Eliciting users' demand for interface features

Oded Nov
New York University
onov@nyu.edu

Han Su
New York University
suhan@nyu.edu

ABSTRACT
How valuable are certain interface features to their users? How can users' demand for features be quantified? To address these questions, users' demand curve for the sorting feature was elicited in a controlled experiment, using personal finance as the user context. Users made ten rounds of investment allocation across up to 77 possible funds, thus encountering choice overload, typical of many online environments. Users were rewarded for positive investment returns. To overcome choice overload, users could sort the alternatives based on product attributes (fees, category, fund name, past performance). To elicit their demand for sorting, the experimental design enabled users to forgo 0%-9% of their reward in return for activating the sorting feature. The elicited downward sloping demand curve suggests a curvilinear relationship between sorting use and cost. More broadly, the study offers a way to quantify user demand of UI features, and a basis for comparison between features.

Author Keywords
Choice overload; cost-benefit; demand; economics; features; feature economics; revealed preference; user interface.

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
A fundamental UI question that has received relatively little attention in the HCI literature, is the nature of user demand for interface features: that is, to what extent a certain user interface feature is valuable to its users, from the user's perspective rather than the designer's or the website being used. While multiple studies examined the effects of design on user behavior [10, 17, 22, 27], these studies did not examine the utility the user assigns to the features she chooses (or not) to use.

CHI 2018, April 21–26, 2018, Montreal, QC, Canada

ACM ISBN 978-1-4503-5620-6/18/04 $15.00
https://doi.org/10.1145/3173574.3173879

Investigating the value of UI features to their users, and the tradeoffs users perceive in using them, is important for better understanding of the fundamental characteristics of user behavior. It is also critical for designers who need to understand the limits of the value of UI features: if there is a limited number of features that can be included in any given UI, then the designer needs to know which ones are most desirable to users. Understanding the patterns of user demand for features is therefore necessary for making informed design decisions and for comparing other design elements and the tradeoffs between them.

Estimating the demand for goods is a fundamental question in economics [16]: assuming an environment of goods and resource scarcity, on both the supply (availability of desired goods) and the demand sides (availability of resources to spend on them), the desirability of a good is reflected in the resources (money, time, attention) consumers are willing to forgo in order to own or use it. As a result, organizations spend considerable time, effort and money to study the demand characteristics for the goods and services they offer to their customers.

In the context of user interfaces, features seem to have similar characteristics of scarcity, of both supply and demand: on the supply side, in any given UI, designers face numerous limitations, including screen size and the number of features that can be included. On the demand side, users have limited resources of time, attention and patience. Given these limited resources, users have implicit expectations about the utility to be gained as a result of spending these scarce resources on using any given features.

This approach of considering HCI as a setting in which scarce resources are being spent and utilities compared, echoes a growing recognition among HCI researchers of the need to use economic theory and tools in the study of HCI: treating features as economic goods is important if we are to make informed decisions about the allocation of design resources – both from the designer's perspective (which features are more effective in invoking desired user behavior) and from the user's perspective (i.e. which features are more desirable to their potential users). But while the former perspective has been well studied [1, 10, 23, 28], there has been little HCI research on the demand side for UI design, and the ways we can empirically elicit the characteristics of such demand.

In this paper, we focus on what we can term as *feature economics*, and make a number of contributions to the HCI literature. First, we provide a conceptualization and empirical analysis of UI features as economic goods: we conceptualize users' choices as informed transactions, in which users engage in an exchange of scarce resources, in return for access to goods (UI features). While in practice users don't usually have to pay for using UI features, thinking about the value of features this way enables a theoretical value comparison across different features, just as money can be used as a way to consider the relative value of alternative goods. Second, we establish a methodology for elicitation of demand for UI features. The same methodology can be applied in other settings, and the resources in which the "price" is denominated can be easily changed. Third, we make a translational contribution by incorporating concepts from economic theory in HCI research. Finally, we advance the understanding of UI features in the specific user context of consumer finance. With these contributions, we advance a growing research agenda and calls for more use of economic theory in the study of HCI [5, 9, 20, 24, 29, 41, 48].

Related work

Recent work on the role of economics as an analytic framework through which to study HCI [24, 41], included issues such the return on investment in HCI [9], the utility of UI features [43] and the positive and negative values of specific UI characteristics, such as their aesthetic value [2] and annoyance for users [18]. Other research focused on the cognitive and attentional aspects of users' behavior [6, 11, 15, 34, 44].

