Adoption of technology-mediated learning in the U.S.☆

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Abstract

Technology-mediated learning (TML) has been a growing trend among higher education institutions in the U.S., especially after the inception of e-commerce. In this paper, we develop an analytical framework that focuses on the relationship between the extent of TML adoption and students’ return from a higher education degree. This framework is used to derive hypotheses about how adoption levels should vary based on the institutional and student characteristics of a university. Using an extensive data set for the 2000–2001 academic year, our empirical work supports hypotheses concerning the importance of the quality and location of institutions as well as students’ time value on the TML adoption decision. Specifically, we find that TML is used more in lower-ranked universities, in states with high population densities, and at the graduate than the undergraduate level. These results provide insights on the kind of institutions and program offerings that stand to gain the most from adopting TML.

Keywords: Technology-mediated learning; Internet

1. Introduction

Recent developments in information technology (IT) and the commercialization of the Internet have generated new opportunities for the delivery of education and allowed many higher education institutions to bring their resources closer to a broad base of potential users.† As university administrators see the strategic advantages of using IT in penetrating new market segments, they encourage its use by faculty members [12,33]. For instance, the population of online master of business administration students enrolled at 200 accredited schools rose to more than 100,000 in 2002 [8]. Online enrollment at University of Phoenix...
increased from around 50,000 in 2002 to about 125,000 in 2004, and Business Week cited it as one of the top 10 most profitable IT firms [5]. Furthermore, the growth of online enrollments shows no sign of abating. According to the Sloan Consortium, nearly 3.2 million students took at least one online course during the fall 2005 term, a substantial increase over the 2.3 million reported the previous year. The more than 800,000 additional online students is more than twice the number added in any previous year. These developments suggest that the U.S. higher education sector has started to embrace the information age.

While the overall use of IT in the delivery of education has been increasing, the design of online programs varies from one institution to another. Typically, universities require some physical presence on campus when offering online programs. For example, Duke University expects its global executive online MBA students, who pay more than $100,000 in tuition and fees, to physically attend classes for 11 weeks [8]. Purdue University’s executive MBA program has six two-week residency requirements spread across 22 months, a design that allows students to meet their educational goals while simultaneously fulfilling their ongoing job responsibilities. Students continue to interact with their professors from a distance in between the residency periods. On the other hand, some Ivy League schools such as Harvard University and the University of Pennsylvania do not offer online MBA degrees [13].

This study addresses the following research question: What are the important institutional and student characteristics that affect the adoption of technology-mediated learning (TML) as a substitute for on-campus education? Despite the empirical evidence in the literature that suggests TML may successfully replace face-to-face classes [16,35], little is known about the facilitating factors. Therefore, information on such institutional and student characteristics would provide academic administrators guidance in adopting information technology into their curricula. These insights could also enable better decision making in improving the value of degrees offered in the higher education market. Today, almost 90% of higher education institutions use information technology to deliver learning to more than 2 million remote students in the U.S. However, without more insights into the above research question, these adoption decisions are made without adequate information and understanding, and therefore can lead to unsuccessful ventures.

Despite the importance of the higher education sector in the U.S. economy, the strategic use of TML has received limited research attention at best. The overwhelming majority of information systems (IS) research on TML has focused largely on the student level of analysis and has provided an understanding of the critical enabling role of IT in learning environments [1,25,24,32,34]. However, there is also a need for research that takes a broader perspective on the impact of TML. In their research commentary, Alavi and Leidner [2] called for a greater depth and breadth in this area and stressed the lack of studies that focus on the organizational and program levels. At the program level they identified the design of hybrid degrees that combine traditional and virtual forms of instruction as an important future research area. With the exception of Ozdemir and Abrevaya [30], who longitudinally explore the adoption of various TML technologies, there is little or no research that examines the organizational factors that impact TML adoption.

As a step toward extending knowledge in this area, we explore the types of higher educational settings that are more suited to utilize the new opportunities enabled by IT. While emphasizing the impact of technology adoption on customer preferences, we focus on the hybrid model—part online, part traditional. To our knowledge this is the first study in the TML area that provides an analytical framework grounded on economic theory and the first to systematically analyze an extensive data set on TML adoption across the U.S. We find that factors related with the quality and location of institutions as well as the opportunity cost of education for students impact the level of adoption in the sector. All else being equal, we find that the predicted level of the extent of TML adoption is more than three times as much for Tier 4 doctoral institutions than those in the top tier. Furthermore, the extent of adoption is more than three times as much at the graduate level than the undergraduate level for master’s institutions. We expect our findings to be of particular interest to researchers of TML and technology adoption, administrators of public and private institutions, and education policy makers at both federal and state levels.

