Lessons Learned from Creating a Course Advising Tool

Judy Goldsmith
University of Kentucky

Joan M Mazur
University of Kentucky

Lessons Learned from Creating a Course Advising Tool

Nicholas Mattei
NICTA and UNSW
Sydney, Australia
nsmattei@gmail.com

Thomas Dodson
University of Pennsylvania
Philadelphia, PA, USA
tcdodson@gmail.com

Joshua T. Guerin
University of Tennessee at Martin
Martin, TN, USA
jguerin@utm.edu

Judy Goldsmith
University of Kentucky
Lexington, KY, USA
goldsmit@cs.uky.edu

Joan M. Mazur
University of Kentucky
Lexington, KY, USA
jmazur@uky.edu

ABSTRACT

We detail some lessons learned while designing and testing a course selection tool for undergraduates at a large state university. Between 2009–2011 we conducted two surveys of over 500 students in multiple majors and colleges. These surveys asked students detailed questions about their preferences concerning courses selection, advising, and career paths. We present data from this study which may be helpful for faculty and staff who advise undergraduate students. We find that advising software tools can help both students and human advisors in terms of rote requirement checking and basic course planning, but nothing can replace an in person advising session.

Categories and Subject Descriptors

K.3.1 [**Computing Milieux**]: COMPUTERS AND EDUCATION—*Computer Uses in Education*

General Terms

Human Factors, Measurement

Keywords

Academic Advising, Advising Support Software, Advisor Attitudes, Course Selection, Decision Support, Student Attitudes

1. INTRODUCTION

At our university, students are required to meet with an advisor each semester before signing up for the following semester's courses. Advising duties are split between faculty members and full-time administrative staff whose primary or secondary duties include professional advising. The advisors have access to the students' transcripts and are expected to know the course offerings for future semesters, requirements of the undergraduate degrees, prerequisite chains for the department's courses, possible career opportunities, and the courses that will best prepare students to meet their post-graduation goals both in industry and academia. Advisors should also be able to guide the students in selecting courses that are best suited to their abilities and goals. Finally, advisors should be able to refer students to support services, including academic support, special needs services, and counseling. What makes advising challenging is the need to personalize advice for full-time and part-time students, transfer students, and students changing majors after satisfying some of their previous major's requirements.

Ideally the student and advisor keep in regular contact, with the advisor playing a supporting role in the student's continued development and formulating short and long term goals for the student based on their individual needs and interests. The reality is that most students usually see their advisor once per semester for 15 to 30 minutes, and sometimes see a different advisor each semester. Advisors may have their own agenda. Some may want to make certain that particular courses have high enough enrollment, while some may assume that they know what students want. Some of the advisors in our study get extremely high evaluations from both students and faculty—usually those who take the time to talk with students and help them understand how to set and achieve suitable goals.

We are working on developing an automated advising support system to augment the advisor-student relationship. By allowing students to explore course offerings, possible future scenarios, and the probabilistic outcomes of those future scenarios, we hope our system will allow students to enter their mandatory advisor meetings more conversant in their options. This preparation would allow the human advisor to spend less time explaining the course offerings and requirements, and more time on career counseling, student support, and goal clarification. In addition, the system would provide a tool for the advisors to explore and evaluate options with the students.

In recent years, there has been enormous growth and innovation in available online education tools and modalities. There is ongoing work, both commercial and academic, in academic advising tools. However, we argue that the continued development of online advising tools has not kept pace with development of course delivery, educational theory about online education, or education evaluation systems. In the process of designing an advising system, we have done preliminary surveys about what students want from advisors, and what advisors wish to offer. The results of those surveys are guiding our own development of advising support tools, and we hope they will be useful to others engaged in similar development.

We believe that some of our findings are particular to computer science, because our students have curriculum-influenced biases and specific career expectations. For instance, we saw a very strong bias by the students toward advising information related to the effect a given course would have on their future careers. We conjecture that students in less professional employment oriented majors might be less focused on direct career application. We also conjecture that our students are more comfortable with the use of computers and online tools than the student body at large.

