

# SmartChoice:

## An Online Recommender System to Support Low-Income Families in Public School Choice

*David C. Wilson, Suzanne Leland, Kenneth Godwin, Andrew Baxter, Ashley Levy, Jamie Smart, Nadia Najjar, and Jayakrishnan Andaparambil*

■ Public school choice at the primary and secondary levels is a key element of the U.S. No Child Left Behind Act of 2001 (NCLB). If a school does not meet assessment goals for two consecutive years, by law the district must offer students the opportunity to transfer to a school that is meeting its goals. Making a choice with such potential impact on a child's future is clearly monumental, yet astonishingly few parents take advantage of the opportunity. Our research has shown that a significant part of the problem arises from issues in information access and information overload, particularly for low socioeconomic status families. Thus we have developed an online, content-based recommender system, called SmartChoice. It provides parents with school recommendations for individual students based on parents' preferences and students' needs, interests, abilities, and talents. The first version of the online application was deployed and live for focus group participants who used it for the January and March/April 2008 Charlotte-Mecklenburg school choice periods. This article describes the SmartChoice Program and the results of our initial and follow-up studies with participants.

Families whose children attend schools that are not making adequate yearly progress (AYP) under the guidelines of the 2001 No Child Left Behind (NCLB) Act are granted the legal right to make an important decision—whether to send their child to a different school. When this occurs, school districts must give students the option of moving to a school that is meeting its AYP goals. However, across the country, fewer than 6 percent of eligible students take advantage of this provision of the law (GAO 2004, Brown 2004, Howell 2006). Part of the theory of action behind NCLB, and public school choice more generally, is that giving parents information about school performance and allowing students to leave low-performing schools will improve student outcomes and force poorly performing schools to improve. However, this provision of NCLB has largely failed to be effective because parents must (1) be able to identify which schools will improve their child's performance and (2) actively make choices about their child's education. Research has shown that poor tactical implementations of NCLB policy can effectively strip parents, particularly low-income parents, of their legal options and rights, discouraging and limiting practical participation and ultimately creating a culture of disincentive to exercise choice rights under current policy.

Our applied research program examines whether a comprehensive community program, collectively referred to as the SmartChoice Program, centered on a computer-assisted decision support system, SmartChoice, can help to overcome this implementation problem in current education policy. The decision system provides personalized recommendations for individual students based on parents' preferences and students' needs,

interests, abilities, and talents. In general, the SmartChoice Program studies the extent to which (1) incentives for participation and (2) personal assistance in the decision process can increase choice behavior among low-income and minority families who occupy the majority of NCLB-designated schools in our region. SmartChoice applies core user modeling, personalization, and content-based recommender system techniques to accomplish its goals.

We deployed the first version of SmartChoice in January 2008 for use by over 50 real end-user participants. The initial SmartChoice user population was limited to participants selected for our pilot study. Participants used the system as support for the January 2008 Charlotte-Mecklenburg magnet school choice period and the subsequent March–April 2008 general school choice period. We expect SmartChoice access for participants remained available until the next school choice period, and our hope is to update the system for the next school choice period and expand the user population for additional studies. Full evaluation of the pilot study choice results will not be available until follow-up studies with current users are completed at the end of the current school year. We view the current SmartChoice deployment as a closed beta that serves as a focus for discussing the application of recommender systems and related techniques to the domain problem of school choice. This article expands upon preliminary results first reported in Wilson et al. (2008).

In order to motivate the application, this article begins with an introduction to the school choice domain. It goes on to detail the need for recommender support in school choice, and it identifies some common erroneous user-choice behaviors as potential design considerations. The article provides a brief overview of recommender systems in general, and it describes the modeling and recommendation approaches employed in SmartChoice. The article describes the initial deployment and study results from the school choice periods, as well as a follow-up study several months later, and it concludes with discussion and future directions.

## NCLB: The Law of Choice

The No Child Left Behind Act (U.S. Department of Education 2001) is just one example of the type of instrument that is likely, in various incarnations, to mark education policy in the coming years—one that combines additional resources and new rights for low-income students. Supporters and opponents of No Child Left Behind agree that the legislation marked a revolutionary change in the federal government's role in education (Meier and Wood 2004, Kim and Sunderman 2004, McDermott and Jensen 2005). In one stroke NCLB

changed the requirements for continued funding of Title I schools (those schools with high percentages of students at or near the federal poverty line). After the passage of NCLB, to continue the funding stream, districts must use outcome-based evaluations and show that individual schools have met AYP goals. If a school does not meet AYP goals for all ethnic and income groups for two consecutive years, the district must offer students in the school the opportunity to transfer to a school that is meeting its goals.

Research on the implementation of NCLB has discovered several obstacles to effective reform. School districts have been slow to alert parents of their right to choose and typically give parents less than three weeks to investigate their options, make a choice, and apply for the school transfer. In addition, districts often fail to give parents good options to their current school (Howell 2006).

The most important barriers to choice, however, are procedural complexity, parents' lack of information, and their unwillingness to choose. Despite being notified by their school district, many low-income parents are unaware of their right to choose and of the fact that their school failed to meet its AYP goals for two consecutive years (Howell 2006). Those parents who are aware of the options NCLB guarantees often are confused about the choice process and believe they lack the capacity to choose wisely (Howell 2006; Leland, Godwin, and Baxter 2007). This often leads to a conscious decision not to exercise school choice options.

## Parents' Decision Not to Decide

In order for choice provisions targeted at low-income parents to raise the achievement of their children, at least two conditions must hold: (1) low-income parents must participate in the choice process; and (2) they must be able to evaluate their child's likely success at a prospective school.