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3 Although TML can also be used to enhance and complement on-campus education, we do not have a measure of this complementarity since our data on TML only include information on classes where remote learning via certain technologies is the main mode of education; the data do not provide information about on-campus classes that are supported by TML. The analysis of complementarity is therefore beyond the scope of this paper and an important future research direction.
4 We refer to TML as synchronous and asynchronous instruction delivered to remote locations via a combination of computer, communication, and data management technologies.
The analysis in this paper is also related to the multi-disciplinary technology adoption literature. Contemporary theoretical models in economics aim to explain patterns of diffusion based on the inherent differences among firms [23]. Recent IS research on information technology adoption also focuses more on the characteristics of organizations that facilitate adoption, including the ability to assimilate new technologies, organizational size, and sophistication of IT infrastructures, among others [4,11,15]. Orlikowski and Barley [29] recently suggested IS researchers take institutional factors into account, which are particularly important in our context given the exceptionally complex nature of the U.S. higher education sector and its multitude of products [28]. These studies provide further support for our focus on institutional factors.

In Section 2 we discuss a parsimonious economic framework that derives the value of a higher education degree for individuals. In Section 3 we use this framework to derive hypotheses about the institutional and student characteristics that facilitate TML adoption. The hypotheses are tested using a data set obtained from surveys of Department of Education and U.S. News & World Report. We present the data and the empirical results in Section 4 and provide concluding remarks in Section 5.

2. A framework for TML adoption

The characterization of the higher education market discussed in this section is based on not-for-profit institutions seeking to enhance students’ return to schooling. Nevertheless, there are similarities between the current model and the more typical models found in the information systems literature. For example, differentiation of universities based on quality (discussed next) is similar to the vertical differentiation concept typically employed in the literature. Also, the idiosyncratic value that students derive from attending a university (discussed in the next subsection) is similar to horizontal differentiation.

Consider a market with $M$ universities competing for a heterogeneous student population. Universities are indexed by the superscript $i \in \{1, 2, \ldots, M\}$ and are differentiated with respect to location, size, quality of education, and the characteristics of their student bodies. The university with index $i$ provides education at a quality level $q^i$ to $E^i$ students. For simplicity, each university offers a single degree that may be interpreted either as an undergraduate or a graduate one. Universities aim to retain their student bodies in the face of competition from other schools. Since students with a high preference for a university will choose to attend that university regardless of the strategic actions of other universities, the best strategy for each university is to focus its efforts on the students who are close to being indifferent between choosing their school over others; we refer to these students as their marginal students. Thus, each university is viewed as acting so as to maximize the net value of its product to its marginal student subject to a zero-profit condition. In doing so, we adopt the Nash equilibrium framework in which each university takes as given the behavior of other universities.

2.1. Students’ value for higher education

The literature on the return to schooling indicates that years of schooling, work experience, measures of college selectivity, and student ability capture the major determinants of the logarithm of one’s earnings [10,21,27,14,26]. For the marginal student, the wage upon graduation from the institution is then given by $w(a^i, q^i, t)$, where $a^i$ denotes the student’s ability, $q^i$ denotes the institution’s quality level, and $t$ denotes the $(q^i > 0)$ quality of past education, $(q^i > 0)$ and work experience $(q^i > 0)$.

A prospective student defers income in order to invest in human capital. As is standard in the literature (for example, see [27]), postponement of earnings due to schooling is tantamount to a reduction of an individual’s remaining earning span. Denoting the potential earning span by $n$, the already accumulated work experience of the typical student at the time of entering the degree program by $z$, the required duration of studies by $d$ (all in years), and the discount rate by $r$, the present value of an individual’s remaining lifetime earnings after graduating from institution $i$ is

$$V^i_R = \sum_{j=1}^{n-z-d} \frac{w(a^i, q^i, z_c + j - 1)}{(1 + r)^{j+d}},$$

where $z_c$ is the work experience on completing the degree program, which may differ from the experience $z$ at the time of entry if the individual works during his or her studies.

Students incur a location-related expense $L^i$ to attend university $i$. They either travel daily to campus if they live close by or relocate to the vicinity if they are far away. Students also derive an idiosyncratic consumption value $a^i$ from attending the institution, which ensures that different students attend different universities in

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3 Later in Section 2.4 we discuss how this approach can incorporate alternative objectives such as net tuition or enrollment maximization.
equilibrium.\footnote{Higher education is a differentiated good due to the variety of offerings. Students’ preferences for a university can vary based on the characteristics of its degree programs, campus, social atmosphere, past attendance of a family member, or other factors. We use $\zeta$ to capture such idiosyncratic preferences.} The value of a higher education degree is thus defined by:

$$V^i = \zeta^i + V^i_{G} + V^i_{T} - L^i,$$

where $V^i_{T}$ denotes the value of the earnings of the students from working while at school, given their experience on entering the degree program.

2.2. The characteristics of TML

Universities can introduce TML into their curricula at various levels. Let $k^i$ denote the level of adoption by institution $i$ measured in terms of the number of students it enrolls in TML courses relative to its total enrollment. Delivering courses using IT may affect the value of a higher education degree in a number of ways. One benefit of TML is the convenience of being able to fit educational commitments into the work schedule (i.e., students can take courses at nights or on weekends). Accordingly, we say that students in the market can spend $f(k^i)$ proportion of their time to work at their outside opportunities, where this proportion increases with the level of TML adoption ($\frac{df}{dk^i} > 0$). The function $f(\cdot)$ takes values between zero and one given that individuals have limited time for work- and school-related commitments. With this characterization, students gain $f(k^i)d$ years of work experience during their $d$ years of schooling. The net present value of earnings while at school reflects the value of time flexibility of TML and equals

$$V^i_{T}(k^i) = \sum_{j=1}^{d} \frac{f(k^i)w(a^i, 0, z + f(k^i)(j - 1))}{(1 + r)^j},$$

where the wage of the student while attending the school depends on the student’s ability and work experience.