Additionally, the results of our user testing may have implications for the way that human advisors interact with their students by means of text-based communications (i.e., e-mail). Our advising system provides the user with specific recommendations based on statistical models of advising. However, the presentation of this information is made by providing plaintext explanations or arguments that explain *why* a particular course of action is the best. Our discussion of effective text-based explanations may be of particular relevance in situations where e-mail is used as a secondary (in the case of a traditional advising setting) or even primary form of communication between advisors and advisees (in the growing settings of distance education and e-learning).

2. BACKGROUND AND MOTIVATION

Academic advising, for many, is a full time job that requires as much commitment, preparation and care as teaching. There is significant research into the theory of advising by incorporating principled pedagogical goals into the advising process and providing practical directives for practitioners [6, 12]. The availability of high-quality advising services has been identified as an area of great importance in higher education. Frequent, high-quality academic advising has been shown to have a positive effect on GPA, satisfaction in the advising process, perceived value of education, and attrition rates (both directly and indirectly) [10,11,14,19]. Additionally, recent research has shown that minority and otherwise disadvantaged students can benefit the most from quality advising services [1].

The links between the availability and quality of academic advising services and lowered attrition rates may be of particular consequence for Computer Science, where attrition rates are often particularly high. The University of Illinois at Urbana-Champaign reported an attrition rate over a five year period of approximately 25% [17]. Because students frequently come into computer science programs with key skills deficits and incorrect preconceived notions about the actual focus of the discipline, it has been postulated that academic advising may be of particular importance for mitigating attrition rates in computer science [2].

Recent research has also demonstrated that computer-based advising tools can be used to consolidate and simplify complicated advising information for the student and advisor, and that such systems can have a measurable impact on student satisfaction in the advising process [5].

The perceived importance of advising software in the academic advising experience is also reflected by the actions of colleges and universities, many of which currently provide access to online advising tools of varying complexity. Several large public universities in the US license software from College Source, specifically their u.achieve product. This course requirement checking tool is integrated with the universities course signup system to provide customized degree audits for students. Ideas from recommendation systems have created more advanced systems that play a more active role in the interaction between student and advisor. A program at Austin Peay State University can help students select courses based on their predicted grades, elicited interests, and graduation requirements [21]. Other researchers are working on learning good advising through the use of collaborative filtering [16].

While such systems are a step in the right direction, we argue that their efficacy may be limited by two important factors. First, while these systems provide recommendations about the next course of action they are missing a rather critical idea of *explaining* the rationale behind their recommendations. Second, recommender systems and collaborative filtering systems typically do not consider uncertainty of the outcomes of advising actions or the potential long-term effects of this uncertainty.

The notion of explaining why a particular course has been recommended is unlikely to be foreign to experienced academic advisors (e.g., you should take course X to better prepare yourself for course Y). At the moment, only a few existing systems attempt to do this [3, 4, 9]. Explanation is an important part of recommendation [18]. Involving users in dialogue can improve the probability that recommendations are considered valid and adopted [13].

The notion of uncertainty of outcomes is likely to present difficult reasoning challenges, regardless of quality of advisor. Even for good advisors, asking humans to make plans in domains in which the outcomes of actions are uncertain (e.g., course selection for students) invites many cognitive biases. Humans are demonstrably poor at reasoning with uncertainty and are subject to, for example, framing bias [20]. Explanation generated by an automated tool which is not subject to these cognitive biases can, sometimes, help them to reason more correctly about possible outcomes.

Our system generates arguments that are designed to convince the user of the "goodness" of the recommended action based on the internal mathematical model of advising[1]. This model is designed to be robust even in the face of uncertain actions, as is evident by the multiple possibilities evaluated in its explanations. Our system presents, as a paragraph, an argument that tries to convince the student to take a particular course in the next semester—a system which considers multiple courses per semester is a focus of future research. The underlying policy can be tailored to the student's preferences and abilities. An additional case-based algorithm generates an argument by analogy to the past performance of other students, enhancing transparency and persuasiveness [15]. It attempts to convince the user to adopt the recommendation by demonstrating that other students have taken the same course sequence and succeeded. Explanations take the following form:

> The recommended action is taking *Introduction to Program Design and Problem Solving*, generated by examining possible future courses. It is the optimal course with regards to your current grades and the courses available to you. Our model indicates that this action will best prepare you for taking *Introduction to Software Engineering* and taking *Discrete Mathematics* in the future. Additionally, it will prepare you for taking *Algorithm Design and Analysis*. Our database indicates that with either a grade of A or B in *Introductory Computer Programming* or a grade of A or B in *Calculus II*, you are more likely to receive a grade of A or B in *Introduction to Program Design and Problem Solving*, the recommended course.