Academic research on NCLB's choice provisions reveals that few NCLB parents have exercised the right to choose an alternate school. Kim and Sunderman (2004) studied 10 urban school districts and discovered that fewer than 3 percent of eligible students requested a transfer to a different school. These findings were corroborated by a national study conducted by the GAO, which estimated that fewer than 1 percent of eligible parents had participated in the choice provision (GAO 2004). Howell (2006) found that only 3.8 percent of NCLB-eligible students in Massachusetts applied for a transfer. Brown (2004) supplies the highest nationwide estimate at 5.6 percent of eligible students.

Howell (2006) also revealed that although parents with children enrolled in NCLB schools

claimed that they were familiar with its provisions, the majority were unaware that their child was enrolled in an NCLB-sanctioned school. Howell concluded that if advocates of NCLB are to boost participation, the options provided to parents must be in a format that encourages them to participate in the choice process (p. 174).

Our own research underscores Howell's finding. In 2006, our project team held focus groups with parents whose children attend NCLB-sanctioned schools to investigate why they did not choose an alternative to their assigned school. We found that the principal reasons were (1) they were unaware of their choices; (2) they feared that they would make an incorrect choice and reduce their child's educational opportunities; (3) they found the information difficult to use, and it made them feel confused and ill-informed about their available options; and (4) they did not trust their school system (Leland, Godwin, and Baxter 2007).

### Need for Recommendation

A key aspect of the argument for the early advocates of public school choice was that it would force all schools to improve because a high percentage of parents would be informed about school quality. They would become well-informed because having the right to select their children's schools would give parents the incentive to become informed (Coons and Sugarman 1978, Chubb and Moe 1990). The difficulty with this argument is that parents have very little information about schools, even in districts with expansive public school choice (Ambler 1994, Schneider et al. 1997, Godwin and Kemerer 2002, Dunk and Dickman 2003).

The information low-income families have about schools tends to come from two easily seen cues: (1) the composition of a school's student body and (2) the school's average scores on standardized testing. Some parents believe that schools with fewer minorities or with more high-income families are better schools for their child (Leland, Godwin, and Baxter 2007). While these relationships may hold in the aggregate, for individual students they often are misleading. For example, research by Southworth and Mickelson (2007) shows that schools that are predominantly Anglo and high-income often place African American students in tracks with low-performing students and that this reduces their academic achievement. Thus minority parents who choose a predominantly white school may harm rather than help their child.

The other, largely unhelpful, cue that parents use to evaluate schools is the average end-of-grade test scores. Our focus groups found that almost all parents believe that peer effects are important in a

child's academic growth and that their child will learn more the higher the average test score at a school. But some research suggests that this view is often incorrect.

Hoxby and Weingarth (2005) demonstrate that choosing a school based on the aggregated test score can be unwise because peer effects are neither uniform nor linear. On average, having higher-achieving peers is better than having lower-achieving peers. But Hoxby and Weingarth discovered that students whose achievement scores are substantially above or below the modal score of their peers do not learn as much as students whose scores are closer to the mode. Thus, selecting a school on the basis of higher test scores could harm rather than help a student.

In another study of the impact of NCLB choice on student outcomes, Hastings and Weinstein (2007) find that achievement test scores for students who enroll in an alternate school rather than stay in an NCLB-sanctioned school increase if the new school's average test score is greater than one school-level standard deviation higher than their NCLB school. In line with the Hoxby and Weingarth findings, however, the research found that the effect of moving to a school with higher test scores is greatest for students whose prior test scores are substantially above average.

Paul Hill (2007) writes that parents not only need to be informed about choice and the options available to them, they "need rich information about what different schools offer and how effective those schools are with children who have different interests and learning styles." To match a student with a school, the parent needs to know how well the available schools have educated students with similar interests, backgrounds, and skills to their child. But unless the parents are econometricians with the appropriate dataset, they cannot obtain the information they need (McCaffrey et al. 2003).

Overall, previous research concerning school choice by low-income parents indicates that what low-income parents need and want is an individualized, easy-to-understand recommendation that comes to them in a nonnumeric way (Leland, Godwin, and Baxter 2007; Hill 2007).

### Recommender Systems

Recommender systems have gained considerable interest since the 1990s as a means of helping users to deal with ever-increasing problems of information overload (Resnick and Varian 1997). Algorithmic developments to date have given rise to a variety of different basic recommendation techniques and strategies (Burke 2002). *Content-based* techniques, for example, rely on the availability of descriptive metadata that captures the essence of

the items available for recommendation. As a simple illustration, a movie recommender might make use of descriptive features including genre, actor, and summary plot information as the foundation for similarity assessment techniques to match a target user's profile interests (Rosenstein and Lochbaum 2000; Basu, Hirsh, and Cohen 1998; Soboroff and Nicholas 1999; Smyth and Cotter 2001).

*Collaborative Filtering* techniques provide an alternative strategy that relies on ratings-based user profiles instead of descriptive meta-data (Schafer et al. 2007, Konstan et al. 1997, Smyth and Cotter 2001, Terveen et al. 1997). Suitable items for recommendation are identified not because their description matches them with a target user, but rather because these items have been liked by users who are similar to the target user in terms of how they have rated other items. So a collaborative filtering movie recommender knows nothing about a movie's genre or actors, but it does know that other users have liked this movie and that these users have demonstrated a similar taste to the target user, having liked and disliked many of the same movies in the past.

*Demographic* techniques make recommendations based on demographic classes, by analyzing personal attributes of the user (Krulwich 1997). Likely items for recommendation are identified because clusters of users with similar personal attributes have demonstrated similar needs or tastes. So a demographic movie recommender could, for example, focus on the language spoken or geographic region as a basis for recommendation. Thus in general, content-based methods rely on item-item (Sarwar et al. 2001) and item-user (Sarwar et al. 2000) similarities whereas collaborative filtering and demographic methods rely on user-user similarities (Konstan et al. 1997, Krulwich 1997).

