Market User Interface Design

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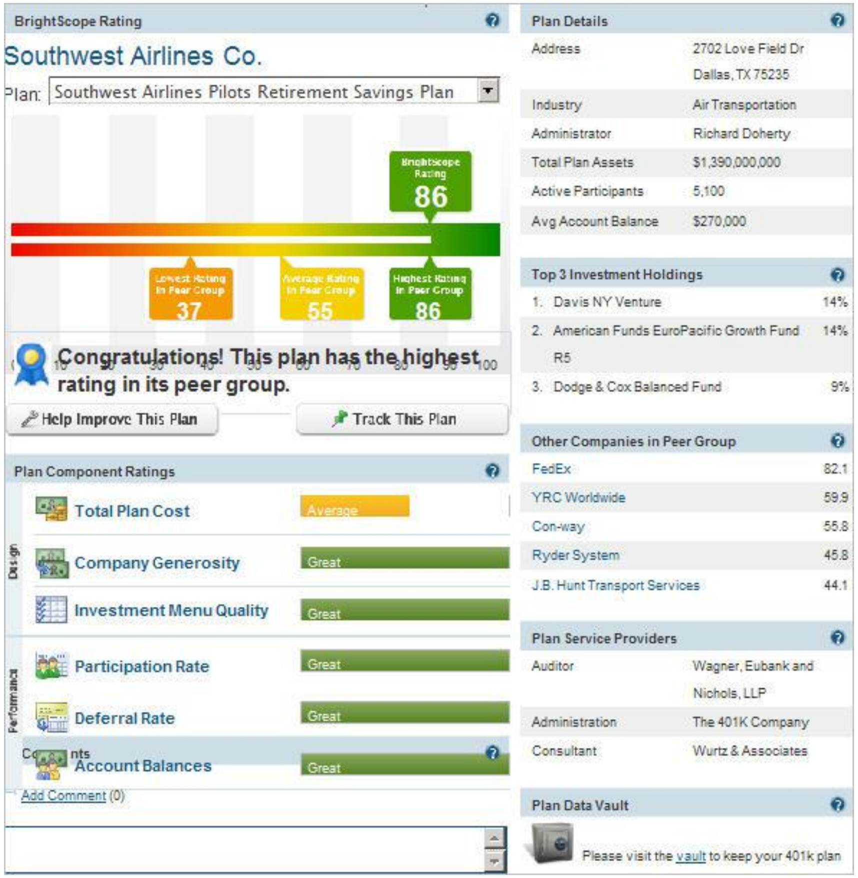
Cafeteria Design

- Re-arranging cafeteria choices increases/decreases the consumption of food items by up to 25%

401(k) Plan Design



- More choices in 401(k) plan selection leads to fewer employees enrolling.

A new Way of Online Shopping

Humans vs. Econs (Thaler & Sunstein)

- **Econs**
  - Perfectly rational
  - Unlimited time to make a decision
  - Unbounded computational resources for deliberation

- **Humans**
  - Cognitive costs
  - Bounded time (opportunity costs)
  - Bounded computational resources

- "Choice architecture" matters for humans!
- In electronic markets: many decisions of small value

UI + Market Design

UI Design ⟷ **Market Design**

- Why is UI design important:
  - 1st point of contact
  - UI design constrains the market design
  - UI defines how users express preferences
  - UI defines amount of “cognitive costs”

Trade-off: UI/Market Complexity vs. Expressiveness

- Our earlier work: “Hidden Market Design”
  - *Hide* market complexities
  - *Maintain* high efficiency of the market

Market User Interface Design

- Market User Interface:
  1. Which information is displayed to the user?
  2. What choices/how many choices are offered to the user?

- Research Questions:

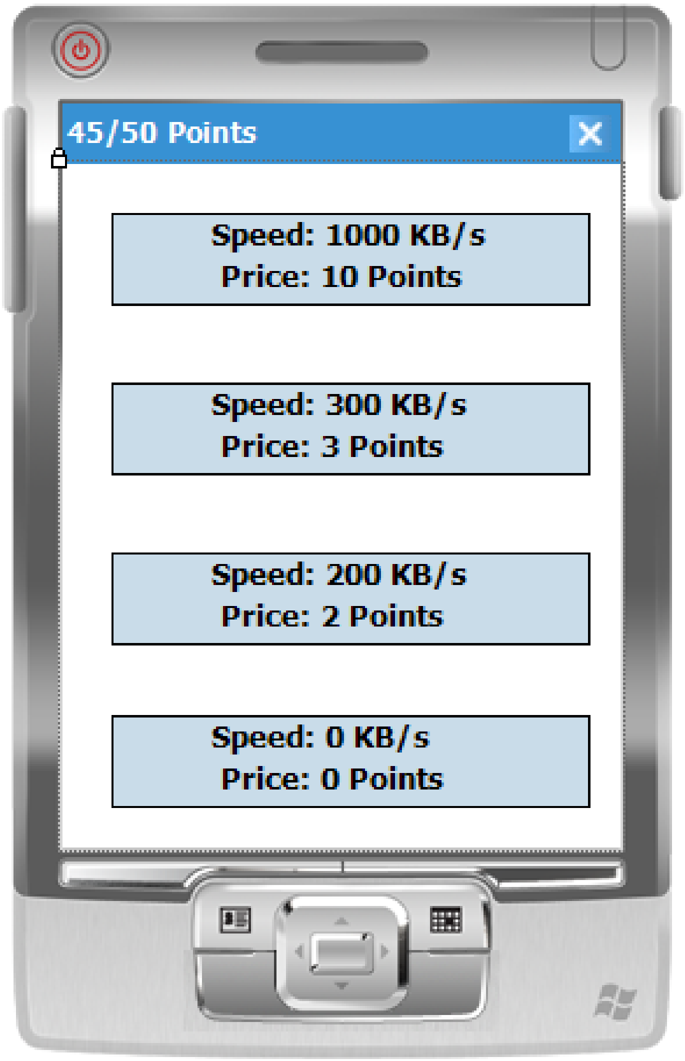
  What is the optimal market user interface given that users have cognitive costs?