The goal of this research is to explore the impact of explanation on the adoption of recommended courses of action in uncertain domains. In order to understand what makes a good explanation in our initial target domain, academic advising, we interviewed many students and advisors about features that make advice compelling, and what goes into student decisions regarding course selection.

3. SURVEY RESULTS

Our data were collected from two anonymous surveys during the 2009–2010 and 2011–2012 academic years. The 2009–2010 survey was focused on identifying students' needs and attitudes, specifically about advising. The 2011–2012 survey was conducted after the construction of our system in order to gauge the effectiveness of our explanations in an advising domain. Unless otherwise noted, all data comes from the Explanation System Survey.

Advising Attitudes and Needs Survey (AANS): Over the course of the Fall 2009 and Spring 2010 semesters we surveyed approximately 326 students enrolled in our university's Introduction to

[1]Technical details of our system [3, 4] and model building procedures [7,8] can be found in our other publications about the system.

Computer Programming course (the first course in our major sequence). Because an introductory computer programming course is required of all engineering majors within our college, we received responses primarily from some form of Engineering (including Civil, Computer, and Electrical Engineering), Computer Science, Mathematics, Education, and Physics, with the remaining responses primarily listing their major as "Undeclared" or "Other."

This survey was conducted prior to the development of our advising explanation system. The survey was exploratory: we sought to discover whether there was a need for more advanced computational advising tools, and in what capacity such tools would serve. Along with demographic information for classification purposes, we collected data regarding the frequency with which students sought university advising services, why they sought out an advisor, whether they used the online tools provided by the university, and how valuable they perceived their advising experiences to be.

Explanation System Survey (ESS): After the development of our advising system we conducted a large user study encompassing both target users of our system and domain experts (advisors). In our target user survey we surveyed 65 students enrolled in introductory computer science courses (CS group). These courses are open to all students, so a variety of majors are represented including computer science, computer engineering, electrical engineering, physics, math, and mechanical engineering. We also surveyed 130 students enrolled in introductory psychology courses (PSY group), which are also open to all students. The students surveyed included majors in psychology, biology, social work, family sciences, and undecided majors. This variety allows us to make more general statements about the types of advice that different students would prefer.

Paper surveys were handed out with narratives based on two fictional, but plausible students. Both students are about half-way through completing a minor in their respective course of study: one student is doing very well (about a 3.5 GPA) and one is struggling (2.3 GPA). Survey respondents were asked to evaluate the advice our system generated for these students. From the demographic portions of the survey we know that most (more than 75%) of the students who took the survey in CS and PSY were within 2 semesters (plus or minus) of the fictional students and, in general, had GPA's close to the the fictional high achieving student.

In our domain experts survey we conducted a survey of 10 advisors in order to gain perspective on how domain experts feel about our system and to validate our results against their advice. The advisors were computer science faculty advisors, general College of Engineering advisors, and staff advisors from the College of Arts and Sciences advisors.

When we authored our study instrument we had a variety of study goals in mind. In addition to demographic information, we wanted to know when and where users would interact with our system, what they thought about the advice generated by our system, subjective user and expert assessments of our system on various features, and what factors users and experts would want to add to our system. We included questions regarding their perceptions of the advising process and specific factors affecting their decisions. We do not provide a full analysis of the survey results in this paper. Instead, we are focused on the attitudes of students about advising and general attitudes about automatic course advising tools. Additional results can be found in our other papers on this topic [3, 4].