A wide variety of recommender systems have been deployed online for commercial, educational, and community-building purposes (Montaner, López, and de la Rosa 2003; Burke 2002; Schafer, Konstan, and Riedl 1999; Herlocker, Konstan, and Riedl 2000). In our work, we employ primarily content-based techniques to match users and students with schools that are expected to provide improvements in academic achievement. Content-based recommender systems often employ classification learning algorithms as the foundation for recommendation. Typical models underlying content-based recommendation include decision trees, nearest neighbor approaches, relevance feedback, probabilistic methods, and linear classifiers (Pazzani and Billsus 2007). We adopt a linear classifier approach for modeling student achievement that is based on existing educational and behavioral science models (Tekwe et al. 2004). The stakes are fair-

ly high in real-world adoption of school choice recommendations, so we were particularly interested in beginning with an approach to achievement modeling that has a solid grounding in the domain. The two main components in content-based recommendation are (1) to measure the relevance of candidate items to the target user and (2) to select the most relevant items for presentation as a recommendation set. The following sections provide an overview of these aspects in the SmartChoice recommendation approach.

## Student Achievement Model

Using achievement, demographic, and enrollment data for approximately 74,000 students in Charlotte-Mecklenburg Schools (CMS) in third through eighth grades from 2004–2006, we estimated the effect of attending a particular school on a particular student's growth in his or her composite math and reading standardized end of grade exams. In order to model the expected performance improvement relationship between a given student and potential schools, we employed a simple fixed-effects model (SFEM) (Tekwe et al. 2004), computed using ordinary least squares regression. The baseline SFEM is shown in equation 1, where  $y$  is the dependent variable representing the change in composite (math + reading) z-score (standardized by grade and year) from the year prior to the current year for student  $j$  at school  $i$ ;  $x$  is a vector of regressors;  $\alpha$  is the individual effect, and  $\epsilon$  is the error term.

$$y_{ij} = \alpha + x_{ij}\beta + \epsilon_{ij} \quad (1)$$

The  $\beta$  vector of coefficients is interpreted as the value added by individual schools resulting from the model fit.

Some of the characteristics we accounted for include the student's ethnicity, gender, socioeconomic status, prior test scores, learning disabilities, and parents' education level, as well as the estimated effect of repeating a grade or being in a new school. Unlike some models that estimate a school's "value-added" effect on student achievement, our model intentionally did not attempt to control for some school-level variables (for example, percentage of students who are free lunch eligible) in estimating the school's effect on achievement. We made this choice on the grounds that what is important to parents is what their child will actually experience at the school given precisely the variables that models used for accountability reasons often attempt to isolate from the estimate of the school's effectiveness (for example, Ballou, Sanders, and Wright [2004]; McCaffrey et al. [2004]; Raudenbush [2004]; Rubin, Stuart, and Zanutto [2004]).

To address possible year-to-year fluctuations in these school-level factors that would influence our

estimates of a school's effect, we pooled regressions over three years of data (2004, 2005, 2006), so that the school effects from the regressions were three-year averages. We also clustered the standard errors by student so they should be robust to both heteroscedasticity and serial correlation. Furthermore, given the segregation of Charlotte-Mecklenburg area neighborhoods and a student assignment policy based primarily on a student's residence, we were concerned that we might extrapolate effects to schools that had enrolled few if any students with a specific combination of characteristics (for example, black males not eligible for free lunch). To address this concern, we estimated separate models for 18 such combinations so that the confidence intervals for school effects in such cases would be wide enough to reflect the degree of uncertainty for a particular type of child. We ran each set of 18 regressions twice—once for elementary school students and once for middle school students.

We trained and then tested our models on distinct subsamples, selecting the models that maximized the accuracy of our predictions. We found that, on average, students who changed schools to one that our algorithm predicted would improve their scores experienced statistically and substantively greater improvements in test scores than both students who changed to schools that our algorithm predicted would not be appropriate for them and students who did not change schools. Our team includes members with significant domain expertise both in the general theory and practice of school choice, as well as with CMS in particular. The final student achievement model was tested extensively and validated by our domain experts.

## Recommendation Strategy

As one can imagine, making good recommendations in this domain is of paramount importance. Thus in making recommendations, we adopt a conservative analysis of the expected performance improvement results for a particular student to obtain a set of "recommendable" schools. Our analysis filters examine the point estimates and confidence intervals from the achievement models. Here we discuss two of the filters employed, along with our baseline clustering approach. The fundamental criterion for our recommendable schools is that they should not allow a reduction in expected academic performance improvement.

### Recommendable Schools

As a baseline, we first conduct a meta-analysis of the results, examining aspects of the model rather than the domain. Results that have a poor statistical grounding with our dataset are discarded out of

hand. For example we do not consider schools for which the model does not have enough data to make a prediction (naturally) or schools that have significant zero crossings in the confidence interval.

At the domain level, because a student's baseline option is to remain at the currently scheduled school for the next year, we analyze the recommendations relative to a student's expected performance improvement at the scheduled school. Schools that have a confidence interval falling completely below the scheduled school are not included. In addition, schools with only modest relative overlap on the scheduled school's lower confidence interval are considered to have a low probability of matching the baseline, and they are also not included. If, for some reason, a student does not have a currently scheduled school, the analysis is made relative to the grand mean.

### Clustering Recommendations

In order to make the best possible recommendations, we would like to determine whether one school shows an unequivocal performance improvement relative to others. Taking confidence intervals into account, this amounts to clustering across a partially ordered set. We have adopted a clustering approach, which groups recommendable schools into clusters, where (1) each cluster has a definite rank in relation to the other clusters and (2) within each cluster, a candidate school has a definite rank relative to the other candidates.

In clustering, we select the recommendable candidate with the least upper bound on its confidence interval as the baseline. Candidates with significant confidence interval overlap to the baseline are grouped into the same cluster. Then the next unassigned candidate with the least upper bound on its confidence interval is selected, and the process is repeated until no candidates remain. In essence, all entries in a "better" cluster must have a least lower bound that is greater than the lowest least upper bound in the "worse" cluster(s).