- Lab study with 53 users
- 53 users x 55 games x 6 time steps ≈ 17,500 data points

Outline

1. Introduction: UI Design & Market Design
2. The 3G Bandwidth Allocation Game
3. Experiment Design and Results
4. Conclusion

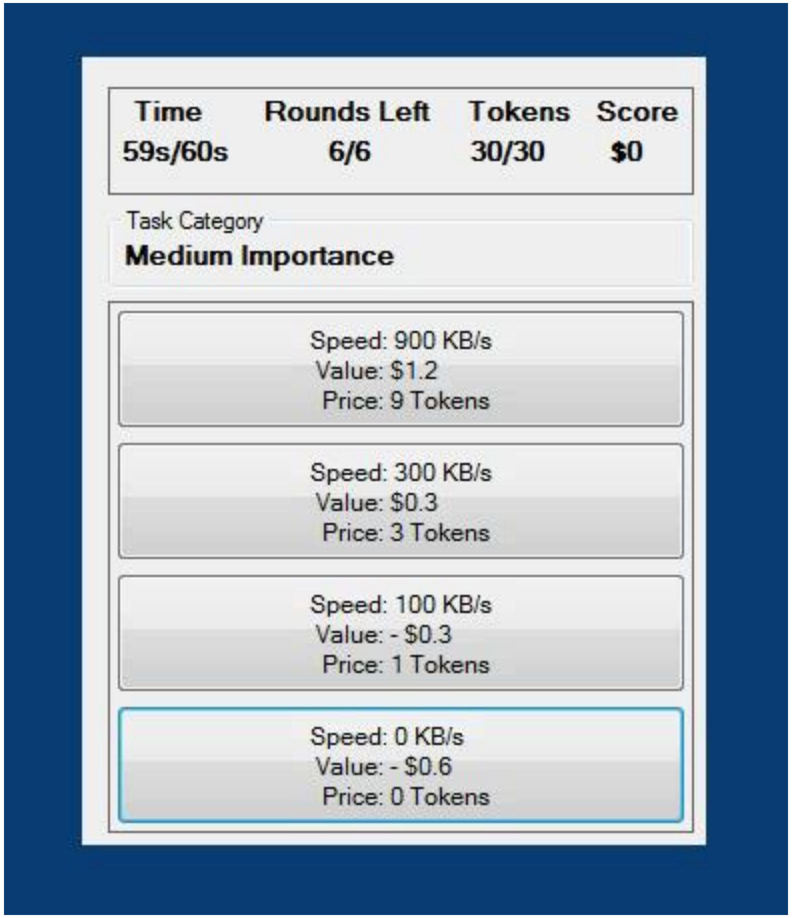
A Bandwidth Market User Interface



- What can we change about this market UI?

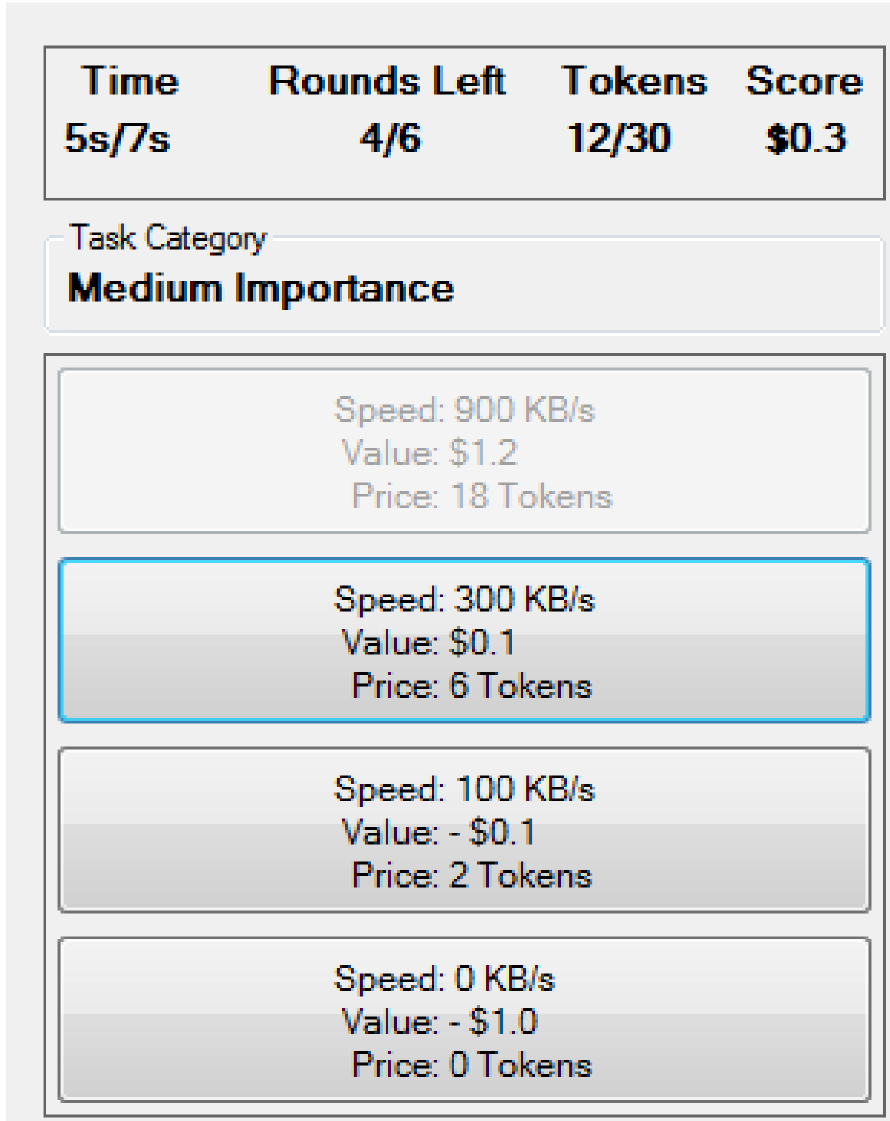
- We tested 4 UI Design Levers:
  1. # of choices
  2. Fixed vs. changing prices
  3. Fixed vs. situation-dependent choice sets
  4. UI optimized for optimal or behavioral play

