Users' Preference Share as a Criterion for Hierarchical Menu Optimization

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ABSTRACT

Recently developed computer-aided design (CAD) tools automate design of rational hierarchical user menu structures. Proper choice of the optimization criterion is the key factor of success for such a CAD tool. We suggest user preference share as a novel metric of menu layout performance. It has clear economic grounds and is sound for management. We show how the preference share of a menu layout can be evaluated from laboratory experiments and predicted using the experimental menu navigation time and menu layout characteristics. Although navigation time is the most important factor, sometimes the faster does not mean the better. The logical compliance of a menu is also valuable for users.

Author Keywords

Menu-driven system; hierarchical menu optimization; optimization criterion identification; user experience; menu testing and assessment.

ACM Classification Keywords

H.5.2. Information interfaces and presentation (e.g., HCI): User Interfaces.

INTRODUCTION

Hierarchical command menus have long history but they are still an essential UI element for any computer software like 30 years ago. A menu is the first element seen by a user on the display of a novel smartphone or a public terminal.

Since early 1980s methods for automated design of hierarchical user menus were a valuable application of formal methods to human-computer interaction. Recently several computer-aided design (CAD) tools [3, 11, 13, 14, 19, 27, 28] were proposed. They employ combinatory algorithms to efficiently optimize various metrics of hierarchical menu performance. However, there is still no common agreement on what a good menu is or which performance metric should be optimized: predicted user navigation time [11, 13, 14, 20], a mixture of performance (navigation time) and consistency (logic) [3] or some synthetic metrics [27, 28].

There are many obstacles on the way of adopting user menu CAD tools by designers. In particular, it is hard to prove the optimized design to outperform the others [25]. Most performance metrics are not sound for managers who operate in terms of added value and return: the gain in navigation time does not answer the question how many customers will prefer this product to the competing one.

We propose the *preference share* (the share of the user population preferring the considered menu layout to the competing one) as an optimization criterion for hierarchical menu optimization tools. The preference share is related to menu layout attributes and performance metrics (navigation time) in a series of experiments with students. We show that the preference is affected primarily by the navigation time but also by structural attributes and logical compliance of a pair of compared menus. In conclusion, implications to menu optimization are outlined together with open issues and perspectives.

LITERATURE REVIEW

Our research is related to several lines of HCI literature: automated UI design, predictive models of user behavior, user menu performance and user experience studies, organizational problems of HCI.

To reduce menu design to the optimization problem one needs a predictive model of menu performance. Traditionally, the key performance metric was the target item selection time [20]. Earlier models [7, 17, 20, 22] accounted only for the menu breadth and item position, labels' size and popularity, alphabetic sorting. SDP model [9] (and its extension [10] to scrolling and hierarchical menus) also incorporated expert behavior via decision time according to Hick-Hyman Law and pointing time according to Fitts' Law. The recent model [4] employs the gaze distribution to predict behavior in linear menus.

Starting from [6], the concept of semantic similarity of a search item to the other items on a panel (originated from [23]) is accounted in navigation time prediction. The recent model [8] of this sort explains the observed menu search behavior as a result of a reinforcement learning process.

Menu design should take into account semantics of menu items to avoid senseless item groupings and unsound panel titles. Nevertheless, advanced semantics-aware predictive models of navigation time are rarely used directly in the literature. The criterion in [3, 19] bases on the SDP model from [9] with a correction term added to favor good label compliance. A similar approach is adopted in [27], except that a synthetic metric is used instead of the navigation time. The choice of summand weights is not justified.

Consistency is an optimization constraint in [13] and [14], i.e., a simple navigation time predictor (serial search time in [13] or a more general expression in [14]) is minimized on a constrained feasible set limited only to semantically consistent menu layouts. In [11] authors minimize the navigation time affected by *semantic quality* of menu items. Recent progress in menu optimization is summarized in [5].

