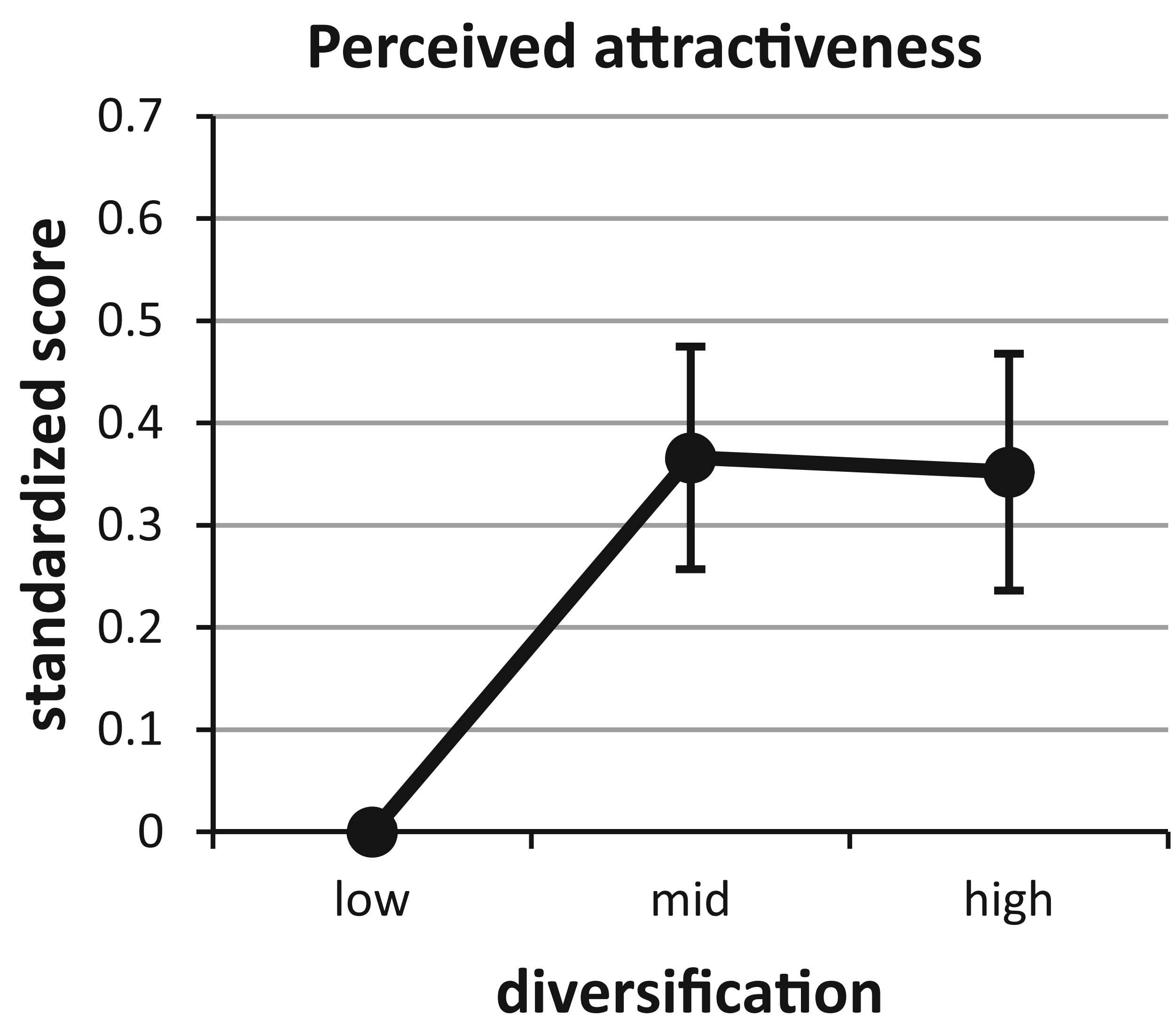
Structural model



Willemsen et al.: "The Role of Latent Feature Diversification on Choice Difficulty and Satisfaction", UMUAI 2016

