Understanding user preferences and goals in recommender systems

Martijn Willemsen
Human-Technology Interaction

EnCHIReS Workshop
ACM EICS 26 June 2017

Explaining the user experience of recommender systems
Netflix tradeoffs popularity, diversity and accuracy

AB tests to test ranking between and within rows

Source: RecSys 2016, 18 Sept: Talk by Xavier Amatriain
We don’t need the user: Let’s do AB Testing!

Netflix used 5-star rating scales to get input from users (apart from log data)

Netflix reported that they did an AB test of thumbs up/down versus rating:
Yellin (Netflix VP of product): “The result was that thumbs got 200% more ratings than the traditional star-rating feature.”

So is the 5-star rating wrong? or just different information?
We don’t need the user: Let’s do AB Testing!

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So is the 5-star rating wrong? or just different information?


However, over time, Netflix realized that explicit star ratings were less relevant than other signals. Users would rate documentaries with 5 stars, and silly movies with just 3 stars, but still watch silly movies more often than those high-rated documentaries.
Behavior versus Experience

Looking at behavior…
- Testing a recommender against a random videoclip system, the number of clicked clips and total viewing time went down!

Looking at user experience…
- Users found what they liked faster with less ineffective clicks…

Behaviorism is not enough!
(Ekstrand & Willemsen, RecSys 2016)
We need to measure user experience and relate it to user behavior…
We need to understand user goals and develop Rec. Systems that help users attain these goals!
Algorithms

Accuracy: compare prediction with actual values

Recommendation: best predicted items

Choose (prefer?)

Experience!

dataset
user-item rating pairs

90% of work in Recommender Systems
User-Centric Framework

Computers Scientists (and marketing researchers) would study behavior.... (they hate asking the user or just cannot (AB tests))
User-Centric Framework

Psychologists and HCI people are mostly interested in experience...
User-Centric Framework

Though it helps to triangulate experience and behavior...
User-Centric Framework

Our framework adds the intermediate construct of perception that explains why behavior and experiences changes due to our manipulations.
User-Centric Framework

- And adds personal and situational characteristics

Relations modeled using factor analysis and SEM

Choice difficulty and satisfaction in RecSys
Applying latent feature diversification

Understanding the role of latent feature diversification on choice difficulty and satisfaction

Martijn C. Willemsen¹ · Mark P. Graus² · Bart P. Knijnenburg³

Abstract People like variety and often prefer to choose from large item sets. However, large sets can cause a phenomenon called “choice overload”; they are more difficult to choose from, and as a result decision makers are less satisfied with their choices. It
Seminal example of choice overload

Less attractive
30% sales
Higher purchase satisfaction

More attractive
3% sales

From Iyengar and Lepper (2000)

Satisfaction decreases with larger sets as increased attractiveness is counteracted by choice difficulty.

Can we reduce difficulty while controlling attractiveness?
Dimensions in Matrix Factorization

Dimensionality reduction
Users and items are represented as vectors on a set of latent features

Rating is the dot product of these vectors (overall utility!)

Gus will like Dumb and Dumber but hate Color Purple

Latent Feature Diversification: high diversity with equal attractiveness
Latent Feature Diversification

System (OSA)
Psychology-informed Diversity manipulation

Perception (SSA)
Increased perceived Diversity & attractiveness

Experience (EXP)
Reduced difficulty & increased satisfaction

Interaction (INT)
Less hovers
More choice for lower ranked items

Choice Satisfaction

<table>
<thead>
<tr>
<th>Diversification</th>
<th>Rank of chosen</th>
</tr>
</thead>
<tbody>
<tr>
<td>None (top 5)</td>
<td>3.6</td>
</tr>
<tr>
<td>Medium</td>
<td>14.5</td>
</tr>
<tr>
<td>High</td>
<td>77.6</td>
</tr>
</tbody>
</table>

Higher satisfaction for high diversification, despite choice for lower predicted/ranked items
### Algorithms