In this way, we know that all entries in a "better" cluster are definitely and significantly better than at least some of the entries in a "worse" cluster. And while some of the entries in the "worse" cluster may have confidence intervals that potentially put them above some of the entries in a "better" cluster, they could just as easily fall in range of the definitely worse category. Such entries are considered tainted by the latter possibility and conservatively relegated to the lower-ranked cluster.

### Intracluster Candidate Ranking

Within each cluster, a relative ranking of the candidates is determined. We use the size of a confidence interval as a proxy for the degree of uncertainty in a given point estimate. Point estimates

Figure 1. SmartChoice User Registration.

are first normalized to the overall cluster interval. We then normalize the point estimates to reflect the uncertainty of their associated intervals in relation both to (1) the least uncertainty estimate within the cluster and (2) the overall uncertainty measure of the cluster itself. This gives us a relative measure of the uncertainty of a particular estimate in comparison to other estimates within the cluster. The resulting score is used to rank candidates within the cluster.

### Making Recommendations

Given the size of a recommendation list  $k$ , the default recommendation mode is to select the best ranked candidates from the best ranked clusters until the recommendation set is full. We have developed functionality to allow more flexible navigation of the recommendation space, focusing for example on special programs, but it was decided not to deploy this functionality for our initial study. As with the student achievement model itself, the application of the student achievement model in the SmartChoice recommendation approach was tested extensively and validated by our domain experts prior to deployment.

We note that it is entirely possible to receive an empty recommendation list, either in the case that a student's current school is already the best of the best, or the underlying data is inconclusive. In

these situations, we provide appropriate notification to the user. Often, recommender systems would employ a heuristic to avoid users feeling like their interaction has not been worthwhile (for example, random or serendipitous selection). In the school choice domain, however, such heuristics are not appropriate. Instead, we provide users with a reference list, where they can select from any available school. Thus users can still access supporting school information, but since it is their own selection, it does not carry the authority of a recommendation.

### Initial Deployment

SmartChoice is deployed in a commercial web-hosting environment using a typical Linux, Apache, MySQL, and PHP (LAMP) baseline platform, and the application employs a custom model-view-controller architecture. Since we deal with potentially sensitive user data, particular development attention has been paid to addressing web application security issues, and all user-data interactions take place over secure HTTP connections.

### Interface Development

We fielded focus-group usability tests at several stages of development in fall and winter 2007, which resulted in significant improvements to

**SmartChoice**  **Choosing the right school**

| [Log Out](#) | Logged in as: Janice

Allen's Information (page 1 of 6)

**Student First Name**  
Allen

**Is Allen a male or a female?**  
 Male  
 Female

**Does Allen receive lunch assistance?**  
 Free Lunch  
 Reduced Lunch  
 Neither

**When was Allen born?**  
 Birth Month: April  
 Birth Day: 17  
 Birth Year: 1998

(to my SmartChoice students page) < > (to student information page 2)

Figure 2. SmartChoice Student Information I.

interface and interaction characteristics. These included initial question review, paper prototype interaction, and online prototype interaction. The goal of the pretests was to develop a user-friendly interaction model that allows parents and students to investigate various schools based on the students' interests and any requirements the parents may have such as distance from home or the presence of an after-school program. In particular, we wanted to accommodate participants with low digital literacy. Major feedback points resulted in (1) minimizing the number of data questions for the user model (which affected student achievement model choices), (2) streamlined site navigation and presentation (in particular, a simplified recommendation list), and (3) significant updates to question wording and options.

Conceptually, the SmartChoice interaction model works as follows. Using data supplied by the family, SmartChoice estimates a student's academic outcome for each school in CMS at the appropriate level. Recommendable schools with the best expected performance improvement are listed along with the student's assigned (home) school. SmartChoice provides presentation alternatives for the family to review by setting preferences for availability of district-provided transportation and special programs available at the school. A check mark circled in green indicates that the school

meets the preference, and an X mark circled in red indicates that the school does not. Information is also provided on school categories and distance between school and home address, as well as a link to a more detailed school profile page. Based on previous parent focus-group studies (Leland, Godwin, and Baxter 2007), our domain experts wanted to limit ordering effects in presentation. Thus recommended school sets are presented without an explicit ordering indicator, such as a rank number.

### Example Interaction

To illustrate a typical interaction with SmartChoice, consider a hypothetical parent Janice who has a son Allen. Janice would first register with the system, as shown in figure 1.

She might then indicate that she is looking for a school for her fifth-grade, Latino son who enjoys math but currently requires programs to assist him in acquiring English. Example student information screens are shown in figures 2 and 3.

In the recommendation list, SmartChoice provides basic preference feedback, showing estimated distance to the user's address, along with visual cues for whether a school (1) is a Title I school (those schools with high percentages of students at or near the federal poverty line), (2) has a magnet program, (3) will provide transportation to Allen, or (4) has a specific selected type of magnet

Figure 3. SmartChoice Student Information II.

program. An example school results list is shown in figure 4. Janice can select a particular school from the list to see additional details, as shown in figure 5.

## Initial Studies

The research site for SmartChoice is the Charlotte-Mecklenburg School District, an urban, predominantly minority school district in Charlotte, North Carolina. In 2007, children in approximately 8200 families in CMS (98 percent are people of color, 92 percent low income) attended low-performing schools that qualified for NCLB's choice provision.

From the beginning of January 2008, we made SmartChoice available to a closed pilot-study group of more than 50 parents with children in third to seventh grade. There were two primary choice periods. In January 2008, parents made choices for the magnet school assignment lottery. Results of the magnet school assignment selections became available in mid-March, and parents then had the opportunity to apply for general school reassignment until early April 2008.