Applying economic theory to the study of users' choices in the context of user interfaces, Toomim et al [43] used the concept of utility to inform HCI design, building on the notion of *revealed preference* [30] – the idea that agents' preferences can be revealed and compared by observing their choices between multiple goods. Viewing utility as the extent to which a user prefers a particular choice over others, and considering all factors of functions and usability that affect users' preference and use, Toomim et al [43] suggested that *Utility*(A) > *Utility*(B) when a user chooses to use interface A instead of interface B. building on this notion, they developed a framework for eliciting a crowdsourcing labor supply curve given interface variations. Using an online crowdsourcing tasks they investigated the relationship between task price, UI aesthetics and ease of use on worker supply. In a similar vein, others [7, 14, 40] developed and tested methods and tools to determine efficient and fair pricing of crowdsourcing tasks.

Previous studies developed methods and tools for estimating labor *supply* at different price points, and within different environments. However, these studies did not consider users' *demand* for features as they make user interface use choices.

Research on the relationship between design, user behavior and utility explored the tradeoffs represented by the availability of different features to users [11, 45]. For example, Tseng and Howes [44] studied users' visual search strategies applied in response to constraints imposed by the ecology of online images.

In the context of personal finance, HCI research is relatively new and is growing rapidly, reflecting a surge in FinTech investment and the proliferation of online financial products available to consumers in recent years [35]. Prior work on the role of HCI in people's financial behavior explored, for example, how people manage and think about their money [26, 36, 47], how they make decisions about saving [20], how financial information can be packaged in novel ways to assist with comparing potential investments [21], and how real-time information about financial transactions leads to better understanding of economic transactions [12].

Our focus is on the use of sorting [19, 42, 46], which is ubiquitous in online and offline UIs that enable comparison between multiple alternatives. Sorting is a common feature in various domains, facilitating comparisons of flights, movies, universities, and financial products. When making choices in such online environments, where many alternatives are present, users often encounter choice overload [4, 8]. The ability to sort long lists of alternatives by desired attributes, enables users to avoid the choice overload [25], primarily by reducing their choice set. Using sorting, users can focus their attention on specified subsets of alternatives that reflect their preferences – for example, by considering on alternatives sorted by high quality or low price.

RESEARCH QUESTIONS

Examining user behavior under design variations, we build on prior work [11, 44, 45] and focus on users' utility as the conceptual approach through which to study interface choices. We use the money-metric of utility [38, 43] to consider the value of a UI feature's availability to the user. The money-metric of utility has the advantage of comparability of the results across interfaces, features and situations. The relationship between feature, utility and cost can be described as: *Utility*(using the feature) – *Utility*(not using the feature) = *Utility*(cost(A)) where cost(A) is the monetary equivalent of a cost of using the feature. It is important to note that while we use monetary cost, there are other ways to operationalize cost, for example, as an interface's aesthetic value [2], or alternatively users' time or annoyance.

We first need to check if features are similar to most economic goods, in that a tradeoff exists between how much the user wants to use them and what scarce resources they are willing to forego in order to do that. To that end, the first question concerns the attributes of the relationship between use and cost:

RQ1: What is the tradeoff between feature cost and use at different cost levels?

Furthermore, since the utility consumers gain from most goods differs from one person to another, we expect users to differ in the value they will assign to features and the cost they would be willing to incur in order to use the feature. A second question is therefore:

RQ2: How does demand for features change based on user characteristics?

A third question concerns the net effect of using features in the personal finance context: to what extent users' benefits exceeds their costs. Clearly, the answer is highly dependent on how benefit and cost are measured, and is specific to the circumstances in which features are used. However, to set a baseline for future research on demand elicitation, two questions warrant analysis:

RQ3: Does the ability to sort lead users to perform better than without it? At what cost level does sorting become ineffective?