**Rating?**

- **Experience!**
- **Choose (prefer?)**
- **Recommendation:** best predicted items

**Accuracy:** compare prediction with actual values

**dataset**
user-item rating pairs

Table:

<table>
<thead>
<tr>
<th>User</th>
<th>Movie 1</th>
<th>Movie 2</th>
<th>Movie 3</th>
<th>Movie 4</th>
<th>Movie 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wijnand</td>
<td>2</td>
<td>...</td>
<td>3</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>Martijn</td>
<td>...</td>
<td>4</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Chris</td>
<td>4</td>
<td>2</td>
<td>5</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Mark</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Maurits</td>
<td>4</td>
<td>5</td>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Eric</td>
<td>3</td>
<td>...</td>
<td>5</td>
<td>...</td>
<td>3</td>
</tr>
</tbody>
</table>
Preference elicitation

improving the input...

Preference Elicitation (PE) is a major topic in research on Decision Making
I even did my PhD thesis on it... ;-)
What can Psychology teach us about improving this aspect?
Role of memory in ratings
Rating support
Cold start problem: please rate this movie…
Does it matter if the preference you provide (by rating) is based on recent experiences or mostly on your memory? We don’t have data on the time between consumption and rating…

Take a proxy: Time from release date

Koren finds increasing ratings with the age of the movie (positivity effect?)

Or just ask the users!
Results

247 users, 4212 ratings

Users rated movies they have seen and when that was (week, month, … 3 years or longer)

Rating distributions:

• Only 28% seen in the last year
• # Positive ratings decrease with time
• 1\textsuperscript{st} timeslot: 60% 4/5 star
• Last timeslot: only 36%
Multilevel model:
Random intercepts for movies and users

high-rated versus low-rated: both show regression towards the mean

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Std. Err.</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>intercept</td>
<td>2.95</td>
<td>0.15</td>
<td>19.05</td>
</tr>
<tr>
<td>time</td>
<td>0.29</td>
<td>0.13</td>
<td>2.31</td>
</tr>
<tr>
<td>highrated</td>
<td>1.62</td>
<td>0.22</td>
<td>7.43</td>
</tr>
<tr>
<td>time$^2$</td>
<td>-0.09</td>
<td>0.02</td>
<td>-3.55</td>
</tr>
<tr>
<td>Time x highrated</td>
<td>-0.73</td>
<td>0.18</td>
<td>-4.10</td>
</tr>
<tr>
<td>Tine$^2$ x highrated</td>
<td>0.11</td>
<td>0.03</td>
<td>3.26</td>
</tr>
</tbody>
</table>
How can we train a recommender system..
   If ratings depend on our memory this much…

Problem lies partly in the type of judgment asked:
   Rating is separate evaluation on an absolute scale…
   Lacks a good reference/comparison

Two solutions we explored:
   Rating support
   Different elicitation methods: choice!
Joint versus Separate Evaluation (Hsee, 1996)

Evaluations of two job candidates for a computer programmer position expecting the use of a special language called KY.

<table>
<thead>
<tr>
<th></th>
<th>Candidate A</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education</td>
<td>B.Sc. computer Sc.</td>
</tr>
<tr>
<td>GPA (0-5)</td>
<td>4.8</td>
</tr>
<tr>
<td>KY Experience</td>
<td>10 KY programs</td>
</tr>
</tbody>
</table>

Mean WTP (in thousands):

<table>
<thead>
<tr>
<th></th>
<th>Separate</th>
<th>Joint</th>
</tr>
</thead>
<tbody>
<tr>
<td>$WTP</td>
<td>$32.7 k</td>
<td>$31.2 k</td>
</tr>
<tr>
<td>$WTP</td>
<td></td>
<td>$33.2 k</td>
</tr>
</tbody>
</table>
Rating support interfaces
Using movielens!

Can we help users during rating to make their ratings more stable/accurate?

We can support their memory for the movie using tags.
We can help ratings on the scale using previous ratings as exemplars.