Game Demo



Time
59s/60s
Rounds Left
6/6
Tokens
30/30
Score
$0
Task Category
Medium Importance
Speed: 900 KB/s
Value: $1.2
Price: 9 Tokens
Speed: 300 KB/s
Value: $0.3
Price: 3 Tokens
Speed: 100 KB/s
Value: - $0.3
Price: 1 Tokens
Speed: 0 KB/s
Value: - $0.6
Price: 0 Tokens

Game Demo


Time
Rounds Left
Tokens
Score
5s/7s
4/6
12/30
$0.3
Task Category
Medium Importance
Speed: 900 KB/s
Value: $1.2
Price: 18 Tokens
Speed: 300 KB/s
Value: $0.1
Price: 6 Tokens
Speed: 100 KB/s
Value: - $0.1
Price: 2 Tokens
Speed: 0 KB/s
Value: - $1.0
Price: 0 Tokens

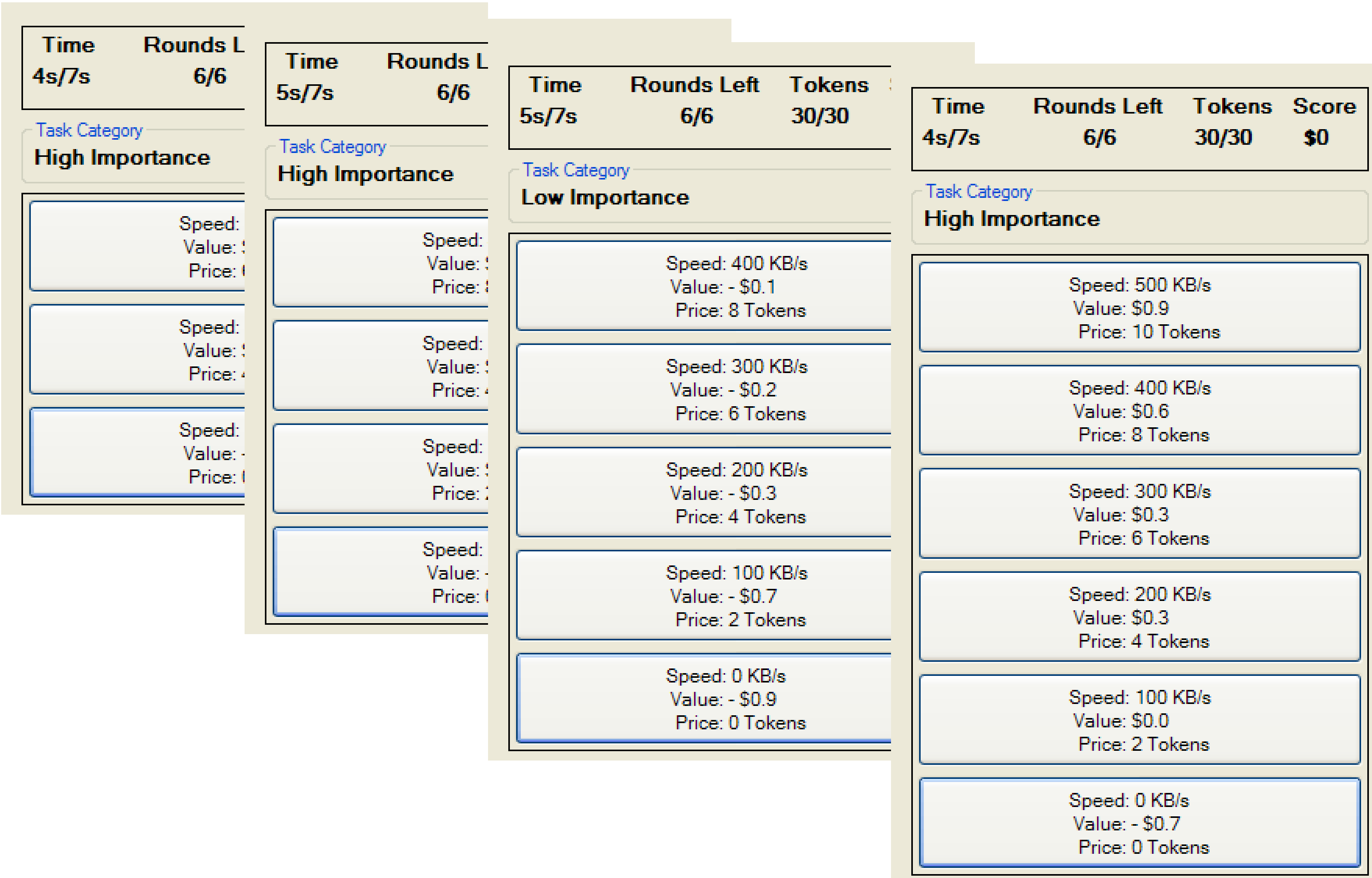
