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Course Satisfaction in Engineering Education Through the Lens of Student Agency Analytics

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***Abstract*—This Research Full Paper presents an examination of the relationships between course satisfaction and student agency resources in engineering education. Satisfaction experienced in learning is known to benefit the students in many ways. However, the varying significance of the different factors of course satisfaction is not entirely clear. We used a validated questionnaire instrument, exploratory statistics, and supervised machine learning to examine how the different factors of student agency affect course satisfaction among engineering students ($N = 293$). Teacher's support and trust for the teacher were identified as both important and critical factors concerning experienced course satisfaction. Participatory resources of agency and gender proved to be less important factors. The results provide convincing evidence about the possibility to identify the most important factors affecting course satisfaction.**

***Index Terms*—course satisfaction, student agency, exploratory statistics, supervised machine learning**

I. Introduction

Satisfaction experienced in learning and educational situations is beneficial for the students [1], and the importance of emotions in enhancing learning and achievement is recognized in the field of learning sciences [2]. From the viewpoint of learning activities in higher education, cognitive, motivational, social, and emotional aspects are tightly intertwined. Therefore, both experienced course satisfaction and affective experience in the form of active agency [3] are essential constructs in understanding and supporting students in higher education.

Previous research identifies numerous aspects which highlight the essential role of positive emotions in learning [1], [2], [4]. Previous research has also identified that student-perceived overall satisfaction is linked with learning in several ways (e.g., [5]–[10]). Furthermore, studies stress the central role of agency in high-order learning processes (e.g., [11]). However, a comprehensive perspective is needed to fully grasp the meaning of experienced educational satisfaction in a variety of complex learning processes. Moreover, the link between the overall course satisfaction and student-experienced agency has not been studied previously.

Recently developed Student Agency (AUS) Scale [12] provides a possibility for a multidimensional examination of the association between course satisfaction and student-experienced agency. Based on the multidimensional view on the construct, the AUS includes several dimensions relating to purposeful learning (e.g., efficacy, opportunities for participation, and instructor's support), which in the previous studies (e.g., [13]) have been examined separately and found to be related to course satisfaction.

The purpose of this paper is to explore the relationship between course satisfaction and student-experienced agency in engineering education. Exploratory analysis and supervised machine learning are used to achieve this study purpose. In terms of the course satisfaction, we apply the measurement of customer satisfaction via the Net Promoter Score (NPS) [14] used in business. On the part of student agency, we utilize student agency analytics developed in the previous stage of research [15]. Finally, we use exploratory analysis and different classifiers to assess how the student agency factors affect experienced course satisfaction. The results contribute to the operationalization of course satisfaction and the broader understanding of its underlying factors.

II. Theoretical background

A. Student agency

Student agency is a central concept, for example, in the *OECD Learning Compass 2030* [16], [17], which "is an evolving learning framework that sets out an aspirational vision for the future of education" [16, p. 2]. In the framework, student agency relates to identity, sense of belonging, motivation, hope, self-efficacy, growth mindset, and a sense of purpose [18, p. 4]. In engineering education, students' exertions of agency affect, for example, to the decisions to continue their degrees [19], [20]. Also, pressure towards student agency in higher education has turned the focus on student capabilities

[21]. The central role of student agency in the contemporary discourse about future education invites researchers to explore its meaning and relationships with other concepts.

In this paper, we utilize a multidimensional conceptualization of student agency in a higher education context (Fig. 1), and the validated Agency of University Students (AUS) Scale [12], [22] to examine students' agency experiences at the course level. In AUS Scale, student agency refers to a *student's experience of having access to and use of personal, relational, and participatory resources for purposeful, intentional, and meaningful action and learning*. Personal resources encompass a student's competence and self-efficacy beliefs, with the former referring, for example, to a student's sense of understanding the course contents and the latter to a broader self-confidence as a learner in the course. Relational resources include the aspects related to teacher – students (power) relations in the course, which manifests themselves as a student's sense of getting support from the teacher, of being treated equally, and of trust to the teacher in the course. Participatory resources cover the factors that maintain both personally meaningful and intentional and interactive action in the course. In line with Su [3], agency is seen as intrinsically intertwined with learning as an affective experience, cognition, and action in the courses and learning relations.

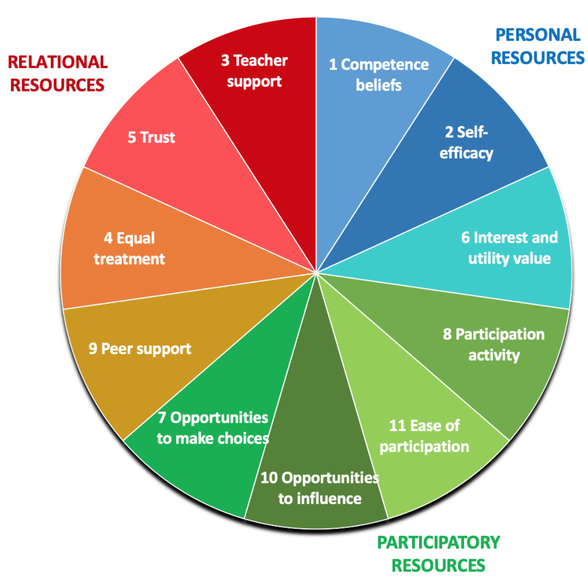

Fig. 1. The AUS model [12]

B. Course satisfaction in engineering education

In general, satisfaction towards a product or a service is a multifaceted phenomenon [23]. Student satisfaction is a continually shaped student's subjective evaluation of different experiences and outcomes relating to education [1]. Basically student satisfaction is ensued if the perceived performance meets or exceeds the student's expectations, and dissatisfaction will emerge in the opposite case [1]. Our study examines engineering students' satisfaction relating to a particular course they have attended. Thus, the concept of course satisfaction refers to the student satisfaction relating to a specific course.

Course satisfaction is an important component in successful learning. Studies suggest, for example, that course satisfaction has an effect on general academic satisfaction [5], [6]. In particular, it is linked to retention and academic locus of control [7], [8], as well as attrition [9] and approaches to learning [10]. Furthermore, satisfaction in academic life relates to the experienced life satisfaction in general [6].