Different algorithms were suggested to select an optimal (or nearly optimal) menu layout: exhaustive enumeration in [13], genetic meta-heuristics in [19, 27], linear genetic algorithms in [28], combination of greedy hill-climbing and ant colony optimization in [3], a greedy heuristics of guaranteed quality in [11, 14]. So, a good approximation to optimal menu layout can be calculated in reasonable time.

We propose a user experience-based metric of menu quality. Measuring user perception of hierarchical menus has long tradition. Influence of menu depth and breadth onto subjective preferences [16] and onto subjective perception of task complexity [15] were studied. Later the menu type was related to performance and preference [18, 21]. Many experimental studies relate user performance (time and accuracy) to personal abilities (with age being the main factor) [2] but difference in subjective perception as a function of personal abilities is less studied.

It is commonly understood that "…the primary task for menu designers is to create a sensible, comprehensible, memorable and convenient semantic organization…" [26]. For instance, menu item content is known to affect accuracy rather than navigation time [1], clear labels and functional groupings are known to affect user perception of a menu, but, to our experience, the direct effect of semantic effects on user preference has never been distinguished from the indirect effect (good semantics enhances navigation time [8] which, in turn, affects user subjective perception).

We follow [23] in proposing performance metrics that reflect the value added by the technology and relate user preferences to attributes of hierarchical menu structure and content both directly and indirectly (through their effect to performance metrics, e.g., navigation time and accuracy.)

PREFERENCE SHARE AS OPTIMIZATION CRITERION

A good hierarchical menu design is the one preferred by users, i.e., by customers who buy a product the menu being the part of. So, a relevant criterion for menu optimization should be based on user experience. A product is typically designed for some population of users (the target audience), and hence, a product should be designed to maximize the *preference share*, i.e., to be preferred by as many users in the population as possible.

This means that the prospective menu layout should not be evaluated *per se*, but in comparison with alternative layouts forming the context. For example, a manually designed layout can be a good competing alternative when a new menu is designed. If the menu enhancement process is considered, the existing menu layout can be chosen as a baseline for comparison. If an obvious competing design exists, one should design a new menu layout that will be preferred to the competitor's menu layout.

To calculate the preference share $P(x, y)$ of menu layout x to menu layout y (i.e., the fraction of user population preferring x to y) one needs to relate it to the measurable attributes of the user population and of both menu layouts.

A user population can be split into representative classes $c \in C$ (popular user audiences, e.g. adults, novices, disabled persons, etc.) Then the preference share of menu layout x to menu layout y is calculated as $P(x, y)=\sum_{c\in C}P^c(x, y)\cdot Vol(c)$, the sum of preference shares $P^c(x, y)$ of all classes $c \in C$ weighted by $Vol(c)$, normalized volumes of classes in the population (so that $\sum_{c\in C}Vol(c) = 1$).

The preference share $P^c(x, y)$ of user class c adds up from preferences of its members. Consider a user $i \in c$. His or her preferences of menu layout x to menu layout y are modeled with a number $P_i(x, y)$ being equal to unity if he or she prefers x to y, and equal to zero otherwise (set $P_i(x, y) = 0.5$ in case of indifference). Then $P^c(x, y) = \sum_{i\in c} P_i(x, y) / \#(c)$, where $\#(c)$ is user count in class c.

Individual preferences are driven by five major groups of factors (or variables). 1) User personal characteristics fix the character, computer skills, cognitive, or motor abilities; 2) Structure characterizes the hierarchy of compared menus (their breadth, depth, labels' consistency, etc.); 3) Menu design or appearance of compared menus (linear, iconic, or split menus, labels' size and color, etc.); 4) Ecology of menu usage explains the context (time pressure, repetitiveness of tasks, learning time, price of the error); 5) Performance metrics reflect the evidence of menu usage – the selection time, accuracy, menu cancellations, etc. The first four groups are independent, while performance metrics can be predicted (see the thin arrows in Figure 1).