Our pilot study took place in the West Boulevard Corridor of Charlotte, where about half of the NCLB schools in the district are located, during the choice application period. Each Saturday during the choice application period the SmartChoice team invited parents to come to the West Boulevard Branch of the public library to use

SmartChoice to select schools, where we provided dedicated computing and printing setups for participants. A number of additional smaller sessions were held through the second choice period, but the majority of participants came through the January sessions. We were particularly interested in having low-income, minority parents whose children attend schools eligible to transfer to a higher performing school. Parents also were invited to the Urban Restoration Center in the midst of several public housing projects in Charlotte.

Working with the Stratford-Richardson YMCA, the West Boulevard Neighborhood Coalition, the West Boulevard Public Library, and a number of other not-for-profit organizations, 56 parents came to our locations in Charlotte's West Boulevard neighborhood to use SmartChoice. Recommendations were prepared for a total of 81 students. We also helped 40 parents in going online to the CMS choice website where they made their school choices for the 2008–2009 school year.

We assigned participants to one of three groups: those who received no assistance in using the program; those who received a general orientation to the program but little additional assistance; and those who had a personal advisor to assist them whenever they had difficulty using the program. A team of undergraduate and graduate students from our university participated in assisting users. During the SmartChoice sessions participants (1) registered for the program and site access, (2) went

# SmartChoice

✓
Choosing the right school

| Log Out |
Logged in as: Janice

### Schools to consider for Allen

Based on what you have told us about Allen, below is a list of schools where students like Allen have improved test scores over the past few years.

show if school has special program: Center for Leadership and Global Economics

show if school in school bus zone: |  blue |  none |

rough "as crow flies" distance to your address (if possible)

<a href="#">Mint Hill Middle</a>	11 mi	<input type="checkbox"/>	<input type="checkbox"/>
<a href="#">Jay M Robinson Middle</a>	17 mi	<input checked="" type="checkbox"/>	<input type="checkbox"/>
<a href="#">Coulwood Middle</a>	13 mi	<input type="checkbox"/>	<input type="checkbox"/>
<a href="#">Bishop Spaugh Community Academy Middle</a> [*T1]	11 mi	<input type="checkbox"/>	<input type="checkbox"/>
<a href="#">Robert F Kennedy Middle</a> ⓘ	17 mi	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
<b>Reference School Information</b>			
<a href="#">Alexander Graham Middle</a> (scheduled)	12 mi	<input checked="" type="checkbox"/>	<input type="checkbox"/>
<a href="#">Smith Language Academy</a> ⓘ [ < details ] ⓘ	13 mi	<input checked="" type="checkbox"/>	<input type="checkbox"/>

(to check student information)   (to my SmartChoice students page)

Figure 4. SmartChoice School Recommendations.

through a full initial SmartChoice recommendation session (with significant, moderate, or no counseling support, depending on study group assignment), and (3) provided feedback on the experience in an exit interview for the initial session. Once registered, participants have standard web access to SmartChoice.

## Results

We have compiled results on our initial SmartChoice study in three parts. First, we captured qualitative feedback in exit interviews from the participant sessions. Second, we conducted a follow-up survey in May 2008, and third, we conducted a follow-up focus group in October 2008.

We begin with the exit interviews. Although all 56 participants completed the SmartChoice program, only 51 completed the exit survey about their experiences. Of the 51 parents who completed the interviews, 17 were in each group (significant, moderate, or no counseling support). Parents in the group that did not receive any assistance took the longest average time to complete the program (about 22 minutes per student), and two of these indicated that they thought the amount of time required to complete the program was too long. In the groups that received personal assis-

tance, 28 of 34 thought the assistance was an essential aspect of the program while the other 6 indicated that they thought the assistance was useful but not essential. The fact that all of the individuals who did not receive assistance finished the program suggests that the 6 were probably correct for most parents, but having assistance available reduced substantially the average amount of time it took parents to complete the program.

When asked what they liked least about the program, the participants who had an opinion on this question wanted more information on schools. In particular, they wanted information about how students, parents, and teachers normally interacted in the schools. Another set of parents wanted to know how the state rated each school and wanted to know the average test scores at the schools. It is not currently possible to provide the information concerning interactions in the schools. Although we can provide the average test scores, it is unclear as to whether this information will be misleading to parents. The goal of SmartChoice is to predict how well a particular student will perform at a school, not how well the average student at the school performs. This remains a question for future study. A question on how satisfied participants were with SmartChoice support from their initial session was included as part of the online interaction, which gathered an additional response. As

# SmartChoice Choosing the right school



## Robert F Kennedy Middle

Address : 4000 Gallant Ln, Charlotte, 28273  
 Phone : (980) 343-5540  
 School Hours : 8:00 - 15:00

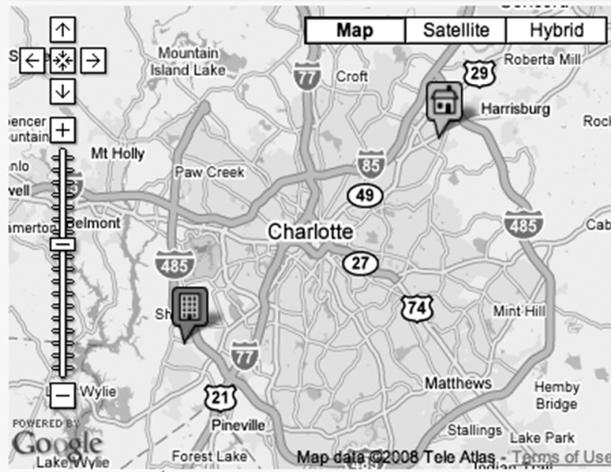
### School Information

School Enrollment 653  
 Magnet Program Yes

### Free and Reduced Lunch

Free 56.36 %  
 Reduced 11.94 %  
 Paid 31.7 %

### School Location



### Student Ethnicity

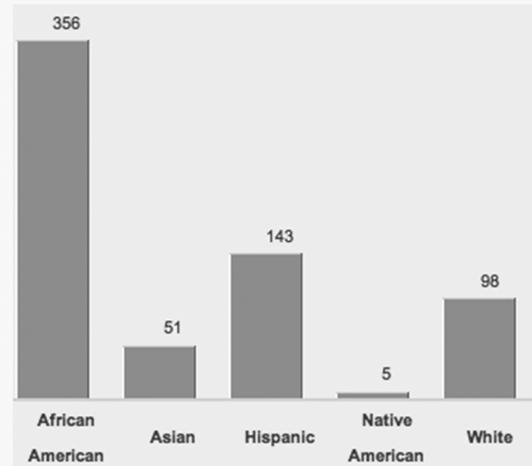


Figure 5. SmartChoice School Detail.

shown in table 1, a majority of participants were very satisfied with the support provided.

