

Lessons Learned from Development of a Software Tool to Support Academic Advising

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Abstract— We detail some lessons learned while designing and testing a decision-theoretic advising support tool for undergraduates at a large state university. Between 2009 and 2011 we conducted two surveys of over 500 students in multiple majors and colleges. These surveys asked students detailed questions about their preferences concerning course 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 support software tools can augment the student-advisor relationship, particularly in terms of course planning, but cannot and should not replace in-person advising.

Index Terms—Computer science education, Educational technology, Engineering education

I. INTRODUCTION

At the University of Kentucky, students in both the College of Engineering and the College of Arts and Sciences 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 and academic 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

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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; the advisor plays a supporting role in the student's continued development and formulates short and long term goals for the student based on their individual needs and interests. The reality is that most students see their advisor once per semester for 15 to 30 minutes, sometimes see a different advisor each semester, and sometimes see multiple advisors who are not necessarily in communication with one another. 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 have developed components of 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 on more formulaic aspects of advising, such as 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 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 support 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

Engineering, Computer Science, or other majors which have a strong career focus within the curriculum. Indeed, we saw a very strong bias in the student responses toward advising information related to the effect a given course would have on their future careers. We also conjecture that students in technical majors are more comfortable with the use of computers and online tools than the student body at large; though this distinction may become less important as technology continues to saturate our day-to-day lives.

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 support system provides the user with specific recommendations based on the results of decision-theoretic planning algorithms applied to models of student goals and statistical models of student performance. 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).

Finally, we note that while the explanations presented in this paper are specific to the surveyed programs at the University of Kentucky, the explanation system itself was designed to be domain-independent [17], [18]. That is, the algorithms which generate the explanation do not depend on the specifics of the degree program, and the system was designed to permit modification of the underlying statistical model in order to support varying levels of student autonomy found at different institutions.

II. 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 [1], [2]. 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) [3]–[6]. Additionally, recent research has shown that minority and otherwise disadvantaged students can benefit the most from quality advising services [7].

The links between the availability and quality of academic advising services and lowered attrition rates may be of particular consequence for Engineering and Computer Science, where attrition rates are often particularly high. The University of Illinois at Urbana-Champaign reported a first-year attrition rate of Computer Science majors of approximately 25% [8] over a 5 year period. A study by Moller-Wong and Eide [9] revealed similar trends across Engineering disciplines — 30% of students tracked in the study had left college entirely within 5 years, while 55% had

either left school or moved to a non-engineering major. A more recent study conducted at Rowan University [10] — a college which has embraced current “best practices” with respect to student retention, and retention of female students in particular — reported a retention rate of roughly 89%, without the usual gender gap. A single-cohort study at North Carolina State University found a 3-year attrition rate of 17% for students in the 2002 cohort [11], while another study of the 2003 cohort at a major Australian research university found that 35% of students had left engineering by the end of the 6-year study period [12], with a 28.5% 3-year retention rate.

Because students frequently come into engineering programs with key skills deficits and, particularly in the case of Computer Science, 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 [13]. Hartman et al. [10] found that students with lower mathematics SAT scores and less experience with high school math and science classes were significantly more likely to leave the program, while students who participated in discipline-specific engineering organizations were significantly more likely to be retained. Indeed, both of these are factors that can be addressed through pre-enrollment academic advising, by offering support to either direct students to more appropriate programs or to resources that can address key skills deficits, while encouraging them to become active in on-campus engineering organizations.

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 [14].

The perceived importance of advising support 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. Concepts from algorithms developed for recommender systems have been integrated into 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 [15]. Other researchers are working on advising support systems which use collaborative filtering algorithms [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 critical idea — *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 [17]–[19]. Explanation is an important part of recommendation [20]. Involving users in dialogue can improve the probability that recommendations are considered valid and adopted [21].

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 [22]. Explanation generated by an automated tool which is not subject to these cognitive biases can, sometimes, help them to reason about possible outcomes [21], [23].

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 advising¹. 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. Also, a case-based algorithm generates an argument by analogy to the past performance of other students, enhancing transparency and persuasiveness [26]. 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.

An additional algorithm was added to later iterations of our software [18], specifically addressing student concerns raised in the Explanation System Survey. The algorithm is a probabilistic case-based calculation of the time from the

current state to a user-defined goal (e.g., graduation or passing a particular “capstone” course) and presents a sentence in the following form:

Past students have taken *Software Engineering* and accomplished their goal of *achieving a passing grade in Algorithm Design and Analysis* in four or fewer semesters from the current state.

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.

III. 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 the University of Kentucky’s Introduction to 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 Computer Science students, with a smaller representation from other Engineering disciplines — including Civil, Computer, and Electrical Engineering — as well as 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 support 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

¹Technical details of our system [17], [18] and model building procedures [24], [25] can be found in our other publications about the system.