Preferences of each class of users are elicited from experiments. Our experiments are limited to the available audience (undergraduate and off-campus students), but in the future representative classes should be chosen to support menu design focused on particular user groups.

Below we fix the user population, menu design and ecology, so preference shares are predicted from menu structure variables and aggregated performance metrics.

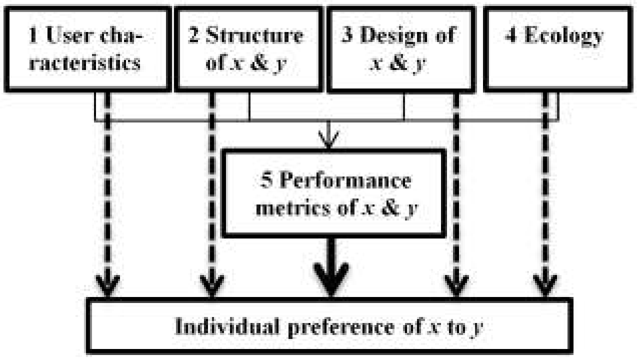

Figure 1. Factors affecting user preference of menu layout *x* to *y*. Dashed lines mean that the effect groups of factors 1-4 on the preferences cannot be mediated by performance metrics.

EXPERIMENT

Our experimental setup is similar to that of [16]. Subjects assess hierarchical menus solving standard tasks of finding a metal-working tool with a sequence of choices of its features on menu panels. The features include the tool name (drill, mill, cutter), manufacturer (YG-1, Dijet, QCT, Hammond, HAM, Carmex), length (shorten, normal, long), the diameter (micro, mini, small, normal, big, extra), the use (rough cut, finishing, uncooled cut), the material (carbide, high-speed steel, replaceable insert). A task definition presented to users combines exact, iconic, and synonymic stimuli (see Figure 2).

We use a rather complex (yet, realistic) environment based on the standard Delphi GUI. Tool features are distributed to menu levels (see example in Figure 3). Ten distinct menu layouts were prepared with widely varying breadth and depth, breadth distribution by levels, and order of feature selection (see Table 1).

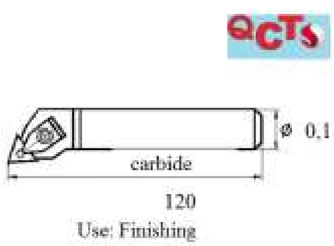

Figure 2. Task definition: exact, synonymic and iconic stimuli.

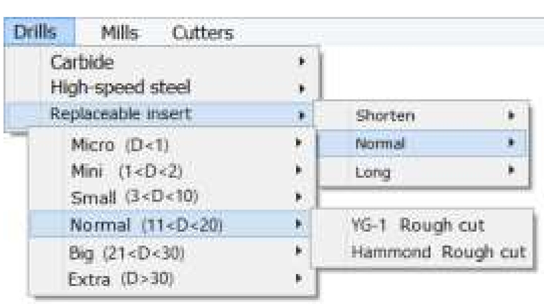

Figure 3. The Menu 1 (translated).

Menu No	Level No	Features	Menu breadth
1	**1**	Tool name	3
	2	Material	3
	3	Length	3
	4	Diameter	6
	5	Manufacturer + Use	**2**
2	**1**	Manufacturer	6
	2	Diameter	6
	3	Name + Material + Length + Use	**9**
3	**1**	Tool name + Use	**9**
	2	Manufacturer	6
	3	Material + Length + Diameter	**6**
4	**1**	Manufacturer	6
	2	Material + Length	**9**
	3	Diameter + Tool name + Use	**6**
5	**1**	Tool name	3
	2	Manufacturer	6
	3	Material	3
	4	Length + Use + Diameter	**6**
6	**1**	Diameter	6
	2	Use	3
	3	Material	3
	4	Tool name	3
	5	Length + Manufacturer	**2**
7	**1**	Tool name: Drills & Cutters – see Menu 1 Tool name: Mills – see Menu 5	3
8	**1**	Manufact.: YG-1, QCT, Hammond – see Menu 4 Manufact.: Diget, HAM, Carmex – see Menu 2	6
9	**1**	Tool name: Drills & Cutters – see Menu 1 "Mills" + Use (3 items)	**5**
	2	Manufacturer	6
	3	Material + Length + Diameter	**6**
10	**1**	Mills – see Menu 5 Diameter	**7**
	2	Use	3
	3	Material	3
	4	Tool name	2
	5	Length + Manufacturer	**2**

Table 1. Specification of menu layouts assessed.