Differences





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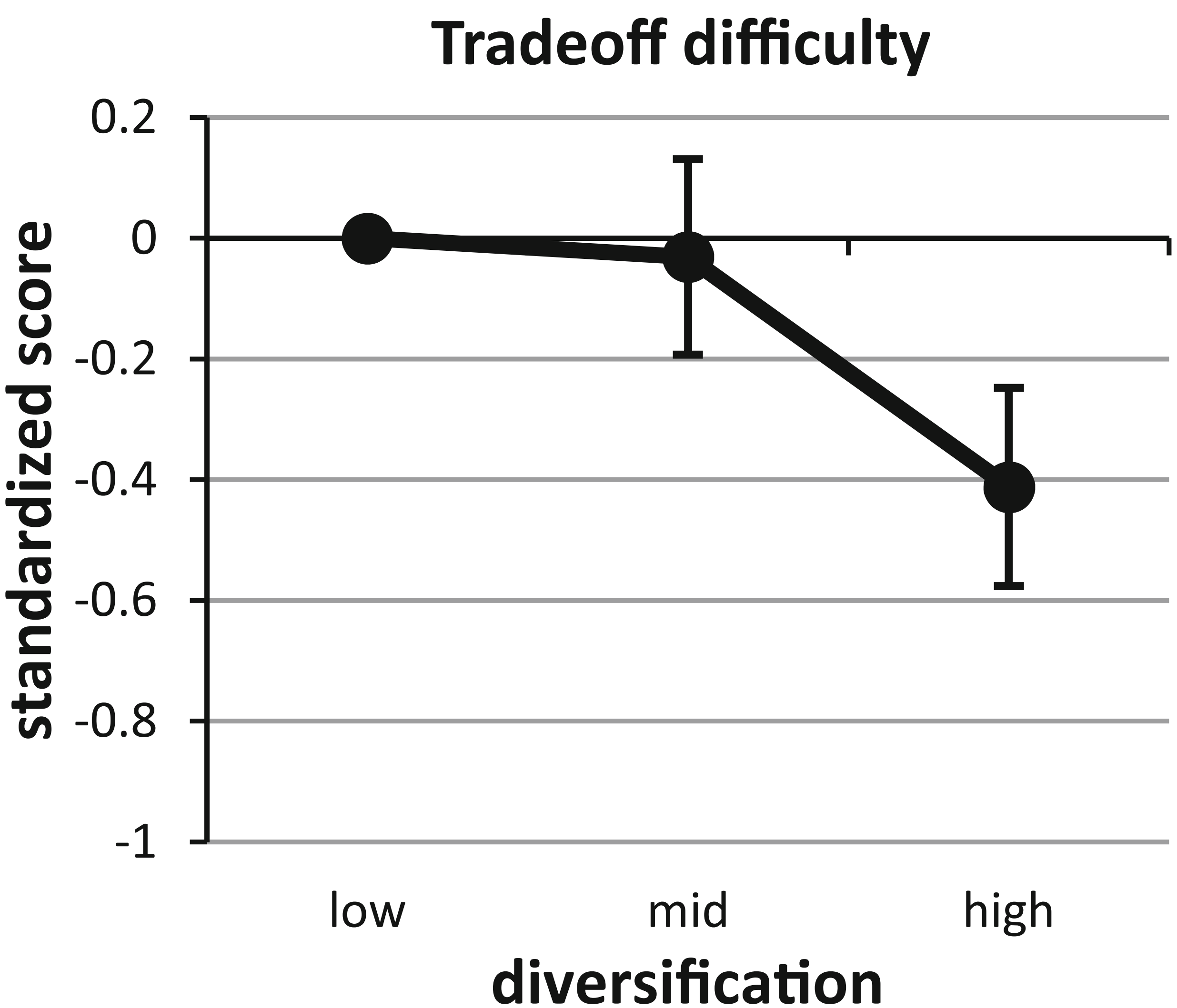