MDP Formulation of the Game

- Formalize as a Markov Decision Process (MDP):
  - **State** space: Budget x Round x Values x Prices
  - **Actions**: Each affordable choice
  - **Transitions**: deterministic for budget/round, random for values/prices

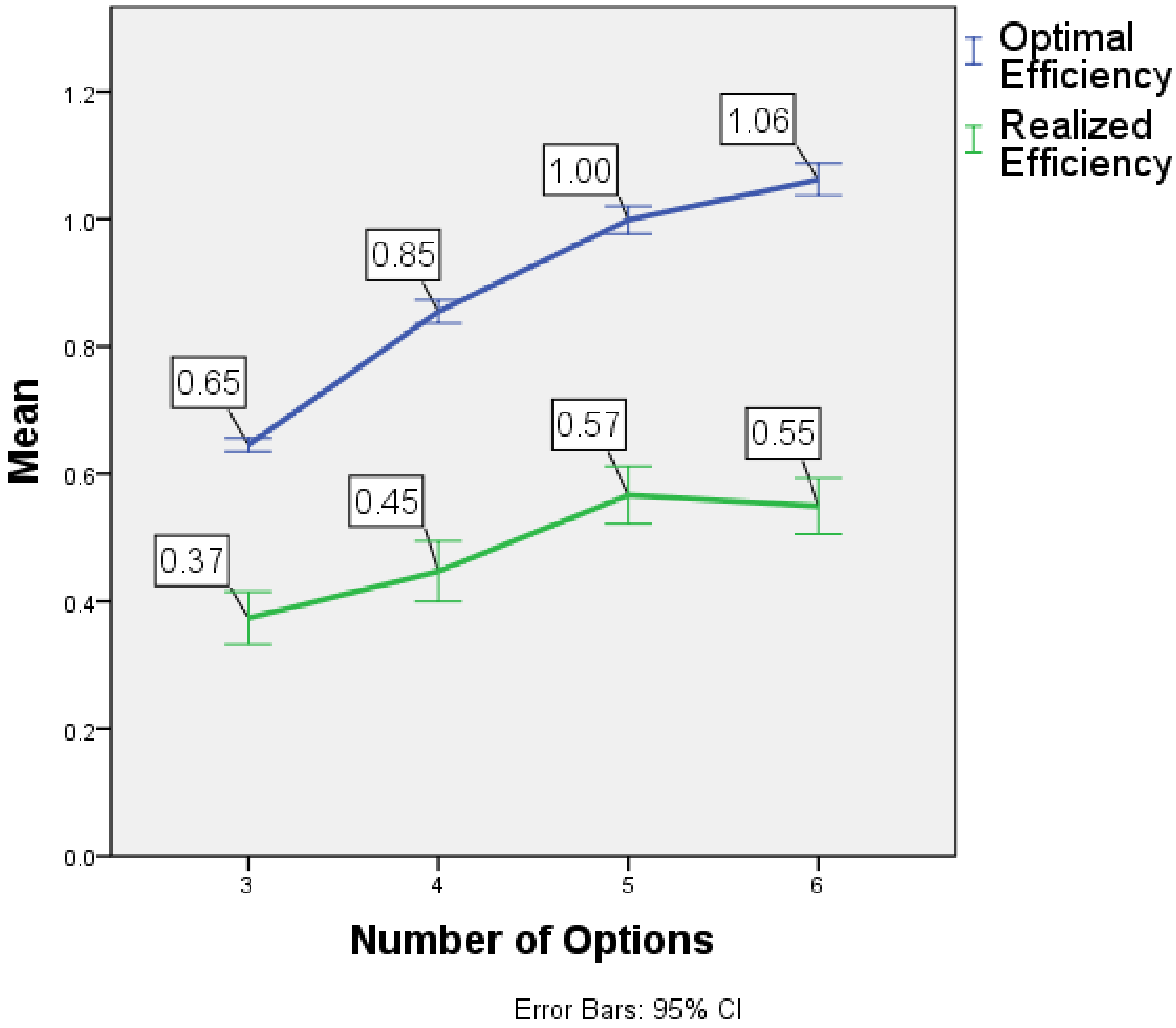
- Solve the game optimally→ becomes gold standard

- Compute Q-values of each state-action pair:
  Q(s,a) = expected value from taking action a in state s, and
  following optimal policy afterwards

1. Design Lever: Number of Choices



Number of Choices & Efficiency (1/2)



Number of Choices & Efficiency (2/2)