METHODOLOGY

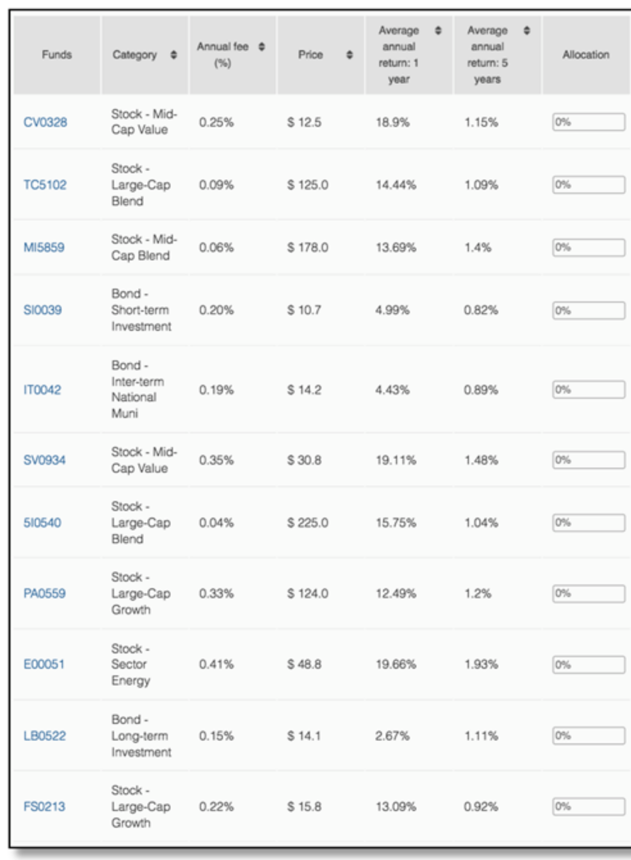
To address our research questions experimentally, we used the domain of personal finance, which has a number of advantages: first, much of consumers' interaction with financial products takes place online. When people want to save or borrow money, they can do so through user interfaces that consist of hundreds (and in some cases thousands) of choices they can potentially select from, and which require assessing trade-offs between potential risk, reward and other factors. This is a natural setting in which to study choice overload; second, extant research demonstrates how choice overload of financial products impacts consumers' choices [3, 31, 39], often leading to reduced consumer welfare (e.g. by not saving enough for retirement); third, in the context of personal finance, the benefits to the user associated with their choices (e.g. return on investment) and the cost associated with it (the price paid for the financial product) are more easily conceptualized, quantifiable and measureable as money amounts than the benefit to users in many other settings. Using money is a common and practical way of studying people's utility [43]

To elicit a person's demand for an economic good in a setting of scarce resources, economic theory suggests setting a cost the user will have to forgo for the good [30]. This way, the person needs to choose the good against some other resources, and the price they are willing to pay reflects the utility of that good to them. In a personal finance context, where a common goal is to achieve a financial outcome, identifying the amount of money users would be willing to forgo in order to use a feature as they consider their investment options, is a practical way to elicit their demand for that feature.

Experimental procedure

We used a randomized between-subjects experiment where users made investment decisions, to study their demand characteristics. After completing a short demographic and investment experience survey, users were asked to go through 10 investment rounds in which they were tasked with allocation a fixed budget to any combination of investment alternatives of their choice, using up to 77 different funds (see Figure 1). The investment alternatives were given fictional names, but were based on common financial products such as stock and bond funds, representing different levels of risk/reward prospects. This is a realistic scenario, similar to many investment environments people face when they save towards retirement, their children's education or other purposes. Funds' performance in the experiment was based on real historic market data, but this was unknown to the users. Every round, users allocated their budget across funds, and once they submitted their allocations, were informed of the return on their investment. Users then proceeded to the next round.

The large number of investment alternatives presented to users was intentionally designed to lead them to encounter choice overload [3, 31, 39], typical of many online environments, ranging from e-commerce, to movie rating to dating platforms [13].



Funds	Category	Annual fee (%)	Price	Average annual return: 1 year	Average annual return: 5 years	Allocation
CV0328	Stock - Mid-Cap Value	0.25%	$ 12.5	18.9%	1.15%	0%
TC5102	Stock - Large-Cap Blend	0.09%	$ 125.0	14.44%	1.09%	0%
MI5859	Stock - Mid-Cap Blend	0.06%	$ 178.0	13.69%	1.4%	0%
SI0039	Bond - Short-term Investment	0.20%	$ 10.7	4.99%	0.82%	0%
IT0042	Bond - Inter-term National Muni	0.19%	$ 14.2	4.43%	0.89%	0%
SV0934	Stock - Mid-Cap Value	0.35%	$ 30.8	19.11%	1.48%	0%
5I0540	Stock - Large-Cap Blend	0.04%	$ 225.0	15.75%	1.04%	0%
PA0559	Stock - Large-Cap Growth	0.33%	$ 124.0	12.49%	1.2%	0%
E00051	Stock - Sector Energy	0.41%	$ 48.8	19.66%	1.93%	0%
LB0522	Bond - Long-term Investment	0.15%	$ 14.1	2.67%	1.11%	0%
FS0213	Stock - Large-Cap Growth	0.22%	$ 15.8	13.09%	0.92%	0%