3.1 Student Attitudes

Overall, the survey validated our method of advising support. High levels of agreement are shown between the students' decision-making and the framing of the arguments generated by the model-based and case-based explanation system: 47 of 62 (75%) in the CS group and 104 of 130 (80%) in the PSY group indicated that they considered how past students in their situation performed and/or how a course would prepare them for future courses to be important when making a decision. The latter method corresponds exactly to our model-based method of explanation. The suitability of argument by analogy in this domain was also validated: 38 of 62 (61%) in the CS group and 65 of 130 (50%) in the PSY group indicated that they considered the performance of past students in their situation.

Other survey results highlight the ability of our system to support the advisor-student relationship. The students seemed to be very goal focused: 42 of 62 (68%) in the CS group and 100 of 130 (76%) in the PSY group responded that course requirements were an important factor in deciding what courses to take. The model which our tool uses incorporates course requirements implicitly, and the version presented in [4] explicitly addresses student concerns about time to graduation.

However, more than 50% of the students in both groups who responded to these questions (38 students in the PSY group and 25 in the CS group) had concerns about subjective factors of courses. These concerns included how many projects were assigned, what the professor was like, and whether taking two particular courses concurrently make for a particularly difficult semester. While a more complex model of student preferences could take some of these subjective factors into account, this result more than any other underscores the utility of our tool as an advising *support* system (rather than a replacement advisor), reducing the amount of time spent discussing the more formulaic aspects of course selection.

3.1.1 Predicted Usage Patterns

Most students responded that they would use the system at home before and/or while talking to an advisor. 31 of 44 (70%) in the CS group and 95 of 121 (78%) in the PSY group responded that they would use the tool at home, while 14 of 44 (32%) in the CS group and 64 of 121 (53%) in the PSY group responded that they would use the tool while talking to an advisor. Students were allowed to select multiple respones, and overall 84% in the CS group and 87% in the PSY group responded that they would use the tool either at home *or* while talking to an advisor—the intended use pattern.

There was a very small group of students, 7 of 44 (15%) for CS and 27 of 165 (16%) for PSY, that said they would use our system *instead of* talking to an advisor. This seems to correspond with our observations that some students view advising as a chore due to difficulties of scheduling time to meet an advisor. In fact, the relatively low percentage who would choose to use completely automated advising is encouraging.

3.1.2 Opinions About Automatic Systems

About 50% of the PSY group and 40% of the CS group wanted to work through some "what if" scenarios. These included rearranging proposed courses and looking at different expected time to graduation and other factors. If these users had been able to interact with our explanation system they could have built and tested these scenarios in real time, a true benefit of our system. Additionally, about 10% of students in both groups expressed interest in working through whole plans of study for multiple semesters or entire academic tenures. Our system currently allows students to walk through their study one semester at a time, sequentially; visualizing the advice concurrently across multiple semesters is another key area where our system could be of benefit in the future.

A handful of students (less than 5%) wanted to know what we meant by "augment." They asked for more specific learning factors that a course would improve and how this would translate to their future success. In order for our system to answer these questions, a significantly more complicated model-building process would be required. This is an example of an area of inquiry in which a human advisor would be invaluable.

There was a small fraction, less than 8% of CS students and no PSY students, who wanted to see more numbers and statistics in our system instead of our conversational explanations, indicating that perhaps a minority exists who are more comfortable reasoning with more objective factors, and whose concerns are not adequately addressed by the current advising process.

3.2 Advisor Attitudes

We surveyed 10 advisors, including faculty members who perform academic advising, advisors attached to a single department, and advisors who see students in multiple areas within a single college. Our small sample size does not allow us to present as a complete a statistical comparison as we would like, but we can still draw some conclusions about how advisors view the role of our system.

Nearly all advisors, across all categories, saw requirements as the most important priority when recommending courses to students. This criteria was rated as the first priority for 9 of 10 advisors surveyed. In stark contrast to the students, 7 of 10 advisors rated drawing analogy between the current student and past student performance as the least important aspect of advising.

Advisors rated our data as being generally correct with a median of 4.0/5.0 and generally clear with a median of 3.0/5.0. The advisors saw our advice for the struggling student as less clear and less correct because our system did not (and could not) engage the student in a discussion about choosing another major. In fact, when advisors did raise issues about the quality of our advice, it was generally in response to subjective factors. Advisors felt that our advice, while technically correct in most instance, left out many important factors that could only be gleaned and responded to by an in-person interview.