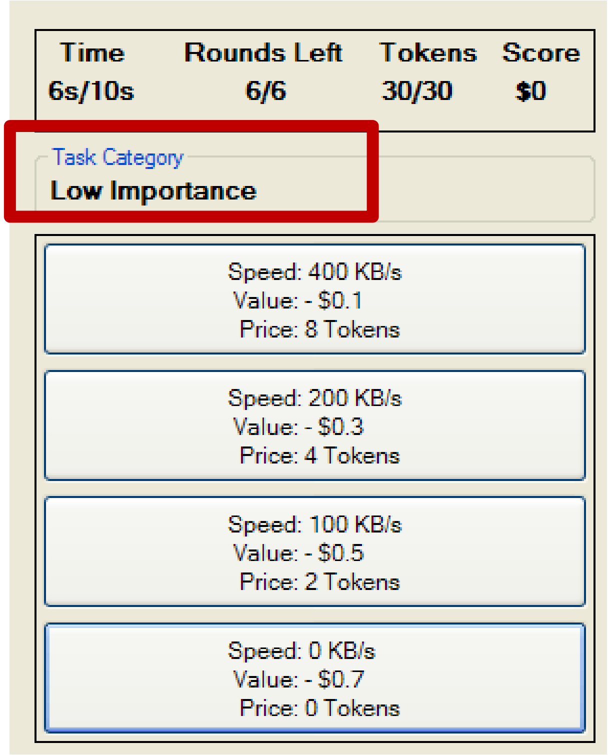
Factors/Covariates	Coefficients
Intercept	0.639**** (0.0441)
numOptions=3	-0.178**** (0.0459)
numOptions=4	-0.106**** (0.0278)
numOptions=5	0.015 (0.0291)
changingPrices=0	-0.169**** (0.0397)
Model Fit (QICC)	144.177

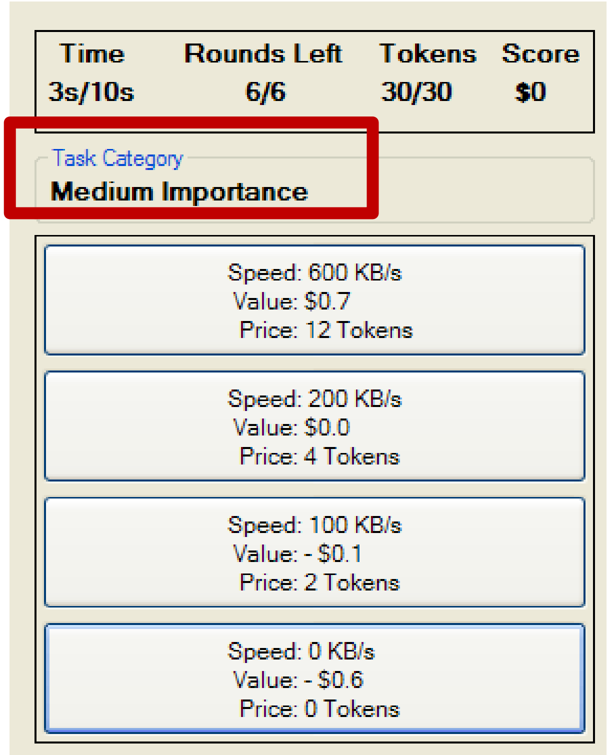
Compared to numOptions=6

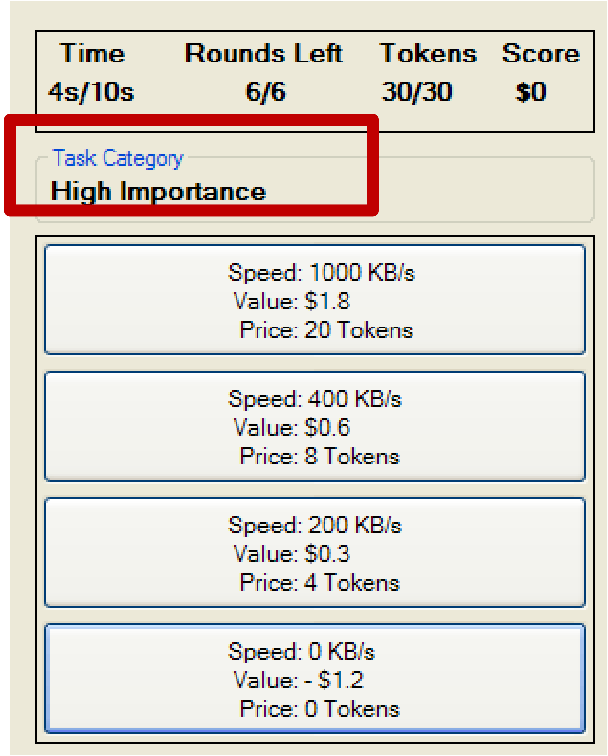
- Repeated measures linear regression (using GEE) for the dependent variable Efficiency. The individual coefficient is statistically significant at the *10% level, the **5% level, the ***1% level, and at the ****0.1 % level.

2. Design Lever: Fixed vs. Changing Choices

- We don't know users' values → learning:
  - Each choice is a signal from the user
  - Learn a mapping from context to value estimate
  - Present users with situation-dependent choices!