Figure 1. Investment allocation page: Users were presented with 77 alternative funds to which they could allocate their budget. All funds included sortable information on five attributes.

To motivate participants, the compensation consisted of a fixed participation compensation of $1.5 and a bonus that was calculated as a percentage of participants' investment return. If the return on the investment was negative, no bonus was given. In the experiment, the average net bonus per user was $2.01 (SD=0.78). This compensation structure represents a substantial incentive for users to pay attention to the investment alternatives and consider ways to enhance their return.

To overcome choice overload, users could sort the 77 investment alternatives presented to them by up to five fund attributes - fees, asset category, fund name, past short term performance and past long term performance. To elicit their demand for sorting, the experimental design required users to forego (or "pay") a fraction of their bonus from the round they were in (to be given to them if they make a positive return on their investment) in order to activate the sorting feature for the fund attribute they were interested in, for that round. The size of the fraction users had to forego in order to use the sorting feature each time ranged between 0%-9% of their bonus for that round. This fraction (or cost) was randomly assigned to users, and remained fixed for each user throughout their 10 investment rounds. The cost was presented each round above the fund list, and when users attempted to sort the sortable columns, a dialog box appeared with a request to confirm that they are willing to forego the fraction of their reward in return for activating the sort button for that column, that round.

While there may be alternative costs for the use of features (e.g. time, annoyance, screen real estate), we chose monetary cost for two reasons: first, using the same "currency" for the expected benefits and costs associated with feature use, enables users to easily compare them. Second, money is an effective way to compare the value of different goods, and since we seek to establish a methodology that enables a comparison of user demand across different UI features, money can serve as a useful apparatus.

Participants

Participants were recruited via Amazon Mechanical Turk. Participation was limited to U.S. users with a record of at least 100 tasks at an approval rate above 99%. 361 users were randomly assigned to one of the 0-9% price levels, with the number of users in each price group ranging between 29-44. Users' average age was 35.4 and 41.2% were female.

RESULTS

To answer the first research question concerning the tradeoff between cost and feature use, we first checked if users would be less likely to use the sorting feature if they had to forgo some of their reward for it. Economic theory suggests that choosing to pay for an economic good indicates that the good is perceived as valuable to the buyer [16, 30]. We used a chi-square test to compare the likelihood that users will activate the sorting feature at least once across all cost levels. We found that 72.4% of the users activated the sorting function at least once when the activation came at no cost to them, compared to 17.6%-44.7% (depending on the cost) who chose to activate the feature when the cost was higher than zero (Pearson chi-square = 39.448, $p<0.001$).

Next, to investigate the characteristics of user demand for sorting, we analyzed the relationship between the number of times a user activated the sorting feature per round and the cost they had to incur as a result (see Figure 2). Users could activate sorting up to five times each round, since each column (or fund attribute) required its own activation. Sorting behavior varied across users, however, only 6.4% of the users activated sorting more than once per round on average. The fitted demand curve was elicited using a general non-linear regression, resulting in a downward sloping demand curve and curvilinear relationship between sorting use and cost (R2=0.172, $p<0.001$).

A question that these findings raise is whether the differences in feature activation stem from users' sensitivity to price at all cost levels, or is it that users may simply be reluctant to pay for a UI feature at all. To answer this question, we regressed the number of sorting activations on cost and user characteristics, but excluded from the analysis all users in the zero price condition (that is, we included only users who had to pay if they wanted to activate the feature). We found a significant and negative effect of price on sorting activations (beta = -0.338, $p<0.001$), and no effect of investment experience, gender and age.