Movielens has a tag genome and a history of ratings so we can give real-time user-specific feedback!

Tag Interface

- Provide 10 tags that are relevant for that user and that describe the movie well
- Didn’t really help…
Exemplar Interface

Support rating on the scale by providing exemplars:

Exemplar: Similar movies rated before by that user for that level on the scale

This helped to anchor the values on the scale better: more consistent ratings
But what are preferences?
Ratings are absolute statements of preference…

But preference is a relative statement…

Preferences are **constructive**: People **develop/construct** their preferences while making a decision (Bettman et al. 1998)

So why not ask users to choose and have the recommender adapt to that?

Which do you prefer?
Several recent examples using different PE methods

Loepp, Hussein & Ziegler (CHI 2014)

• Choose between sets of movies that differ a lot on a latent feature

Chang, Harper & Terveen (CSCW 2015)

• Choose between groups of similar movies
• By assigning points per group (ranking!)
Accuracy:
compare prediction with actual values

Recommendation:
best predicted items

Interaction between user and Rec. System!

Choose (prefer?)

Experience!

dataset
user-item rating pairs

Algorithms

test the output!
Choice-based preference elicitation

Choices are relative statements that are easier to make

Better fit with final goal: finding a good item rather than making a good prediction

In Marketing, conjoint-based analysis uses the same idea to determine attribute weights and utilities based on a series of (adaptive) choices

Can we use a set of choices in the matrix factorization space to determine a user vector in a stepwise fashion?

How does this work? Step 1

**Iteration 1a:** Diversified choice set is calculated from a matrix factorization model (red items)

**Iteration 1b:** User vector (blue arrow) is moved towards chosen item (green item), items with lowest predicted rating are discarded (greyed out items)
How does this work? Step 2

**Iteration 2:** New diversified choice set (blue items)

**End of Iteration 2:** with updated vector and more items discarded based on second choice (green item)
Evaluation of Preference Elicitation

- **Choice-based PE:** choosing 10 times from 10 items
- **Rating-based PE:** rating 15 items
- After each PE method they evaluated the interface on
  - interaction usability in terms of ease of use
    - e.g., “It was easy to let the system know my preferences”
  - **Effort:** e.g., “Using the interface was effortful.”
  - effort and usability are highly related (r=0.62)
- **Results:** less perceived effort for choice-based PE
  perceived effort goes down with completion time
Behavioral data of PE-tasks

Choice-based PE: most users find their perfect item around the 8\textsuperscript{th} / 9\textsuperscript{th} item and they inspect quite some unique items along the way.

Rating-based: user inspect many lists (Median = 13), suggesting high effort in rating task.
Perception of Recommendation List

- Participants evaluated each recommendation list separately on Choice Difficulty and Satisfaction.
- More satisfied with choice-based list: less difficult, less obscure items (popularity prevails!)

```
+-----------------+     
| Choice-Based List |     
|                  |     
|                  |     
|                  |     
|                  |     
|                  |     
|-----------------+     
| Intra List Similarity     
| 14.00 (4.51)  
| p<.01     
|                  
| Difficultly     
| -.240 (.145)  
| p<.1     
| -2.407 (.381)  
| p<.001     
| Obscurity     
| -.479 (.111)  
| p<.001     
| -.257 (.045)  
| p<.001     
|                  
| Satisfaction with Chosen Item     
```
New version with trailers

With trailers less popular movies are chosen

no reduction in satisfaction!

Algorithms

Accuracy:
compare prediction with actual values

Recommendation:
best predicted items

Goals

Choose (prefer?)

Experience!

Recommending to help users achieve their goals

understand the input!

dataset
user-item rating pairs

Rating?

dataset
user-item rating pairs

Experience!

Accuracy:
compare prediction with actual values
How recommenders can help users achieve their goals

Research with Alain Starke (PhD student)

To be presented
At RecSys 2017
Recommending for Behavioral change

- Behavioral change is hard…
  - Exercising more, eat healthy, reduce alcohol consumption (reducing Binge watching on Netflix 😊)
  - Needs awareness, motivation and commitment

Combi model:

Klein, Mogles, Wissen
Journal of Biomedical Informatics, 2014
What can recommenders do?