In addition to learning-related effects, Browne et al. [24] found a moderate positive correlation between global satisfaction towards college and a willingness to recommend the college. Also, Mustafa et al. [25] found out that student satisfaction has a positive effect on students' willingness to promote the educational institution. Thus, it might be possible to categorize the experienced course satisfaction similarly to customer satisfaction (the willingness to promote a product or a service, c.f., [14]).

Several issues have been identified to contribute to the students' course satisfaction. Paechter et al. [13] found out that students' achievement goals, the instructor's support, expertise along with students' opportunities for self-regulated and collaborative learning, motivation, and the clarity of the course structure all contribute to course satisfaction and learning achievements. They also argue that competence beliefs are essential factors in course satisfaction. Komarraju et al. [26] found out that career self-efficacy, i.e., an individual's self-efficacy beliefs that one can complete the tasks and purposefully construct a career path, was one of the explaining factors of course and major subject satisfaction. McFarland and Hamilton [27] suggest, for example, that by enforcing appropriate course prerequisites, one could expect to find higher course satisfaction both in traditional and online instruction. In an online course context, Bolliger [28] reported that the course satisfaction of students is influenced by instructor variables, technical issues, and interactivity. Furthermore, Richardson et al. [29] report that quality of teaching, support for studying, and fair and clear course assessment correlated positively with the overall course satisfaction. Their results showed that teaching and support had the highest correlation with overall satisfaction.

Lynch et al. [30] identified eleven significant factors influencing engineering students' satisfaction that broadly concern interaction with the instructor, providing real-world connections, delivering meaningful content, advancing problem-solving and group work, and promoting student motivation. Similarly, González-Rogado et al. [31] found out that the usefulness of course content for future professionals, the methodology employed in the educational process, and the teamwork carried out throughout the course were related to course satisfaction in engineering education. The instructional design might also affect student satisfaction. For example, Kerr et al. [32] concluded that studies examining flipped learning in engineering education reported positive gains in student satisfaction.

Also, aspects that might have a biasing effect on assessing course satisfaction have been identified. For example, male students tend to give lower ratings as compared to females when evaluating teaching [33]. However, Leao et al. [34] found no difference in general course satisfaction between genders in the context of engineering education. Student-experienced course satisfaction can be influenced by the students' potential bias against female teachers, and teachers with non-native speaking backgrounds and instructors among students with high expectations of the course sometimes receive more favorable evaluations [35].

In general, student satisfaction seems to be a complex and multifaceted phenomenon with many influencing factors. Interestingly, many of the different elements affecting course satisfaction are also related to the dimensions of the student agency construct, for example, teacher support, trust for the teacher, and competence beliefs (see Fig. 1) [12]. Thus, the novel approach chosen for this study is to examine the relationship between student agency and course satisfaction.

III. Research questions

The present study aims to i) examine a way to quantify and categorize student-assessed course satisfaction and ii) explore the relationship of course satisfaction and student agency. Thus, more specifically we set the following research questions:

RQ1: Can course satisfaction be categorized similarly to the willingness to promote a product or a service?

RQ2: Is there differences in the dimensions of student agency between different course satisfaction experiences?

RQ3: What are the most important student agency factors contributing to experienced course satisfaction?

To answer the RQ1, we compare statistically the similarity and association between net promoter score (c.f., [14]) and course satisfaction (Section V-A). To answer the RQ2, we assess the differences in each dimension of student agency between the course satisfaction groups (Section V-B). To answer the RQ3, we use supervised machine learning methods to find out the most important features contributing to the classification accuracy (Section V-C).

IV. Data and methods

A. Research data

The research sample consists of questionnaire responses of engineering students ($N = 293$) in a higher education institution (ISCED Level 6) studying courses about basic IT skills and mathematics for engineers. The courses belonged to the engineering students' curricula and they were common to all engineering students regardless of their line of study. The courses consisted of lecturing and small group teaching. The data were collected using an online questionnaire, which was administered at the end of the courses before the final course grades were announced. Respondents' ages ranged from 18 to 52 years ($Mdn = 21, M = 23.6, SD = 5.8$) with 23% identified as female. The majority of the students were at the beginning of their studies, and their total amount of completed study credits (ETCS) ranged from 0 to 260 ($Mdn = 0, M = 21.0, SD = 46.4$).

B. Measures

1) Course satisfaction: The traditional approach of quantifying student satisfaction is to measure the student's overall satisfaction with an aggregate single-item measure [1]. Satisfaction scores are prone to a ceiling effect [36], which means that the respondents' scores cluster toward the high end of the scale [37]. Kleiss et al. [38] tested several scales for assessing medical patient satisfaction and found that an 11-point ordinal scale (range 0–10) approached the most normal distribution. As the use of a 0–10 scale is quite common, they claim the scale is also more familiar to respondents. However, it raises the question of what values or thresholds should be used to depict satisfaction and dissatisfaction. As there is no agreement of the optimal way of measuring course satisfaction [38], we chose 0–10 Likert-type item as a starting point. Furthermore, we adapt the categorization idea used in the Net Promoter Score™ (NPS) [14].

Net Promoter Score measures the customers' willingness to recommend a product or a service [14]. In the calculation of NPS, respondents are divided into three categories based on their answers on a 0-10 scale. Respondents answering 9 or 10 are categorized as promoters of a service or a product. Respondents answering 7 or 8 are passives, and respondents answering 6 or less are called as detractors. The actual net promoter score is the difference between the percentages of promoters and detractors. NPS has received wide criticism and, contrary to the original claims [14], studies suggest that it does not have a significant effect on business performance [39]. However, the approach allows us to examine the proposed categorization of the students into three satisfaction categories. Adapting the idea behind NPS, students were categorized as satisfied, neutrals, and dissatisfied. The course satisfaction category was then used in the exploratory analysis, and as the predicted variable in supervised learning.