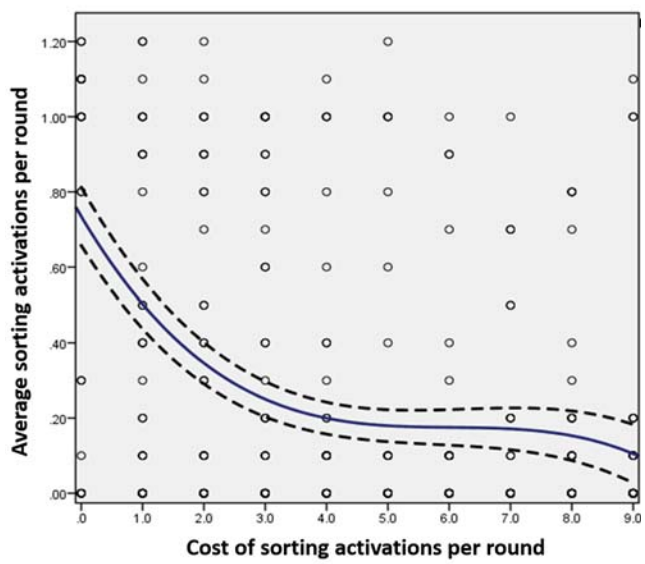


Figure 2. Elicited demand for the sorting feature: average sorting activations per round as a function of activation cost. Dashed lines represent a 95% confidence interval.

Addressing our second research question concerning the effects of users' personal characteristics on the demand for sorting, we regressed the number of sorting activations on age, gender, investment experience and cost, this time for all users. In addition to a significant negative effect of price, we found a significant negative effect of investment experience and age on feature activation (beta = -0.149, p=0.003; beta =

-0.136, p=0.007 respectively). That is, controlling for other factors, younger and less investment-savvy users tended to activate the sorting feature more. This finding may reflect the confidence of more experienced investors in their ability to achieve acceptable investment returns without the need for (and the cost of) assistance that sorting may provide.

To address the third research question, we ran a regression to analyze the relationship between the number of sorting activations and users' total return on investment, controlling for demographics, investment experience and feature activation cost. We found that sorting was significantly and positively associated with users' return on investment (beta = 0.289, p<0.001). When we considered the effect on net investment return (i.e. users' total return minus feature activation cost), the correlation weakened, but remained significant (beta = 0.168, p=0.004). Overall, therefore, sorting helped users achieve higher returns on their investments.

DISCUSSION AND CONCLUSION

How valuable are certain UI features to their users? How can demand for features be quantified? Addressing these questions is critical for understanding users and making informed design decisions, yet they received little attention in the HCI literature. Understanding how people value the sorting feature is a first step in this direction.

To answer our research questions, we elicited the demand for the sorting feature through a controlled experiment, using personal finance as the user context, and creating intentional choice overload for users in order to lead them to use the sorting feature. An analysis of the use of this feature as a function of its cost offers a method for learning about users' perception of the utility of the feature, which is necessary for considering design choices tradeoffs.

With the experimental design used in this study, we attempted to make the process as realistic as possible: users were incentivized by investment performance-based reward, thus ensuring they authentically act on their perceived costs and benefits. And by recruiting MTurkers, whose time represents an opportunity cost, we implicitly provided incentives for users to engage in strategies that save them time (and therefore have a monetary value). The design used in this study suggests external validity, yet future research would benefit from a field experiment to further validate our approach.

The results of the experiment point to a downward sloping demand curve – a consistent pattern of decreased feature use as a function of increased feature cost. This is consistent with the demand pattern for most economic goods [16]. The findings also suggest that the differences in the level of feature use across cost levels are the result of users' varied sensitivity to cost at multiple cost levels: we observed a curvilinear relationship between use and cost, such that demand for sorting decreases substantially at low cost levels, and then almost flattens when the cost exceeds a small fraction of the reward (4% in our case – see Figure 2). We observed a similar pattern in the likelihood that users will agree to pay at all for using the sorting feature.