Changing Choices & Efficiency

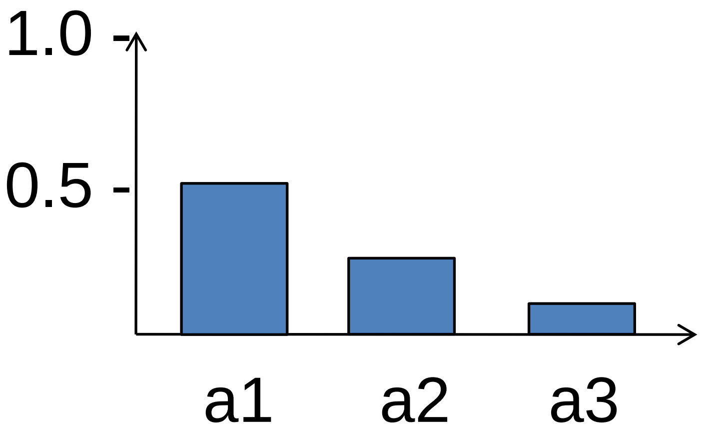
Factors/Covariates	Coefficients
Intercept	0.405**** (0.0410)
changingChoices	0.077** (0.0376)
Model Fit (QICC)	106.552

- Repeated measures linear regression (using GEE) for the dependent variable Efficiency. The individual coefficient is statistically significant at the *10% level, the **5% level, the ***1% level, and at the ****0.1 % level.

3. Design Lever: UI Optimization

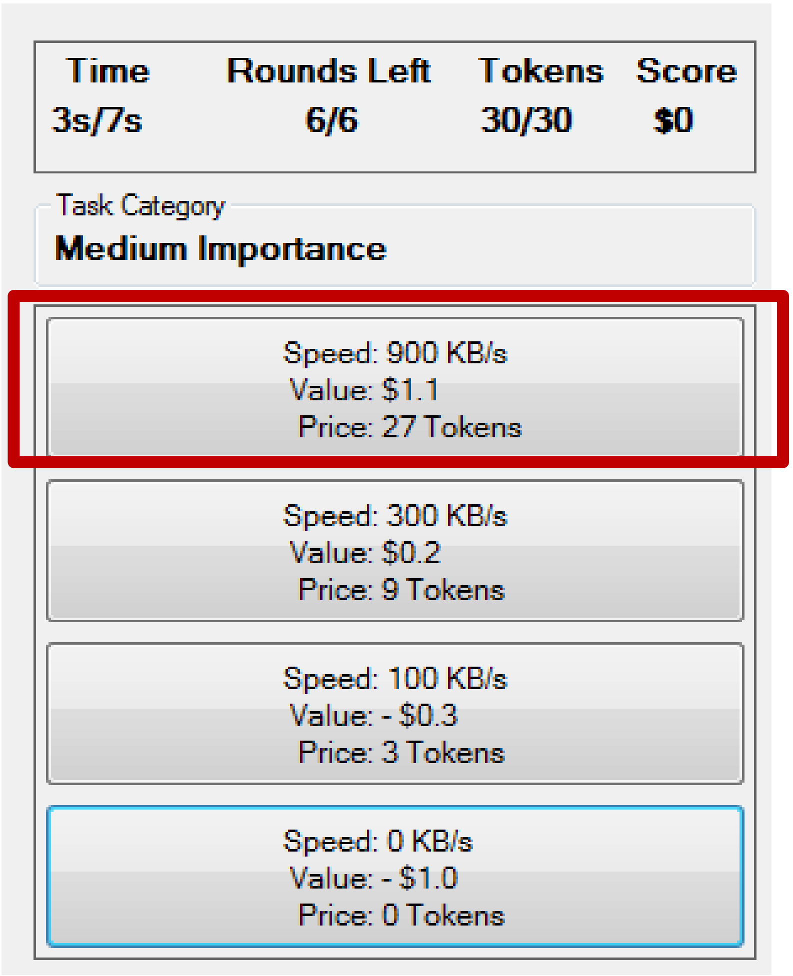
- Quantal-Response Model:

