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FACTORS THAT PREDICT DIFFERENTIAL ONLINE VERSUS FACE-TO-FACE COURSE OUTCOMES: EVIDENCE FROM GERMANY AND THE UNITED STATES

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Introduction

By 2013, over 40 million college students took online classes worldwide; by 2017, that number should triple (Atkins, 2013). If online courses have lower completion rates, they may hinder degree completion. It is therefore essential to identify which students are at highest risk of failing or dropping out of those courses if they enrol in them online, so that interventions can be targeted to those students at highest risk.

Research questions

This study explores the interaction between the online medium and student characteristics in predicting subsequent course outcomes. Specifically we ask:

1. Which student characteristics exacerbate or mitigate differences in rates of online versus face-to-face course retention and successful course completion?
2. Which characteristics make students more likely to drop out of college after taking an online course? And to what extent do online course outcomes explain subsequent college dropout?

Online Learning and Higher Education in the U.S. and Germany

This study aims to look for generalizable patterns beyond a single culture, and the goal is to compare models across national boundaries. Germany's educational system has sufficient similarities with the U.S. to make comparison feasible, while simultaneously diverging from the U.S. in a number of ways, and thus providing for generalizability beyond U.S. culture. The U.S. and German education systems both have a recent history of rapid enrolment expansion and struggle with upward educational mobility in comparison to international averages (McAdams, 2002). Additionally, both the U.S. and Germany have an education structure that is organized primarily at the state level (Eurydice, 2007). However, the German system's early tracking results in proportionately fewer students obtaining a tertiary educational credential (29% versus 44% in Germany versus the U.S. (OECD, 2014). While U.S. institutions usually charge tuition, public colleges in Germany are tuition-free. And in contrast to the liberal arts education model that prevails in the U.S., where students typically choose a major after two years of college, in Germany students must apply to a department at college entrance and take all of their courses within that department. German colleges also rarely have dormitories or the supplemental student services typically found in the U.S. (McAdams, 2002).

Online Outcomes

Many meta-analyses suggest no positive or negative effect of learning outcomes online versus face-to-face as measured by exams or course grades (e.g. Bernard et al., 2004). However, there have been studies that have reported higher online dropout rates (e.g. Jaggars, 2011; Johnson & Mejia, 2014). Despite this, there is little research on the effects of online course-taking on college persistence and completion, and available results are mixed (e.g. Jaggars, 2011; Shea & Bidjareno, 2014; Wladis, Conway, & Hachey, 2016).

One major difficulty with determining whether or not online courses put students at higher risk of course or college dropout is that students are not randomly assigned to take courses online. Online learners are more likely to be female, older, married, active military and to have other "non-traditional" characteristics (e.g. delayed college enrolment; part-time enrolment; financially independent) (Shea & Bidjerano, 2014; Wladis, Hachey, & Conway, 2015). Online students also tend to be first generation students, to have higher academic preparation, to be white, native English speakers, and to have applied for or received financial aid (Xu & Jaggars, 2011; Athabasca University, 2006). However, research on demographic variables is conflicting (Jones, 2010); it is still unclear how differing characteristics interact to affect student retention in online courses.

Investigations of student characteristics as predictors of outcomes online-versus-face-to-face have been mixed and inconclusive, and almost none of them have directly tested the interaction between various factors and the course medium. To accurately assess whether a factor puts a student at greater risk in the online environment specifically, one must analyze the *interaction* between that factor and course medium, while simultaneously controlling for self-selection into online courses. Only a few studies have considered these interactions (Xu & Jaggars, 2013; Wladis, Hachey, & Conway, 2015), and both of these studies excluded important life factors (e.g. whether the student had children) that correlate simultaneously both online enrolment and college outcomes.

Methodology

Data source and sample

This study uses two samples: (a) 9,663 students with 37,442 course records, from the 18 two- and four-year colleges in the City University of New York (CUNY) system in the U.S.; and (b) 337 students with 1,607 courses records, from 30 colleges and universities in Bavaria, Germany. Students in both samples were selected if they were enrolled in a course in the sample frame, which consisted of online and comparable face-to-face courses offered during the 2014-2015 fall/winter semester at one of the CUNY colleges or through the *Virtuelle*

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Hochschule Bayern in Germany (an online platform for multiple universities). At the end of the semester, both samples were invited to participate in an online survey.