The issue of subjective factors was key for the advisors. They felt that, "there is no need to put a computer between two humans that need to communicate." It was very clear that advisors in our sample were worried that students, if given access to our system, would skip the person to person advising process in favor of a machine—a concern that was not validated by the results of the student survey. 7 of the 10 advisors said they would rarely or never use our system or recommend our system to students. All three of the advisors who suggested giving students access to our system did so with the caveat that students should still be required to meet with a human advisor to clear up any comments or concerns that the student would have.

The experienced advisors did not always agree with our system, and some times not with each other. There was some radically different advice from one advisor to the next given the same proposed advising situation. This may be an area where a better understanding of the broad trends in the student data could support the advice that advisors are generating for their students; facilitating advisors to make good decisions, supported by data.

The consensus from the advisors surveyed is that advising is hard. No two students are the same, and advisors need to be prepared to direct students to other resources, such as counseling, testing, and other majors. The advisors also argued that students are good at figuring out what courses they want—the advisors' real job is to advise them about subjective factors such as workload, career preparedness, and setting and achieving realistic goals.

4. COMPARING STUDENT ATTITUDES

Figures 1 through 5 show selected results of our survey in more detail. In some of these cases we have separated out groups of students to compare the attitudes of students with higher and lower GPA's and students that are earlier or later in their academic tenure.

Figure 1 shows that students with high GPA's are actually more negative about some of the advising products in general. They are more likely to refer to advising as "Mostly Useless" and don't see advising as an opportunity to receive information about courses. However, over 50% of both groups are positive about the advising experience.

Figure 2 shows that the high GPA students are more focused on meeting requirements and how the advisor came to their recommendation. One interpretation of this data is that higher achieving students are more goal oriented. The immediate goals of such students could consist of successfully completing courses and earning a degree. Such students appear to be more concerned with satisfying degree requirements and understanding how the advice given to them by an advisor may or may not directly apply to them, hence the somewhat higher rates of selection for "How The Course Meets Graduation Requirements," and "How The Advisor Came To Their Recommendation," respectively.

Figure 3 shows students earlier in their career are more focused on meeting course requirements. We conjecture that, by later stages, students know what they need to do and don't perceive this advice as being as important. Additionally, students who have been in tertiary education longer place more value on advisors telling them what other students in the past have done. Students in the 5–8 semester cohort are concerned about career advice while those in the other two groups, we conjecture, have either already figured out what they are going to do (9+ semesters) or aren't even thinking about it (0–4 semesters).

Figure 4 from the AANS survey shows that students are very career focused. The highest percentage of students want courses that directly tie to their careers. Additionally, students want good grades, but also want to learn a lot in a course. They are somewhat concerned about the difficulty or easiness of the course, but much more interested in whether it completes any of their requirements. In that way, they are very goal oriented, and it appears that a safe assumption is that the primary goal of most students is graduation with a good GPA.

Figure 5 from the AANS survey shows the results when students are asked to compare the importance of different elements. We see that a course being required is the overwhelmingly most important thing to students when selecting a course. Following this, perceived grade, time of day, and subject matter interest are ranked closely as Somewhat Important or Very Important. These results are echoed by responses from the ESS survey shown in Figure 6, which shows that students perceive required-ness and time of day to be most important.

5. DISCUSSION AND CONCLUSIONS

In our surveys and this paper, we asked what explanations make academic advice compelling and convincing. The primary lesson for advisors is that this is not one-size-fits-all. There is clear variability, even within students in two or three large intro classes in CS and PSY, in what students think about when choosing classes, and what they want from advisors and advising software.