We measured students' course satisfaction with two questions. First, respondents were asked to evaluate their overall satisfaction relating to the course ("How satisfied you were with the course? "). To compare the course satisfaction scale with the NPS, later in the questionnaire, we also asked how probably the respondent would recommend the course to their fellow students ("How probably would you recommend this course to a fellow student? "). Same as originally in the NPS [14], both items were measured using a Likert-type item in a 0 to 10 point scale. Value of 0 indicated an answer "no at all" and value 10 "very satisfied / very likely". To assess the applicability of the idea of NPS in assessing course satisfaction, we make a comparative analysis of the two scales. In a similar comparison, Laitinen [40] examined the library patrons' satisfaction and willingness to recommend a library service. He found that the two evaluation metrics converge; however, there was a statistically significant difference at the highest grades.

2) Student agency: Student agency was measured using the AUS scale, which consists of items measuring student agency at the course level. AUS scale captures three main domains of agency resources, and their respective eleven dimensions (Fig. 1): A. Personal resources (1. Competence beliefs, 2. Self-efficacy), B. Relational resources (3. Equal treatment, 4. Teacher support, 5. Trust), and C. Participatory resources (6. Participation activity, 7. Ease of participation, 8. Opportunities to influence, 9. Opportunities to make choices, 10. Interest and utility value, 11. Peer support). A student's responses to the AUS questionnaire will give us knowledge on the extent the student perceives to have personal resources, affordance for supportive relations, as well as opportunities for active participation and influencing the course. Also, students answered two open-ended questions about supportive and restrictive aspects experienced during the course.

C. Data analysis

The first step in analyzing student agency was to calculate the values of agency dimensions as factor values for each respondent [15]. We reverse-scored the inverted items using linear scaling and calculated the agency factors using the factor pattern matrix of the AUS factor model. The calculated agency factors were scaled to the original range $[1, 5]$ of the Likert scale. A Spearman's rank-order correlation was used to assess the similarity and association between students' answers to the course promoting scale and course satisfaction scale. Kruskal-Wallis H was used to compare the difference of medians within agency dimensions and how strongly the medians are separating the different satisfaction groups [41]–[43]. Mann-Whitney U was used to compare the pairwise difference of medians between each course satisfaction groups in all student agency dimensions [44]. In the exploratory analysis of the course satisfaction and student agency, the statistical analyses and visualizations of the associations between student agency and course satisfaction were executed in *R* 3.6.1 [45] using *ggplot2* and *ggpubr* packages.

We used supervised machine learning to analyze the feature importances, in other words, the important dimensions of student agency affecting course satisfaction. The supervised analysis (Section V-C) was performed using *Python* 3.7.1 and different classifiers implemented in the *scikit-learn* package. We trained one linear (logistic regression), and three non-linear (support vector machines with Gaussian kernel, random forest, and gradient boosting) classifiers to predict the binary course satisfaction score (i.e., the satisfied category). The support vector machine classifier was trained using *scikit-learn*'s *SVC* with a parameter search over the regularization parameter *C* and the width of the Gaussian kernel *gamma*. The *LogisticRegression* classifier was trained with a parameter search over *C* and the penalty *l*. The *RandomForestClassifier* was trained with a search over the number of maximum features and the *GradientBoostingClassifier* with a search over the learning rate and the maximum depth.

V. Results

A. Comparing course satisfaction and willingness to recommend the course

Adapting the NPS method [14], we divided the respondents to three groups based on their course satisfaction score (Fig. 3). Students scoring their course satisfaction as 9 or 10 were classified as satisfied (c.f., promoters in NPS), students scoring 7 or 8 were classified as neutrals (c.f., passives), and students scoring their course satisfaction as 6 or below were classified as dissatisfied (c.f., detractors). The distribution of the satisfaction scores is similar to other studies assessing experienced satisfaction towards a service or a product (e.g., [40]). The majority of the students were classified as neutrals ($n = 136; 46\%$). The second-largest group was the satisfied students ($n = 88; 30\%$), and a quarter of the students were classified as dissatisfied ($n = 69; 24\%$) based on their answers to the course satisfaction item.

To validate the aforementioned approach, we examined the relationship between the course satisfaction item (”How satisfied you were with the course? “) and the course recommendation item (”How probably would you recommend this course to a fellow student? “). A total of 47% of the respondents scored equal scores on both scales, and the mean difference between scores was 0.81 in the 0–10 scale. The association between items was measured using the Spearman's rank correlation coefficient ($\rho = 0.71$), which indicated a strong positive monotonic association (Fig. 2). It is worth noting that the items still measure different constructs. However, students scored the same or close to the same score in both items. While there was deviating individual responses, the results indicate that both items behaved similarly.

We examined the relationship between the reported course satisfaction and gender, because the previous literature [33] has identified that gender might affect the reported educational satisfaction. We did not find any statistically significant difference between the reported course satisfaction and gender ($Mdn = 8$ for both). However, the result has to be interpreted carefully because data contained only 23% of the responses by female students.

To further validate the categorization of the groups, we examined the open-ended answers of the student agency questionnaire about the experienced support and restrictions in the course. Table I presents the count data of the occurrences of the mentioned support and restrictions of learning in each satisfaction group. If a student wrote an answer in the questionnaire to the question about supporting aspects in the course, it was counted as one occurrence of support. Similarly, if a student wrote an answer to the question about experienced restrictions in the course, it was counted as a restriction of learning. Responses containing only statements like ”nothing“ and ”don't know“ were removed. The results showed that 50% of the satisfied students reported restrictions, which was less compared to the students in other groups. Also, students in the satisfied group reported more likely only support in the course (25% of the satisfied students) comparing to the other

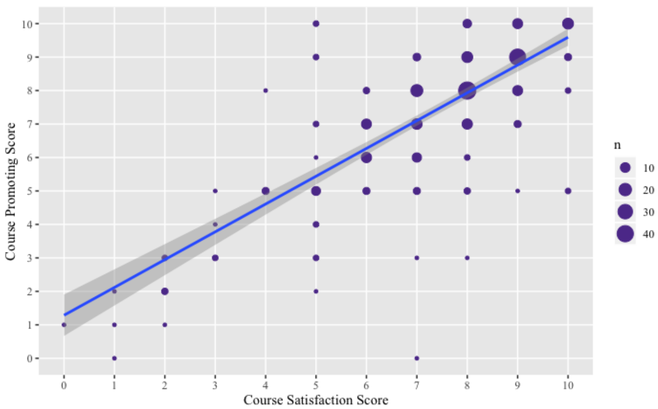

Fig. 2. Ordinal scatterplot and a regression line depicting the association of variables measuring students' assessed course satisfaction and willingness to recommend the course to a fellow student.

