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Modelling and Managing Learner Satisfaction: Use of Learner Feedback to Enhance Blended and Online Learning Experience

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ABSTRACT

A key concern for most institutions and instructors is whether students are satisfied with their learning experience. However, relatively few studies have unpacked what the key drivers for learner satisfaction are in blended and online courses. Using logistical regression modelling, learner satisfaction data of 62,986 learners in 401 undergraduate blended and online modules was analyzed. The data included over 200 potential explanatory variables based on learner and module learning design characteristics. Findings indicate that learning design has a strong and significant impact on overall satisfaction for both new and continuing learners. Learners who are more satisfied with the quality of teaching materials, assessment strategies, and workload are more satisfied with the overall learning experience. Furthermore, long-term goals of learners (i.e., qualifications and relevance of modules with learners' professional careers) are important predictors of learner satisfaction. Individual learner characteristics are mostly insignificant, indicating that despite a wide diversity of learners studying at the Open University, UK, the underlying learning experiences are similar. Future research should focus on how learning design changes can enhance the learning experiences of students.

Subject Areas: learning analytics, learning design, learner satisfaction, logistical regression modelling, online learning.

INTRODUCTION

As the number of learners taking e-learning, distance learning, online learning courses and MOOCs across the globe reach unprecedented levels (Johnson, Adams Becker, Estrada, & Freeman, 2015; Sharples et al., 2014), there is an opportunity for researchers and senior administrators to benefit from learning analytics and learning science approaches to understand and unpack the complex dynamics of learning. As argued by Tempelaar, Rienties, and Giesbers (2015, p. 157), "learning

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analytics provide institutions with opportunities to support learner progression and to enable personalized, rich learning."

A key concern for most post-secondary institutions and instructors is whether students, or learners in general, are satisfied with their learning experience (Kember & Ginns, 2012; Marsh, 1982; Onwuegbuzie et al., 2007). Besides the obvious long-term advantages of having "satisfied customers" who are more likely to return for follow-up education or who share their positive experiences with peers (Gu, Schweisfurth, & Day, 2010), an increasing number of institutions are using student evaluation instruments to monitor and improve the teaching and learning experience (Arbaugh, 2014; Eom, Wen, & Ashill, 2006; Rienties, 2014). In particular, in the United Kingdom (UK) student evaluation scores are important as higher educational institutions are ranked every year based upon learner satisfaction surveys, as measured by the National Student Survey (Ashby, Richardson, & Woodley, 2011; Callender, Ramsden, & Griggs, 2014). Substantial financial and reputational rewards can be reaped when post-secondary institutions listen and act upon what students say to improve their teaching and learning experience.

The analysis of learner satisfaction surveys allows teachers and managers to search for unobserved patterns and underlying information in learning processes (Gasevic, Rosé, Siemens, Wolff, & Zdrahal, 2014; Rienties, 2014). In a recent important study measuring which factors predicted learner satisfaction and academic performance amongst 48 MBA online and blended learning modules in the United States, Arbaugh (2014) found that learners' behavior, as measured by social presence, predicted learner satisfaction and academic performance. In contrast, the technological environment used in these 48 modules did not significantly predict learners' learning experience and performance. Arbaugh (2014, p. 352) therefore argued that "a resource-strapped business school may get the most 'bang for its buck' by allocating resources towards developing instructors when contemplating how best to support its online and blended offerings."

Rienties, Toetenel, and Bryan (2015) built on the study by Arbaugh, comparing 40 learning designs at the Open University UK (OU) which were linked with learner behavior in the Learning Management System (LMS), learner satisfaction, and academic performance. They found that the way in which instructors designed online courses significantly influenced how learners engaged in the LMS over time. Furthermore, and particularly important for this special issue, the learning design of online modules significantly impacted learner satisfaction, whereby online modules with strong content focus were rated significantly higher by learners than online modules with a strong learner-centered focus, particularly with regard to activities requiring communication between peers and interactivity .

By linking large data sets across a range of over modules in online and blended learning settings, both studies (Arbaugh, 2014; Rienties et al., 2015b) point to the important notion, often ignored in educational science, that in analyzing the impact of learning design on learner satisfaction and academic performance across a range of modules, a cross-sectional study may provide crucial (generalizable) insights beyond the specific research findings within a single module or discipline. At the same time, a limitation of the study of Arbaugh (2014) is the exclusive focus on MBA modules at one institution, which may limit generalizations of the findings to other disciplines. Similarly, our own study comparing 40 learning designs across the OU consisted of only a snapshot of modules per discipline and level, thereby again potentially limiting generalizability of the findings.

This study builds on the two prior studies but focuses on a substantially larger and wider spread of modules at different levels and disciplines. By analyzing 62,986 learners' satisfaction in a total of 401 undergraduate blended and online modules, a holistic perspective of learner satisfaction will be provided, thereby enhancing the generalizability of our findings. In line with principles of learning analytics, by taking into consideration both the learning design characteristics of the 401 modules and individual learner characteristics (e.g., demographics, prior education, socio-economic status) using logistical regression modeling the research question what are the key drivers of learner satisfaction is examined.

ONLINE LEARNER SATISFACTION

The measurement of learner satisfaction is important to higher education institutions to help them pinpoint their strengths and identify areas for improvement (Eom et al., 2006; Kember & Ginns, 2012; Marsh, 1982; Zerihun, Beishuizen, & Os, 2012). Most institutions in the United States and United Kingdom systematically collect learner satisfaction and academic performance data which can be considered to reflect key learning outcomes (Baldwin & Blattner, 2003; Kember & Ginns, 2012; Rienties, 2014). Learner performance refers to the percentage of learners who pass a module or qualification, whilst learner satisfaction refers to how learners rate their experience at the end of a module or qualification.

According to Baldwin and Blattner (2003), learner evaluation results were historically only used to improve teaching and learning. Over the years, a range of standardized student evaluation instruments have been developed, such as the Course Experience Questionnaire (Ramsden, 1991), National Student Survey (Ashby et al., 2011; Callender et al., 2014), and Students' Evaluations of Educational Quality questionnaire (Marsh, 1982). The increased availability of learning evaluation instruments and results has, in particular, provided management with greater opportunity to compare academics across-the-board regarding 'teacher effectiveness' with regard to tenure decisions (Baldwin & Blattner, 2003).