#### Follow-Up Survey: May 2008

Follow-up surveys were conducted by telephone interview in May 2008, and we received responses from 31 participants. From the respondents, 25 total school choice lottery applications were completed, with 6 parents filling out applications for 2 children. This represents a 61 percent (19/31) active choice rate for respondents filling out at least one lottery application. Even if we counted nonrespondents as nonchoosers, we have an active choice rate of 34 percent (19/56). In light of his-

torical choice rates at fewer than 7 percent exiting NCLB home schools, the results are very encouraging.

Parents followed SmartChoice recommendations for a total of 12 of 25 children entered in the lottery (48 percent of respondents' students). Again, even if we counted nonrespondents as nonchoosers, we have a followed recommendation rate of 15 percent, again comparing favorably with historical choice rates. Of the 25 children entered in the lottery, 15 received one of their top three choices (60 percent). Overall, 83 percent of participants would participate in the program again, if it were continued in future school choice periods.

Responses	Satisfaction
30	Very Satisfied
20	Satisfied
2	Dissatisfied
0	Very Dissatisfied
4	<i>no answer</i>

Table 1. Satisfaction with SmartChoice Support.

We received very positive qualitative feedback as well. One part of the survey asked “What did you like the most about the SmartChoice program?” Of the 31 respondents, 22 responses cited the information provided through the online system as part of their response. For example, one participant felt that the information provided was close to the options she was looking at. A second participant liked that suggestions were provided based on individual student characteristics. A third participant appreciated the organization of information in bringing up options that might not otherwise have been considered. A fourth participant liked that the system was easy to navigate, made good matches, and helped with deciding on schools. A fifth participant liked being able to know what school would make the participant’s child do better. Responding to what they disliked about the program, only two responses cited the information provided through the online system as part of their response. Two participants were dissatisfied with the locations of the suggestions, and one of those participants did not like the suggested schools overall.

### Follow-Up Focus Group: October 2008

A follow-up focus group was conducted in October 2008. Part of the goal was to track feedback over time, but the goal also included maintaining contact with the participants in order to help track outcomes at the end of the school year. Much of the feedback centered on issues of recruitment, participation, and incentives, but we did receive some good feedback in relation to the SmartChoice system.

Following is the primary feedback transcribed as relating to the system from the focus group.

“The program needed to have more information about the magnet programs. It hinted at it but it was not detailed.”

“Needed to know more about what was offered.”

“It was easy to look at different schools.”

“It was a flash shot of what you are looking for.”

“It was self explanatory.”

“Yes. It does make you look at it [CMS and education] differently.”

“The whole thing is good, helpful information especially for new people.”

“I liked the program. I told my nephew about it.”

## Discussion and Future Work

We plan to keep in touch with participants, and we hope to establish test score outcomes at the end of the current school year in relation to system participation. While a larger study will be necessary to draw general conclusions, we have shown that the SmartChoice program can be effective in (1) facilitating exploration of options in school choice and (2) providing recommendations that participants are comfortable enough with to act upon in making a selection with high stakes.

In general, while we are employing recommender systems techniques, we believe that it is important not to frame system recommendations as such. Rather, we present them as “schools to consider.” We recognize that the domain space is enormously complex (for example, with peer effects, teacher or school or curriculum churn, and many other factors), and that SmartChoice focuses on a limited, but important aspect of that space. We are up to the challenge, however, and we are actively working to secure funding to build SmartChoice out to a full generally available deployment. Beyond making SmartChoice generally available, there are myriad refinements to be made. We are considering latent growth curve modeling of student achievement (Singer and Willett 2003, Bollen and Curran 2006) to increase the precision of modeling estimates. We know that it is important to present recommendations in a way that conveys meaning balanced with complexity (Herlocker, Konstan, and Riedl 2000). There is a significant proportion of parents in our NCLB areas who face serious digital divide (Haythornthwaite 2007) and digital literacy (Hargittai 2005) issues, and both recommender and online usability concerns are a major factor in our design considerations. We are also hoping to incorporate a stronger, but straightforward, interface for exploration of the recommendation space, such as in the FindMe systems (Burke, Hammond, and Young 1997).

Ultimately, our goal is to provide a straightforward and solid foothold as a starting point in the face of information overload within a highly complex space. We do so in the context of an overall community program to help parents take advantage of NCLB choice provisions and to at least consider their decision options. In this way, we hope to

facilitate the development of more active choosers, and, hopefully, better futures for our kids.