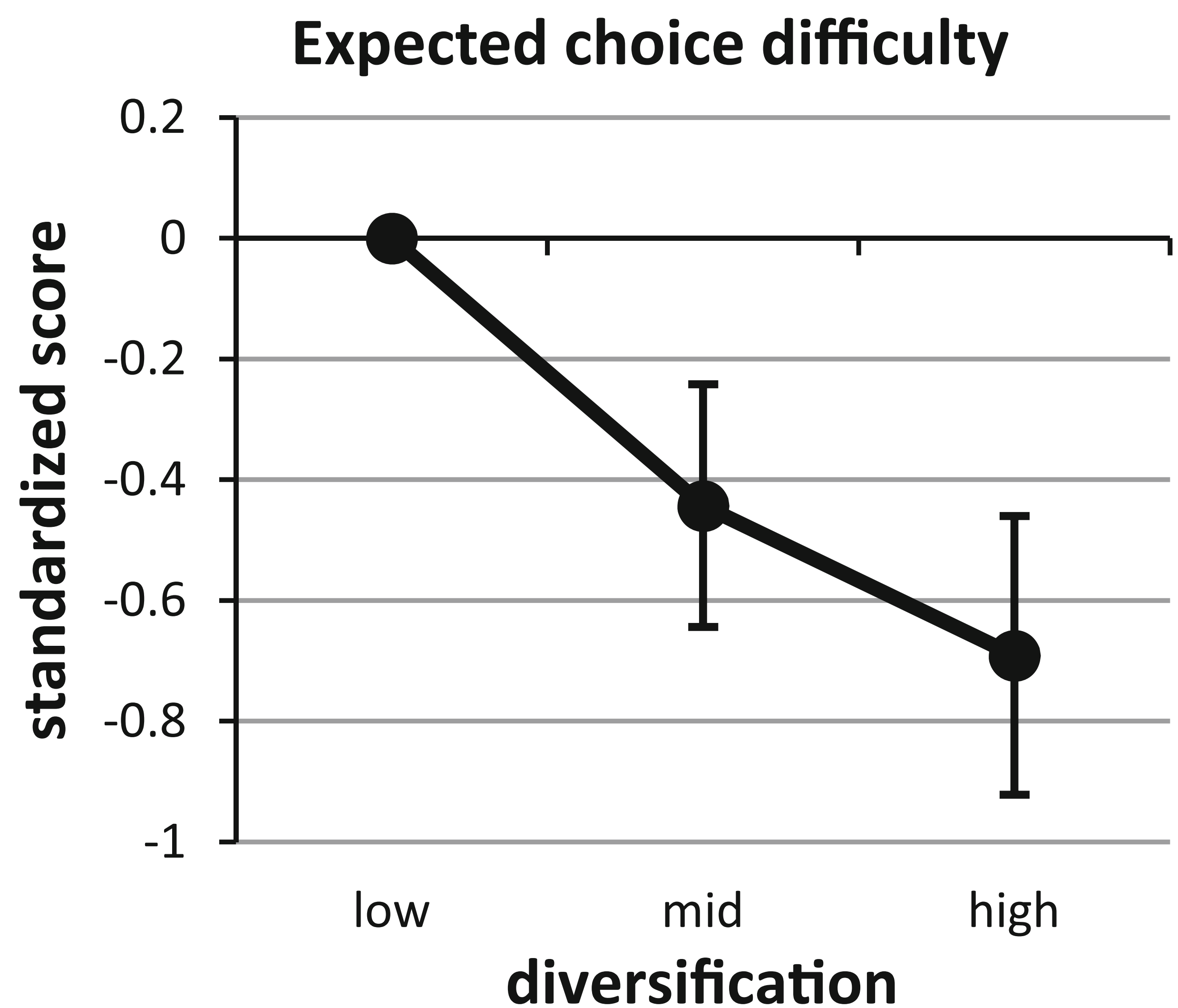

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Experiment 4