While the use of learner satisfaction surveys is common practice in many universities, there remain several critics of the appropriateness of these questionnaires (Baldwin & Blattner, 2003; Moskal, Stein, & Golding, 2015; Titus, 2008). For example, a recent study by Rienties (2014) indicated that the vast majority of academics were resistant to change in the method of learner satisfaction evaluations, despite the fact that change led to three times more qualitative feedback and the faster turn-around of feedback. Underlying this resistance was concern that learner satisfaction results were used by management primarily in making tenure purposes, rather than for making improvements in learning design (Rienties, 2014; Rienties, Li, & Marsh, 2015a). Other scholars question whether questionnaire instruments can reliably assess learning experience. For example, Titus (2008) found that learners primarily filled in questionnaires based upon their emotional reaction to a 'good experience' (friendliness and helpfulness of instructor, enthusiasm of the instructor, etc.).

According to a large-scale review of common learner satisfaction instruments by Onwuegbuzie et al. (2007), elements such as whether teachers are learner-centered, experts, and/or "connectors" are typically not explicitly incorporated into learner evaluations of instruction. A limitation of most learner survey instruments is the lack of focus on key elements of rich learning, such as interaction, assessment, and feedback. For example, Zerihun et al. (2012) argued that most learner satisfaction instruments are teacher-centered, focusing on what the instructor does in the learning environment, rather than what learners actually do, how they engage, and whether learning occurred. In addition, learner satisfaction and performance tend to be reviewed as independent outcomes with little consideration of what drives the outcomes and, in particular, whether their key drivers are interrelated (which is the focus of this article). In the next section, the literature on how learner satisfaction has been linked with the way instructors design and implement online learning environments is reviewed.

Learning Design and Learner Satisfaction

Over the last twenty years, a range of pedagogical approaches and learning designs have been suggested to improve the experience of learners in higher education as well as their achievement (Conole, 2012). Few pedagogical approaches have been robustly analyzed to ascertain whether they actually lead to consistent learning designs that enrich and improve learner outcomes (Arbaugh, 2014; Conole, 2012; Rienties et al., 2015b). Conole (2012, p. 121) described learning design as "a methodology for enabling teachers and or designers to make more informed decisions in how they go about designing learning activities and interventions, which is pedagogically informed and makes effective use of appropriate resources and technologies." Learning design data is not typically captured in a comprehensive or systematic way at most institutions, although several universities in the USA have recently adopted the Quality Matters (QM) framework (https://www.qualitymatters.org/, see also Swan, Matthews, Bogle, Boles, & Day, 2012). However, combining (proxies of) learning design data with learner outcome data may lead to crucial insights into how learning design choices made by instructors influence learner satisfaction.

Several recent studies have tried to close the loop in terms of linking learner satisfaction to actual learning behavior and outcomes. Learning analytics data from LMS may be a potential treasure trove for educational researchers, such as data on clicking behavior, posts in discussion forums, or the viewing frequency of videolectures (Rienties et al., 2015b; Tempelaar et al., 2015). For example, Siemens, Dawson, and Lynch (2013) suggested that in addition to LMS data, data collected as learners are undertaking authentic learning tasks need to be included to represent the complexity of education. However, a recent longitudinal study of over 100 learning process variables and over 900 learners following a blended mathematics course that included 40 different proxies of LMS behavior indicated that LMS behavior only predicted 10–15% of explained variance (Tempelaar et al., 2015). In other words, simple proxies of learning activities may only explain a limited amount of "real" learning and learning satisfaction in particular.

Using a structural equation model of 397 learners in the US in an online course, Eom et al. (2006) found that learner satisfaction was a significant predictor of learning outcomes. Similarly, in an online MBA program consisting of 43 modules and involving 659 students, Marks, Sibley, and Arbaugh (2005) found that learning experience was significantly impacted by instructor-student interaction, followed by student-student interaction and student-content interaction. In another survey-study of 16 e-learning courses in Taiwan with 295 participants, Sun, Tsai, Finger, Chen, and Yeh (2008) found that six dimensions influenced learning satisfaction, namely learner, institution, course, technology, design and environment. As indicated by Rienties et al. (2012), an analysis of 117 learning designs of blended and online remedial education indicated that course discipline significantly influenced how teachers designed courses and which combination of pedagogical approaches and technologies were used. A recently developed predictive model at the OU for assessing which students will still be present at particular fee liability points by Calvert (2014) indicated that several student characteristics (e.g., socio-economic, disability, previous education), student progression (e.g., number of credits obtained, false starts), the types of modules studied (e.g., length, duration), and the qualification being sought significantly influenced student retention.

Building on the above research on learner satisfaction, learning design, and the availability of data sets on learner characteristics and learning designs at the OU, Rienties et al. (2015a), in a review for the Quality Assurance Agency, identified seven theoretical blocks of core constructs that may have an impact on overall learner satisfaction at the OU. This article extends the theoretical relevance of the model and adapts (Figure 1): In particular, while several of the above studies rely primarily on self-reported data, we were keen to include independently measured data about learner characteristics and module design. Two blocks are specifically related to learning design, while four blocks are related to characteristics of learners, such as (previous/current) educational progress, demographics and concurrency. Each block is now discussed.