In addition, the quality of education may be a function of $k^i$ because the educational experience on-campus and online can be quite different. An individual’s present value of remaining lifetime earnings after graduation (as a function of the level of TML adoption) becomes

$$V^i_{G}(k^i) = \sum_{j=1}^{n-z-d} \frac{w(a^i, q^i(k^i), z + f(k^i)d + j - 1)}{(1 + r)^j + d}.$$ TML may reduce location-related expenditures. Closely located students need not travel for courses offered online; far away students may decide not to relocate beyond a certain level of TML adoption. Both situations imply a reduction in $L_i \left( \frac{dL_i}{dk^i} < 0 \right)$. The value of institution $i$’s degree as a function of its level of TML adoption can now be stated as

$$V^i(\zeta^i, k^i) = \zeta^i + V^i_{G}(k^i) + V^i_{T}(k^i) - L^i(k^i).$$

Subtracting from $V^i$ the cost of tuition, students compare across the institutions and pick the one that offers the highest net value.

2.3. The optimal level of TML adoption

In competition among universities for students, the decision regarding the adoption of new technology can be considered in terms of how such adoption furthers the objective of maximizing the net value of the marginal students, the ones most likely to change their school choice based on such technology adoption decisions.

Let $C^i$ denote the per-student cost of TML adoption $k^i$ as a function of the extent of adoption, a cost that will be reflected in tuition payment and thus reduce the net value of TML adoption to the student. Students incur higher TML-related costs at higher levels of adoption ($\frac{dC^i}{dk^i}$). As long as the change in the value offered to the marginal student net of the adoption cost is positive for some $k^i>0$, institution will adopt TML. Then the problem of this institution can be formally stated as

$$\max_{k^i} \Pi^i = V^i(\zeta^i, k^i) - C(k^i)$$

subject to $k^i \in [0,1]$.

Assuming the net value of TML is positive for some level of adoption and taking as given the response of other institutions ($j \in \{1, \ldots, M\}$ and $j \neq i$), university $i$ chooses its optimal level of TML according to the following first order condition in equilibrium (all arguments are dropped for notational simplicity):\footnote{While corner solutions are possible, studying only the interior solution serves the purpose of deriving testable hypotheses about TML adoption. We assume the existence of diminishing returns and convex costs such that second-order conditions for a maximum are met.}

$$\frac{d\Pi^i}{dk^i} = \frac{d}{dk^i} (V^i_{G} + V^i_{T} - L^i) - \frac{dC^i}{dk^i} = 0.$$
Finally, a reduction in per-student costs to expanding the education offered to the marginal student allows for the maximum increase in net tuition revenue that the university can expropriate. In the case of enrollment maximization, if the marginal student who attends the university is similar to the students who were very close in their decision to come, but picked other schools, then maximizing the net value of the education offered to the marginal student may be exactly the type of behavior that will lead to the largest increase in acceptance rates among students who previously would have turned down the university.

Another potential objection to our analysis is that it may not capture the strategic nature of the technology adoption decision, a decision whose value may depend on the actions of others. Dynamic theories on technology adoption offer two related factors that may influence the adoption decision of a firm: stock and order effects. The stock effect results from the assumption that the benefit of adopting a new technology decreases as the number of previous adopters increases. The implication for this study is that other institutions’ TML adoption may limit the additional benefits an adopting institution may provide to its students. In our context, the stock effect could be important if the competitors’ TML adoption changes the nature of students who apply to universities that have not adopted TML. For instance, it may be that the characteristics of the marginal applicant to such universities is altered such that the new marginal applicant places less value on TML.

The order effect results from the assumption that the return to a firm from adopting a new technology depends upon its rank in the order of adoption, with early movers achieving a greater return than late movers. Again, this effect may arise in our context due to a change in the composition of the student body. Empirical studies do not offer any conclusive evidence about the importance of stock and order effects. Baptista [6] reports mixed results, while Hannan and McDowell [20] and Karshenas and Stoneman [23] find no evidence of any stock or order effects and argue that if stock and order effects have any real-world relevance, it is limited at best to very major innovations. Still, the issues related with a dynamic analysis of TML adoption suggest interesting future research directions, both in terms of theory development and data collection and analysis.