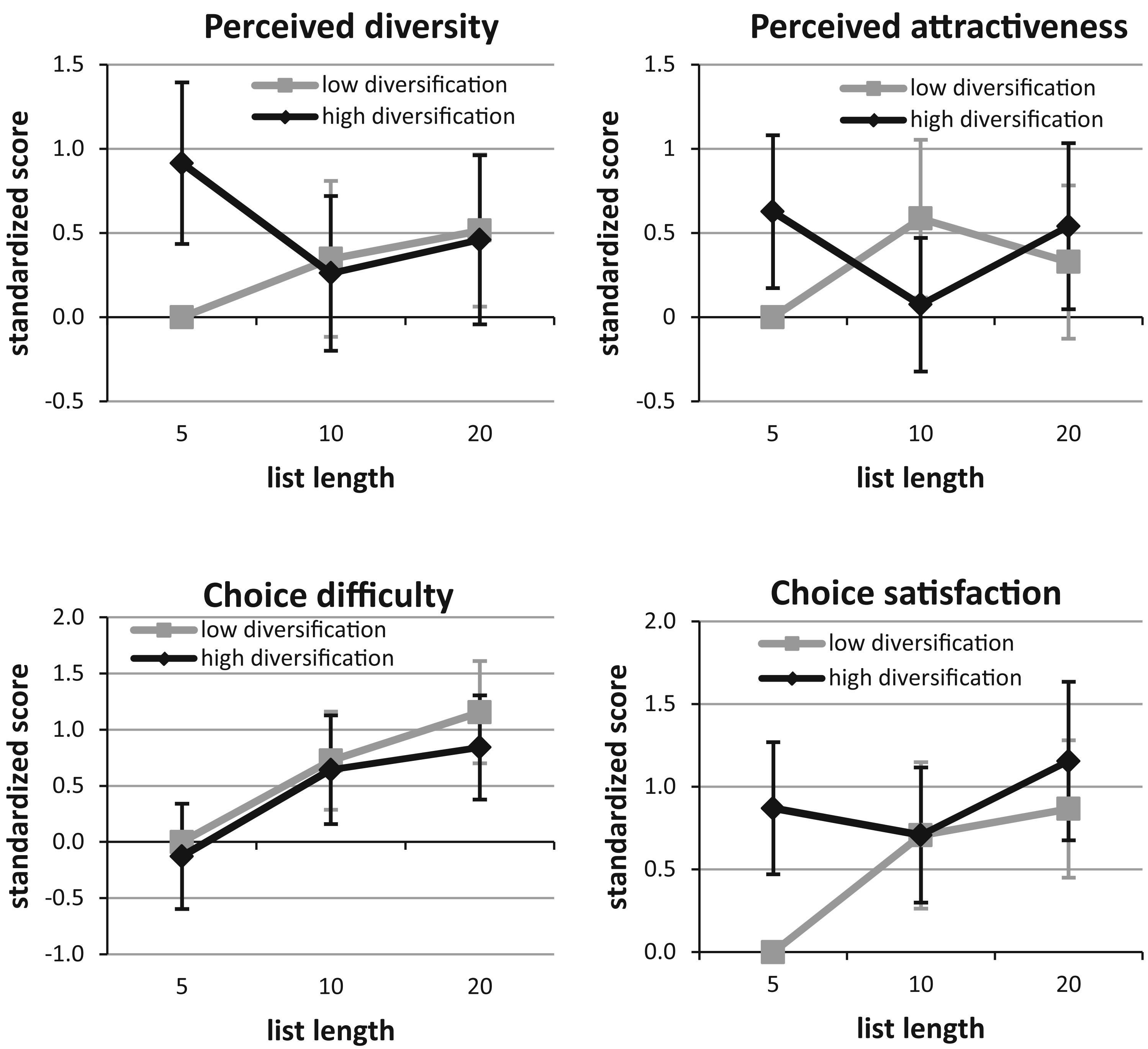
Does the result depend on list length?