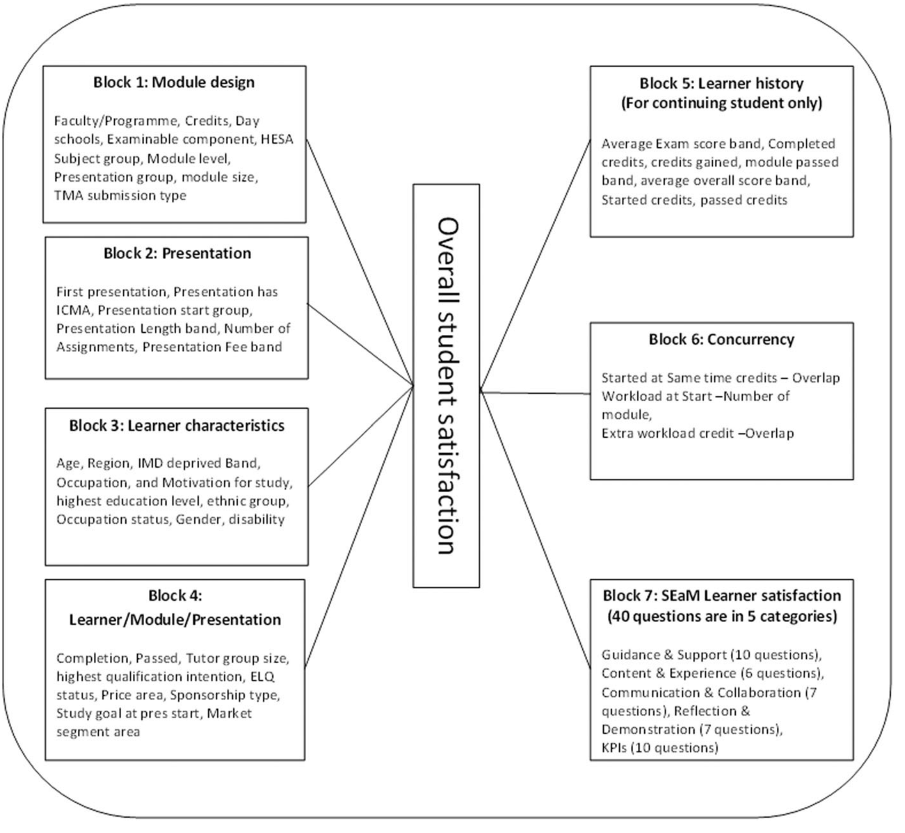
Block 1 Module Design

A vast body of research has found that module design and the role of the instructor are essential in creating a good learning experience (Arbaugh, 2014; Arbaugh & Duray, 2002; Eom et al., 2006; Marks et al., 2005; Sun et al., 2008). Furthermore, recent findings indicate that learning design is influenced by its disciplinary context (Conole, 2012; Marks et al., 2005; Rienties et al., 2012) and organizational culture (Rubin & Fernandes, 2013). In particular, course structure and specific learning design elements such as the types and frequency of assessment (Eom et al., 2006; Richardson, 2013; Sun et al., 2008), the duration of the module (Calvert, 2014), the level of the taught module (Toetenel & Rienties, 2016), and module size in terms of number of learners enrolled has been previously found to have an influence on learning satisfaction.

Block 2 Presentation

A particular feature of many online and distance education programs is that a module is presented at several time points during the year (Hess & Saxberg, 2013). Although the overall blue-print of the respective module will be the same, instructors at the OU make subtle changes (e.g., timing of online assessments,

Figure 1: Selected variables for modelling each block.



question items) in learning design from presentation to presentation. Similarly, the composition of the tutors that support groups of learners will most likely be slightly different. Consistent with Arbaugh (2014), beyond the overall module design it is important to take into consideration any subtle alterations in learning design and support in the particular presentation of a module.

Block 3 Learner Characteristics

Several studies seem to indicate that demographic and socio-economic factors nested within learners may have an impact on learning. These include previous educational experience (Calvert, 2014; Tempelaar et al., 2015), gender (Arbaugh, 2014; Arbaugh & Duray, 2002; Herman, 2014), age (Arbaugh & Duray, 2002; Ke & Xie, 2009), social-economic status (Calvert, 2014), and employment status (Littlejohn & Margaryan, 2014). At the same time, several studies indicate that demographic factors including gender and age have a limited or no significant influence on learner satisfaction (Arbaugh, 2014; Marks et al., 2005). Furthermore, the motivation to study may be an important factor in learning and learning satisfaction in particular. Controlling for individual learner characteristics may therefore be essential for understanding and unpacking the factors that drive learning satisfaction.

Block 4 Learner/Module/Presentation

Beyond the relatively stable individual learner characteristics described in block 3, the OU collects specific data about each learner for each module and presentation available. For example, academic retention and completion (Marks et al., 2005), study goals at the start of the presentation (Eom et al., 2006), price area, Equivalent or Lower Qualification (ELQ) status, and whether the tuition fee is sponsored or not (Calvert, 2014) may influence learners' perceptions about their learning experience.

Block 5 Learner History

It is important to recognize that there may be substantial differences in learning experiences between learners who start an online course for the first time and those who have been studying online at a particular institution for some time (Arbaugh, 2014; Arbaugh & Duray, 2002). Previous research has found that continuing learners may have developed learning and coping mechanisms for 'surviving' in online learning environments (Arbaugh, 2014; Calvert, 2014), while new learners might still need to adjust their learning approach to a new learning context. Several recent predictive learning analytics models seem to indicate that previous educational experiences in particular (Calvert, 2014; Tempelaar et al., 2015) are good proxies for successful learning. Another reason for distinguishing new from continuing learners is that continuing learners may be more sensitive to (changes in) learning design choices for the next module they follow, as they have developed coping mechanisms based upon previous learning design experience. In particular, successful completion of (parts of) modules and gaining credit will have an impact on these coping mechanisms (Calvert, 2014), but at the same time might influence learners' perceptions about the learning design of a particular module. It is therefore important to distinguish between the learner satisfaction of new distance learners from that of learners who have been studying at a distance for several modules already.

Block 6 Concurrency

Given that most distance learners study part-time, there is considerable lexibility in the number of modules and credits that can be followed at any point in time (Arbaugh & Duray, 2002; Calvert, 2014; Eom et al., 2006; Sun et al., 2008). While some learners may be able to study various modules at the same time, for other learners the concurrence of multiple modules might actually hamper their overall learning progress and learner satisfaction (Calvert, 2014). Furthermore, some modules may have substantial learning synergies (e.g., similar disciplinary focus) or compatible assessment deadlines (e.g., assignment 1 in week 4 for module 1, week 4 for module 2), while for other modules it may be more difficult to manage time effectively.

Block 7 SEaM Learner Satisfaction

Overall learner satisfaction might be influenced by factors included in the learner satisfaction survey. In the past thirty years, the OU has consistently collected learner feedback to further improve the learning experience and learning designs. Consistent with other learner satisfaction instruments (Marsh, 1982; Onwuegbuzie et al., 2007; Zerihun et al., 2012), the Student Experience on a Module (SEaM) questionnaire is implemented at the OU. The Student Experience on a Module Survey (SEaM) institutional survey was introduced in 2012/13 and combined two previous surveys using a census approach, thereby inviting all learners on all modules to participate. It consists of a total of 40 questions in three themed sets, (1) the module overall (10 items), (2) teaching, learning and assessment (14 items), and (3) feedback on the tutor (16 items).