It is clear that many students will use advising software if it allows them to explore "what-if" scenarios, and if it provides clear, understandable explanations for its recommendations, particularly in terms of other students' experiences. These preferences carries over, we expect, to human advising: students appreciate explanations that begin, "Many students who have had similar grades in

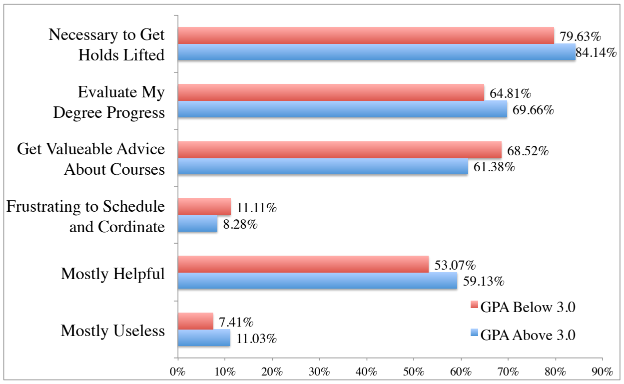

Figure 1: Student answers to the question, "I view visiting my advisors as..." broken down by those students with a 3.0 or better GPA ($N = 145$) and those below a 3.0 GPA ($N = 54$). Students were allowed to select multiple options.

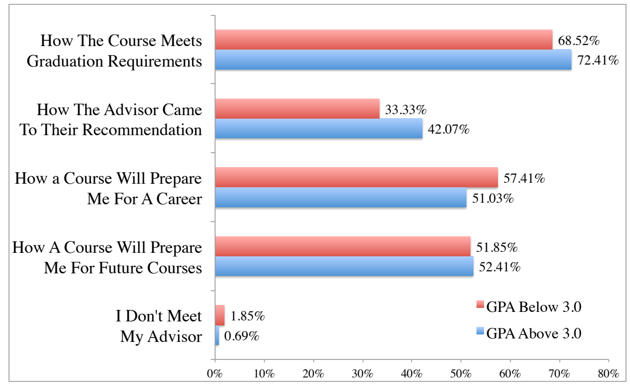

Figure 2: Student answers to the question, "When receiving advice from an advisor I like that the advisor explain..." broken down by those students with a 3.0 or better GPA ($N = 145$) and those below a 3.0 GPA ($N = 54$). Students were allowed to select multiple options.

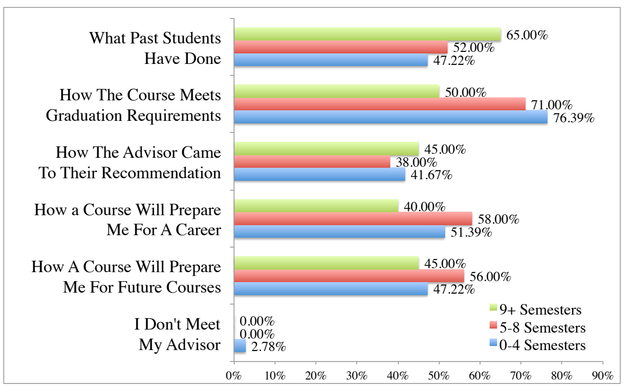

Figure 3: Student answers to the question, "When receiving advice from an advisor I like that the advisor explain..." broken down by those students attending a tertiary institution for 0-4 semesters ($N = 70$), 5-8 semesters ($N = 100$), and 9+ semesters ($N = 20$). Students were allowed to select multiple options.

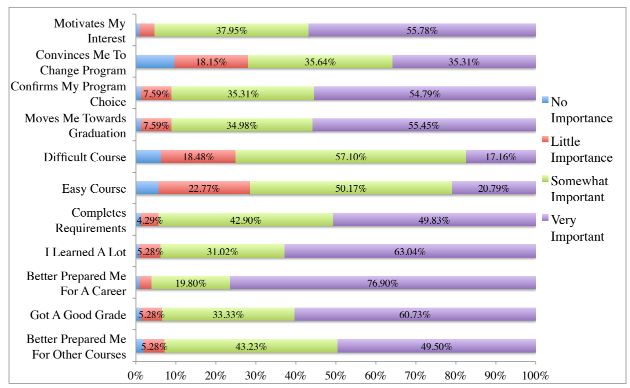

Figure 4: Student answers to the question, "What factors do you consider important in making a course valuable to you?" from the AANS survey. Students were required to choose one of the options along the scale shown, $N = 313$.

these specific courses have gotten these grades in this course." This is of interest, since it was a technique the advisors did not like to use. We conjecture that they feel it de-emphasizes the uniqueness of the individual student or implicitly sets expectations which may cause the student to become discouraged when he or she is not able to "live up" to previous students' performances.