## References

- Ambler, J. 1994. Who Benefits from Educational Choice: Some Evidence from Europe. *Journal of Policy Analysis and Management* 13(3): 454–476.
- Ballou, D.; Sanders, W.; and Wright, P. 2004. Controlling for Student Background in Value-Added Assessment of Teachers. *Journal of Educational and Behavioral Statistics* 29(1): 37–65.
- Basu, C.; Hirsh, H.; and Cohen, W. W. 1998. Recommendation as Classification: Using Social and Content-Based Information in Recommendation. In *Proceedings of the Fifteenth National Conference on Artificial Intelligence*, 714–720. Menlo Park, CA: AAAI Press.
- Bollen, K., and Curran, P. 2006. *Latent Curve Models: A Structural Equation Perspective*. New York: Wiley-Interscience.
- Brown, C. 2004. Choosing Better Schools: A Report on Student Transfers under the No Child Left Behind Act. Washington, DC: Citizens' Commission on Civil Rights.
- Burke, R.; Hammond, K.; and Young, B. 1997. The Find-Me Approach to Assisted Browsing. *IEEE Expert* 12(4): 32–40.
- Burke, R. 2002. Hybrid Recommender Systems: Survey and Experiments. *User Modeling and User-Adapted Interaction* 12(4): 331–370.
- Chubb, J., and Moe, T. 1990. *Politics, Markets, and America's Schools*. Washington, DC: Brookings Institution.
- Coons, J., and Sugarman, S. 1978. *Education by Choice: The Case for Family Control*. Berkeley, CA: University of California Press.
- Dunk, E. V., and Dickman, A. 2003. *School Choice and the Question of Accountability: The Milwaukee Experience*. New Haven, CT: Yale University Press.
- GAO. 2004. No Child Left Behind Act: Education Needs to Provide Additional Technical Assistance and Conduct Implementation Studies for School Choice Provision. Report to the Secretary of Education GAO-05-7, U.S. Government Accountability Office, Washington, D.C.
- Godwin, K., and Kemerer, F. 2002. *School Choice Tradeoffs: Liberty, Equity, and Diversity*. Austin, TX: University of Texas Press.
- Hargittai, E. 2005. Survey Measures of Web-Oriented Digital Literacy. *Social Science Computer Review* 23(3): 371–379.
- Hastings, J., and Weinstein, J. M. 2007. No Child Left Behind: Estimating the Impact on Choices and Student Outcomes. Technical Report 13009, National Bureau of Economic Research Working Paper Series, Cambridge, MA.
- Haythornthwaite, C. 2007. Social Facilitators and Inhibitors to Online Fluency. In *Proceedings of the 40th Annual Hawaii International Conference on System Sciences*. Los Alamitos, CA: IEEE Computer Society.
- Herlocker, J. L.; Konstan, J. A.; and Riedl, J. 2000. Explaining Collaborative Filtering Recommendations. In *CSCW '00: Proceedings of the 2000 ACM conference on Computer Supported Cooperative Work*, 241–250. New York: ACM Press.
- Hill, P. T. 2007. NCLB School Choice and Children in Poverty. In *Standards-Based Reform and the Poverty Gap*, ed. A. Gamoran. Washington, DC: Brookings Institution.
- Howell, W. 2006. Switching Schools? A Closer Look at Parents' Initial Interest in and Knowledge about the Choice Provisions of No Child Left Behind. *Peabody Journal of Education* 81(1): 140–179.
- Hoxby, C., and Weingarth, G. 2005. Taking Race out of the Equation: School Reassignment and the Structure of Peer Effects. Technical report, Department of Economics, Harvard University, Cambridge, MA.
- Kim, J., and Sunderman, G. 2004. Does NCLB Provide Good Choices for Students in Low-Performing Schools? Technical report, The Civil Rights Project at Harvard University, Cambridge, MA.
- Konstan, J. A.; Miller, B. N.; Maltz, D.; Herlocker, J. L.; Gordon, L. R.; and Riedl, J. 1997. GroupLens: Applying Collaborative Filtering to Usenet News. *Communications of the ACM* 40(3): 77–87.
- Krulwich, B. 1997. Lifestyle Finder: Intelligent User Profiling Using Large-Scale Demographic Data. *AI Magazine* 18(2): 37–45.
- Leland, S.; Godwin, K.; and Baxter, A. 2007. Examining School Choice through the Eyes of Parents. Paper presented at the Annual Meetings of the Midwest Political Science Association, Chicago, IL, April 12–15.
- McCaffrey, D.; Lockwood, J.; Koretz, D.; and Hamilton, L. 2003. Evaluating Value-Added Models for Teacher Accountability. Technical report, Rand Corporation, Santa Monica, CA.
- McCaffrey, D.; Lockwood, J.; Koretz, D.; Louis, T.; and Hamilton, L. 2004. Models for Value-Added Modeling of Teacher Effects. *Journal of Educational and Behavioral Statistics* 29(1): 67–101.
- McDermott, K. A., and Jensen, L. S. 2005. Dubious Sovereignty: Federal Conditions of Aid and the No Child Left Behind Act. *Peabody Journal of Education* 80(2): 39–56.
- Meier, D., and Wood, G. H. 2004. *Many Children Left Behind: How the No Child Left Behind Act Is Damaging Our Schools*. Boston: Beacon Press.
- Montaner, M.; López, B.; and de la Rosa, J. L. 2003. A Taxonomy of Recommender Agents on the Internet. *Artificial Intelligence Review* 19(4): 285–330.
- Pazzani, M. J., and Billsus, D. 2007. Content-Based Recommendation Systems. In *The Adaptive Web: Methods and Strategies of Web Personalization*, ed. P. Brusilovsky, A. Kobsa, and W. Nejdl, 325–341. Berlin: Springer-Verlag.
- Raudenbush, S. 2004. What Are Value-Added Models Estimating and What Does This Imply for Statistical Practice? *Journal of Educational and Behavioral Statistics* 29(1): 121–129.
- Resnick, P., and Varian, H. R. 1997. Recommender Systems. *Communications of the ACM* 40(3): 56–58.
- Rosenstein, M., and Lochbaum, C. 2000. Recommending from Content: Preliminary Results from an E-Commerce Experiment. In *CHI '00 Extended Abstracts on Human Factors in Computer Systems*, 291–292. New York: ACM Press.
- Rubin, D.; Stuart, E.; and Zanutto, E. 2004. A Potential Outcomes View of Value-Added Assessment in Education. *Journal of Educational and Behavioral Statistics* 29(1): 103.
- Sarwar, B.; Karypis, G.; Konstan, J.; and Riedl, J. 2000. Analysis of Recommendation Algorithms for E-Com-

### Are You Reading This Issue Online?

One of the benefits of AAAI membership is immediate online access to *AI Magazine*, and notification of new issues. AAAI members are automatically registered for these important benefits—but only if we have your e-mail address! Contact the Membership Department for details.

merce. In *Proceedings of the 2nd ACM Conference on Electronic Commerce*, 158–167. New York: ACM Press.