Research Question

Although most postsecondary institutions across the globe collect learner satisfaction data, few institutions have such rich data sets on learners and learning design as the OU. By taking into consideration the seven blocks of learner and learning design characteristics of 401 undergraduate modules and individual learner characteristics ($n = 62{,}986$) using logistical regression modeling of 200 potential explanatory, we aim to unpack what the key drivers are for learner satisfaction.

The purpose of the analysis is to identify which aspects of the learning experience are most associated with overall expressions of satisfaction. In particular, we are interested in exploring whether satisfaction with learning design is more important than module and learner characteristics, and whether new learners differ in their experiences from those who already have experience with online learning. Identification of the key factors of the learning experience that are most closely related to satisfaction with learning design provides a clear evidence base for action.

METHODOLOGY

The study took place at the OU which is the largest higher education provider of online distance education in Europe. Unlike 'traditional' universities, the OU does not restrict enrolment on the basis of previous attainment, thereby resulting in a widely varied learner population (Calvert, 2014; Richardson, 2013). Given its size, a large amount of learner satisfaction data is collected at the OU amongst its 200,000 learners. This study explores the construct of learner satisfaction based on data collected via the SEAM questionnaire. Learners were sent an invitation to participate two to three weeks before the end of a module. The surveyed learners were those on the presentations that ended between August 1st, 2013 and July 31st, 2014 and thus had results available by August 13th, 2014. All learners regardless of their completion status were included (i.e., to control for non-response bias).

Dependent Variable (Target Variable)

Consistent with Sun et al. (2008), one dependent variable was used in the study, overall learner satisfaction ('Overall, I am satisfied with the quality of this module'). The variable was coded as a binary variable; Satisfied *(*Definitely agree/agree*)* was coded as 1 and unsatisfied *(*Definitely disagree/disagree/Neither agree nor disagree*)* was coded 0.

Independent Variables (Predictors)

Given the flexibility of OU study, learners from various backgrounds can choose very different paths and approaches for studying (Ashby et al., 2011; Calvert, 2014; Richardson, 2013). A large amount of information (>200 variables) related to studying at the OU was available, all of which could be potential predictors of overall learner satisfaction. The variables were split into the seven blocks described earlier.

Data Analysis

The SAS Enterprise Guide 4.3 and SAS Enterprise Miner 6.2 software packages were used for data interrogation and analysis respectively. The data was cleaned for missing values and outliers. Missing values were an issue mainly for the survey questions. Where data was missing, it was identified as a valid category for the survey questions and included in the analysis. Each block of selected variables was modeled in groups for each model. A comprehensive descriptive analysis was conducted to discount variables that were unsuitable for satisfaction modeling. Potential multicollinearity was investigated and any highly correlated predictors were identified. The most appropriate variables were methodically selected in based on (exploratory and confirmatory) factor analyses (see the Appendix PAF OUTPUT) and key driver analysis. Variables that were statistically significant from each block were then combined and modeled to identify key predictors in the final model of learner satisfaction.

Consistent with previous studies (Agresti, 1996; Hosmer & Lemeshow, 2004), logistic regression analysis was used to measure the degree of influence of the seven blocks of predictors on learner satisfaction. The stepwise regression model procedure was applied to each block, and validation misclassification was used as the selection criterion when evaluating the step with the most optimum model solution. Stepwise selection begins with sequentially adding the independent variables with the smallest p-value below the entry cut-off ($p < 0.05$). All included variables were evaluated based on the statistical significance criteria. The sequence terminated when all remaining variables had a p-value lower than the pre-determined cut-off. The stepwise regression was conducted for all seven blocks to limit the number of variables in the final model. Logistic regression coefficients were interpreted by transforming the logit into an odds ratio (Borenstein, Hedges, Higgins, & Rothstein, 2009; Konstantopoulos, 2008). The odds ratio is the change in the odds of the outcome occurring. Multiple solutions were tested within each block, so the fits of the logistic regression models were assessed using the SAS Miner model comparison node with Kolmogorov-Smirnov Goodness-of-Fit Tests. Two final models for predicting overall learner satisfaction were obtained for continuing and new learners respectively.

Table 1: Predicting undergraduate continuing learners' overall learner satisfaction: results from logistic regression analysis (in order of magnitude)

	DF	Wald x2	*P**	Odds Ratio Estimates (Definitely disagree vs. Definitely agree)
Q34 Teaching materials	4	864.465	<0.001	0.014
Q36 Assessment	5	224.998	<0.001	0.136
Q13 Qualification aim	5	114.658	<0.001	0.296
Q5 Integration of materials	5	89.979	<0.001	0.308
Q3 Advice & guidance	5	66.488	<0.001	0.331
Q14 Career relevance	5	38.702	<0.001	0.544
Q23 Tutor knowledge	5	38.167	<0.001	0.530
Q9 Assignment instructions	5	37.591	<0.001	1.008
Q11 Assignment completion	5	36.198	<0.001	0.669
Q35 Workload	5	31.396	<0.001	0.478
Q6 Method of delivery	5	24.196	<0.001	0.678
Module credits (10 vs. 60)	4	17.370	<0.01	1.878
Module level (Level 1 vs. others)	4	11.946	<0.05	0.854
Module exam component (Portfolio vs. others)	5	11.423	<0.05	0.411
% of planned module life cycle (25% less vs. others)	4	10.603	<0.05	0.726

**Significant at the p <.05 level.*

RESULTS

Undergraduate Continuing Learner Satisfaction Modelling

The results in (Table 1): indicate that for undergraduate continuing learners, satisfaction with the *teaching materials* (Q34) provided on the module is the most important driver of overall satisfaction. Learners who were less happy with the quality of teaching materials were 99% less likely to be satisfied with the overall quality of the module compared to those who had positive feedback, the difference being significant ($p < 0.001$). Learners' satisfaction with the *assessment on modules studied* (Q36) was the second most important driver of overall learner satisfaction. Learners who reported dissatisfaction with their assessment were 86% less likely to have positive overall learner satisfaction than those who had a more positive experience of assessment.

The results also suggest that learners were 70% less likely to have positive overall learner satisfaction if *the modules they studied did not contribute to the achievement of their wider qualification aim* (Q13). Furthermore, satisfaction with *advice and guidance provided for studies on modules* (Q3), and *the career relevance of knowledge and skills developed through studies* (Q14) were also among the top 6 important drivers of overall learner satisfaction. Other factors such as *helpfulness of tutor knowledge* (Q23)*, clear assignment instructions* (Q9) *completion of assignment* (Q11)*, workload* (Q35) *and method of delivery of teaching materials and learning activities* (Q6) were all important drivers of overall satisfaction. This shows that learning design related factors have a significant impact on learners' overall satisfaction above and beyond learner or module related characteristics. Furthermore, improvement in learning design will help increase overall learner satisfaction.