Another strong finding is that students want to see the longer-term impacts of course choices. What prerequisites are fulfilled by the recommended courses, and what chains of dependent courses are begun? What courses will they be better prepared for, directly and indirectly, by the recommended courses? Finally, how will the recommended courses prepare them for post-college opportunities, either directly or by preparing them for future useful courses?

We noticed that students with higher GPAs had, on average, different expectations and desires. These diverse needs suggest that advisors should be flexible in the reasoning they present to support their advice. Some students want reassurance that they are on track for a career, and others seem to simply enjoy school. In computer science and engineering, it seems that educational careers are often framed in terms of job preparation. While many students find these topics to be important, we also see that many students value subjective factors such as the topics of the courses (90%), expected workload, professor, and (always!) time of day.

We have not explored advising support systems which account for subjective factors. Students expressed a desire for information about what we would call "hidden factors," how a course would prepare them for future classes and for post-graduation experiences. It is clear that the weights students put on high grades versus time to graduation versus other subjective factors depend on the individual students. Human advisors can offer their own subjective evaluation of course difficulty, popularity, etc. Some of this information can be gleaned from standardized teaching and course evaluations as well as word of mouth. We were surprised to learn that the students surveyed focused on more easily evaluated factors such as time to graduation and GPA. We conjecture that those two factors will provide important, albeit incomplete, bases for more personalized explanations.

E-advisors can help both students and human advisors, but they should not replace human advisors. Based on responses from Computer Science vs. other students, that our students distrust computer-generated advice more. These responses from students and advisors underscore the importance of having a human in the loop for

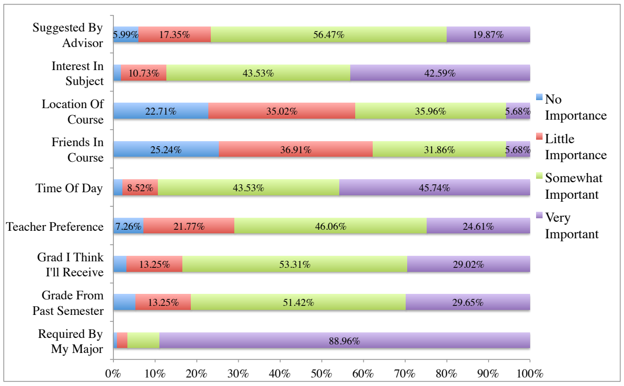

Figure 5: Student answers to the question, "Please rate the importance of the following factors when selecting a course," from the AANS survey. Students were required to choose one of the options on along the scale shown, $N = 317$.

	Borda Score	Average List Position
Required By My Major	855	1.70
Time Of Day	674	2.61
Interest In Subject	657	2.70
Professor Teaching The Course	580	3.09
Grade I Anticipate Receiving	556	3.20
Suggested By My Advisor	485	3.56
Grades From Other Courses In Previous Semesters	421	3.88
Friends In Course	380	4.09
Location Of Course	338	4.30

Figure 6: Student responses when asked to rank the elements in order of importance to them when deciding to take a course; unranked elements were assumed to be tied, at the end, of a student's list. Borda scoring is used to compile the score with the top element receiving 6 points and the last element in a list receiving 0 points, $N = 200$.

creative problem solving, subjective analysis, deep understanding of their university or college system, and most of all, the personal attention that good advisors offer. We hope that our initial findings about what students want from the advising process offer something useful to advisors.

Acknowledgements

This work is supported by the National Science Foundation, under grants CCF-1049360, ITR-0325063, and IIS-1107011. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

NICTA is funded by the Australian Government through the Department of Broadband, Communications and the Digital Economy and the Australian Research Council (ARC) through the ICT Centre of Excellence program.

Most of the work on this project occurred while all the authors were at the University of Kentucky. We would like to thank Elizabeth Mattei for her help with the statistical analysis, Jennifer Doerge for her helpful feedback on advising (and generally being an example of a great advisor), and the members of the UK AI–Lab, especially Robert Crawford, Daniel Michler, and Matthew Spradling for their support and helpful discussions. We are also grateful to the anonymous reviewers who have made many helpful recommendations for the improvement of this paper.