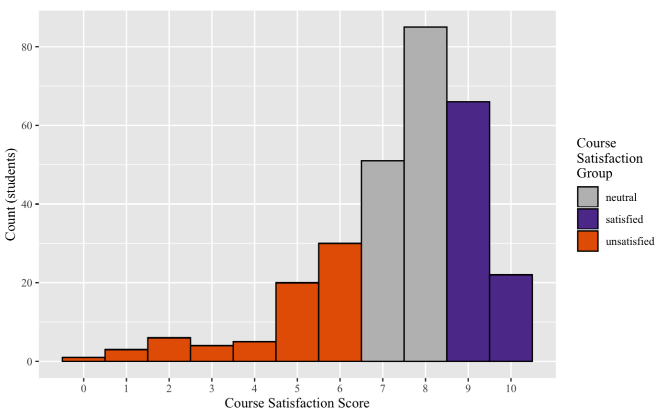

Fig. 3. Course satisfaction scores and division to neutral ($n = 136; 46\%$), satisfied ($n = 88; 30\%$), and dissatisfied ($n = 69; 24\%$) groups.

groups. Students classified as dissatisfied reported more often restrictions (75% of the dissatisfied students), and they were more likely to report only restrictive aspects (19%) comparing to students in other satisfaction groups. In general, satisfied students experienced more support, and dissatisfied students reported more likely restrictions. The result provides support for the categorization of the course satisfaction scale. However, further research is needed to get more insight into the student experiences and validation of the cut-off values.

TABLE I
OPEN-ENDED ANSWERS OF STUDENTS IN DIFFERENT SATISFACTION GROUPS

Answers reporting...	Dissatisfied	Neutral	Satisfied
support	58%	71%	68%
restrictions**	75%	60%	50%
only support***	1%	16%	25%
only restrictions*	19%	6%	7%
no answer	23%	24%	25%

Fisher's exact test for count data: $^{***}p < .001; ^{**}p \approx .005; ^{*}p \approx .011$

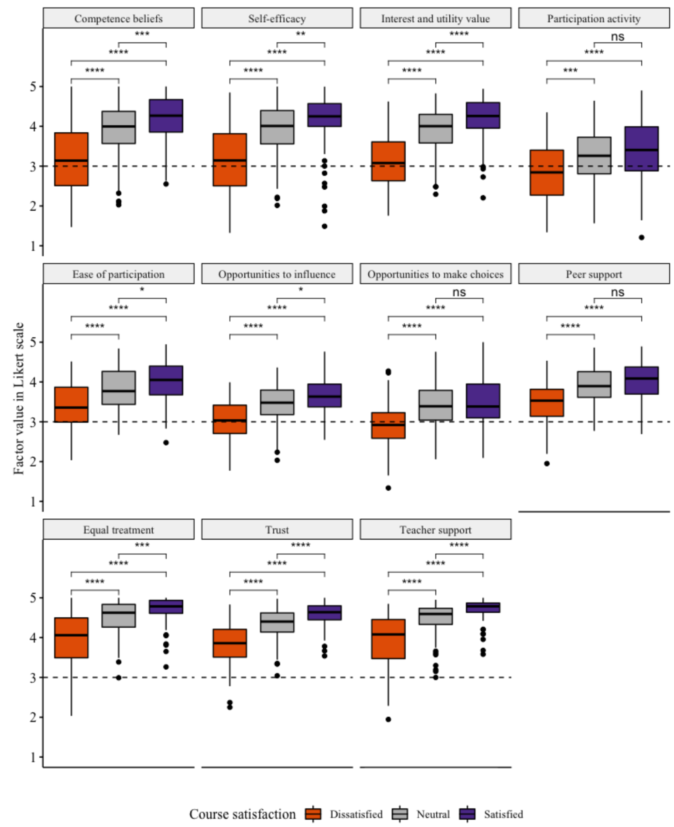

Fig. 4. Student agency in each course satisfaction category and pairwise statistical significance using Mann-Whitney U statistics.

B. Analysis of course satisfaction and student agency

We used the Kruskal-Wallis H test to determine if there were differences in the scores of the student agency dimensions between the three satisfaction category groups of students: the dissatisfied ($n = 69$), neutral ($n = 136$), and satisfied ($n = 88$). Distributions of student agency scores were similar for all course satisfaction groups, except in the dimensions of equal treatment, trust, and teacher support, as illustrated in the boxplots in Fig. 4. The medians of student agency scores were statistically significantly different between the course satisfaction groups in every dimension of student agency ($p < .001$). In general, students assessed the experienced resources of agency as lower in the lower satisfaction categories.

Kruskal-Wallis H can be used to evaluate the importance of different student agency dimensions in separating the course satisfaction categories [42], [43]. A high test statistic H indicates a strong separation of the medians, which in turn implies that the particular feature is more relevant in separating the different groups compared to features having lower test statistic score [42]. The order of the student agency dimensions concerning how strongly they separate the three satisfaction categories according to the H statistics is the following: teacher support ($H = 93$), trust for the teacher ($H = 90$), interest and utility value ($H = 82$), competence beliefs ($H = 63$), equal treatment ($H = 62$), self-efficacy

($H = 61$), opportunities to influence ($H = 52$), peer support ($H = 40$), ease of participation ($H = 39$), opportunities to make choices ($H = 37$), and participation activity ($H = 21$).

Subsequently, pairwise comparisons were performed using Mann-Whitney U statistics. The test can detect differences in the spread and shape of the distribution in addition to differences in medians, which can all be important features of the data [44]. Based on this post hoc test, the differences were statistically significant, as presented in Fig. 4, in all other cases except between satisfied and neutral categories in the dimension of participation activity, opportunities to make choices, and peer support.

In cases of equal treatment, trust for the teacher, and teacher support, the statistically significant differences might occur because of differences in the shape of the distributions. For example, satisfied categories in the dimensions mentioned above have small spread compared to other categories making them critical concerning course satisfaction: a slight decrease in the critical dimensions increases the chance of belonging to the lower satisfaction categories. In other dimensions of student agency where the difference was statistically significant, the difference can be characterized as a shift in location, which in turn can be described as a difference in medians [44]. In addition, we examined the relationship between gender and student agency dimensions and did not find any statistically significant differences.