As indicated at the bottom of (Table 1): only a few module characteristics had a significant impact on overall learner satisfaction. These included *module level, credits and exam component,* and *progress of their planned life cycle*. Learners studying relatively short 10 credit modules were twice as likely to be satisfied with their learning compared to those studying for long and intensive 60 credit modules. Learners studying at level one (i.e., year 1) were 15% less likely to be satisfied than their counterparts studying at other undergraduate levels. Learners on modules that had portfolios as an examinable component were 59% less likely to have positive overall learner satisfaction than those on modules with exams and projects. Learners on newly developed modules, especially those on modules that were less than 25% of the way through the planned module life cycle, were 27% less likely to be satisfied with their overall learning experience. These variables have a significant impact on overall learner satisfaction. However, their importance was less pertinent than other learning design related variables.

Interestingly, none of the learners' characteristics (e.g., gender, age, ethnicity, prior education) had an impact on overall learner satisfaction once learning design was included in the modeling. This indicates that no matter what the OU learner's background, their overall learner satisfaction was mainly driven by module design and learning experience. These findings imply that a well-designed module may help to increase online learners' learner satisfaction regardless of the cohort background in terms of demographics and previous learning experience.

Undergraduate New Learner Satisfaction Modelling

Although individual learner characteristics did not significantly influence learner satisfaction amongst learners who already had experience studying at the OU, it is important to investigate whether any individual factors influence learner satisfaction amongst new learners who have just started studying for an online degree. The number of significant predictors in (Table 2): was smaller than for continuing learners as reported in (Table 1): but similar patterns were found. The results indicated that a number of predictors contributed to overall learner satisfaction. The most significant predictors of overall learner satisfaction were dominated by the SEaM survey questions for new learners. Learners who were less satisfied with *Teaching materials* (Q34) were significantly less likely to be satisfied with overall learning compared with their counterparts with a more positive perception. Those who were unhappy with their *Assessment* (Q36), the *Advice & Guidance* (Q3) provided on modules they studied, or *Integration of Materials* (Q5) were less likely to be satisfied with overall learning. Furthermore, *Career Relevance* (Q14) and the

Table 2: Predicting new undergraduate overall learner satisfaction: results from logistic regression analysis (in order of magnitude)

	DF	Wald x2	p^*	Odds Ratio Estimates (Definitely disagree vs. Definitely agree)
Q34 Teaching materials	4	102.629	<0.001	0.014
Q36 Assessment	4	46.398	<0.001	0.061
Q3 Advice & guidance	4	34.982	<0.001	0.190
Q5 Integration of materials	4	27.803	<0.001	0.373
Q14 Career relevance	5	20.647	<0.001	0.985
Q13 Qualification aim	5	17.521	<0.05	0.143
Age (Over 60s vs. Under 21)	5	15.188	<0.001	0.303

*Significant at the $p < 0.05$ level.

relevance of the module towards *Qualification Aim* (Q13) also had an impact on learners' overall learner satisfaction.

In contrast to undergraduate continuing learners, module characteristics did not have a significant impact on overall learner satisfaction, as none of the variables related to module characteristics appeared to be significant predictors. The only difference in the predictors for the new learner model compared to the continuing learner model was *age*, which was the only predictor related to learners' characteristics. Overall, the predictors were closely linked to the learning design of modules, suggesting again that learner satisfaction with learning design is a better driver of overall satisfaction than the characteristics of modules, presentations, and learners. Consistent with previous research (Arbaugh, 2014), a better module learning design may therefore help to improve overall learner satisfaction.

DISCUSSION AND IMPLICATIONS

For most institutions and instructors around the globe, whether their students are satisfied with their learning experience is a key concern (Kember & Ginns, 2012; Moskal et al., 2015; Onwuegbuzie et al., 2007). In a competitive, global educational market place, having satisfied 'customers' is a key component of sustainable strategies for post-secondary institutions to keep investing and developing their teaching and learning practices. This study analyzed the learner satisfaction experiences of 62,986 learners following 401 undergraduate blended and online modules at the largest university in Europe. Consistent with learning analytics approaches (Gasevic et al., 2014; Rienties et al., 2015b; Siemens et al., 2013; Tempelaar et al., 2015), it has unpacked the key drivers of learner satisfaction by linking various data sets on seven blocks of learning design and learner characteristics.

Over the last twenty years, a range of pedagogical approaches and learning designs have been implemented to improve the experience of online and blended learners (Arbaugh, 2014; Conole, 2012; Eom et al., 2006; Marks et al., 2005; Swan et al., 2012). Few pedagogical approaches have been robustly analyzed to ascertain whether they actually lead to consistent learning designs that enrich and improve learner satisfaction (Arbaugh, 2014; Rienties et al., 2015b). Building on these studies, the current study compared the learner satisfaction of learners who started an online course for the first time, and those who had been studying online for some time, and who may have developed learning and coping mechanisms for 'surviving' in online learning environments. This represents an important addition to the research on learning satisfaction, as most studies have focused on students who have successfully completed several courses. As indicated by the analysis, new students have substantially different learning experiences than students who have already successfully passed several courses. In a competitive higher education market in which it is essential to retain existing customers but also attract new customers, the analysis indicates that higher educational institutions may need to use differentiation strategies to satisfy the needs of new and existing online learners.

Our first and most important finding is that our proxies for learning design had a strong and significant impact on overall satisfaction for both new and continuing learners. Learners who were more satisfied with the quality of teaching materials, assessment strategies, and workload were significantly more satisfied with the overall learning experience. A vast body of research has highlighted that instructional design and the quality of learning materials are crucial in creating an effective online learning experience (Arbaugh, 2014; Sharples et al., 2014; Sun et al., 2008; Tobarra, Robles-Gómez, Ros, Hernández, & Caminero, 2014). Furthermore, previous research (Ashby et al., 2011; Hattie, 2009; Marks et al., 2005) has found that assessment and feedback strategies are important indicators of learning performance and learner satisfaction in particular. However, we believe that the current study is the first to provide such strong, robust evidence given the diversity and richness of the 401 module designs, the size of the sample, and the ability to control for over 200 variables in terms of individual learner characteristics and module learning design.