The logic of some menus was intentionally injured in various ways. Many panels join two or more features (e.g., the menu item is “Carmex, finishing”.) Menus 1-6 are *symmetric* (i.e., the order of feature selection is the same for all target items) while menus 7-10 are *skewed* (menu 7 inherits the structure of Menu 1 for drills and cutters and the structure of Menu 5 for mills, menu 8 inherits the structure of Menu 1 for drills and cutters and the structure of Menu 5 for mills). The top panel in menus 9 and 10 is *combined*, it suffers from *mixed logic*: in Menu 9 two out of 5 items are tool names, Drills and Cutters, while the rest three items are Mills joined to the tool use; in Menu 10 six diameter items are equipped with Mills (see Figure 4a.) The hypothesis to be tested was that users dislike joined menu panels since the items are hard to read and dislike combined panels since they break the logic and cause errors. A real-life example of mixed logic is the top menu of MS Word 2010 (see Figure 4b): Insert and View are *actions*, File, References, and Mailings are *objects*, Review is a *process*. All menu layouts shared the same set of 324 target items.

During the experiment a subject sequentially assesses 11 menu layouts (one of 10 layouts from Table 1 is presented twice to estimate the effect of experience on user navigation time and preferences) with 2 min rest between the menus. In each menu a series of search tasks is performed. A task picture is displayed for 30 sec, and then the next of 12 tasks is displayed in a cycle (tasks were chosen to cover uniformly the paths in a menu.) User actions (mouse and keyboard) are logged each 10 msec. After 5 min of task execution the usability score from –5 (the worst) to 5 (the best) is assigned to the menu. In the end of the experiment the subjects write informal comments explaining the scores and providing their vision of an ideal menu.

In Experiment I 48 volunteers (graduate students of the Engineering department) meet Menu 1 to 10, and then again Menu 1. In Experiment II 19 off-campus students (23-41 y.o.) meet menus in another order (4, 3, 8, 2, 10, 7, 6, 1, 9, 2, 5) to check robustness of preference prediction to menu presentation order.

RESULTS

Analyzing User Comments

Semantic analysis is used to analyze user comments. General subjective menu characteristics found in comments are “handy”, “simple”, and “reasonable/ consistent” (70, 25, and 22 occurrences respectively). Other popular words characterize menu structure: order of feature selection is (37 comments), depth (32 comments), breadth (26 times). Joined panels are criticized in 21 comments, combined panels are blamed 18 times, and 16 complaints concerned skewed menus (those having different order of feature selection in different submenus, like Menus 7 and 8). Natural sorting (e.g. alphabetic) was demanded 16 times.

Only 10 comments noticed fast navigation and just 2 comments disclosed selection errors as a valuable factor. We conclude that the effect of process variables (e.g., navigation time) is not realized by users. The results resemble those of the survey [3] of menu designers (e.g., “understandability” of a menu is the main design concern.)

Analysis of the vision of an ideal menu shows that 30% subjects prefer deeper menus (6 hierarchical levels) to joining several features on a single panel. The rest 70% are ready to join two (or even more) features on a panel to keep the depth in the range from 3 to 4 levels. These results are in line with the common knowledge [7, 15, 16] that shallow menus are better in terms of performance and preference. Finally, most users find that the tool name and the manufacturer should be selected on the first two levels.