C. Important factors contributing to course satisfaction

Finally, we predicted whether the students were satisfied with the course (i.e., belonged to the satisfied category). Traditional educational studies mostly use simple linear classifiers for predicting a categorical variable. However, many studies have shown that these are often outperformed by non-linear classifiers (see, e.g., [46]–[48]). To test which method works best for our data, we employed four popular classifiers: The traditional linear logistic regression (LR) and three non-linear classifiers, namely support vector machine (SVM) with Gaussian kernel, gradient boosting (GB), and random forest (RF), in comparison.

As input features, we utilized the eleven agency factors and gender. Gender was added as a control variable based on the previous literature (e.g., [33]). For all classifiers, we divided our data into training (80%) and test (20%) using a stratified split according to satisfaction category. We then used a five-fold cross-validation grid-search over the training data to determine the best parameters. As some classifiers are sensitive to unscaled data, we utilized min-max scaling to normalize the data into the range $[0, 1]$ (determining the scaling coefficients from the training set and applying them to the test set).

Similarly as in [49], we employed a pipeline on the training data chaining the different steps (preprocessing with and without scaling of data) and the five-fold grid-search over the different parameter settings together. The best combination (best preprocessing and best parameter settings) returned by the pipeline was then used to predict the dependent variable of the test set that was untouched the entire time during model training and metaparameter selection.

Table II summarizes for all classifiers the best preprocessing and best parameters from the cross-validated grid-search, and the performance on the test set. Figure 5 shows the receiver operating characteristic (ROC) curves [50] for the test sets for all classifiers with their best parameters. In Table II, the performance is summarized as area under the ROC curve (AUC) [51]. The AUC measures the area underneath the ROC curve and is equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one. When comparing different classifiers on average, a higher AUC value indicates better classification performance. As can be seen from the table and figure, random forest provided the best performance.

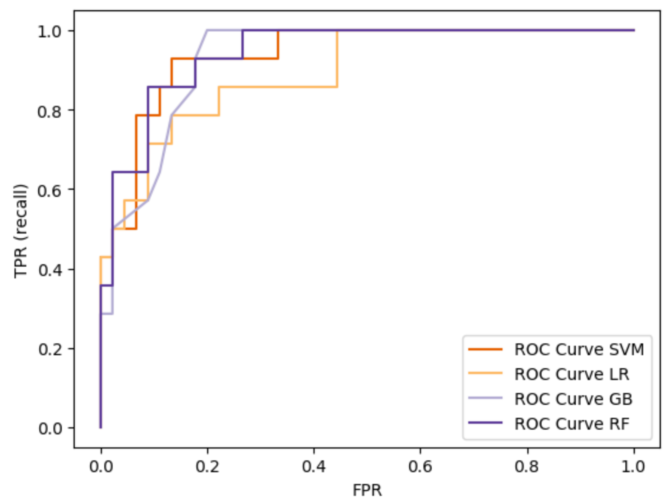

Fig. 5. ROC curves of the test set for the four classifiers predicting the satisfied category.

Figure 6 shows the feature importances for the best random forest model. Similar to results from Kruskall-Wallis H, the interest, trust, and teacher support student agency dimensions contributed the most, while the gender seemed less important when predicting the course satisfaction. Moreover, the dimensions of participatory resources in student agency were less important to predict the course satisfaction compared to the other resources of agency. Gender was the least important predictor of all features.

We also tried predicting the multinomial output (i.e., all three categories: dissatisfied, neutral, and satisfied) using the same input variables and classifiers as described above. However, as can be expected, the prediction performance for these multinominal classifiers was worse than for the binary ones. The random forest model performed again the best with a micro-averaged F1 score of 0.678, while support vector machines, logistic regression, and gradient boosting achieved micro-averaged F1 scores of less than 0.6. The feature importances of the best multinomial random forest classifier were very similar to the ones from the binary random forest model. Only the feature importances of teacher support and trust for

TABLE II
THE BEST PREPROCESSING AND PARAMETERS ON THE TRAINING SET AND PERFORMANCE (AUC) FOR THE TEST SET.

Classifier	**Best preprocessing**	**Best parameters**	**AUC**
Support vector machines	Min-max scaling	$'C' : 10, 'gamma' : 0.001, 'kernel' : rbf$	0.938
Logistic regression	Min-max scaling	$'C' : 100, 'penalty' : l2$	0.894
Gradient boosting	None	$'learning\_rate' : 0.01, 'max\_depth' : 1$	0.929
Random forest	None	$'max\_features' : 2$	0.943

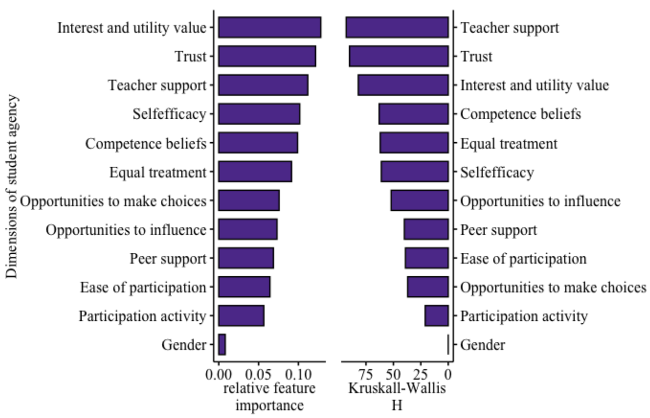

Fig. 6. Feature importances of the best random forest model predicting the satisfied category and the values of the Kruskall-Wallis H statistics in each dimensions of student agency depicting the separation of course satisfaction medians.

the teacher were reversed (i.e., teacher support was the second, and trust for the teacher was the third important variable).

VI. DISCUSSION

Positive experiences are fundamental in learning, and prior work has identified several issues having an impact on experienced satisfaction in learning situations. In engineering education, for example, Lynch et al. [30] found that interaction with the instructor, providing real-world connections, delivering meaningful content, advancing both problem-solving and group work, and promoting student motivation are among the factors influencing experienced course satisfaction. However, experienced satisfaction in learning is a complex phenomenon, and the significance of different factors affecting course satisfaction is not yet fully resolved. In this study, we examined how the various dimensions of student agency in engineering education contribute to student-reported course satisfaction.