Measures

This research utilizes three measures of student outcomes: *successful course completion*, or whether the student successfully completed a course with a C- or higher (the typical standard to receive major or transfer credit), *course failure*, or whether the received a grade below a C- in a course (rather than earning a higher grade or dropping the course) and *college persistence*, or whether the student re-enrolled in college in the subsequent full semester. In the German dataset, a 1.0–3.5 grade was equated to C- or higher in the U.S., since this is the criteria used by most Bavarian Universities when they evaluate U.S. transcripts). However, we note that criteria for credit in the major and for transfer credit seem to be much more variable in Germany than in the U.S. The main independent variable (IV) of interest, course medium, was dichotomized to face-to-face or fully online, based on Sloan Consortium definitions (Allen & Seaman, 2010). Covariates included: whether the student had a child (and age of youngest child); gender; race/ethnicity; age; work hours; income; parental education; developmental course placement; marital/cohabitation status; immigration generational status; native speaker status; college level (two-year, four-year, or graduate); G.P.A; and number of credits/classes taken that semester. For the German dataset, ethnicity, developmental course placement, and college level were not collected as they are not relevant to the German higher education structure. Various non-linear versions of variables were explored, and as a result age is squared in the subsequent analyses because this better reflected the relationship observed between age and the various outcomes explored in this study.

The survey used included scales measuring: motivation to complete the course; course enjoyment/engagement; academic integration (i.e. interaction with faculty/students outside class); self-directed learning skills; time management skills; preference for autonomy; and grit (i.e. perseverance and passion for long-term goals). Confirmatory factor analysis using structural equation modelling (SEM) was used on each country’s datasets separately to model items for each scale as predictors of a single latent construct. Error covariance terms were added between some individual items based on theory, prior to estimation. Some items from the motivation and grit scales were eliminated because of poor performance during SEM. For the final scales, average variance extracted (AVE) was 0.50 or greater, indicating convergent validity, and composite reliability (CR) ranged from 0.77 to 0.89, indicating good reliability(Hair, Anderson, Tatham, & Black, 1998); SRMR ranged from 0.000 to 0.059, supporting the operationalization of each scale as a single factor structure (Hu & Bentler, 1999).

Analytical Approaches

Courses for which valid grades did not exist were dropped. Multivariate multiple imputation by chained equations was used to impute values for survey questions with missing responses, using all IVs chosen for subsequent analyses. Depending on variable type, binomial, ordered,

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or multinomial logit models, or predictive mean matching on three nearest neighbours was used for imputation. A median of 2.6% and 3.3% of data were missing in each imputed variable in the U.S. and German samples respectively. After preliminary tests for stability of model estimates, final imputed datasets contained 35 and 10 imputations, for the U.S. and German data respectively.

Propensity scores, indicating the probability of online enrolment, were generated for each student using logistic regression and included all of the IVs used in the subsequent analyses; scores were averaged across imputed datasets. Initially data were weighted prior to propensity score matching to account for survey non-response, but since preliminary models with and without weights were substantially similar, subsequent analysis was performed without sample weights. Matched datasets were generated for U.S. and German data using single nearest-neighbour matching with replacement because this approach yielded the best balance on the covariates, based on the standardized bias for each imputed variable averaged across imputations. In addition, the distribution of each variable was compared across both matched datasets, to ensure that the distributions for each covariate were similar in both groups of the matched sample. The median standardized bias across variables was 2.6% for the U.S. and 4.0% for the German dataset. Based on Rubin's (2001) rule of thumb that standardized bias should be approximately below 25% after matching, the matched dataset achieved good balance on all covariates. Distribution of propensity scores was evaluated before and after matching, and both datasets showed significant overlap in the region of common support.

Each dataset was formatted into two distinct datasets: the first dataset was used to run multilevel mixed-effects logistic regression models with student as the first-level and course as the second-level factors, in order to control for unobserved heterogeneity between courses; the second dataset was used to run multilevel models with course as the first-level and student as the second-level factors, in order to control for unobserved heterogeneity between students. The KHB decomposition method (Kohler, Karlson, & Holm, 2011) was used to calculate direct and indirect effects, in order to explore the relationship between online course outcomes, student characteristics, and subsequent college persistence. Standard errors during KHB decomposition were computed using clustering by course, to account for the multi-level data structure.

