Socially Cued Mental Models

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Abstract
We investigate how initial mental models of a photo sharing website are shaped by observing the behavior of existing users. We manipulate experimentally whether content with critical or popular appeal is highlighted as the best content on the website. Despite interacting with uniform site content and interface design, user's mental models are significantly influenced by social cues embedded in content highlighting behavior, manifesting differential behavioral explanations, audience perceptions, and predictions of unseen features. Results are interpreted within a specific theory of socialized mental models.

Keywords
Socialized mental models, user-generated content

ACM Classification Keywords
H.5.3. Group and organization interfaces: Theory and models.

General Terms
Design, experimentation, theory

Introduction
Designers of social technologies often face the problem of building user interfaces in which much of the information presented is user-generated and consequently beyond their control. A socially meaningful part of this information, particularly for novice users, is the way in which existing users interact

with the system: e.g., through contributing, categorizing, and commenting on content. By revealing cues about the user community, typical content, and system dynamics, these visible actions stand to substantially influence users' mental impressions of a novel system.

The relationship between conceptual understanding of a software system, formalized as mental models (MMs), and interface elements that afford particular ways of usage has been extensively studied in design research [11]. MMs are loosely characterized as cognitive structures that allow users to make sense of unfamiliar technologies and predict how a system might respond to their actions. For instance, the MM for a search engine typically includes an understanding of keywords and result relevance, based on interface affordances like search boxes and ordered lists. On the other hand, the MM of a social system based on user-generated content is fundamentally linked to the specific social context of user interactions within it. For instance, a user is likely to construe the affordance of publishing content online rather differently if they are exposed to others sharing personal tidbits with their friends, as opposed to discussing current news with a broad audience.

We present a specific conceptualization of MMs that recognizes such social contingencies, and describe an experiment in which manipulation of a social cue changes users' MMs of a system despite maintaining an identical interface and the same content on the system.

Social Influences on New Users

Studies of online communities find broad support for a relationship between new user behavior and socially meaningful actions of others. For instance, newcomers that receive community feedback on their initial contributions are more likely to participate again [4, 6]. Even mere exposure to greater activity from friends on a social network website can have similar effects [1].

Making public the preferences of other users can be a powerful source of social influence, creating greater divergence and unpredictability in eventual user preferences [14]. Purchase intentions and ratings of a product sold online can be mediated by perceptions of the extent to which others would be willing to buy it [16]. Predictive models of content ratings on user-generated content sites like Digg.com find social influence to be a strong explanatory factor [7]. Together, such findings suggest mechanisms through which MMs could be subject to similar influence.

Mental Model Theory

MMs are a framework for explaining how people understand complex systems through interaction, and how these understandings are exercised, particularly in novel situations. However, experimental studies of MMs are relatively rare, and there is little consensus about what exactly constitutes an MM [13].

Early investigations of MMs focused on whether a "conceptual understanding" of the workings of a device would improve learning and performance on complex tasks [3, 5, 17]. MMs were manipulated by varying the form (conceptual vs. rote) of instruction provided. People supplied with conceptual instruction about unfamiliar devices (e.g., a reverse polish notation calculator) generally performed better than those without; this was attributed to the ease with which functional inferences about the system could be drawn from conceptual information [5].

Studies of MMs of information retrieval systems focused on eliciting different search strategies employed by users, based on different assumptions about the underlying workings of the system [9, 15]. Models were differentiated by their knowledge content, rather than by differences in the processes of drawing inference.

Payne lists the following three widespread notions of MMs: domain-specific knowledge collections, cognitive "problem spaces" that allow people to carry out mental simulations to predict system behavior, and finally structural analogues of the physical world [13]. Functionally, therefore, MMs in this view serve to answer "what-if" questions about the system. A study of browser navigation [2] illustrates this: users that possessed an appropriate structural understanding of browser history (stack vs. list) were able to more accurately simulate system behavior (e.g., "what if I were to press the back button now?").