With our first research question, we strived to find an adequate solution for measuring course satisfaction. Lacking the explicit guidance from the previous research literature for measuring course satisfaction, we devised an initial measuring scheme applied in this paper. Following Kleiss et al. [38], we opted to use a single Likert-type item on 0–10 scale. We then compared the answer scores between items measuring course satisfaction and willingness to recommend the course. Similarly to the previous studies [24], [25], we found out that the items had a positive correlation. Finally, we adapted the idea similar to NPS [14] to categorize the experienced course satisfaction into three categories (i.e., dissatisfied, neutral, satisfied) for further analysis. To answer the RQ1, we conclude that course satisfaction could be categorized similarly to customer satisfaction.

The second research question involved finding out the differences in the dimension of student agency between different satisfaction categories. Our findings indicate that dissatisfied students reported more often restrictive aspects, and satisfied students reported more often only supportive aspects in their learning. In general, the resources of student agency were experienced as lower in the lower satisfaction categories compared to more satisfied students in every dimension of student agency. To answer the RQ2, we conclude that there were significant differences in the dimensions of student agency between different course satisfaction categories. The results are consistent with a previous research, in which students with lower agency experiences reported a variety of restrictive aspects in their learning [52]. Contrary to the previous research suggesting that male students tend to give lower evaluations in an educational context [33] and similar to Leao et al. [34], we did not find any difference in satisfaction scores between the genders in the research sample.

The last research question aimed to find out what are the most important factors of student agency contributing to course satisfaction. By using training data, untouched test data, grid search, and different classifiers, we found out that random forest classifier was able to predict the satisfied category with a high AUC score. In general, all non-linear classifiers performed better than the linear logistic regression, which might be an indication of the complex and non-linear nature of course satisfaction. To answer the RQ3, we conclude that the three most important student agency dimensions of the model were interest and utility value, trust for the teacher, and teacher support. In terms of methodological triangulation [53], the same dimensions were identified in a slightly different order when using Kruskal-Wallis H statistics to quantify the separation between all three satisfaction categories. The results comply with the previous research that found teacher support to be one of the most influencing factors relating to satisfaction towards school and studying [6], [13]. The dimensions relating to participation (i.e., ease of participation, participation activity) were examples of the less important factors. Again, gender did not prove to have a noteworthy predictive power.

Most notably, our study highlights the differences in relevance among various factors and experiences affecting the perceived satisfaction in learning. Some factors (e.g., interest and utility value, self-efficacy) can be considered as *important*. However, some factors can be regarded as both important and *critical* (e.g., teacher support, trust for the teacher), which means that a small decrease in the critical factor can more likely cause a decline in experienced course satisfaction comparing to a non-critical factor. In the case of *less important* or unimportant factors, their predictive or separative power concerning course satisfaction is not significant (e.g., participation activity, gender).

A. Limitations and future work

Although student agency used in this study is a multidimensional construct, it is only one of the many possible constructs that could be used in examining the factors affecting course satisfaction. Future studies should aim to explore and analyze the important and especially the critical factors affecting course satisfaction in greater detail. The explorations should utilize a variety of different constructs from other points of view than student agency (e.g., approaches to learning [10], model of domain learning [54]).

Also, measuring and quantifying a complex phenomenon like course satisfaction is challenging. Our initial scheme for the measurement is a starting point and should be more thoroughly validated both quantitatively and qualitatively. Notably, the thresholds of the different satisfaction categories need to be carefully examined in future studies. Multinomial linear regression using the whole satisfaction scale would be one option in future research. Here the use of multinomial regression would have required more observations in the lower part of the satisfaction scale. Students' open-ended answers about support and restrictions in learning seem to yield relevant information about student agency, which should be investigated more in-depth using, for example, natural language processing techniques.

VII. Conclusion

In summary, we have examined the factors affecting course satisfaction in the context of engineering education by utilizing student agency analytics, exploratory statistics, and supervised machine learning. This study contributed to the measurement of course satisfaction and to the analysis of its underlying factors. The results provide evidence about the important, critical, and less important dimensions of student agency affecting experienced course satisfaction. From the dimensions of student agency, teacher support and trust for the teacher turned out to be both important and critical features, interest and utility value was important, and the dimensions relating to participation were less important with respect to the course satisfaction in engineering education. We expect the results to broaden the understanding of student agency and course satisfaction, and provide both educators and educational institutions capabilities to promote effective aspects of learning.

Practical implications of our study relate to the possibility of taking carefully into consideration especially the most important and critical factors affecting course satisfaction. Experienced satisfaction influences widely and positively students' learning [5], [6], and this might be worth to take into account throughout the educational system. A practical future application serving teachers could be, for example, a learning analytics system providing predictive information about course satisfaction in advance. Educational institutions also benefit from concentrating on the important aspects of course satisfaction as student satisfaction has a positive effect on students' willingness to promote their *alma mater* [25]. Finally, because of its relation to learning achievements [13], the course satisfaction is an important aspect in actionable learning analytics fulfilling the promises of "understanding and optimising learning and the environments in which it occurs" [55]. Finally, we hypothesize that if course satisfaction could be used as a proxy for learning outcomes and achievements, it might prove to be a valuable construct in various applications of learning analytics.

References

[1] K. M. Elliott and D. Shin, "Student satisfaction: An alternative approach to assessing this important concept," *Journal of Higher Education Policy and Management*, vol. 24, no. 2, pp. 197–209, 2002.

[2] R. Pekrun and L. Linnenbrink-Garcia, "Academic emotions and student engagement," in *Handbook of research on student engagement*, S. L. Christenson, A. L. Reschly, and C. Wylie, Eds. New York: Springer-Verlag, 2012, pp. 259–282.

[3] Y.-H. Su, "The constitution of agency in developing lifelong learning ability: The 'being'mode," *Higher Education*, vol. 62, no. 4, pp. 399–412, 2011.