Finally, our analysis may also be viewed from a “cannibalization” standpoint. Cannibalization is essentially a product segmentation problem that has been studied primarily in the marketing literature. In our context, cannibalization occurs if TML offers a current student a higher-valued product than the standard on-campus education. One may interpret our analysis as focusing on universities’ choices of the optimal levels of cannibalization for their marginal students. A school that

\[
\sum_{j=1}^{n-z-d} \frac{1}{(1+r)^{j-d}} \left( \frac{dw}{dL^i} \frac{dq^j}{dk^j} + \frac{dw}{df} \frac{df}{dk^j} \right) + \sum_{j=1}^{d} \frac{1}{(1+r)^j} \left( \frac{df}{dk^j} \frac{df}{dw} \frac{df}{dL^j} \right) = \frac{dC^i}{dk}.
\]

Thus, the optimal level of TML for institution \( i \) is a function of \( \frac{df}{dk^j} \), \( \frac{dw}{df} \), and \( \frac{dC^i}{dk^j} \), among others:

\[
k^* = g \left( \frac{dq^i}{dk^j}, \frac{dw}{df}, \frac{dL^i}{dk^i}, \ldots \right).
\]

Eq. (8) provides a number of comparative statics results. Given that the wage increases with the quality of education obtained (\( \frac{df}{df} > 0 \)), universities at which the effect of TML adoption on the quality of education is greater (i.e., higher \( \frac{df}{dk^j} \)) will find a higher level of TML adoption optimal, other things being equal. Given that students can work more during schooling due to the time convenience of TML (i.e., \( \frac{df}{df} > 0 \)), an increase in the opportunity cost of work contributes positively to the left-hand side of Eq. (8), and similarly raises the optimal level of adoption. Following the same logic, greater savings from location-related expenditures due to TML (i.e., lower \( \frac{df}{df} \)) increases the optimal level of adoption. Finally, a reduction in per-student costs to expanding TML (i.e., lower \( \frac{df}{df} \)) facilitates adoption.

We next provide a discussion on how alternative characterizations of the higher education market would affect the analytical results. In Section 3, we use Eqs. (8) and (9) to derive our hypotheses. The empirical work is presented in Section 4.

### 2.4. A discussion of alternative frameworks

We have assumed that educational institutions adopt TML to maximize the net educational value offered to their “marginal” students. One might object to this view, and instead argue that university administrators are more interested in the objective of maximizing the tuition payments net of costs that could be extracted from existing students or maximizing the level of enrollments, or some combination of the two. However, our analysis is not necessarily inconsistent with these alternative objectives. For instance, in the case of tuition maximization, if the level of tuition is constrained by the willingness to pay of the marginal student, then maximizing the net value of the education offered to this marginal student allows for the maximum increase in net tuition revenue that the
chooses a high essentially perceives its students as placing a higher value on “cannibalization”, and thus provides more opportunities for that to occur.

3. Hypotheses

Given the factors presented in Eqs. (8) and (9), in this section we derive four hypotheses regarding the institutional and student characteristics that render adoption of TML more attractive.

3.1. The effect of quality

In Section 3 we have shown that an improvement in the effect of TML adoption on the quality of education \( \left( \frac{dQ}{dTML} \right) \) increases the optimal level of adoption. In other words, institutions that find it harder to deliver TML at a quality similar to or higher than that of their traditional offline offerings will benefit less from adopting the technology. The literature provides insights about the kind of institutions that may have such a difficulty. A comprehensive review of the empirical literature on TML indicates that TML tends to be as effective as traditional modes of course delivery [16]. Compared with traditional students, TML students find it easier to access course materials, learn the material equally well, find classes less boring, and are quite satisfied with the medium of learning. On the other hand, online courses do not exhibit the physical amenities offered by a college, such as lab facilities and recreational centers. Further, there may be less social presence and more interaction difficulty in TML courses since networking with professors and interacting with other students outside of classes is much easier within a campus atmosphere. Therefore, we posit that highly ranked universities with extensive physical resources (such as labs, research centers, and professors) may encounter significant setbacks in improving their education using TML simply due to technological limitations in delivering the resources that have been designed to be consumed in a campus environment. Note that such resources raise institutions’ rankings as well. For example, in categorizing institutions into four tiers, U.S. News & World Report takes information on student quality, faculty resources, and financial resources as inputs to its surveys. Taking the U.S. News tier of an institution as a proxy for the effect of TML on educational quality, we thus state the following hypothesis:

**Hypothesis 1.** Controlling for size, institutions in higher tiers have a lower proportion of their enrollment in TML courses than those in the lowest tier.

Arguably, public/private status can be another proxy for the effect of TML adoption on the quality of education \( \left( \frac{dQ}{dTML} \right) \) because the educational experience at private and public schools can be quite different even if they have similar physical resources on-campus. Public institutions receive support from state and local governments (see Table 1), which indirectly leads them to pack more students into classrooms. A simple regression analysis confirms this statement. We have collected data from 2003 U.S. News survey results (percent of classes with less than 20 students and with more than 50 students) and Department of Education’s Integrated Post-secondary Data System (public/private status and size). Controlling for size, we find that public institutions have significantly larger classes than private institutions (see Table 2). It follows that students at private universities who are accustomed to greater face-to-face interaction with their professors in small classrooms are likely to experience a loss of value when their institutions start to deliver part of the curriculum online. To the extent that interaction with