Results

This section describes factors that had a significant interaction with the online environment in predicting course and college outcomes. This means that the *difference* in outcomes online versus face-to-face is significantly different for distinct factor values. However, the direction or significance of the interaction alone does not provide any information about the relative outcomes of these groups overall, just about how outcomes *change* for these groups across different course mediums.

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Course retention and successful course completion

Results of multi-level logistic regression models for course-level retention in the U.S. and German revealed the following constructs were significant predictors of lower relative risk online: higher enjoyment/engagement in the specific course taken; higher levels of academic integration; higher levels of grit; higher work hours; Black ethnicity; male gender; being a community college student; and being foreign-born. For the German dataset, only being native-born, and taking fewer courses were associated with lower risk online.

Results of the multi-level logistic regression models for successful course completion in the U.S. and German dataset revealed the following constructs were all associated with lower relative risk online in at least one of the models: lower levels of academic integration or autonomy; not having a child under the age of six; being in the lowest income category (as compared to the highest); having parents who have completed a graduate degree (as compared to not completing high school); being foreign-born; having a spouse or live-in partner; being a four-year college student (compared to two-year); and having a G.P.A above 3.0 (compared to below 2.0). For the German dataset, lower levels of self-directed learning skills, higher levels of grit, having a child, having higher work hours, and having a higher GPA were all associated with having lower relative risk of course dropout online.

For the U.S. dataset, the most consistent predictor of both course retention and successful course completion was being foreign-born. Across all versions of the U.S. dataset, native-born students were at greater risk online compared to foreign-born students, and this was particularly true for native-born students for whom both parents were also native-born. Native-born students with one or no native-born parents were also at increased relative risk online, but the difference was less pronounced. Higher levels of academic integration were associated with less risk online, but only when comparing outcomes in the same course taken online by one set of students and face-to-face by another set of comparable students, and not when comparing different courses taken online versus face-to-face by the same student.

In terms of successful course completion, in the U.S. dataset having a child under six years old was associated with higher risk online, although this interaction was only significant when comparing outcomes in the same course for different students who took the course online versus face-to-face. Lower rates of autonomy were also consistently associated with lower risk online in all versions of the U.S. dataset, although this interaction was only significant when comparing outcomes across different online and face-to-face courses taken by the same student. Being married or having a live-in partner was also associated with lower risk online in all versions of the U.S. dataset, although this interaction was only significant for one of the matched datasets. And finally, GPA's above 3.0 (in comparison to below 2.0) were also consistently associated with less risk online in both the U.S. and Germany, although this relationship was not significant in all versions of the data.

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College persistence

College persistence in the subsequent semester was analyzed for the U.S. student-level datasets (since persistence is an outcome at the student level, it was not assessed for the course-level datasets). Instead of assessing the interaction of each IV with the medium of the course in the sample frame, the interaction between each factor and whether or not the student had ever taken an online course was assessed. The following factors had a significant interaction with the fully online medium in predicting college persistence in at least one dataset, putting online students at higher risk of college dropout: lower levels of academic integration; higher levels of motivation; lower levels of grit; fewer work hours; being older; Hispanic ethnicity; being a native English speaker; and taking fewer credits. Being a native English speaker was significant across both the matched and unmatched datasets. Aside from being a native speaker, other factors that were consistent across both matched and unmatched dataset (but only significant in one of the two) were: grit; work hours; age; Hispanic ethnicity; and number of credits taken.

This study also explored the extent to which the subsequent college persistence of online students could be directly related to the outcomes of their online courses, and to what extent it is likely related to other characteristics which also increase the likelihood of taking an online course. The KHB decomposition method was used to calculate the direct, indirect, and total effect of taking a fully online course on subsequent college persistence as mediated by successful course completion, while controlling for the variables included as covariates. No significant indirect effect were observed, suggesting that online students are not more likely to drop out of college immediately after, or due to, the outcomes of the online course; rather, it seems that other student characteristics may be significant in determining college persistence.

Discussion

Limitations

This study analyzes data from a large U.S. university system and from a large German province in order to increase generalizability and validity, but still has some limitations. While the CUNY system is highly diverse and likely generalizable to a wider U.S. student population, it is not necessarily nationally representative. CUNY does not have rural campuses, so caution should be exercised before extending any results taken from the CUNY dataset to students who attend rural colleges. The German dataset contained data from students at rural, suburban, and urban colleges, but not all patterns observed for German data may be relevant to the U.S. Further, while this study has attempted to control for a wide array of factors, it is unlikely that any study could include them all. Online students are more likely to have more "complicated" lives that include experiences that are difficult to measure or quantify, but that influence both decisions to enrol online and subsequent course and college outcomes. Further exploring and refining of factors that may impact online course enrolment should be a focus of future educational research to conduct well-controlled observational studies about cross-cultural online outcomes.