[4] C. Kim and R. Pekrun, "Emotions and motivation in learning and performance," in *Handbook of Research on Educational Communications and Technology*, J. M. Spector, M. D. Merrill, J. Elen, and M. J. Bishop, Eds. New York, NY: Springer-Verlag New York, 2014, pp. 65–75.

[5] N. D. Aitken, "College student performance, satisfaction and retention: Specification and estimation of a structural model," *Journal of Higher Education*, vol. 53, no. 1, pp. 32–50, 1982.

[6] A. G. Danielsen, O. Samdal, J. Hetland, and B. Wold, "School-Related social support and students' perceived life satisfaction," *Journal of Educational Research*, vol. 102, no. 4, pp. 303–320, 2009.

[7] Y. Levy, "Comparing dropouts and persistence in e-learning courses," *Computers and Education*, vol. 48, no. 2, pp. 185–204, 2007.

[8] Y. Lee and J. Choi, "A structural equation model of predictors of online learning retention," *The Internet and Higher Education*, vol. 16, pp. 36–42, Jan. 2013.

[9] J. E. Edwards and L. K. Waters, "Involvement, ability, performance, and satisfaction as predictors of college attrition," *Educational and Psychological Measurement*, vol. 42, no. 4, pp. 1149–1152, 1982.

[10] M. Baeten, E. Kyndt, K. Struyven, and F. Dochy, "Using student-centred learning environments to stimulate deep approaches to learning: Factors encouraging or discouraging their effectiveness," *Educational Research Review*, vol. 5, no. 3, pp. 243–260, 2010.

[11] C. I. Damşa, P. A. Kirschner, J. E. B. Andriessen, G. Erkens, and P. H. M. Sins, "Shared epistemic agency: An empirical study of an emergent construct," *Journal of the Learning Sciences*, vol. 19, no. 2, pp. 143–186, 2010.

[12] P. Jääskelä, A.-M. Poikkeus, K. Vasalampi, U. M. Valleala, and H. Rasku-Puttonen, "Assessing agency of university students: validation of the aus scale," *Studies in Higher Education*, vol. 42, no. 11, pp. 2061–2079, 2017.

[13] M. Paechter, B. Maier, and D. Macher, "Students' expectations of, and experiences in e-learning: Their relation to learning achievements and course satisfaction," *Computers and Education*, vol. 54, no. 1, pp. 222–229, 2010.

[14] F. F. Reichheld, "The one number you need to grow," *Harvard Business Review*, vol. 81, no. 12, pp. 46–54, 124, 2003.

[15] P. Jääskelä, V. Heilala, T. Kärkkäinen, and P. Häkkinen, "Student agency analytics: learning analytics as a tool for analysing student agency in higher education," *Behaviour and Information Technology*, 2020.

[16] OECD, "Concept note: OECD learning compass 2030," 2019, accessed 2020-06-05. [Online]. Available: https://www.oecd.org/education/2030-project/teaching-and-learning/learning/learning-compass-2030/OECD_Learning_Compass_2030_concept_note.pdf

[17] J. Dunn, K. Salmela-Aro, V. Talreja, T. Abiko, N. Steinemann, C. Leadbeater, T. Bentley, A. Grayling, D. Kunin, N. Walt, A. Toutant, R. Allen, H. Haste, and P. Bishop, "Education 2030 - conceptual learning framework: Background papers," 2017, accessed 2020-06-05. [Online]. Available: https://www.oecd.org/education/2030-project/contact/Conceptual_learning_framework_Conceptual_papers.pdf

[18] OECD, "Conceptual learning framework: Student agency for 2030," 2019, accessed 2020-06-05. [Online]. Available: http://www.oecd.org/education/2030-project/teaching-and-learning/learning/student-agency/Student_Agency_for_2030_concept_note.pdf

[19] N. Ahmed, B. Kloot, and B. I. Collier-Reed, "Why students leave engineering and built environment programmes when they are academically eligible to continue," *European Journal of Engineering Education*, vol. 40, no. 2, pp. 128–144, Mar. 2015.

[20] M. M. Camacho, S. M. Lord, C. E. Brawner, and M. W. Ohland, "Climate in undergraduate engineering education from 1995 to 2009," in *2010 IEEE Frontiers in Education Conference (FIE)*, 2010, pp. T2H–1–T2H–6.

[21] M. Blackie, K. le Roux, and S. McKenna, "Possible futures for science and engineering education," *Higher Education*, vol. 71, no. 6, pp. 755–766, 2016.

[22] P. Jääskelä, K. Vasalampi, P. Häkkinen, A.-M. Poikkeus, and H. Rasku-Puttonen, "Students' agency experiences and perceived pedagogical quality in university courses," Paper presented at ECER 2017, 22 – 25 August, Copenhagen, Denmark, 2017.

[23] V. Zeithaml, L. Berry, and A. Parasuraman, "The nature and determination of customer expectation of service," *Journal of Marketing Sciene*, vol. 21, no. 1, pp. 1–12, 1993.

[24] B. A. Browne, D. O. Kaldenberg, W. G. Browne, and D. J. Brown, "Student as customer: Factors affecting satisfaction and assessments of institutional quality," *Journal of Marketing for Higher Education*, vol. 8, no. 3, pp. 1–14, 1998.

[25] Z. Mustafa, N. Basri, N. Z. Abidin, N. R. M. Suradi, Z. M. Ali, F. A. A. Shahabudin, and M. R. Ab Hamid, "Modeling of engineering student satisfaction," *Journal of Mathematics and Statistics*, vol. 8, no. 1, pp. 64–71, 2011.

[26] M. Komarraju, J. Swanson, and D. Nadler, "Increased career Self-Efficacy predicts college students' motivation, and course and major satisfaction," *Journal of Career Assessment*, vol. 22, no. 3, pp. 420–432, 2014.

[27] D. McFarland and D. Hamilton, "Factors affecting student performance and satisfaction: Online versus traditional course delivery," *Journal of Computer Information Systems*, vol. 46, no. 2, pp. 25–32, 2005.

[28] D. U. Bolliger, "Key factors for determining student satisfaction in online courses," *International Journal on E-learning*, vol. 3, no. 1, pp. 61–67, 2004.

[29] J. T. E. Richardson, J. B. Slater, and J. Wilson, "The national student survey: development, findings and implications," *Studies in Higher Education*, vol. 32, no. 5, pp. 557–580, 2007.