A second important finding is that long-term goals of learners (i.e., qualifications and relevance of modules to learners' professional careers) are important predictors of learner satisfaction. If a module was not sufficiently linked with wider qualification aims, the results indicated that learners were 70% less likely to have positive overall learner satisfaction. As most OU learners are adult learners who combine family lives with professional careers, the relevance to professional practice to learning design is a key concern for them, and this should also be in the mindsets of instructional designers.

A third important finding is that several module characteristics (i.e., number of credits, level, type of exam, maturity of module design) had an important influence on learner satisfaction, but a large number of potential indicators from the Block 1 Module and Block 2 Presentation did not significantly influence learner satisfaction. One possible reason why discipline differences and several proxies for instructional design (e.g., number of online assessments, blended vs. online) did not have a significant effect on learner satisfaction may relate to the rather basic categorizations of these proxies. We hope to extend our analyses with more detailed learning design mapping data using the Open University Learning Design Initiative (OULDI) tool, whereby more fine-grained information about design principles and learning activities per module are available (Rienties et al., 2015b; Toetenel & Rienties, 2016).

A fourth and final important finding is that individual learner characteristics do not play a more pronounced role in predicting overall learner satisfaction. Blocks 3–6 from (Figure 1): seemed to have limited impact on whether learners were satisfied with their learning experience. There was one exception amongst new learners whereby older learners, especially those aged over 60, were 70% less likely to have positive overall learner satisfaction consistent with Ke & Xie, 2009, but the reasons behind this need to be further explored. It is important to understand this difference among undergraduate new learners as the OU learner population has substantially changed in the past 5 years, and there are now more early career learners registered to study online and use distance learning. In a way, our findings provide encouragement for instructional designers and instructors in blended and online courses as learners are not necessarily negatively influenced by their prior education and demographic background. While some research indicates that ethnic minority students (Richardson, 2013) and women (Herman, 2014) seem less successful in online learning settings, our large scale study seems to indicate that learner characteristics play only a minor role in learner satisfaction.

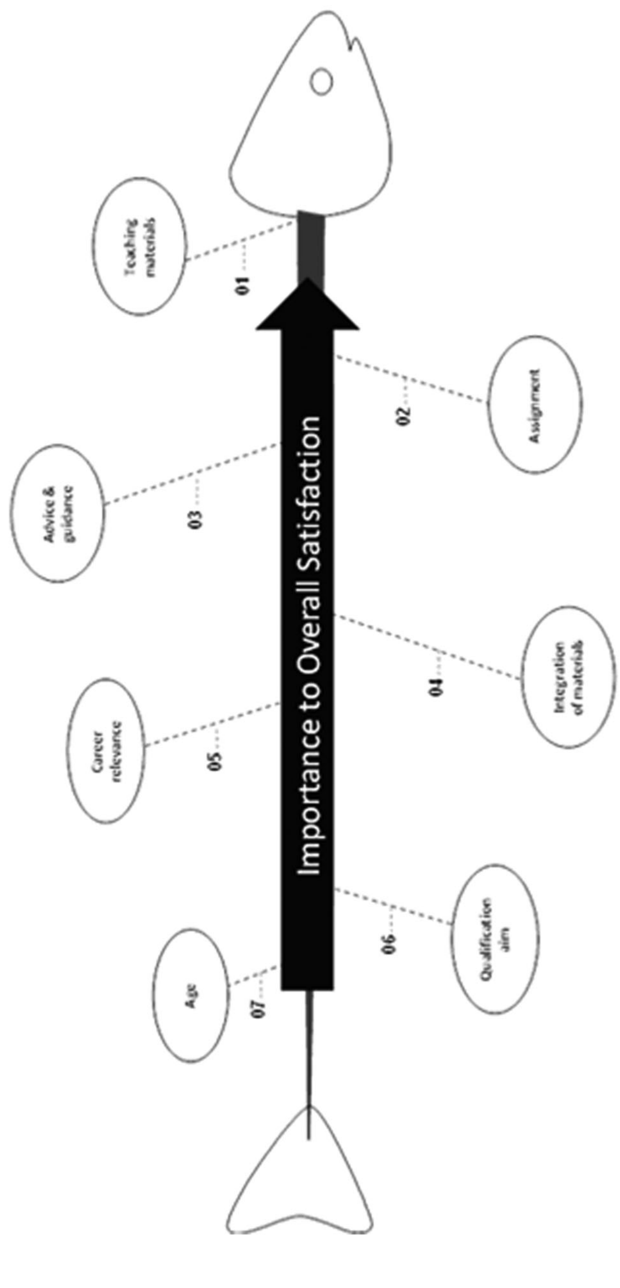
The analysis has evaluated learner satisfaction data in order to inform principles of good practice in learning design. The robustness of the findings is supported by the size of the data sets being considered. Key to the methodology used is the consideration of how learning design impacts learner satisfaction, and in particular, provides guidance to module teams in terms of what they can focus on to improve learning outcomes. As the technical analysis may be rather complex, we have translated the findings into two visualizations (Figures 2 and 3): The key drivers of learner satisfaction are illustrated, whereby the variables closer to the right have a stronger impact on learner satisfaction than those positioned on the left. Although the key parameters in (Figures 2 and 3): are fairly similar, it is important to acknowledge that the drivers for learning might be subtly different for new online learners and those who already have experience with online learning. Given the larger number of fish bones present for undergraduate continuing learners, this might signal that experienced online learners might have more advanced, complex expectations of what leads to a satisfactory learning experience. Overall, the indicators provide clear guidelines for instructional designers and instructors about which elements to focus on in terms of enhancing and maintaining learner satisfaction in blended and online environments.

Limitations and Future Research

A first and obvious limitation of the research is that several of the items of the SEaM survey loaded heavily on overall learner satisfaction. This may be considered to be an artifact since learners were completing the respective surveys at one point in time, whereby other individual learner characteristics and learning design proxies were measured independently at different time intervals. Nonetheless, the findings do indicate that not all 40 items strongly predict overall learner satisfaction, and most items not related to learning design and professional careers were dropped in the logistical regression modeling. Furthermore, several Block 1–2

Figure 2: Overall satisfaction modelling: undergraduate continuing learners.