Predicting Individual User Preferences

We predict $P_i(x, y)$, where i is the user, x and y are menu layouts. So, there are 5280 observations in Experiment I (11 menus give 110 unique pairs for each of 48 subjects), and 2090 observations in Experiment II (for 19 subjects).

Menu structure is characterized with menu depth (# of hierarchical levels), menu breadth on level 1 to 5, # of joined panels, “skewed menu” dummy for menus 7-10, and “mixed logic panel” dummy for menus 9 and 10. The order of features’ presentation (which is important, according to user comments) is captured with the variables of the form “# of Feature” = “Panel level” + 0.25·(“Feature No on the joined panel” – 1). For instance, “# of Diameter” = 3 and “# of Use” = 4.25 in Figure 3.

Since $P_i(x, y) = 1 - P_i(y, x)$, the regression must be symmetric, and we employ tradeoffs [24] of menu structure characteristics as predicting variables. For instance, the breadth tradeoff $\Delta\text{Breadth}(x, y) := \text{Breadth}(x) - \text{Breadth}(y)$.

For user i in menu x performance metrics include average task completion time $t_i(x)$, performed task count $n_i(x)$, average success rate (% of accomplished tasks) $r_i(x)$, and average time of successful task completion $s_i(x)$. It is shown in [9] that navigation time depends crucially on user expertise. In Experiment I every user meets Menu 1 twice, in the beginning and in the end of the experiment, when users navigate 12% faster in average. To test the hypothesis that a subject makes allowance for his or her experience during menu assessment, the “net” performance metrics are built by applying a linear transformation so that the “net task completion time” nt_i in Menu 1 is equal to that in Menu 11. The tradeoffs of performance metrics and their “net” analogues are also used as predictors.

User characteristics are captured with 35 variables obtained from psychophysiological tests (Eysenck personality, Ravena IQ, Landolt rings, numbers memorizing) executed after Experiment I. These variables appear less significant (in a binary classification tree they appear only at Level 5) so we skip further details.

If individual preferences could be predicted with objective user characteristics, the preference share would be constructed for any user class and, hence, for any target audience with no additional experiments.

a)

b)

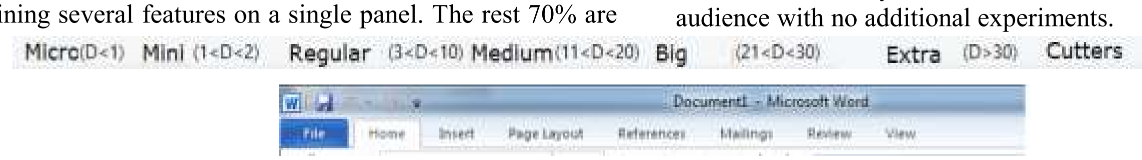

Figure 4. Examples of menu panels with mixed logic.

We tried several popular classification techniques (*k*-nearest neighbors, naïve Bayes, logistic regression, support vector machine, and random forest classifier) but, unfortunately, the accuracy is unsatisfactory: logistic regression with $L1$ regularization wins with Mean area under ROC curve 0.72 (Mean precision 0.75 and recall 0.79) for 1:1 random sub-sampling cross-validation. We can only conclude that user preferences are determined not only by performance metrics: menu structure and user characteristics are also significant. So, dashed lines in Figure 2 do exist.

Predicting Preference Share

Introduce the new predicting variables. For user i and a pair of menus x and y *dominance of task completion time* is defined as $D_i^t(x, y) \coloneqq \operatorname{sign}(t_i(x) - t_i(y))$. *Dominance* of the other performance metrics is defined in the same fashion.

The preference share $P(x, y)$ is calculated by averaging individual preferences over subjects and is predicted with a linear regression using tradeoffs and dominances of performance metrics (also averaged over subjects) and menu structure tradeoffs as predictors. Each dataset gives 110 observations (unique pairs of 11 menus). Only a half of observations are independent, so regression accuracy figures are adjusted to real sample size.