[30] P. Lynch, S. Sangelkar, G. Demeo, and B. Morkos, "The ICDM methodology improving undergraduate engineering student motivation, satisfaction, and performance," in *2017 IEEE Frontiers in Education Conference (FIE)*, 2017, pp. 1–7.

[31] A.-B. Gonzalez-Rogado, F. J. García-Peñalvo, M. Borham, S. Olmos-Migueláñez, and M. J. Rodríguez-Conde, "Key factors for determining student satisfaction in engineering: A regression study," *International Journal of Engineering Education*, vol. 30, no. 3, pp. 576–584, 2014.

[32] B. Kerr, "The flipped classroom in engineering education: A survey of the research," in *2015 International Conference on Interactive Collaborative Learning (ICL)*, 2015, pp. 815–818.

[33] C. N. Tatro, "Gender effects on student evaluations of faculty," *Journal of Research and Development in Education*, vol. 28, no. 3, pp. 169–173, 1995.

[34] C. P. Leão, F. Soares, A. Guedes, M. T. Sena Esteves, G. Alves, I. M. Brás Pereira, R. Hausmann, and C. A. Petry, "Is students' satisfaction in electrical engineering courses influenced by gender?" in *2017 International Conference on Engineering, Technology and Innovation (ICE/ITMC)*, 2017, pp. 1362–1369.

[35] Y. Fan, L. J. Shepherd, E. Slavich, D. Waters, M. Stone, R. Abel, and E. L. Johnston, "Gender and cultural bias in student evaluations: Why representation matters," *PLoS One*, vol. 14, no. 2, p. e0209749, 2019.

[36] C. K. Ross, C. A. Steward, and J. M. Sinacore, "A comparative study of seven measures of patient satisfaction," *Med. Care*, vol. 33, no. 4, pp. 392–406, 1995.

[37] O. Garin, "Ceiling effect," in *Encyclopedia of Quality of Life and Well-Being Research*, A. Michalos, Ed. Dordrecht: Springer Netherlands, 2014.

[38] I. I. M. Kleiss, J. T. P. Kortlever, P. Karyampudi, D. Ring, L. E. Brown, L. M. Reichel, M. D. Driscoll, and G. A. Vagner, "A comparison of 4 Single-Question measures of patient satisfaction," *Journal of Clinical Outcomes Management*, vol. 27, no. 1, pp. 41–48, 2020.

[39] N. A. Morgan and L. L. Rego, "The value of different customer satisfaction and loyalty metrics in predicting business performance," *Marketing Science*, vol. 25, no. 5, pp. 426–439, 2006.

[40] M. A. Laitinen, "Net promoter score as indicator of library customers' perception," *Journal of Library Administration*, vol. 58, no. 4, pp. 394–406, 2018.

[41] A. Vargha and H. D. Delaney, "The Kruskal-Wallis test and stochastic homogeneity," *Journal of Educational and Behavioral Statistics*, vol. 23, no. 2, pp. 170–192, 1998.

[42] A. Cord, C. Ambroise, and J.-P. Cocquerez, "Feature selection in robust clustering based on laplace mixture," *Pattern Recognition Letters*, vol. 27, no. 6, pp. 627–635, 2006.

[43] M. Saarela, J. Hämäläinen, and T. Kärkkäinen, "Feature ranking of large, robust, and weighted clustering result," in *Advances in Knowledge Discovery and Data Mining*, ser. Lecture Notes in Computer Science, J. Kim, K. Shim, L. Cao, J. G. Lee, X. Lin, and Y. S. Moon, Eds., vol. 10234. Cham: Springer, 2017, pp. 96–109.

[44] A. Hart, "Mann-Whitney test is not just a test of medians: differences in spread can be important," *BMJ*, vol. 323, no. 7309, pp. 391–393, 2001.

[45] R Core Team, *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria, 2019. [Online]. Available: https://www.R-project.org/

[46] D. C. Gibson and D. Ifenthaler, "Preparing the next generation of education researchers for big data in higher education," in *Big Data and Learning Analytics in Higher Education: Current Theory and Practice*, B. Kei Daniel, Ed. Cham: Springer, 2017, pp. 29–42.

[47] R. Al-Shabandar, A. Hussain, A. Laws, R. Keight, J. Lunn, and N. Radi, "Machine learning approaches to predict learning outcomes in massive open online courses," in *2017 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2017, pp. 713–720.

[48] M. Saarela and T. Kärkkäinen, "Can we automate expert-based journal rankings? analysis of the finnish publication indicator," *Journal of Informetrics*, vol. 14, no. 2, p. 101008, 2020.

[49] M. Saarela, O.-P. Ryynänen, and S. Äyrämö, "Predicting hospital associated disability from imbalanced data using supervised learning," *Artificial Intelligence in Medicine*, vol. 95, pp. 88 – 95, 2019.

[50] T. Fawcett, "An introduction to ROC analysis," *Pattern Recognition Letters*, vol. 27, no. 8, pp. 861 – 874, 2006.

[51] A. P. Bradley, "The use of the area under the ROC curve in the evaluation of machine learning algorithms," *Pattern Recognition*, vol. 30, no. 7, pp. 1145–1159, 1997.

[52] V. Heilala, P. Jääskelä, T. Kärkkäinen, and M. Saarela, "Understanding the study experiences of students in low agency profile: Towards a smart education approach," in *Advances in Smart Technologies Applications and Case Studies*, A. El Moussati, K. Kpalma, M. Ghaouth Belkasmi, M. Saber, and S. Guégan, Eds. New York, NY: Springer, in press.

[53] N. K. Denzin, *The Research Act: A Theoretical Introduction to Sociological Methods*, 2nd ed. New York: McGraw-Hill, 1978.

[54] P. A. Alexander, "The development of expertise: The journey from acclimation to proficiency," *Educational Researcher*, vol. 32, no. 8, pp. 10–14, 2003.

[55] G. Conole, D. Gašević, P. Long, and G. Siemens, "Message from the LAK 2011 general & program chairs," in *Proceedings of the 1st International Conference on Learning Analytics and Knowledge*. New York, NY: ACM, 2011.