Figure 3: Overall satisfaction modelling: undergraduate new learners.



variables did significantly predict learner satisfaction over time. Second, the predictors associated with learning design were based upon learners' self-perceptions and are thus subject to inevitable self-reporting bias issues. Third, the data was inherently hierarchical in nature (Rubin & Fernandes, 2013) but in the analyses all variables were entered at one level. Given the large sample size, including relative and absolute academic performance, and the wide variety of modules included in the modeling, we argue that the focus on learner satisfaction is justified. It is widely accepted in marketing and business that satisfied customers are more likely to continue buy new products. Finally, as the study was conducted within one higher education institution, we encourage researchers to use the logistical regression modeling approach to test, verify, and contrast whether similar key drivers for learner satisfaction are present within their own context.

With increasingly rich data available to institutions, powerful analytics engines (Calvert, 2014; Tobarra et al., 2014; Wolff, Zdrahal, Herrmannova, Kuzilek, & Hlosta, 2014), and skillfully designed visualizations of analytics results (González-Torres, García-Peñalvo, & Therón, 2013) may help institutions and instructors in particular to use the experience of the past to create supportive, insightful models of primary (and perhaps real-time) learning processes. Our findings indicate that learning design parameters (i.e., assessment, career focus, teaching materials, workload) have a strong impact on overall learner satisfaction. A next step in our research is to identify the optimal balance and interactions between these learning design activities, and how we can visualize the impact of these learning design activities to both instructional designers, instructors, and new and continuing learners.

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APPENDIX: PAF OUTPUT

PAF Output for undergraduate learners

The factor pattern matrix indicated there were five factors:

Factor 1: Tutor guidance & Support

KPI-04(Q15) I was satisfied with the support provided by my tutor on this module [KPI-04]

Q18 My tutor met my individual needs for support as they arose, either directly or by referring me to other people in the OU

Q24 my tutor's familiarity with the details of the module helped me learn effectively

Q25 my tutor's broad understanding of the subject helped me learn effectively

Q23 my tutor's knowledge of OU methods and/or regulations helped me learn effectively
Q19 my tutor encouraged me in my studies
Q27 my tutor provided useful guidance about preparing for assignments (TMAs/CMAs etc) on this module
Q16 Contact from my tutor at the start of the module helped me engage positively with the module
Q22 I benefitted from my tutor's help and encouragement in using the online facilities for this module
Q17 I could get in touch with my tutor when I needed to
Q26 my study fits within a professional/work-related context and my tutor's understanding of that context helped me learn effectively
Q20 I attended face to face tutorial activities (e.g. tutorials, day schools) run by my tutor which helped me understand the module concepts and/or prepare for assessment
Q3 I was satisfied with the advice and guidance provided for my studies on this module

Factor 2: Module Satisfaction

KPI-08 (Q38) I would recommend this module to other students [KPI-08]
KPI-09 (Q39) the module met my expectations [KPI-09]
KPI-10 (Q40) I enjoyed studying this module [KPI-10]
KPI-01 (Q31) Overall, I am satisfied with the quality of this module [KPI-01]
KPI-02 (Q32) Overall, I am satisfied with my study experience [KPI-02]
KPI-03 (Q33) the module provided good value for money [KPI-03]
KPI-05 (Q34) Overall, I was satisfied with the teaching materials provided on this module [KPI-05]
Q36 Overall, I was satisfied with the assessment on this module
Q13 this module contributed to the achievement of my wider qualification aim
KPI-06 (Q35) Overall, I was able to keep up with the workload on this module [KPI-06]

Factor 3 – Module contents & experience

Q4 I was able to work with the different teaching materials and learning activities at the times I was required to
Q5 The teaching materials and learning activities were well integrated and helped me to learn
Q1 I was able to find clear information about what to study and when
Q6 I was satisfied with the method of delivery of the different teaching materials and learning activities on this module
Q2 It was easy to navigate my way around the module website to access the online teaching materials and related learning activities

Factor 4 – Collaboration & activities

Q12 Taking part in collaborative activities with other students helped me to learn
Q21 I attended online tutorial activities (e.g. Tutor Group Forums and other online rooms) run by my tutor which helped me understand the module concepts and/or prepare for assessment
Q10 Taking part in optional exercises or activities to test my understanding helped me to learn

Factor 5 – Assessment feedback

Q29 the feedback I got with my marked assignments helped me to learn and to understand the subject better

Q28 the feedback I got with my marked assignments explained why I got the grades I did

Q30 the feedback I got with my marked assignments helped me with future assignments and/or preparing for the EMA/examination

Pattern Matrix[a]

	Factor				
	1	2	3	4	5
KPI04C	.925				
Q18C	.871				
Q24C	.868				
Q25C	.844				
Q23C	.840				
Q19C	.829				
Q27C	.810				
Q16C	.803				
Q22C	.736				
Q17C	.722				
Q26C	.592				
Q20C	.530				
Q3C	.445		.351		
KPI08C		1.017			
KPI09C		.965			
KPI10C		.951			
KPI01C		.811			
KPI02C		.737			
KPI03C		.577			
KPI05C		.576			
Q36C		.471			
Q13C		.355			
KPI06C		.310			
KPI07C					
Q4C			.681		
Q5C			.655		
Q1C			.623		
Q6C			.610		
Q2C			.598		
Q9C			.363		
Q11C					
Q12C				.603	
Q21C	.444			.470	
Q10C				.429	
Q14C				.377	
Q7C				.330	
Q29C	.387				.658
Q28C	.354				.656
Q30C	.411				.588

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 7 iterations.