Between-subjects study: low vs high diversification; list of 5, 10 or 20 items

Measure for each list:

- Perceived list diversity
- List attractiveness
- Choice difficulty
- Choice satisfaction

Differences



Willemsen et al.: “The Role of Latent Feature Diversification on Choice Difficulty and Satisfaction”, UMUAI 2016

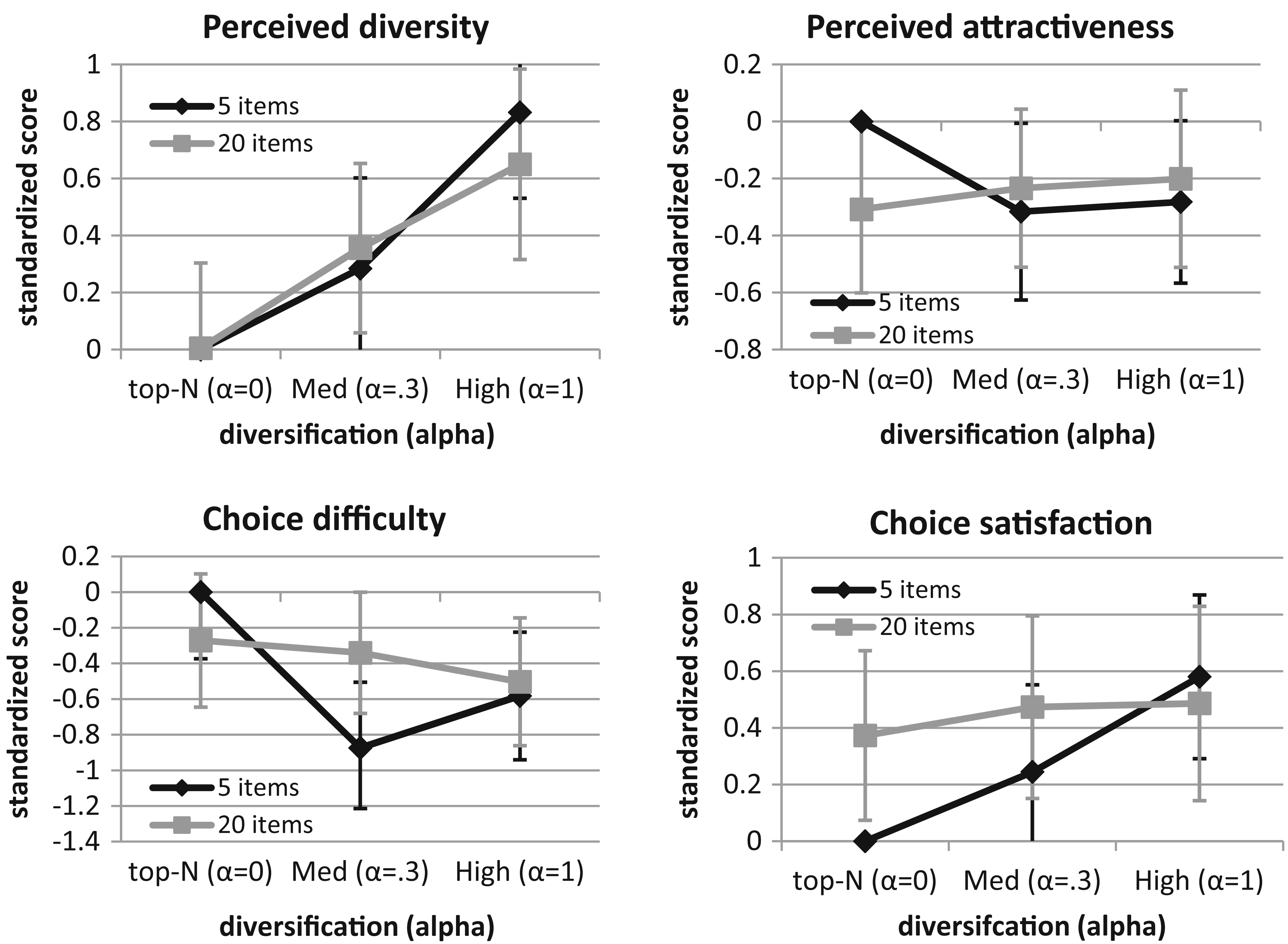
Experiment 5

What about comparing diversification to the Top-N?