The approach presented in this paper can help designers make informed decisions in two ways: first, by comparing users' demand for different UI features - given the multitude of alternative design elements designers can choose from, giving designers tools to assess how users might value different design elements, will enable them to focus on the ones most valued by users. Second, our findings suggest changes in the *price elasticity of users' demand:* price elasticity [16] is a concept in economic theory that refers to the extent to which a change in the cost of a good impacts the demand for it, proportional to the price over quantity. In our case, we see that the demand drops and then almost flattens as a function of increased cost. But the point at which demand flattens, and the rate at which this happens, can very across UI features. Empirical evidence on the differences in slope and elasticity can inform designers about which UI features reflect user value at different cost points, and understand their trade-offs. Consider for example other cost types (e.g. time): understanding demand as a function of time cost can help designers make design choices given the amount of time they expect users to spend on a given web page or app and their goals in visiting it. Overall, generalizing this finding to other features and within different experimental settings, would enable us to better understand users' preferences and the tradeoffs they make in their feature use. Such understanding may potentially inform the use of personalized user interface elements [33, 37], drawing on personal demand data, which can be elicited through multiple pilots and A/B tests.

We used cost and benefits denominated in monetary value to enable users to easily compare the costs and benefits of the sorting. While web destinations are not likely to use the demand information to charge users for them, comparing the demand for features using money [43] offers a rigorous method to compare the desirability of UI features, and their demand elasticities. This way, informed, evidence-based design decisions can be made about tradeoffs, taking into account not only differences between the value users attribute to different features, but also the compared elasticities of such features. For example, a comparison can be made between the demand for sorting vs. filtering at different cost levels. However, other cost "currencies", such as users' time, may be more appropriate in cases where the benefit to the user would be better expressed in such currencies. In future work, the match between the currency of costs and benefits should be considered when eliciting demand for UI features.

The work presented in this study has limitations that future research could address: first, we studied only one feature, in one user setting. Future work can explore other features and other contexts – for example, by studying decisions such as choosing a movie or future education options. Second, our study used monetary costs – yet costs can be operationalized in other ways, including variations of factors that have been studied in prior studies – e.g. time, aesthetics [2] and annoyance [18]. Third, our analysis is incomplete, in the sense that we did not identify the cost level at which the demand for sorting reaches zero. Finding this point would require a substantially larger participant pool, to accommodate many more cost levels, but we assume that such cost exists, beyond which using the feature would be too prohibitive for all users. Future research could explore the limits of demand, as well as the shape of the demand curve in extreme cost ranges.

We conclude with a call for more HCI research using economic theory and tools. As a discipline that studies allocation of scarce resources [32], economics has developed a set of tools and methods to study people's choices in various circumstances. With the growing constraints placed on resources such as users' time, attention and screen real estate, HCI researchers and practitioners can benefit from using more economic theory to better understand users and inform designers.

ACKNOWLEDGMENTS

We thank Andrew Caplin, Daniel Csaba, and Amnon Maltz for useful discussions.

REFERENCES

[1] Erik Andersen, Yun-En Liu, Rich Snider, Roy Szeto, and Zoran Popović, Placing a value on aesthetics in online casual games. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2011. 1275-1278.

[2] Tamar Ben-Bassat, Joachim Meyer, and Noam Tractinsky, "Economic and subjective measures of the perceived value of aesthetics and usability," *ACM Transactions on Computer-Human Interaction (TOCHI),* vol. 13, pp. 210-234, 2006.

[3] Shlomo Benartzi and Jonah Lehrer, *The smarter screen: Surprising ways to influence and improve online behavior*: Portfolio, 2015.

[4] Dirk Bollen, Bart P Knijnenburg, Martijn C Willemsen, and Mark Graus, Understanding choice overload in recommender systems. *Proceedings of the fourth ACM conference on Recommender systems*, 2010. 63-70.

[5] Duncan P Brumby and Andrew Howes, "Strategies for guiding interactive search: An empirical investigation into the consequences of label relevance for assessment and selection," *Human–Computer Interaction,* vol. 23, pp. 1-46, 2008.

[6] Duncan P Brumby, Andrew Howes, and Dario D Salvucci, A cognitive constraint model of dual-task trade-offs in a highly dynamic driving task. *Proceedings of the SIGCHI conference on Human factors in computing systems*, 2007. 233-242.

[7] Justin Cheng, Jaime Teevan, and Michael S Bernstein, Measuring crowdsourcing effort with error-time curves. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 2015. 1365-1374.

[8] Alexander Chernev, Ulf Böckenholt, and Joseph Goodman, "Choice overload: A conceptual review and meta-analysis," *Journal of Consumer Psychology,* vol. 25, pp. 333-358, 2015.