### Table 1

<table>
<thead>
<tr>
<th>Source of funds</th>
<th>Public</th>
<th>Private</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tuition and fees</td>
<td>18.5%</td>
<td>26.5%</td>
</tr>
<tr>
<td>Government appropriations, grants, and contracts</td>
<td>50.1%</td>
<td>8.8%</td>
</tr>
<tr>
<td>Federal</td>
<td>10.4%</td>
<td>7.4%</td>
</tr>
<tr>
<td>State and local</td>
<td>39.7%</td>
<td>1.4%</td>
</tr>
<tr>
<td>Private gifts, grants, and contracts</td>
<td>4.8%</td>
<td>12.4%</td>
</tr>
<tr>
<td>Investment return</td>
<td>30.0%</td>
<td></td>
</tr>
<tr>
<td>Sales and services of educational activities</td>
<td>3.1%</td>
<td>2.3%</td>
</tr>
<tr>
<td>Sales and services of auxiliary enterprises</td>
<td>9.6%</td>
<td>6.7%</td>
</tr>
<tr>
<td>Other sources</td>
<td>13.9%</td>
<td>12.4%</td>
</tr>
<tr>
<td>Total</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th>Variable</th>
<th>Proportion of classes with less than 20 students</th>
<th>Proportion of classes with more than 50 students</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.515</td>
<td>-3.848</td>
</tr>
<tr>
<td>Public</td>
<td>(15.32)*</td>
<td>(52.33)*</td>
</tr>
<tr>
<td>Enrollment (1000)</td>
<td>-0.672</td>
<td>0.708</td>
</tr>
<tr>
<td>Number of observations</td>
<td>-0.011</td>
<td>0.038</td>
</tr>
<tr>
<td>Log pseudo-likelihood</td>
<td>(6.01)*</td>
<td>(15.48)*</td>
</tr>
</tbody>
</table>

*Significant at 1% level.

Absolute value of z-statistic in parentheses.
professors enriches the educational experience, adoption of TML would, in relative terms, have a less favorable effect on the quality of education at private than public universities. We thus take public/private status as another proxy for the effect of TML on the quality of education and have the following hypothesis:

Hypothesis 2. Controlling for size, public institutions have a higher proportion of their enrollment in TML courses than their private counterparts.

3.2. The effect of location

In Section 3 we have also seen that an increase in students’ savings from location-related expenditures (i.e., lower $\frac{dLi}{dt}$) increases the optimal level of adoption. We maintain that this is more likely to happen when students of a university are more geographically dispersed, causing them to incur more travel-related expenses on average during their studies. Take the example of community colleges which almost exclusively serve residents of their states. The students of such schools are likely to drive frequently to campus from work or home and would consider travel-related expenses a significant issue. We conjecture that, all else being equal, mean travel-related expenses increase with the area of the state since this increases the geographical dispersion of the students in that state. Similarly, all else being equal, mean travel-related expenses should decrease with the population of the state ($\frac{dLi}{dt}$) we introduce the following hypothesis:

Hypothesis 3. Controlling for size, to the extent students commute to campus, the proportion of enrollment in TML courses decreases with state population density.

The global village hypothesis (GVH) predicted by prior economics research (see, e.g., [9]) is similar in spirit, but more distant in its context, to Hypothesis 3. According to GVH, Internet technology reduces the importance of distance by decreasing coordination costs both within and between firms and thus enables performing economic activities in isolated areas [18]. The higher marginal returns from the use of communication technologies in remote locations may further facilitate adoption in these areas.

A stream of research, on the other hand, argues that Internet technology requires infrastructure and support services, which are more readily available or less costly in urban settings (see, e.g., [19]). Past case studies and theoretical analyses support both views.

3.3. The effect of the opportunity cost of work

Finally, the comparative statics results suggest that an increase in the opportunity cost of work ($\frac{dw}{dt}$) raises the optimal level of adoption. Note that, compared to new hires, seasoned workers gain less from education and lose more from skipping work because the remaining lifetime earnings decrease and yearly earnings increase with accumulated work experience (see Eq. (3)). Therefore, a marginal increase in the proportion of time available for work while at school benefits experienced individuals more. For example, taking 1 or 2 years off to get a master’s degree may require uprooting a family, disrupting a steady income, and falling behind on work experience. “The No.1 reason people take [online] learning is convenience” says Michael P. Lambert, executive director of the Distance Education and Training Council, an accrediting body for TML [17]. Hiltz and Turoff [22] also indicate that the value of TML to the students is the flexibility of being able to integrate education with the demands of work and family responsibilities. This flexibility is worth more for adult learners, who are more likely to enroll in a graduate rather than an undergraduate program of study. This is not the only reason as to why graduate programs should engage more in TML, however. Graduate students additionally benefit more from TML courses because of being more mature, self-disciplined, and skilled to learn on their own compared to undergraduates. We therefore expect the effect of TML on the quality of education ($\frac{dLi}{dt}$) to be more positive at the graduate level and hypothesize that the time flexibility of TML benefits graduate programs more.