PAF Output for postgraduate learners

The factor pattern matrix indicated there were 7 factors:

Factor 1 Tutor's guidance and Support

Q18 My tutor met my individual needs for support as they arose, either directly or by referring me to other people in the OU

KPI-04(Q15) I was satisfied with the support provided by my tutor on this module [KPI-04]

Q24 my tutor's familiarity with the details of the module helped me learn effectively

Q17 I could get in touch with my tutor when I needed to

Q19 my tutor encouraged me in my studies

Q23 my tutor's knowledge of OU methods and/or regulations helped me learn effectively

Q25 my tutor's broad understanding of the subject helped me learn effectively

Q22 I benefitted from my tutor's help and encouragement in using the online facilities for this module

Q16 Contact from my tutor at the start of the module helped me engage positively with the module

Q26 my study fits within a professional/work-related context and my tutor's understanding of that context helped me learn effectively

Q27 my tutor provided useful guidance about preparing for assignments (TMAs/CMAs etc) on this module

Q3 I was satisfied with the advice and guidance provided for my studies on this module

Factor 2: Module satisfaction

KPI-08 (Q38) I would recommend this module to other students [KPI-08]

KPI-09 (Q39) the module met my expectations [KPI-09]

KPI-01 (Q31) Overall, I am satisfied with the quality of this module [KPI-01]

KPI-10 (Q40) I enjoyed studying this module [KPI-10]

KPI-02 (Q32) Overall, I am satisfied with my study experience [KPI-02]

KPI-03 (Q33) the module provided good value for money [KPI-03]

Factor 3: Relevance & Navigation

KPI-07 (Q37) the learning outcomes of the module were clearly stated [KPI-07]

Q1 I was able to find clear information about what to study and when

Q14 the knowledge and skills developed on this module are relevant to my work or career

Q13 this module contributed to the achievement of my wider qualification aim

Q9 the instructions on how to complete the assignments were clear

Factor 4 Method and delivery of modules

Q6 I was satisfied with the method of delivery of the different teaching materials and learning activities on this module

Q5 The teaching materials and learning activities were well integrated and helped me to learn

KPI-05 (Q34) Overall, I was satisfied with the teaching materials provided on this module [KPI-05]

Factor 5: Collaboration & activities

Q12 Taking part in collaborative activities with other students helped me to learn
Q10 Taking part in optional exercises or activities to test my understanding helped me to learn
Q21 I attended online tutorial activities (e.g. Tutor Group Forums and other online rooms) run by my tutor which helped me understand the module concepts and/or prepare for assessment
Q20 I attended face to face tutorial activities (e.g. tutorials, day schools) run by my tutor which helped me understand the module concepts and/or prepare for assessment

Factor 6: Assessment Feedback

Q28 the feedback I got with my marked assignments explained why I got the grades I did
Q30 the feedback I got with my marked assignments helped me with future assignments and/or preparing for the EMA/examination
Q29 the feedback I got with my marked assignments helped me to learn and to understand the subject better

Factor 7: Module workload

KPI-06 (Q35) Overall, I was able to keep up with the workload on this module [KPI-06]
Q4 I was able to work with the different teaching materials and learning activities at the times I was required to

Pattern Matrix[a]

	Factor						
	1	2	3	4	5	6	7
Q18C	.961						
KPI04C	.923						
Q24C	.840						
Q17C	.827						
Q19C	.826						
Q23C	.821						
Q25C	.780						
Q22C	.735						
Q16C	.706						
Q26C	.693						
Q27C	.610					.354	
Q3C	.566						
KPI08C		.828					
KPI09C		.825					
KPI01C		.743					
KPI10C		.713					
KPI02C		.647					
KPI03C		.570					
Q36C		.322					
KPI07C			.604				
Q1C			.488	.349			
Q14C			.426				
Q13C		.375	.418				
Q9C			.402				
Q2C			.361				
Q7C							
Q6C				.633			
Q5C				.613			
KPI05C		.494		.517			
Q12C					.540		
Q10C					.476		
Q21C	.395				.438		
Q20C	.379				.403		
Q28C	.327					.699	
Q30C	.422					.614	
Q29C	.408					.600	
Q11C							
KPI06C							.641
Q4C				.407			.475

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 10 iterations.

Student Experience on a Module Survey

Q1 I was able to find clear information about what to study and when

Q2 It was easy to navigate my way around the module website to access the online teaching materials and related learning activities

Q3 I was satisfied with the advice and guidance provided for my studies on this module

Q4 I was able to work with the different teaching materials and learning activities at the times I was required to

Q5 The teaching materials and learning activities were well integrated and helped me to learn

Q6 I was satisfied with the method of delivery of the different teaching materials and learning activities on this module

Q7 The library's online resources enhanced my study (e.g. journal articles or ebooks)
Q8 I have declared a disability and was able to work with the teaching materials and learning activities on this module
Q9 The instructions on how to complete the assignments were clear
Q10 Taking part in optional exercises or activities to test my understanding helped me to learn
Q11 Completing assignments on this module consolidated my learning
Q12 Taking part in collaborative activities with other students helped me to learn
Q13 This module contributed to the achievement of my wider qualification aim
Q14 The knowledge and skills developed on this module are relevant to my work or career
Q16 Contact from my tutor at the start of the module helped me engage positively with the module
Q17 I could get in touch with my tutor when I needed to
Q18 My tutor met my individual needs for support as they arose, either directly or by referring me to other people in the OU
Q19 My tutor encouraged me in my studies
Q20 I attended face to face tutorial activities (e.g. tutorials, day schools) run by my tutor which helped me understand the module concepts and/or prepare for assessment
Q21 I attended online tutorial activities (e.g. Tutor Group Forums and other online rooms) run by my tutor which helped me understand the module concepts and/or prepare for assessment
Q22 I benefitted from my tutor's help and encouragement in using the online facilities for this module
Q23 My tutor's knowledge of OU methods and/or regulations helped me learn effectively
Q24 My tutor's familiarity with the details of the module helped me learn effectively
Q25 My tutor's broad understanding of the subject helped me learn effectively
Q26 My study fits within a professional/work-related context and my tutor's understanding of that context helped me learn effectively
Q27 My tutor provided useful guidance about preparing for assignments (TMAs/CMAs etc) on this module
Q28 The feedback I got with my marked assignments explained why I got the grades I did
Q29 The feedback I got with my marked assignments helped me to learn and to understand the subject better
Q30 The feedback I got with my marked assignments helped me with future assignments and/or preparing for the EMA/examination
KPIs
Q31 Overall, I am satisfied with the quality of this module [KPI-01]
Q32 Overall, I am satisfied with my study experience [KPI-02]
Q33 The module provided good value for money [KPI-03]
Q15 I was satisfied with the support provided by my tutor on this module [KPI-04]

Q34 Overall, I was satisfied with the teaching materials provided on this module [KPI-05]
Q35 Overall, I was able to keep up with the workload on this module [KPI-06]
Q36 Overall, I was satisfied with the assessment on this module
Q37 The learning outcomes of the module were clearly stated [KPI-07]
Q38 I would recommend this module to other students [KPI-08]
Q39 The module met my expectations [KPI-09]
Q40 I enjoyed studying this module [KPI-10]

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