[9] Elizabeth F Churchill, "The ROI of HCI," *ACM Interactions,* vol. 24, pp. 22-23, 2017.

[10] Sunny Consolvo, David W McDonald, and James A Landay, Theory-driven design strategies for technologies that support behavior change in everyday life. *Proceedings of the SIGCHI conference on human factors in computing systems*, 2009. 405-414.

[11] Anna Louise Cox and Richard M Young, A Rational Model of the Effect of Information Scent on the Exploration of Menus. *ICCM*, 2004. 82-87.

[12] Meg Cramer and Gillian R. Hayes, The digital economy: a case study of designing for classrooms. *Proceedings of the 12th International Conference on Interaction Design and Children*, New York, New York, 2013. 431-434.

[13] Jonathan D D'Angelo and Catalina L Toma, "There are plenty of fish in the sea: The effects of choice overload and reversibility on online daters' satisfaction with selected partners," *Media Psychology,* vol. 20, pp. 1-27, 2017.

[14] Djellel Eddine Difallah, Michele Catasta, Gianluca Demartini, Panagiotis G Ipeirotis, and Philippe Cudré-Mauroux, The dynamics of micro-task crowdsourcing: The case of amazon mturk. *Proceedings of the 24th International Conference on World Wide Web*, 2015. 238-247.

[15] Ido Erev and Daniel Gopher, "A cognitive game-theoretic analysis of attention strategies, ability, and incentives," *Attention and performance XVII: Cognitive regulation of performance: Interaction of theory and application,* pp. 343-371, 1999.

[16] Robert H Frank, Ben Bernanke, and Louis Dorrance Johnston, *Principles of economics*: McGraw-Hill/Irwin New York, 2007.

[17] Jon Froehlich, Leah Findlater, and James Landay, The design of eco-feedback technology. *Proceedings of the SIGCHI conference on human factors in computing systems*, 2010. 1999-2008.

[18] Daniel G Goldstein, Siddharth Suri, R Preston McAfee, Matthew Ekstrand-Abueg, and Fernando Diaz, "The economic and cognitive costs of annoying display advertisements," *Journal of Marketing Research,* vol. 51, pp. 742-752, 2014.

[19] Rebecca Gulotta, William Odom, Jodi Forlizzi, and Haakon Faste, Digital artifacts as legacy: exploring the lifespan and value of digital data.

Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 2013. 1813-1822.

[20] Junius Gunaratne and Oded Nov, "Informing and Improving Retirement Saving Performance using Behavioral Economics Theory-driven User Interfaces," presented at the Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, Seoul, Republic of Korea, 2015.

[21] Junius Gunaratne and Oded Nov, "Using interactive “Nutrition labels” for financial products to assist decision making under uncertainty," *Journal of the Association for Information Science and Technology,* vol. 68, pp. 1836-1849, 2017.

[22] Juho Hamari, Jonna Koivisto, and Harri Sarsa, Does gamification work?--a literature review of empirical studies on gamification. *System Sciences (HICSS), 2014 47th Hawaii International Conference on*, 2014. 3025-3034.

[23] Eric B Hekler, Predrag Klasnja, Jon E Froehlich, and Matthew P Buman, Mind the theoretical gap: interpreting, using, and developing behavioral theory in HCI research. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2013. 3307-3316.

[24] Simo Hosio, Denzil Ferreira, Jorge Goncalves, Niels van Berkel, Chu Luo*, et al.*, Monetary assessment of battery life on smartphones. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, 2016. 1869-1880.

[25] Eric J Johnson, Suzanne B Shu, Benedict GC Dellaert, Craig Fox, Daniel G Goldstein*, et al.*, "Beyond nudges: Tools of a choice architecture," *Marketing Letters* vol. 23, pp. 487-504, 2012.

[26] Joseph Jofish Kaye, Mary McCuistion, Rebecca Gulotta, and David A Shamma, Money talks: tracking personal finances. *Proceedings of the 32nd annual ACM conference on Human factors in computing systems*, 2014. 521-530.

[27] Predrag Klasnja, Sunny Consolvo, and Wanda Pratt, How to evaluate technologies for health behavior change in HCI research. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2011. 3063-3072.

[28] Ron Kohavi, Randal M Henne, and Dan Sommerfield, Practical guide to controlled experiments on the web: listen to your customers not to the hippo. *Proceedings of the 13th ACM SIGKDD international conference on Knowledge discovery and data mining*, 2007. 959-967.