• Persuasive Technology: focused on how to help people change their behavior:
  – personalize the message…

• Recommenders systems can help with what to change and when to act
  – personalize what to do next…

• This requires different models/algorithms
  – our past behavior/liking is not what we want to do now!

Behaviorism is not enough…!
One of our use cases: How can we help people to save energy?
Our first (old) recommender system using simple MAUT

### Indicate your preference

Here is a list of possible needs. Indicate how important they are for you by clicking **multiple** checkboxes to change your attribute weights.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Less Important</th>
<th>More Important</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low initial effort</td>
<td>8%</td>
<td>33%</td>
</tr>
<tr>
<td>Little continuous effort</td>
<td>11%</td>
<td>22%</td>
</tr>
<tr>
<td>Low initial costs</td>
<td>8%</td>
<td>14%</td>
</tr>
<tr>
<td>Save more energy</td>
<td>8%</td>
<td>14%</td>
</tr>
<tr>
<td>Quick return on investment</td>
<td>14%</td>
<td>10%</td>
</tr>
<tr>
<td>Positive environmental effects</td>
<td>10%</td>
<td>10%</td>
</tr>
</tbody>
</table>

### Make a choice

Here are several recommendations; choose those energy-saving measures from this list which you want to implement.

<table>
<thead>
<tr>
<th>Name</th>
<th>Initial effort</th>
<th>Effort</th>
<th>Energy savings</th>
<th>Return on investment</th>
<th>Env. effects</th>
<th>Comfort</th>
</tr>
</thead>
<tbody>
<tr>
<td>Roof insulation</td>
<td>€3100</td>
<td>€299</td>
<td>1424 kWh/year</td>
<td>10 years</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Laptop instead of a PC</td>
<td>€95</td>
<td>€31</td>
<td>150 kWh/year</td>
<td>3 years</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Turn off PC when absent</td>
<td>€50</td>
<td>€50</td>
<td>8 kWh/year</td>
<td>3 year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Heat laundry</td>
<td>null</td>
<td>null</td>
<td>45 kWh/year</td>
<td>4 year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Close curtains</td>
<td>null</td>
<td>null</td>
<td>5 kWh/year</td>
<td>4 year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shower 3 minutes</td>
<td>null</td>
<td>null</td>
<td>5 kWh/year</td>
<td>4 year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Boiler-heated</td>
<td>null</td>
<td>null</td>
<td>5 kWh/year</td>
<td>4 year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Air-dry clothes</td>
<td>null</td>
<td>null</td>
<td>5 kWh/year</td>
<td>4 year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A++ Fridge/freezer combo</td>
<td>null</td>
<td>null</td>
<td>45 kWh/year</td>
<td>4 year</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Your savings

Here are your selected savings! Show totals in € euro kWh.

<table>
<thead>
<tr>
<th>This is what I want to do</th>
<th>This is what I already do</th>
<th>This is what I don’t want to do</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

You have been using the system for 1 minute. When you press stop, you will be asked a few final questions, after which you can print your savings.

**stop**
Study 3 (AMCIS 2014)

• Online lab study
  • 147 paid pps (79M, 68F, mean age: 40.0)
  • Selected pps interacted for at least 2.5 minutes

• 3 PE-methods, 2 baselines
  • Attribute-based PE
  • Implicit PE
  • Hybrid PE (attribute + implicit)
  • Sort (baseline, not personalized)
  • Top-N (baseline, not personalized)
Study 3 — Results

- Experts prefer Attribute-based PE and Hybrid PE, novices prefer Top-N and Sort (baselines)
  - System satisfaction mediates the effect on choice satisfaction and behavior!