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Overall trends, national comparisons, and implications

Consistent with the literature (e.g. Goodfellow & Lamy, 2009; Shattuck, 2005), we report mixed findings. The most consistent pattern observed across U.S. datasets was that native-born students were at greater risk online than foreign-born students. In Germany, being native-born was also significant, but the relationship was reversed, with native-born students at higher risk online. Perhaps this is due to differences between the U.S. and German datasets: at CUNY, roughly 40% of students are foreign-born, while in Germany foreign students are disproportionately underrepresented in tertiary education, and those who do enter University are often marginalized (Thomasen, 2012). This cultural marginalization may be exacerbated in some way by the online environment.

The number of credits/courses taken was also a significant predictor of differential online versus face-to-face course retention, with students who took more credits/courses at higher risk of online dropout, in both the U.S. and German course-level matched and unmatched datasets (the results were only significant for the German dataset). Since this result was obtained in the course-level datasets where online versus face-to-face courses taken by the same student were compared, this suggests that students with insufficient time for their academics may be more likely to drop an online courses than a face-to-face class, all else being equal.

For successful course completion, G.P.A. was a significant predictor, with the weakest grades in each country associated with higher risk online. However, we note that students with average grades (e.g. 2.0-3.0) did not have significantly different risk online than students with higher or lower grades. It is possible that this pattern of interaction between the online medium and G.P.A. only holds for students at the very top and bottom of the grading scale. This correlates with some previous research that suggests that G.P.A may be a factor in online completion (Xu & Jaggars, 2013), but that for students with average grades it may not be a helpful predictor (Hachey, Wladis & Conway, 2013). Lower levels of grit were also correlated with higher risk online in both the U.S. and German course-level matched and unmatched datasets, although these results were only significant for the German dataset. This may confirm research that suggests that grit may be essential to achievement (Duckworth et al., 2007).

Having a child (or a child under 6 in the U.S. dataset) interacted with the online medium to predict successful course completion in both the U.S. and German datasets (significantly so for the German matched dataset and for both the matched and unmatched U.S. student-level datasets), but parents were at higher risk online in the U.S. dataset and at lower risk online in the German dataset. Repeating the U.S. analysis with a binary variable indicating whether the student had a child instead of whether they had a child under six produced similar results. It may be that student parents are more likely to enrol in online courses if they have greater time constraints, and that these same students are less likely to successfully complete a course. The fact that this pattern was significant in the U.S. only for the student-level dataset (where

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unobserved heterogeneity was accounted for by course and not by student), but not in the course-level dataset (where unobserved heterogeneity by student was accounted for), supports this interpretation. Differences in U.S. versus German patterns may be due to differences in how parents are supported. In Germany, all families (including students) receive paid parental leave (*Elterngeld*) equivalent to up to 67% of their yearly full-time pay that can be taken over 12-24 months after the birth of a child. All parents also receive funds (*Kindergeld*) equivalent to about 200 EUR/month per child, and all children over 12 months are guaranteed publicly subsidized childcare. In contrast, the U.S. has no paid federal parental leave, and the cost of childcare is significantly higher than in Germany, particularly for low-income and single parent households (OECD, 2014). These results suggest that without adequate support for student parents (e.g. childcare, financial aid to reduce work hours), the flexibility that online courses offer may not be enough to compensate for the time demands of parenthood.

Conclusion

Colleges wanting to target interventions to students at highest risk in the online environment may want to focus on students with lower G.P.A's (e.g. under 2.0), student parents, native-born students, students with lower levels of self-reported "grit" and students who are enrolled in higher numbers of courses/credits. But while these are the groups found by this study to be most vulnerable in the online environment, these groups are not necessarily the ones with the poorest absolute online outcomes. For example, for the datasets used in this study, household income was strongly correlated with course and college outcomes even though it was not relevant to the online environment specifically. Lower-income students likely still need significant support in online courses, just as they do in face-to-face classes. In addition to targeting student groups that are vulnerable in the online environment specifically, colleges hoping to improve online retention should continue to support student groups that have historically been identified as at-risk generally.

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