Sarwar, B.; Karypis, G.; Konstan, J.; and Reidl, J. 2001. Item-Based Collaborative Filtering Recommendation Algorithms. In *Proceedings of the Tenth International Conference on World Wide Web*, 285–295. New York: ACM Press.

Schafer, J. B.; Frankowski, D.; Herlocker, J.; and Sen, S. 2007. Collaborative Filtering Recommender Systems. In *The Adaptive Web: Methods and Strategies of Web Personalization*, ed. P. Brusilovsky, A. Kobsa, and W. Nejdl, 291–324. Berlin: Springer-Verlag.

Schafer, J. B.; Konstan, J.; and Riedl, J. 1999. Recommender Systems in E-Commerce. In *EC '99: Proceedings of the 1st ACM Conference on Electronic Commerce*, 158–166. New York: Association for Computing Machinery.

Schneider, M.; Teske, P.; Roch, C.; and Marschall, M. 1997. Networks to Nowhere: Segregation and Stratification in Networks of Information about Schools. *American Journal of Political Science* 41(4): 1201–1223.

Singer, J., and Willett, J. 2003. *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence*. New York: Oxford University Press.

Smyth, B., and Cotter, P. 2001. Personalized Electronic Programme Guides. *AI Magazine* 22(2): 89–98.

Soboroff, I., and Nicholas, C. 1999. Combining Content and Collaboration in Text Filtering. Paper presented at the IJCAI-99 Workshop on Machine Learning for Information Filtering. Stockholm, Sweden, July 31–August 6.

Southworth, S., and Mickelson, R. 2007. The Interactive Effects of Race, Gender and School Composition on College Track Placement. *Social Forces* 86(2) 497–523.

Tekwe, C.; Carter, R. L.; Ma, C.-X.; Algina, J.; Lucas, M. E.; Roth, J.; Ariet, M.; Fisher, T.; and Resnick, M. B. 2004. An Empirical Comparison of Statistical Models for Value-Added Assessment of School Performance. *Journal of Educational and Behavioral Statistics* 29(1): 11–36.

Terveen, L.; Hill, W.; Amento, B.; McDonald, D.; and Creter, J. 1997. PHOAKS: A System for Sharing Recommendations. *Communications of the ACM* 40(3): 59–62.

U.S. Department of Education. 2001. No Child Left Behind Act of 2001. 2001-PL107110. Washington, DC: Government Printing Office.

Wilson, D. C.; Leland, S.; Godwin, K.; Baxter, A.; Levy, A.; Smart, J.; Najjar, N.; and Andaparambil, J. 2008. The Law of Choice and the Decision Not to Decide. In *Proceedings of the 20th Conference on Innovative Applications of Artificial Intelligence*. Menlo Park, CA: AAAI Press.

**David C. Wilson** is an assistant professor in the Depart-

ment of Software and Information Systems at the University of North Carolina at Charlotte. Wilson received his Ph.D. from Indiana University, and his research emphasizes the coordination of intelligent systems techniques with geographic, multimedia, database, Internet, and communications systems in order to elicit, enhance, apply, and present relevant task-based knowledge. Wilson is currently serving as program chair for the Eighth International Conference on Case-Based Reasoning.

**Suzanne Leland** is an associate professor in the Political Science Department at University of North Carolina at Charlotte, where she teaches state and local politics, urban politics, and intergovernmental relations. She has published articles in *Public Administration Review* and *Public Administration Quarterly*. She is also the coeditor of *Case Studies of City-County Consolidation: Reshaping the Local Government Landscape* with Kurt Thurmaier.

**R. Kenneth Godwin** is the Marshall Rauch Distinguished Professor of Political Science at the University of North Carolina Charlotte. His current research interests are models of interest group influence, education policy, and the teaching of tolerance. A recent book, *School Choice Tradeoffs: Liberty, Equity, and Diversity* (with Frank Kemerer), won the bronze medal for the best book in education published in 2002. The book examines various school choice policies and compares their likely outcomes with current educational outcomes. Currently he is studying the impact of recent court decisions on the resegregation of public schools and the impacts of that resegregation on academic outcomes.

**Andy Baxter** is a doctoral student in public policy at the University of North Carolina Charlotte. He is also a resident research Fellow with Charlotte-Mecklenburg schools where he is working on projects related to assessing teacher quality through value-added models. His research interests include program evaluation, value-added modeling, and achievement gaps. He holds an A.B. and M.Div. from Duke University.

**Ashley Levy** is a graduate student in the master's of public administration program at the University of North Carolina Charlotte. She has a fellowship at the Mecklenburg County Board of Elections and has received scholarships from the Bethlehem Center of Charlotte and the McNair Scholars program.

**Jamie Smart** graduated with her B.A. degree in political science from the University of North Carolina Charlotte in 2008. Smart received the experiential learning grant and was a member of the McNair scholars program. She plans to pursue her Ph.D. in political science.

**Nadia Najjar** is the technology officer for Homecorp Realty in Charlotte, North Carolina. She has a B.S. degree in electrical engineering from George Mason University and is currently working towards a Ph.D. in information technology from the University of North Carolina at Charlotte. Her research interests are in the areas of recommender systems and spatial decision support systems.

**Jayakrishnan Andaparambil** graduated with an M.S. degree in computer science from the University of North Carolina Charlotte in 2008. His research interests are in the areas of web development, personalization, and recommender systems.