(no diversification)

Between-subjects study: no (0%) vs medium (30%), high (100%) diversification; list of 5 or 20 items

Differences



Willemsen et al.: “The Role of Latent Feature Diversification on Choice Difficulty and Satisfaction”, UMUAI 2016

Other ideas

Other things that can be done with diversification

Better interaction

Typical ways to interact with a recommender:

Explicit feedback:

- Rating-based (star rating, thumbs up/thumbs down)
- Attribute-based (attribute selection, attribute weighing)
- Knowledge-based/critiquing (Q&A)

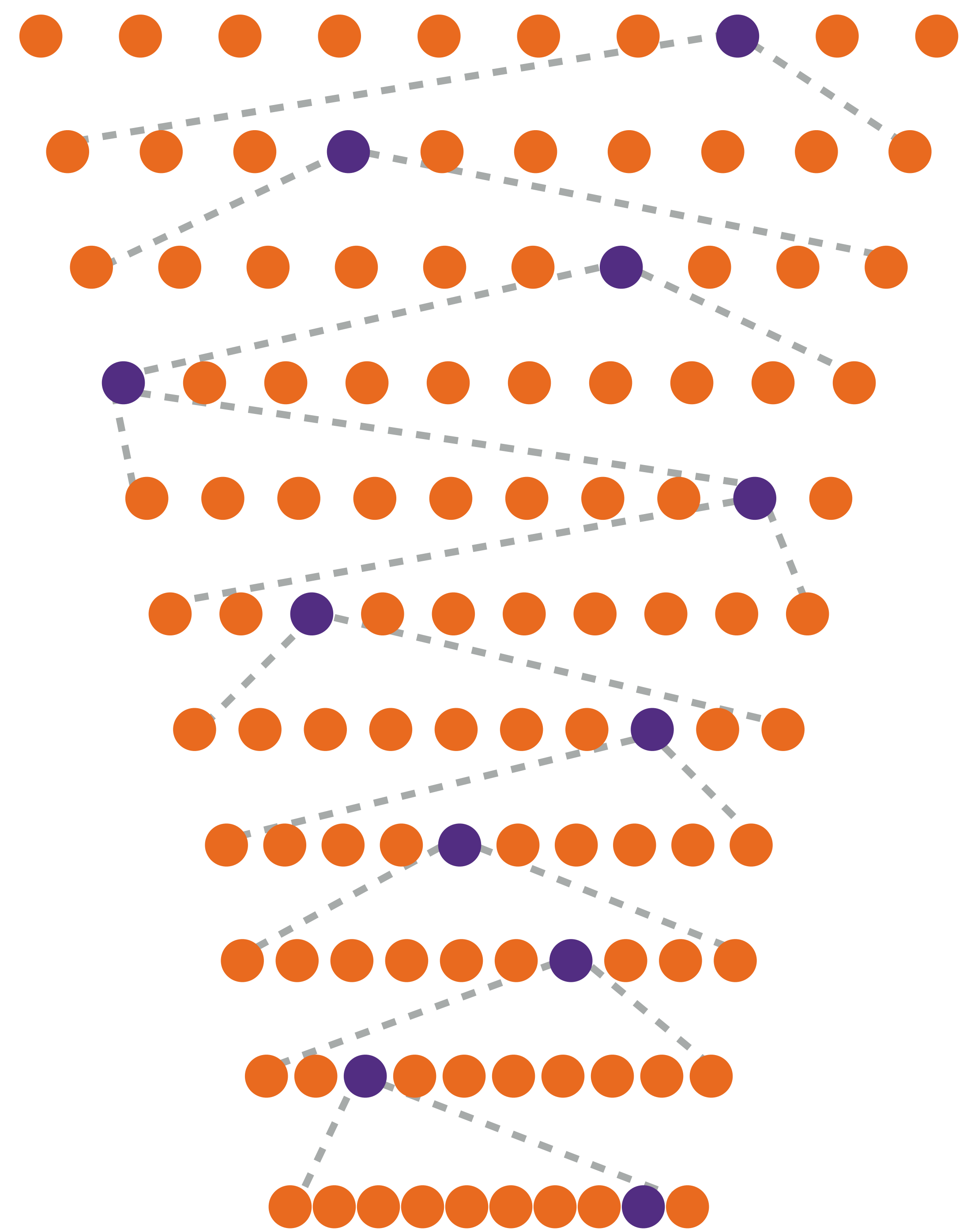
Implicit feedback:

- Browsing (clicks, scrolls, reads)
- Purchasing

Diversity-funnel

General idea:

- Start with very diverse items
- Ask the user to pick one among N
- Make recommendations, decreasing the diversity
- Ask the user to pick again
- After K rounds, the user makes a final decision



Problem

Tested with a movie recommender

Problem: Users tend to pick movies they know

Consequence: The final recommendations are all popular movies (low novelty/serendipity)

Tried to test with trailers, but didn't really work

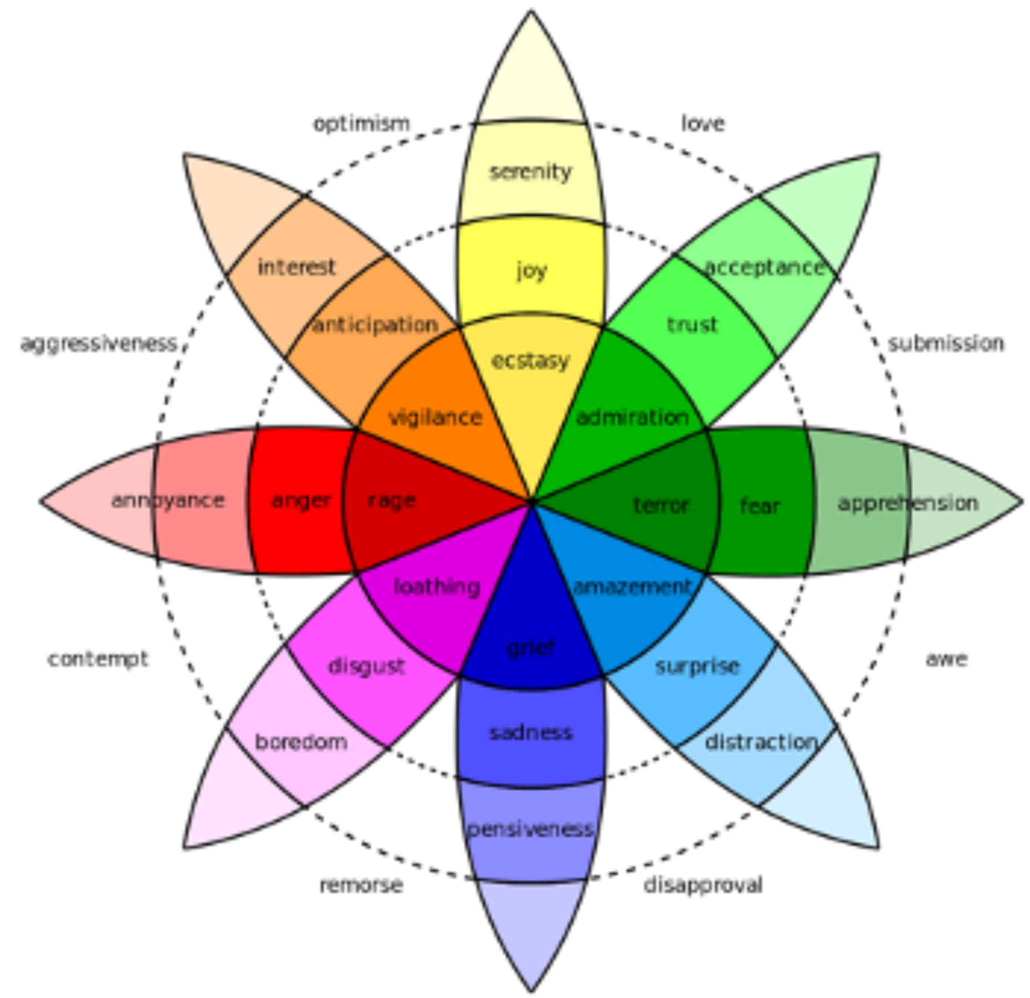
Ways to diversify

Latent feature diversification works well, but difficult to explain

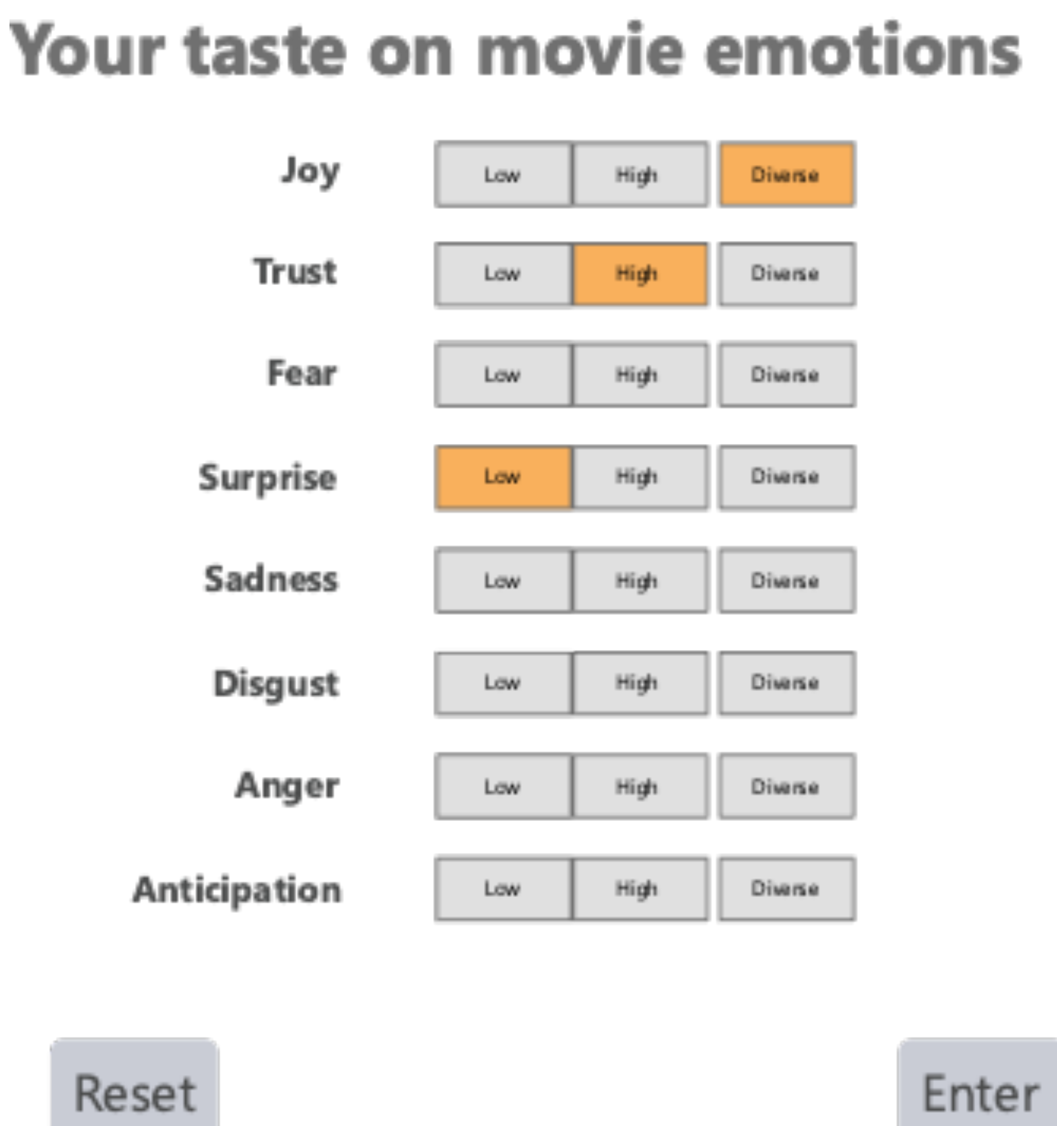
- Latent features have no intuitive explanation

Idea: diversify based on emotions

- Needed: "emotional signature" of movies
- Can be collected from reviews



Ways to diversify



Interaction idea: Filter recommendations by emotions

- Specify low/high value for certain emotions
- Allow for the other emotions to be as diverse as possible

More about this in a few weeks!