Hypothesis 4. Controlling for size, institutions with enrollment in undergraduate and graduate education use TML relatively more in their graduate programs.

4. Empirical analysis

Our empirical analysis is based on data obtained from a nationally representative survey of distance education undertaken by the National Center for Education Statistics (NCES). Part of the Postsecondary Education Quick Information System (PEQIS) of NCES, the survey provides information about the 12-month 2000–2001 academic year. The survey employs a standing panel of 1610 postsecondary education institutions that award associate, bachelor’s, master’s, and doctoral degrees.
inclusion of various types of institutions reflects the exceptionally complex nature of the U.S. higher education sector and its multitude of products [28]. We used the standard Carnegie classifications to manage this complexity. These classifications as well as institutional characteristics such as public/private status, enrollment levels, and revenue sources were obtained from the Integrated Post-secondary Education Data System (IPEDS). IPEDS is the core postsecondary education data collection program for NCES and is built around a series of interrelated surveys to collect institution-level data in such areas as enrollments, program completions, faculty, staff, and finances.

4.1. Data sample

A total of 4175 institutions located in the 50 states and the District of Columbia were eligible for the PEQIS panel. NCES stratified each panel by instructional level (four-year and two-year), control (public and private), highest level of offering (doctor’s, master’s, bachelor’s, and associate), and total enrollment; it sorted institutions within each strata by region (Northeast, Southeast, Central, West), whether the institution had a relatively high minority enrollment, and whether research expenditures exceeded $1 million; it allocated them to the strata in proportion to the aggregate square root of total enrollment, and it sampled institutions within each stratum with equal probabilities of selection. The final PEQIS panel consisted of 1610 institutions, 1500 of which participated, resulting in a 93% response rate. The survey reports the number of TML credit-granting courses (if any) offered at each institution, the number of students enrolled in these courses, and the number of degrees offered solely via TML.  

We examined the adoption of TML for four categories of schools: doctoral institutions, master’s institutions, four-year colleges, and two-year colleges. Seventeen of the 1500 schools that responded to the survey were either not found in IPEDS or reported zero enrollment. Of those found, Carnegie classification of 157 schools were not available. Among the remaining 1326 schools, 127 of them were specialty schools and 157 schools were not available. Among the remaining 1326 schools, 127 of them were specialty schools and thus did not belong to any of the above four categories. Eliminating these schools reduced the sample size to 1199. Population density of each state were found by dividing the population between ages 18 and 65 in 2000 by the area of the state. The population and area of the states were obtained from the U.S. Census Bureau Web site (http://quickfacts.census.gov).

4.2. Tests of hypotheses

We used U.S. News & World Report college rankings as proxies for the effect of TML on the quality of education. In ranking schools, U.S. News & World Report uses several criteria, including selectivity, faculty resources, financial resources, retention rates, and alumni giving, and combines several Carnegie Foundation categories into four: national universities (equivalent to doctoral institutions), regional universities (equivalent to master’s institutions), and liberal arts colleges (equivalent to four-year colleges). Since simultaneity is a concern (i.e., the overall quality of education and the level of TML adoption may affect each other simultaneously), we used the rankings that precede the PEQIS survey by 3 years (1997–1998 academic year). In that year U.S. News & World Report surveyed 182 of the 185 doctoral institutions, 39 of the 285 master’s institutions, and 32 of the 211 four-year colleges in our sample. Doctoral institutions were categorized into four tiers, while master’s institutions and four-year colleges were not tiered but were classified and ranked by region. For the latter two categories we used a binary variable indicating whether an institution was included in the relevant U.S. News & World Report survey. Named Tier 1 for ease of exposition, this variable also conveys information about quality since the surveyed institutions in these two categories were touted as the best in their region and category in the survey. Table 3 lists variable definitions; Table 4 presents the summary statistics.

positive correlation between adoption level and size due to the presumption that TML exhibits increasing returns to scale.

The proportion of enrollment in TML courses to total enrollment deserves some explanation, as it is treated as the decision variable in both the analytical framework and the empirical analysis. In the analytical framework the level of TML adoption \( k' \) is considered to be the institution’s decision, while the empirical measure is obviously a joint decision by the institution and its students. This does not pose a problem because of the way the institution’s objective function is modeled.

The impetus for universities to adopt TML is that they perceive that their students will take TML courses if offered, and students take the offer because they value the benefits of the technology. This is consistent with the analytical framework where institutions act on behalf of their students and maximize the value of their degree offerings, with the net gains associated with the adoption of TML accruing to the students.