6. REFERENCES

[1] Minding the gap. The Economist, November 16th 2013.

[2] T. Beaubouef and J. Mason. Why the high attrition rate for computer science students: some thoughts and observations. *SIGCSE Bull.*, 37(2):103–106, June 2005.

[3] T. Dodson, N. Mattei, and J. Goldsmith. A natural language argumentation interface for explanation generation in Markov decision processes. In *Proceedings of the 2nd International Conference on Algorithmic Decision Theory (ADT-11)*, pages 42–55, 2011.

[4] T. Dodson, N. Mattei, J. T. Guerin, and J. Goldsmith. An english-language argumentation interface for explanation generation with markov decision processes in the domain of academic advising. *ACM Transactions on Interactive Intelligent Systems*, 3, 2013.

[5] T. Feghali, I. Zbib, and S. Hallal. A web-based decision support tool for academic advising. *Educational Technology & Society*, 14(1):82–94, 2011.

[6] V. N. Gordon, W. R. Habley, and T. J. Grites. *Academic advising: A comprehensive handbook*. Wiley, 2011.

[7] J. T. Guerin and J. Goldsmith. Contructing a dynamic Bayes net model of academic advising. In *Proceedings of the Uncertainty in Artificial Intelligence Workshop on Bayesian Modeling Applications*, 2011.

[8] J. T. Guerin, J. Hanna, L. Ferland, N. Mattei, and J. Goldsmith. The academic advising planning domain. In *Proceedings of the 3rd Workshop on the International Planning Competition (WS-IPC-12)*, pages 1–5, 2012.

[9] O.Z. Khan, P. Poupart, and J. Black. Automatically generated explanations for Markov decision processes. In *Decision Theory Models for Applications in Artificial Intelligence: Concepts and Solutions*, pages 144–163. 2011.

[10] M. C. King. Academic advising, retention, and transfer. *New Directions for Community Colleges*, 1993(82):21–31, 1993.

[11] A. Lowe and M. Toney. Academic advising: Views of the givers and takers. *Journal of College Student Retention*, 2(2):93–108, 2001.

[12] Marc Lowenstein. If advising is teaching, what do advisors teach? *NACADA Journal*, 25(2):65, 2005.

[13] T. Mahmood, F. Ricci, and A. Venturini. Improving recommendation effectiveness: Adapting a dialogue strategy in online travel planning. *Information Technology & Tourism*, 11(4), 2009.

[14] B. S. Metzner. Perceived quality of academic advising: The effect on freshman attrition. *American Educational Research Journal*, 26(3):422–442, 1989.

[15] C. Nugent, D. Doyle, and P. Cunningham. Gaining insight through case-based explanation. *Journal of Intelligent Information Systems*, 32:267–295, 2009.

[16] S. Ray and A. Sharma. A collaborative filtering based approach for recommending elective courses. In *Proc. 5th International Conference on Information Intelligence, Systems, Technology and Management (ICISTM 2011)*, pages 330–339, 2011.

[17] J. O. Talton, D. L. Peterson, S. Kamin, D. Israel, and J. Al-muhtadi. Scavenger hunt: computer science retention

through orientation. In *Proceedings of the 37th SIGCSE Technical Symposium on Computer Science Education*, pages 443–447, 2006.

[18] N. Tintarev and J. Masthoff. Designing and evaluating explanations for recommender systems. In F. Ricci, L. Rokach, B. Shapira, and P. B. Kantor, editors, *Recommender Systems Handbook*, pages 479–510. Springer, 2011.

[19] R. W. Titley and B. S. Titley. Academic advising: The neglected dimension in designs for undergraduate education. *Teaching of Psychology*, 9(1):45–49, February 1982.

[20] A. Tversky and D. Kahneman. Judgement under uncertainty: Heuristics and biases. *Science*, 185:1124–1131, 1974.

[21] J. R. Young. The Netflix effect: When software suggests students' courses. *Chronicle of Higher Education*, April 10 2010.