$$P(a_i) = \frac{e^{\lambda Q(a_i)}}{\sum_{j=0}^{n} e^{\lambda Q(a_j)}}$$

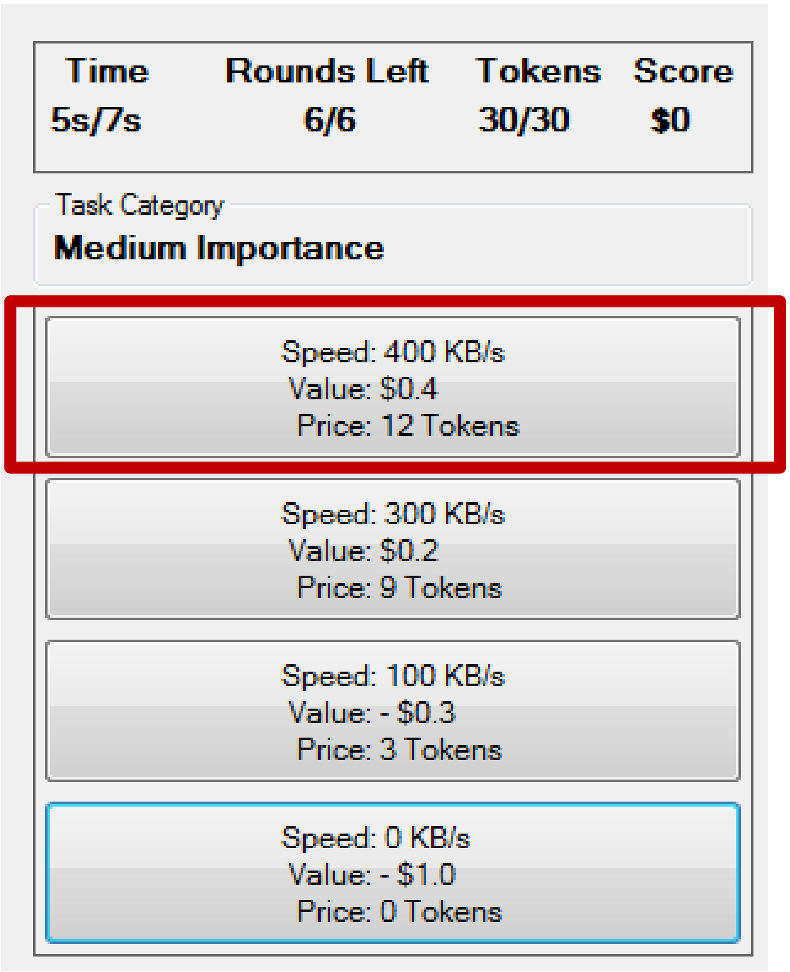


1. **Learning + Model Building:** Compute maximum likelihood estimate of λ.
2. **UI Optimization:** Search through design space, and select best UI (i.e., achieving highest expected efficiency)
   a) Assuming optimal play
   b) Assuming behavioral play (according to user model)
3. **Experiment:** Compare the two resulting UIs

UI Optimization



(a) Optimized for Optimal Play



(b) Optimized for Behavioral Play

UI Optimization & Efficiency (1/3)

Factors/Covariates	(1)
Intercept	0.462**** (0.0501)
changingChoices	0.077** (0.0376)
optimizedForSubOpt	-0.111**** (0.0334)

→ **Lower** Efficiency with UI optimized for behavioral play

What happened?

UI Optimization & Efficiency (2/3)

Factors/Covariates	(1)	(2)
Intercept	0.462**** (0.0501)	0.004 (0.0639)
changingChoices	0.077** (0.0376)	0.08** (0.0367)
optimizedForSubOpt	-0.111**** (0.0334)	-0.119**** (0.344)
Lambda		0.103**** (0.0110)

→ The efficiency depends on users' "degree of rationality"

UI Optimization & Efficiency (3/3)

Factors/Covariates	(1)	(2)	(3)
Intercept	0.462**** (0.0501)	0.004 (0.0639)	0.053 (0.1417)
changingChoices	0.077** (0.0376)	0.08** (0.0367)	0.080** (0.0365)
optimizedForSubOpt	-0.111**** (0.0334)	-0.119**** (0.344)	
Lambda		0.103**** (0.0110)	0.100**** (0.0253)
SmallLambda=1			-0.065 (0.0530)
OptimizedForSubOpt *smallLambda=1			-0.069 (0.0500)
OptimizedForSubOpt *SmallLambda=0			-0.174**** (0.0391)

- Large Losses for “more rational” users
- No statistically significant difference for “less rational” users

→ Suggests: personalized market user interfaces (future work)

Statistical Analysis of Behavioral Effects

- The UI-Optimization (based on quantal-reponse model) achieved lower instead of higher efficiency!

→ **Question: which other behavioral effects are at play?**

- Detailed statistical analysis of “Optimal Choice”: which factors influence users’ decision performance?

Q-Values: Optimal Choices?

Factors	(1)		(2)	
	B	Exp(B)	B	Exp(B)
Intercept	-0.816**** (0.1408)	0.442****	-1.529**** (0.1593)	0.217****
Lambda	0.150**** (0.0180)	1.162****	0.161**** (0.0197)	1.175****
QvalueDiff			5.868**** (0.4353)	353.713****

→ Users respond strongly to Q-value differences

→ are forward-looking in playing the MDP!

UI Complexity and Position Effects

Factors/Covariates	(1)	
	B	Exp(B)
Intercept	-0.341 (0.2664)	0.711
Lambda	0.150**** (0.0189)	1.162****
QvalueDiff	4.428**** (0.5060)	83.741****
female?	-0.151** (0.0687)	0.860**
numChoices	-0.086* (0.0486)	.917*
optRelativeRank=5	-3.884**** (0.9824)	0.021****
optRelativeRank=4	-1.902**** (0.4482)	0.149****
optRelativeRank=3	-1.205**** (0.2692)	0.300****
optRelativeRank=2	-0.619** (0.2784)	0539**
optRelativeRank=1	-0.169 (0.2272)	0.845
optRelativeRank=0	0	1

Loss Aversion

Factors/Covariates	(1)		(2)		(3)	
	B	Exp(B)	B	Exp(B)	B	Exp(B)
Intercept	-0.341 (0.2664)	0.711	-0.339 (0.2584)	0.713	-0.439* (0.2558)	0.645*
Lambda	0.150**** (0.0189)	1.162****	0.150**** (0.0188)	1-162****	0.145**** (0.0197)	1.156****
QvalueDiff	4.428**** (0.5060)	83.741****	4.427**** (0.5039)	83.671****	4.599**** (0.4998)	99.387****
female?	-0.151** (0.0687)	0.860**	-0.151** (0.0695)	0.860**	-0.166** (0.0734)	0.847**
numChoices	-0.086* (0.0486)	.917*	-0.087* (0.0513)	0.917*	-0.065 (0.0584)	0.937
optRelativeRank=5	-3.884**** (0.9824)	0.021****	-3.881**** (0.9925)	0.021****	-4.068**** (1.0438)	0.017****
optRelativeRank=4	-1.902**** (0.4482)	0.149****	-1.900**** (0.4594)	0.150****	-1.853**** (0.4948)	0.157****
optRelativeRank=3	-1.205**** (0.2692)	0.300****	-1.203**** (0.2974)	0.300****	-1.183**** (0.3372)	0.306****
optRelativeRank=2	-0.619** (0.2784)	0539**	-0.617** (0.2967)	0.539**	-0.523 (0.3322)	0.593
optRelativeRank=1	-0.169 (0.2272)	0.845	-0.168 (0.2358)	0.845	-0.178 (0.2493)	0.837
optRelativeRank=0	0	1	0	1	0	1
optimalChoiceNegative?			-0.002 (0.0896)	0.998	-1.314**** (0.2270)	0.269****
currentCategory=2					1.539**** (0.2088)	4.658****
currentCategory=1					0.032 (0.1282)	1.033
currentCategory=0					0	1