As briefly discussed in the previous subsection, one may argue that TML may affect the overall quality of education, and consequently propose TML to be a determinant of school rank. To avoid these simultaneity issues we use 1997–1998 academic year values for the time-variant explanatory variables (enrollments and rankings).\(^{10}\) Denoting the year of the data with a subscript and assuming a linear relationship among the dependent and explanatory variables in Eq. (9), we estimate:

\[
\begin{align*}
\frac{\text{TML enrollment}_{2000}^i}{\text{Total enrollment}_{2000}^i} &= \beta_0 + \beta_1 \text{Total enrollment}_{1997}^i \\
&\quad + \beta_2 \text{Tier 1}_{1997}^i + \beta_3 \text{Tier 2}_{1997}^i \\
&\quad + \beta_4 \text{Tier 3}_{1997}^i + \beta_5 \text{Public}^i \\
&\quad + \beta_6 \text{State population density}^i.
\end{align*}
\] (10)

In testing the hypotheses according to the above specification, we set \( \beta_3 = \beta_4 = 0 \) for master’s institutions and four-year colleges since U.S. News & World Report designates only the top tier in these categories. In other words, for these schools the coefficient for Tier 1 should be interpreted as “being surveyed by U.S. News & World Report.” Similarly, we set \( \beta_2 = \beta_3 = \beta_4 = 0 \) for two-year schools. Further, although we do not expect state population density to be important for doctoral institutions (since a significant majority of their student body resides on campus), we keep this variable in the specification of this category for completeness.

While Hypotheses 1–3 are tested separately for all four categories of institutions, Hypothesis 4 can be tested for only two types, namely doctoral and master’s institutions, because only such schools operate at both the undergraduate and graduate levels. In empirically testing this hypothesis, the graduate and the undergraduate level observations of each university are treated as two different data instances, and a dummy variable (called the graduate dummy) is used to indicate which of the two observations pertains to the graduate level. Each observation includes

\(^{10}\) The reason we used 1997–1998 rankings is because of the availability of data.
data on total enrollment and enrollment in TML courses at the respective level, with the graduate dummy being zero at the undergraduate level and one at the graduate level. Data that are invariant to the two levels (such as tier information, public status, and state population density) take the same values in both observations of a university. The undergraduate and graduate level data for the two categories of universities are pooled to test the difference in the level of adoption between the two levels. While testing, observation pairs for each university are clustered to allow for correlation in the error terms within groups. Note that this approach assumes the same coefficients for the independent variables at the undergraduate and graduate levels, although the results remain relatively similar when the coefficients are allowed to vary. See the specification below.

\[
\frac{TML\ enrollment_{2000}}{Total\ enrollment_{2000}} = \beta_0 + \beta_1 TML\ enrollment_{1997} + \beta_2 Tier_1 + \beta_3 Tier_2 + \beta_4 Tier_3 + \beta_5 public + \beta_6 State\ population\ density + \beta_7 Graduate\ dummy.
\]

The hypotheses are tested using generalized linear models (GLM) based on the work of Papke and Wooldridge [31] who report the superiority of this
methodology in estimating fractional response variables.¹¹ Tables 5 and 6 provide the results of tests of Hypotheses 1–4 for all four categories of schools: doctoral institutions, master’s institutions, four-year colleges, and two-year colleges. We next discuss the tests of hypotheses in their respective order.

The coefficients of Tier 1 are negative for all three types of universities that have this variable and significant for doctoral and master’s institutions. The significance level is less than 1% for doctoral institutions, which is the most visible category in higher education. In this category, the coefficients of tiers increase as we go from Tier 1 to Tier 3, with all being negative. That is, the use of TML decreases with rankings.¹² Predicting the level of adoption for Tier 1 and Tier 4 doctoral institutions using the mean values of explanatory variables shows that, all else being equal, Tier 4 institutions are expected to utilize TML more than three times as much compared to those in the top tier (Tier 4 institutions are predicted to have 2.2% of their total enrollment in TML courses, while the corresponding figure for Tier 1 institutions is 0.6%). These results indicate that reputable universities are less likely to offer TML courses, and thus provide strong support for Hypothesis 1.

Hypothesis 2 is generally not supported. We observe a significant result only for doctoral institutions at the undergraduate level (see the first column of Table 6). The coefficients are positive for all categories except master’s institutions. Perhaps public institutions in this category provide a higher quality education than their private counterparts that they find relatively harder to improve online.

The coefficient of state population density is negative in all four categories but significant only for master’s institutions and two-year colleges. As stated before, most

¹¹ Since a proportion is bounded from below by zero, an alternative method of estimation is the standard censored tobit model. Testing the hypotheses using this model yields similar results, which are available from the contact author.

¹² We have also ran the tests excluding Tier 2 and Tier 3. According to these tests the difference between the coefficients of Tiers 1 and 2 is also significant.