The lines of research reviewed thus far largely ignore the social context of technology use, despite prominent theoretical accounts characterizing MMs as broad structures inclusive of "[the individual], others, the environment and the things with which they interact" [11], pg 17) and the "surrounding world in which user performs the task" [10]. A vital role for social information is also revealed in studies of related cognitive structures. Technological frames [12] specifically address the nature of technologies as social artifacts, whose interpretations can be specific to social groups based on different underlying expectations and assumptions. Team mental models [8] have been used to study how individuals form MMs in relation to the task at hand, incorporating perceptions of member roles, strengths, and weaknesses, as well as the nature of interaction between members. These structures have proven useful for explaining patterns of technology appropriation and team performance.

Drawing on these recent perspectives, we now articulate the notion of MM most relevant to this research. An individual's MM of a social technology represents their understanding of its structure and function, as well as interpretation of the user community and their actions, all situated within the individual's context of use. As in previous work, such a "socialized" MM is formed through user interaction, accommodates explanations of behavior, and allows simulation and prediction of future system actions; the difference is that these interactions, explanations, and predictions allowed to be social in nature. In order to employ and test such an MM experimentally, we chose a scenario involving a photo sharing website, a common type of user-generated content service with visible user actions such as commenting on and evaluating content items.

Hypotheses
H1. New users exposed to existing user behavior containing different social cues relating to content evaluation criteria will form different MMs of an online user-generated content service, manifested in user explanations of observed system behavior.

H2. Different MMs will manifest in users' perceptions of who comprises the existing user community and what content they consider valuable.

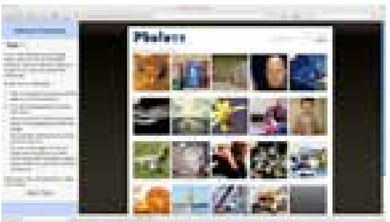


Figure 1. Screenshot of web interface. Left sidebar contains instructions for the participant.

Critical appeal	"Fantastic shot! Love your equipment and ingenuity!"
	"Incredible detail and mood with the rust and frayed lines..."
Popular appeal	"Oh my gosh, that is hilariously wrong! Love it!"
	"Awe! Haha! That's just plain adorable...fantastic shot! Thanks for bringing a smile to my face. =]"

Table 1. Example comments on critical appeal and popular appeal pictures.

H3. Different MMs will manifest in users' predictions of future system behavior, including reactions to new contributions, affiliations with other online services, and the appearance of new content and features.

Method

Participants, design and materials

Participants (N = 56: males, 29 and females, 27) were recruited by email announcements in undergraduate classes at Stanford University. They were compensated for participation with course credits.

We conducted a between-subjects experiment with a single independent variable, content highlighting cue, having two levels: "critical appeal content highlighted" vs. "popular appeal content highlighted". Independent raters (N=19) were employed to find pictures with either type of appeal from public domain online sources. Figure 1 shows a screenshot of the website (called "Photoze.com"): the page showed twenty thumbnails of pictures (ten of each appeal type) ostensibly shared by other users. Depending on condition, a randomly selected set of five critical appeal or five popular appeal pictures was marked as "top" pictures using stars and a "top photo" label. Every participant saw the same mix of pictures overall.

Clicking on the thumbnail revealed the full-size picture and five associated comments. To reinforce the highlighting manipulation, comments on critical appeal pictures were professional in tone, referring to the skill of the photographer and photographic technique. Comments on popular appeal pictures tended to be casual in tone and focused on entertainment value of the picture (see Table 1 for examples).

Procedure

Participants were randomly assigned to experimental condition and asked to perform four tasks. In Task 1, they were instructed to look around the page, and then click on all five "top" pictures and read associated comments. This allowed them to form their initial MMs while being exposed to the highlighting cue. In Task 2, they could click on any seven other pictures. Freely browsing through the site allowed them to further refine their models. In Task 3, they were shown two of the previously seen "top" pictures, and asked open-ended questions about why they had attained "top" status. In Task 4, they were shown four previously unseen pictures (two of each appeal type) and asked to predict which one, if uploaded to the site, would have the best chance of being marked as a "top" picture. Finally, a questionnaire assessed measures (see Table 2) related to target audience, brand affiliation, and predictions about unseen features.

Results and discussion

Table 2 shows a summary of the results, organized by condition. Manipulating an essentially social behavior (the content highlighting cue) produced significantly different understandings of the system. Participants aligned overwhelmingly with the condition-specific highlighting cue when picking a photo that would attain "top" status if uploaded. Participants who observed critically appealing content marked as "top" saw the service as aimed primarily at amateur photographers, oriented towards the technical craft of photography, and likely to affiliate with photography websites. They predicted that experts would be involved with the site through features like forums and articles. Comments were often construed as feedback from a community interested in surfacing the best photography talent.