Towards a better (psychometric) user model

consumers differ in energy-saving capabilities, attitudes, goals, …

• Our prior work did not take that into account…
• Energy-saving interventions are more effective when personalized. But how?
Campbell’s Paradigm (Kaiser et al., 2010)

“One’s attitude or ability becomes apparent through its behavior…”
“Attitude and Behavior are two sides of the same coin…”

Three assumptions for our user model

1. All Energy-saving behaviors form a class serving a single goal: **Saving Energy**

2. Less performed behaviors yield higher **Behavioral Costs** (i.e. are more difficult)

3. Individuals that execute more energy-saving behaviors have a higher **Energy-saving Ability** (i.e. more skilled)
Using **behavioral costs** to order energy-saving measures

Persons indicate which measures they execute

INPUT

Highest Costs

Lowest Costs
The Rasch model

- The Rasch model equates behavioral difficulties and individual propensities in a probabilistic model.

Log-odds of engagement levels (yes/no):

\[ \ln \left( \frac{P_{ni}}{1 - P_{ni}} \right) = \theta_n - \delta_i \]

- \( \theta \) = an individual’s propensity/attitude
- \( \delta \) = behavioral difficulty
- \( P \) = probability of individual \( n \) engaging in behavior \( i \)

- Rasch also determines individual propensities and item difficulties & fits them onto a single scale
Resulting Rasch Scale: Probability of a person executing behavior depends on the Ability - Costs

\[
\ln \left( \frac{P_{ni}}{1 - P_{ni}} \right) = \theta_n - \delta_i
\]
Using Rasch for tailored advice

• Earlier research (Kaiser, Urban) found evidence for a unidimensional scale, but with few items & no advice

• We set out a Rasch-based, energy recommender system that:
  – Shows the measures in order of difficulty (either ascending or descending)
  – Provide tailored conservation advice to users (or not)
  – Include a more extensive set of measures

• Our question: is ordering items on the scale sufficient or do we also need to provide tailored recommendations?
Energy Webshop: Besparingshulp.nl

We arranged 79 energy-saving measures on their behavioral costs.
Webshop for energy-saving measures: Experiment

• We inferred a user’s ability through his current behavior
  – Asking 13 random items from across the entire scale
    *Able to suggest new measures by matching costs & attitude*

• User was subject to one of 4 conditions
  – No tailoring, ascending cost order (‘Most popular’)
  – No tailoring, descending cost order (‘Most difficult’)
  – Ability-tailored, ascending cost order
  – Ability-tailored, descending cost order
### Dependent Measures from the interaction

**Users interacting with the website**
- Behavioral difficulty of chosen measures
- Number of chosen measures
- Clicking behavior

**Evaluative Survey (UX)**
- Perceived Effort
- Perceived System Support
- Choice Satisfaction

**Follow up survey after 4 weeks**
- Extent of implementation of chosen measures

---

#### PERCEIVED EFFORT – survey items

<table>
<thead>
<tr>
<th>Item</th>
<th>Factor Loading</th>
</tr>
</thead>
<tbody>
<tr>
<td>It took me little effort to use the Saving Aid.</td>
<td>0.804</td>
</tr>
<tr>
<td>The Saving Aid takes up a lot of time.</td>
<td></td>
</tr>
<tr>
<td>I quickly understood the functionalities of the Saving Aid.</td>
<td>−0.554</td>
</tr>
<tr>
<td>Many actions were required to use the Saving Aid properly.</td>
<td></td>
</tr>
<tr>
<td>The Saving Aid is easy to use.</td>
<td>0.741</td>
</tr>
</tbody>
</table>

**PERCEIVED SUPPORT – survey items**

<table>
<thead>
<tr>
<th>Item</th>
<th>Factor Loading</th>
</tr>
</thead>
<tbody>
<tr>
<td>I make better choices using the Saving Aid tool.</td>
<td>0.551</td>
</tr>
<tr>
<td>The Saving Aid is helpful to find appropriate measures.</td>
<td>0.608</td>
</tr>
<tr>
<td>The Saving Aid does not help to come to a decision.</td>
<td></td>
</tr>
<tr>
<td>The Saving Aid presents the measures in a convenient way.</td>
<td></td>
</tr>
<tr>
<td>Because of the Saving Aid, I could easily choose measures.</td>
<td>0.678</td>
</tr>
</tbody>
</table>