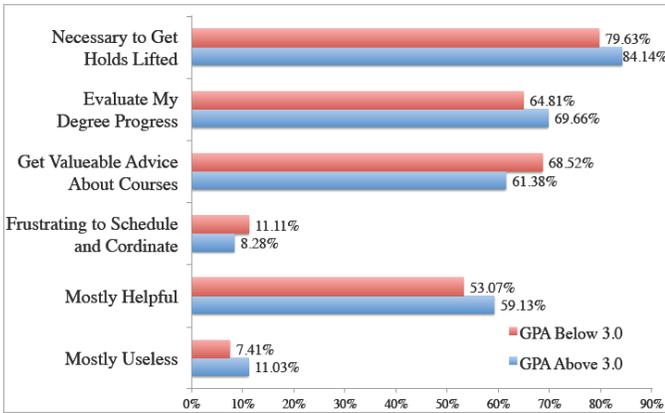


Fig. 1. Student answers to the question, “I view visiting my advisors as...” broken down by those students with a 3.0 or better GPA (N = 145) and those below a 3.0 GPA (N = 54). Students were allowed to select multiple options.

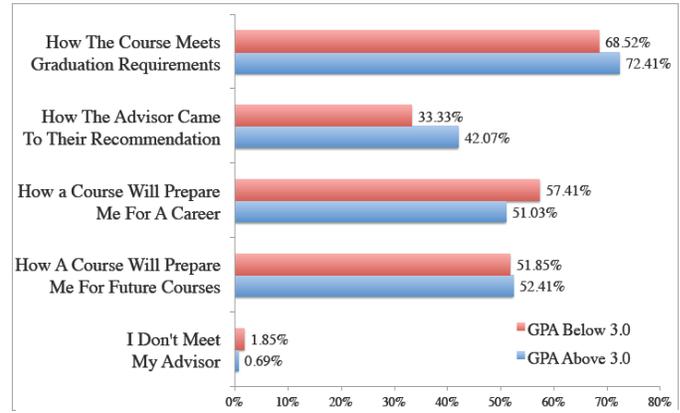


Fig. 2. Student answers to the question, “When receiving advice from an advisor, I like that the advisor explain...” broken down by those students with a 3.0 or better GPA (N = 145) and those below a 3.0 GPA (N = 54). Students were allowed to select multiple options.

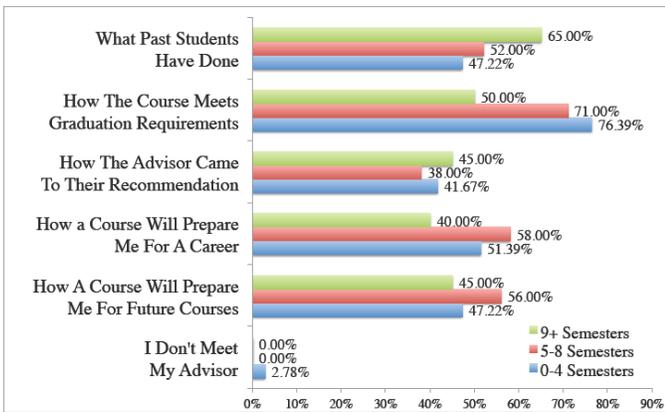


Fig. 3. Student answers to the question, “When receiving advice from an advisor, I like that the advisor explain...” broken down by those students attending a tertiary institution for 0-4 semesters (N =70), 5-8 semesters (N = 100), and 9+ semesters (N = 20). Students were allowed to select multiple options.

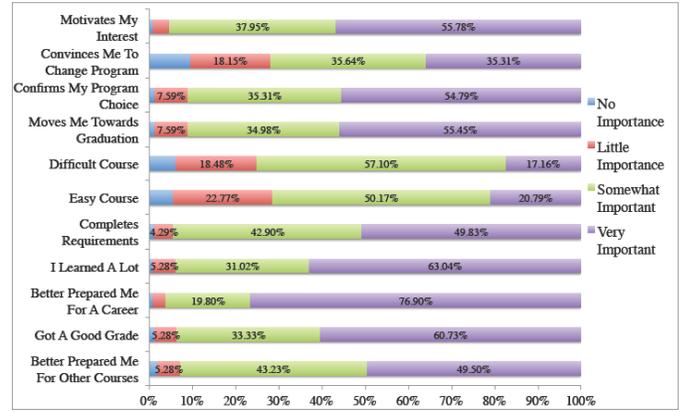


Fig. 4. Student answers to the question, “What factors do you consider important in making a course valuable to you?” from the AANS survey. Students were required to choose one of the options along the scale shown, N = 313.

students. The students surveyed included primarily majored in psychology, but also included 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.