Questionnaire items were rated on 10-pt Likert scales where applicable. Principal component analysis was used to construct composite indexes (all had Cronbach's $\alpha > 0.77$).

H2.b. "Entertainment focus" combines "entertainment value", "humor", "reminds people of good times", and "fun". **"Artistic Focus"** combines "skill of photographer", "artistic interpretation", "composition and lighting"

H3.b. "Casual entertainment affiliation" combines "iambored.com", "yeah-oops.com", "freemyspacelayouts.com", "dailyhaha.com", "vegascheapvacations.com" **"Photography website affiliation"** combines "Istockphotos.com" and "salonickphotography.com"

H3.c. "Expert involvement" combines "Forum where experts answer questions", "Top photographer of the month", and "Featured article from a photography expert". **"Photography technique"** combines "Picture set 'Art of Landscape", "Picture set 'Very long exposures'" and "Nikon DSLR Review"

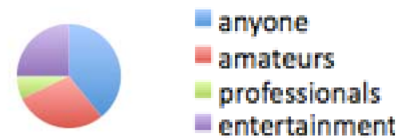
	Measure	Critical appeal cue highlighted	Popular appeal cue highlighted
H1	a. Why certain pictures were marked as "top"	Explanations focused on picture characteristics, frequently citing "skill of the photographer / difficulty in taking the photograph" or specific photo elements like atmosphere or subject.	Instead of picture elements, the most frequent explanation type cited the preferences or actions (such as comments) of "other users/user community".
H2	a. Who is the target audience and why?	Rationale for response often based on existing comments related to photographic technique and camera equipment. 	 Often based on seeing mix of casual and professional content
	b. Picture qualities valued by user community	"Entertainment focus" less valued, ($M = 5.84$, $SD = 1.64$), $F(1,53) = 32.18$, $p < .001$ "Artistic focus" more valued ($M = 8.34$, $SD = 1.21$), $F(1,53) = 29.68$, $p < .001$	"Entertainment focus" more valued ($M = 8.16$, $SD = 1.38$) "Artistic focus" less valued ($M = 5.75$, $SD = 2.17$)
H3	a. Choose picture likely to become "top"	23 participants chose critical appeal pictures vs. 5 chose popular appeal pictures	3 chose critical appeal pictures vs. 25 chose popular appeal pictures
	b. Likely affiliate websites	"Casual entertainment affiliation" less likely ($M = 3.26$, $SD = 1.73$), $F(1, 54) = 4.08$, $p < .05$ "Photography website affiliation" more likely ($M = 6.70$, $SD = 1.70$), $F(1,52) = 4.01$, $p = .05$	"Casual entertainment affiliation" more likely ($M = 4.29$, $SD = 2.01$) "Photography website affiliation" less likely ($M = 5.48$, $SD = 2.01$)
	c. Likely new features and content	"Expert Involvement" more likely ($M = 6.89$, $SD = 1.93$), $F(1,54) = 9.69$, $p < .01$ "Photography technique" more likely ($M = 6.65$, $SD = 1.69$), $F(1,53) = 8.20$, $p < .01$	"Expert Involvement" less likely ($M = 5.33$, $SD = 1.81$) "Photography technique" less likely ($M = 5.35$, $SD = 1.70$)

Table 2. Summary of qualitative and quantitative results from the experiment

In contrast, participants that saw popular appeal pictures marked as "top" thought about the service as humorous entertainment for a more general audience. Picture popularity was based on highest entertainment value in this community. Affiliations with casual entertainment websites were likely, but expert- and technique-related features were not particularly likely or unlikely. Participants attributed a greater role to the actions of others (such as clicks) in determining top content, rather than to objective picture qualities, as was the case in the critical appeal condition.

These results are encouraging, empirically relating established pathways for online social influence to the design-theoretic concept of MMs. Further experiments are required however, that would (1) more clearly discriminate between a socialized MM and a general critical or popular orientation toward the service, and (2) generate ways for identifying which system affordances are likely to exhibit socially contingent interpretations in particular contexts.

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