**CHOICE SATISFACTION – survey items**

<table>
<thead>
<tr>
<th>Item</th>
<th>Factor Loading</th>
</tr>
</thead>
<tbody>
<tr>
<td>I am happy with the measures I've chosen.</td>
<td>0.574</td>
</tr>
<tr>
<td>I think I've chosen the best measures from the list.</td>
<td></td>
</tr>
<tr>
<td>I would have liked to choose different measures than the ones I've chosen.</td>
<td></td>
</tr>
<tr>
<td>It would be fun to perform the chosen measures.</td>
<td>0.550</td>
</tr>
<tr>
<td>The measures I've chosen fit me seamlessly.</td>
<td>0.549</td>
</tr>
</tbody>
</table>
Results Structural Equation Modelling (SEM)

*** p < 0.001, ** p < 0.01, * p < 0.05.

Tailored recommendations → Perceived Support

Perceived Effort

Perceived Support

Choice Satisfaction

.746***

- .767***

- .440*

+
Conclusions

• Tailored recommendations positively affect UX:
  – reducing both perceived and actual effort, users felt more support, and in turn chose more energy-saving measures and were also satisfied about those choices.
  – ability-tailored recommendations are more effective than merely presenting an ordered Rasch scale.

• Do users reach their goals?
  – Although more measures were chosen when higher support was perceived, this was against a reduced difficulty level.
  – Follow up four weeks later showed that users were more likely to perform easier measures (consistent with the rasch scale)

• Cliff hanger: See our RecSys 2017 paper for study 2, in which we use another interface to test how to engage users in more difficult measures…
**Sneak Preview:**

# Besparingshulp

Kies maatregelen die u nog niet toepast maar wel wilt gaan toepassen.
Wanneer u klaar bent gaat u naar uw winkelwagen. Controleer uw keuzes en klik op 'bevestigen'.

<table>
<thead>
<tr>
<th></th>
<th>Basis</th>
<th>Aanbevolen</th>
<th>Uitdagend</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Kleding luchten i.p.v. wassen</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beschrijving</td>
<td>Laat uw kleren een keer luchten in plaats van ze meteen in de wasmand te gooien. Dit kan per week ongeveer 1 wasbeurt schelen.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Besparing</td>
<td>26 kWh/j</td>
<td>€ 5,- p.j.</td>
<td>€ 0,-</td>
<td></td>
</tr>
<tr>
<td>Match</td>
<td>100%</td>
<td>Ga ik doen (0)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| **Koffie zetten zonder warmhoudplaatje** |       |            |           |   |
| Beschrijving | Bij sommige koffiezetapparaten is er aanzienlijk wat stroom nodig voor het warmhoudplaatje. Door bijvoorbeeld een thermoskan te gebruiken kunt u een flinke besparing bereiken en toch uw koffie warm houden. |
| Besparing | 23 kWh/j | € 5,- p.j. | € 0,- |
| Match | 99% | Ga ik doen |   |

| **Thermostaat 1 graad lager zetten** |       |            |           |   |
| Beschrijving | Als u uw verwarming standaard een graadje lager zet, bespaart u tientallen euro's op uw energierekening. Ook zorgt u ervoor dat er minder CO2 wordt uitgestoten. |
| Besparing |   |   |   |
| Match | 99% | Ga ik doen |   |
General conclusions

• Recommender systems are all about good UX
• Taking a psychological, user-oriented approach we can better account for how users like to express their preferences (input) and reach their goals (output)
• Enhancing user interaction (system satisfaction or perceived support) improves both choice satisfaction as well as user behavior!
• Behaviorism is not enough: an integrated user-centric approach offers many insights/benefits!
Questions?

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