To exclude insignificant, noisy, and collinear variables and to avoid overfitting the following variable selection procedure is used. Ten random subsets of participants of Experiment I are picked (each containing approximately a half of subjects.) For each group of subjects the preference share is calculated and predicted using the stepping method of variable selection based on the Fisher statistics [12]: the variable with the lowest probability of F is included in the regression if the probability of F is less than 0.05 and the variable is excluded if its probability of F becomes more than 0.10. A variable is included in the final list (see Table 2) if it is met in at least a half of ten "partial" regressions.

The linear regression with predicting variables presented in Table 2 gives average correlation 0.95 (mean absolute error, MAE = 0.064) on the training set and average correlation 0.90 (MAE = 0.097) on the testing set for 1:1 random sub-sampling cross-validation.

Variable	Coefficient
(Constant)	0.500
Dominance of successful task completion time D^s	–0.313
Dominance of success rate D^r	0.096
"Skewed menu" dummy tradeoff	–0.102
"Mixed logic" dummy tradeoff	–0.125
# of joined panels tradeoff	0.006
Breadth of the 1st level panel tradeoff	–0.033

Table 2. Optimal regression variables and coefficients for preference share prediction using Experiment I data.

To check robustness of prediction with respect to audience and menu presentation order data from Experiment II are used as the testing set and preference shares averaged over all participants of Experiment I are used as a training set. Correlation 0.97 with MAE = 0.055 is obtained on the training set for coefficients presented in Table 2 and correlation 0.84 with MAE = 0.101 is obtained on the testing set (cross-validation on the data of Experiment I gives similar accuracy). Figure 5 shows the scattering plot.

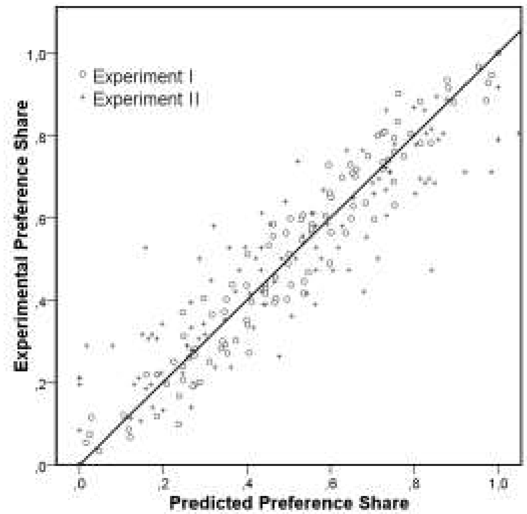

Figure 5. Prediction accuracy of preference share data: Experiment I is used for training and Experiment II for testing.

CONCLUSION

We proposed a new metric of hierarchic menu performance: the preference share of a menu layout to a competing layout. Using preference share as an optimization criterion in CAD systems for menu design automation should fill the gap between the traditional approach to menu performance and the logic of product lifecycle management.

Preference share can be accurately predicted from menu performance and structure variables (see Table 2), but performance metrics alone are not enough. From Table 2 it follows that successful task completion time is responsible for ≈30% of preference share variation ("net" time is not as informative: users do not make allowance for their experience and charge longer navigation time to menu imperfectness.) Accuracy (dominance of success rate) is also an important factor responsible for 10% of preference share variation. Skewedness of a menu and mixed logic decreases the preference share by ≈10%. So, we can expect that if mixed logic was avoided in the main menu of MS Word (see Figure 4b), up to 10% of users would prefer this menu to the current one (*ceteris paribus*).

Although logical compliance of a menu appears more important than "geometry" (breadth or depth), valuable structure variables can, in principle, be calculated for any menu layout. But to use our results in menu optimization tools a predictive model is needed for the dominance of successful task completion time and that of success rate. Probably the most promising approach, which can be the subject of future research, assumes using contemporary predictive models of navigation time [4, 8] to predict individual navigation time for a variety of user characteristics in a population, and then calculating the dominance by averaging individual contributions.

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