Conclusion

- Summary:
  - Introduced “market user interface design” paradigm
  - Analyzed 4 design levers (# choices, price dynamics, choice set composition, UI optimization)
  - Found many important behavioral factors
  - Significant differences between individual users
- Future work:
  - Personalized UIs, dependent on individual user‘s abilities
  - Iterative, real-time UI optimization
- Feedback very welcome: seuken@ifi.uzh.ch
- Thank you for your attention!

Male vs. Female Users: Optimal Choices

Factors	(4)	
	B	Exp(B)
Intercept	-1.398**** (0.1657)	0.247****
Lambda	0.151**** (0.0176)	1.163****
QvalueDiff	5.884**** (0.4358)	359.392****
Age		
female?	-0.130* (0.0716)	0.878*
Fit (QICC)	(3588.483)	

→ Female users miss the optimal choice more often, but...

…male users make more severe mistakes

Male vs. Female Users: Value Loss (1/2)

Factors/Covariates	(1)	
	B	Beta
Intercept	0.138**** (0.0118)	
Lambda	-0.11**** (0.0015)	-0.141****
female?	-0.004 (0.0032)	-0.018
Goodness of Fit (QICC)	36.302	
Cases Considered	All (N=2756)	

Male vs. Female Users: Value Loss (2/2)

Factors/Covariates	(1)		(2)	
	B	Beta	B	Beta
Intercept	0.138**** (0.0118)		0.231**** (0.0154)	
Lambda	-0.11**** (0.0015)	-0.141****	-0.013**** (0.0021)	-0.151****
female?	-0.004 (0.0032)	-0.018	- 0.016*** (0.0056)	-0.066***
Goodness of Fit (QICC)	36.302		24.026	
Cases Considered	All (N=2756)		OptChoice=0 (N=1246)	

→ Male users make more severe mistakes

Loss Aversion (1/2)

Factors/Covariates	(1)		(2)	
	B	Exp(B)	B	Exp(B)
Intercept	-0.341 (0.2664)	0.711	-0.339 (0.2584)	0.713
Lambda	0.150**** (0.0189)	1.162****	0.150**** (0.0188)	1-162****
QvalueDiff	4.428**** (0.5060)	83.741****	4.427**** (0.5039)	83.671****
female?	-0.151** (0.0687)	0.860**	-0.151** (0.0695)	0.860**
numChoices	-0.086* (0.0486)	.917*	-0.087* (0.0513)	0.917*
optRelativeRank=5	-3.884**** (0.9824)	0.021****	-3.881**** (0.9925)	0.021****
optRelativeRank=4	-1.902**** (0.4482)	0.149****	-1.900**** (0.4594)	0.150****
optRelativeRank=3	-1.205**** (0.2692)	0.300****	-1.203**** (0.2974)	0.300****
optRelativeRank=2	-0.619** (0.2784)	0539**	-0.617** (0.2967)	0.539**
optRelativeRank=1	-0.169 (0.2272)	0.845	-0.168 (0.2358)	0.845
optRelativeRank=0	0	1	0	1
optimalChoiceNegative?			-0.002 (0.0896)	0.998

Loss Aversion: Interaction Effect

Factors/Covariates	(1)	
Intercept	-0.433* (0.2514)	0.648*
Lambda	0.144**** (0.0203)	1.155****
QvalueDiff	4.605**** (0.4918)	100.016****
female?	-0.174** (0.0763)	0.840**
numChoices	-0.066 (0.0581)	0.936
optRelativeRank=5	-4.086**** (1.0302)	0.017****
optRelativeRank=4	-1.846**** (0.4798)	0.158****
optRelativeRank=3	-1.186**** (0.3292)	0.305****
optRelativeRank=2	-0.531 (0.3342)	0.588
optRelativeRank=1	-0.186 (0.2476)	0.831
optRelativeRank=0	0	1
[optimalChoiceNegative=1 × oneHigherNegative=1 × currentCategory=2	0.248** (0.1255)	1.281**
[optimalChoiceNegative=1 × oneHigherNegative=0 × currentCategory=2	0.070 (0.4076)	1.073
[optimalChoiceNegative=0 × oneHigherNegative=0 × currentCategory=2]	-1.199 (1.7347)	0.301
[optimalChoiceNegative=1 × oneHigherNegative=1 × currentCategory=1]	-1.038*** (0.4043)	0.354***
[optimalChoiceNegative=1 × oneHigherNegative=0 × currentCategory=1]	-1.575**** (0.3256)	0.207****
[optimalChoiceNegative=0 × oneHigherNegative=0 × currentCategory=1]	0.066 (0.1327)	1.068
[optimalChoiceNegative=1 × oneHigherNegative=0 × currentCategory=0]	-0.322 (0.6351)	0.725
[optimalChoiceNegative=0 × oneHigherNegative=0 × currentCategory=0]	0	1