[29] Airi Lampinen and Barry Brown, Market Design for HCI: Successes and Failures of Peer-to-Peer Exchange Platforms. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, 2017. 4331-4343.

[30] Andreu Mas-Colell, Michael Whinston, and J Green, *Microeconomic Theory*, 2004.

[31] Maureen Morrin, Susan Broniarczyk, J Jeffrey Inman, and John Broussard, "Saving for retirement: The effects of fund assortment size and investor knowledge on asset allocation strategies," *Journal of Consumer Affairs,* vol. 42, pp. 206-222, 2008.

[32] David P Myatt, Hyun Song Shin, and Chris Wallace, "The assessment: games and coordination," *Oxford Review of Economic Policy,* vol. 18, pp. 397-417, 2002.

[33] Oded Nov, Ofer Arazy, Claudia Lopez, and Peter Brusilovsky, Exploring personality-targeted UI design in online social participation systems. *CHI 2013: Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*, Paris, France, 2013.

[34] Kenton P O'Hara and Stephen J Payne, "The effects of operator implementation cost on planfulness of problem solving and learning," *Cognitive psychology,* vol. 35, pp. 34-70, 1998.

[35] Nathaniel Popper, "Silicon Valley Tried to Upend Banks. Now It Works With Them.," in *New York Times*, ed, 2017.

[36] Rasmus Prentow, Rasmus Steiniche, Simone D Johansen, Jeni Paay, Ivan Aaen, and Jesper Kjeldskov, When value is greater than money: a micropayment system in Uganda. *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems*, 2015. 765-772.

[37] Katharina Reinecke and Abraham Bernstein, "Improving performance, perceived usability, and aesthetics with culturally adaptive user interfaces," *ACM Transactions on Computer-Human Interaction (TOCHI),* vol. 18, p. 8, 2011.

[38] Paul Samuelson, "Complementarity: an essay on the 40th anniversary of the Hicks-Allen revolution in demand theory," *Journal of Economic Literature,* vol. 12, pp. 1255-1289, 1974.

[39] Sheena Sethi-Iyengar, Gur Huberman, and Wei Jiang, "How much choice is too much? Contributions to 401 (k) retirement plans," *Pension design and structure: New lessons from behavioral finance,* vol. 83, pp. 84-87, 2004.

[40] Yaron Singer and Manas Mittal, Pricing mechanisms for crowdsourcing markets. *Proceedings of the 22nd international conference on World Wide Web*, 2013. 1157-1166.

[41] Heshan Sun, "Developing an interdisciplinary area of economics and human-computer interaction," *AIS Transactions on Human-Computer Interaction,* vol. 2, pp. 151-166, 2010.

[42] Lucia Terrenghi, David Kirk, Abigail Sellen, and Shahram Izadi, Affordances for manipulation of physical versus digital media on interactive

surfaces. *Proceedings of the SIGCHI conference on Human factors in computing systems*, 2007. 1157-1166.

[43] Michael Toomim, Travis Kriplean, Claus Pörtner, and James Landay, Utility of human-computer interactions: Toward a science of preference measurement. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2011. 2275-2284.

[44] Yuan-Chi Tseng and Andrew Howes, "The adaptation of visual search to utility, ecology and design," *International Journal of Human-Computer Studies,* vol. 80, pp. 45-55, 2015.

[45] Alonso Vera, Andrew Howes, Michael McCurdy, and Richard L Lewis, A constraint satisfaction approach to predicting skilled interactive cognition. *Proceedings of the SIGCHI conference on Human factors in computing systems*, 2004. 121-128.

[46] Jo Vermeulen, Kris Luyten, Elise van den Hoven, and Karin Coninx, Crossing the bridge over Norman's Gulf of Execution: revealing feedforward's true identity. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2013. 1931-1940.

[47] John Vines, Paul Dunphy, and Andrew Monk, Pay or delay: the role of technology when managing a low income. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, Toronto, ON, Canada, 2014.

[48] Susan Wyche and Charles Steinfield, "Why don't farmers use cell phones to access market prices? technology affordances and barriers to market information services adoption in rural Kenya," *Information Technology for Development,* vol. 22, pp. 320-333, 2016.