The EES was limited to paper surveys. As our system becomes more robust we hope to use it in controlled, real-world settings with both students and advisors in order to study its effectiveness. 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 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

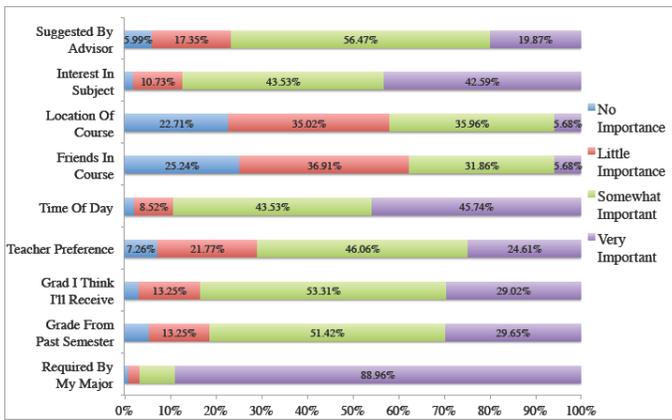
Instead, we advising a advising to papers on th

A. Student

Overall, support. Hi students' de generated t system: 47 in the PSY

Fig. 5. Student following fi Students we shown, N =3

	Borda Score	Average List Position
Required By My Major	855	1.7
Time Of Day	674	2.61
Interest In Subject	657	2.7
Professor Teaching The Course	580	3.09
Grade I Anticipate Receiving	556	3.2
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	4.3



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 in terms of short-term utility, while the former corresponds to our case-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 [18] explicitly addresses student concerns about time to graduation — a common student request in the ESS.

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 an *advising system*), reducing the amount of time spent discussing the more formulaic aspects of course selection.

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 responses, 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.

Engineering and Computer Science students seemed particularly wary of our model, and indicated that they would be less willing to use the tool, if available, than students in other disciplines. When students were asked if they would make use of the advising feature if it was integrated with our

university’s course requirement checking feature — 24 of 44 (55%) for CS and 88 of 120 (73%) for PSY, responded that they would often or always use the recommendation feature.

Many of the students who expressed a preference for not using the tool were worried that it did not take into account *all* their preferences — the more technical among them asked many questions about how the model was built and directly questioned its ability to capture their particular preferences. This again highlights the utility of an advising *support* tool — the students were interested in using the tool as a rote course requirement checker and for gaining a feel of what courses to take. However, they are more comfortable when a human advisor is in place to support them and make the recommendations more personal.

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.

2) *Opinions About Automated 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, comparing expected time to graduation for different course selections, 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; with an appropriate user interface allowing visualization of advice concurrently across multiple semesters, this is a key area where our system could be of benefit in the future, as the algorithm is explicitly designed to allow this kind of exploration.

A handful of students (less than 5%) asked for more specific learning factors that a course would improve and wanted to know 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 where a meeting with a human advisor would be invaluable — highlighting where our system can be used to *encourage* discussion, rather than replace it.

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.

B. 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 (i.e. case-based reasoning) 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 instances, left out many important factors that could only be addressed by face-to-face meetings.

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 supported 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 questions or concerns that the student would have.

The experienced advisors did not always agree with our system, and sometimes 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.

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.

C. Detailed Analysis

Figure 1 shows that students with high GPA’s were more negative about the advising products available to them at the time. They were more likely to refer to advising as “*Mostly Useless*” and didn’t see advising as an opportunity to receive

information about courses. However, over 50% of both groups were 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.

IV. 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 Computer Science and Psychology, in what students think about when choosing classes, and what they want from advisors and advising support software.

It is clear that many students will use advising support 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 carry over, we expect, to human advising: students appreciate explanations that begin,

“Many students who have had similar grades in these specific courses have gotten these grades in this course.” This result is of particular 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 with respect to their particular goals (often, graduation in a “reasonable” amount of time with a high GPA). 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 engineering and computer science, 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 yet explored advising support systems which account for subjective factors. Students expressed a desire for information about so-called “hidden factors,” i.e. *how* a course would prepare them for future classes and for post-graduation experiences. Learning these hidden factors from data, including course descriptions, student grades, and course evaluations is an intriguing area for future research. Additionally, a corpus of data could be collected on-line by the advising support system itself. Such a system would be designed to collect small amounts of preference information from students during the workflow of the tool, without being so intrusive as to ask students to complete survey-style questionnaires.

We were surprised to learn that the students surveyed focused on more easily evaluated factors such as time to graduation and GPA. These two factors will provide an important, albeit incomplete, basis for more personalized explanations. However, it is also clear that the weights students put on high grades versus time to graduation versus other subjective factors depend strongly on the individual. While some of this information can be gleaned from standardized teaching and course evaluations as well as word of mouth, the value of human advisors is that they can offer their own subjective evaluation of course difficulty, popularity, etc. tailored to the goals and abilities of the particular student.

Advising support software, such as the system presented in this paper, can help both students and human advisors by allowing the student to perform rote requirement checking, as well as providing a platform for informed exploration of course choices and possible outcomes, which could facilitate

more productive in-person advising sessions by reducing the amount of time spent on the more formulaic aspects of academic advising. We reiterate that we are exploring an advising *support* system, and that we found no evidence that e-advisors could or should replace human advisors. Indeed, based on responses from students in Engineering and Computer Science, we found that they are *more* likely to distrust an e-advisor than non-engineering students. Responses from students and advisors underscore the importance of having a human in the loop for 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 academic advisors.

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