### Table 5
Proportion of enrollment in credit-granting TML courses, estimated with generalized linear models

<table>
<thead>
<tr>
<th>Variable</th>
<th>Doctoral institutions</th>
<th>Master’s institutions</th>
<th>Four-year colleges</th>
<th>Two-year colleges</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-4.047</td>
<td>-3.108</td>
<td>-4.741</td>
<td>-3.369</td>
</tr>
<tr>
<td></td>
<td>(13.36)**</td>
<td>(9.41)**</td>
<td>(14.39)**</td>
<td>(7.34)**</td>
</tr>
<tr>
<td>Total enrollment (1000) in 1997–1998</td>
<td>-0.005</td>
<td>0.022</td>
<td>0.125</td>
<td>-0.004</td>
</tr>
<tr>
<td></td>
<td>(0.42)</td>
<td>(0.95)</td>
<td>(2.52)**</td>
<td>(0.65)</td>
</tr>
<tr>
<td>Tier 1 in 1997*</td>
<td>-1.266</td>
<td>-0.926</td>
<td>-0.699</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.48)***</td>
<td>(1.83)*</td>
<td>(1.04)</td>
<td></td>
</tr>
<tr>
<td>Tier 2 in 1997</td>
<td>-0.742</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.98)***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tier 3 in 1997</td>
<td>-0.389</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.81)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Public</td>
<td>0.523</td>
<td>-0.560</td>
<td>0.330</td>
<td>0.265</td>
</tr>
<tr>
<td></td>
<td>(1.38)</td>
<td>(1.64)</td>
<td>(0.89)</td>
<td>(0.60)</td>
</tr>
<tr>
<td>State population density</td>
<td>-0.109</td>
<td>-3.534</td>
<td>-0.499</td>
<td>-1.941</td>
</tr>
<tr>
<td></td>
<td>(0.63)</td>
<td>(1.90)*</td>
<td>(0.33)</td>
<td>(3.54)**</td>
</tr>
<tr>
<td>Number of observations</td>
<td>185</td>
<td>285</td>
<td>211</td>
<td>518</td>
</tr>
<tr>
<td>Log pseudo-likelihood</td>
<td>-11.37</td>
<td>-23.61</td>
<td>-9.84</td>
<td>-58.57</td>
</tr>
</tbody>
</table>

Logit link function and robust (White) standard errors are used in the estimation.

Absolute value of z-statistic in parentheses.
*Significant at 10% level.
**Significant at 5% level.
***Significant at 1% level.

* Excluded is Tier 4.

### Table 6
Proportion of enrollment in credit-granting undergraduate and graduate TML courses, estimated with generalized linear models

<table>
<thead>
<tr>
<th>Variable</th>
<th>Doctoral institutions</th>
<th>Master’s institutions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-4.425</td>
<td>-3.738</td>
</tr>
<tr>
<td></td>
<td>(13.80)***</td>
<td>(10.28)***</td>
</tr>
<tr>
<td>Total enrollment (1000) in 1997–1998</td>
<td>-0.010</td>
<td>0.045</td>
</tr>
<tr>
<td></td>
<td>(0.57)</td>
<td>(1.34)</td>
</tr>
<tr>
<td>Tier 1 in 1997*</td>
<td>-1.146</td>
<td>-0.563</td>
</tr>
<tr>
<td></td>
<td>(3.57)***</td>
<td>(1.36)</td>
</tr>
<tr>
<td>Tier 2 in 1997</td>
<td>-0.688</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.16)**</td>
<td></td>
</tr>
<tr>
<td>Tier 3 in 1997</td>
<td>-0.379</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.99)</td>
<td></td>
</tr>
<tr>
<td>Public</td>
<td>0.742</td>
<td>-0.323</td>
</tr>
<tr>
<td></td>
<td>(2.70)***</td>
<td>(1.03)</td>
</tr>
<tr>
<td>State population density</td>
<td>-0.121</td>
<td>-3.761</td>
</tr>
<tr>
<td></td>
<td>(0.72)</td>
<td>(2.48)</td>
</tr>
<tr>
<td>Graduate dummy</td>
<td>0.589</td>
<td>1.288</td>
</tr>
<tr>
<td></td>
<td>(3.21)***</td>
<td>(5.63)**</td>
</tr>
<tr>
<td>Number of observations</td>
<td>370</td>
<td>570</td>
</tr>
<tr>
<td>Log pseudo-likelihood</td>
<td>-25.67</td>
<td>-58.17</td>
</tr>
</tbody>
</table>

The upper seven coefficients represent the estimates for both the undergraduate and graduate degree level data. The coefficient of graduate dummy indicates whether the constant term for graduate level differs from that for undergraduate level. Logit link function and robust (White) standard errors are used in the estimation. Observation pairs for each university are clustered to allow for correlation in the error terms within groups. Absolute value of z-statistic in parentheses.

*Significant at 10% level.
**Significant at 5% level.
***Significant at 1% level.

* Excluded is Tier 4.
of the students of doctoral institutions reside on campus, so the insignificance of the coefficient for this category is expected. This is also true for the four-year colleges because many schools in this category are liberal arts colleges whose students predominantly reside on campus. Thus, at least for schools that have a commuting student body, the location of the institutions seems to impact the level of TML adoption, supporting Hypothesis 3.

Hypothesis 4 predicts that institutions offering undergraduate and graduate education should use TML relatively more at the graduate level. Estimates of the pooled undergraduate and graduate level data suggest that doctoral and master’s institutions use TML more in their graduate programs. The coefficient of graduate dummy is significantly positive with less than 1% p-value for both types of universities (see Table 6). All else being equal, the predicted level of the extent of adoption is more than three times as much at the graduate level than the undergraduate level for master’s institutions and about 80% more for doctoral institutions.

Allowing variation for the coefficients on the set of all independent variables at undergraduate and graduate levels leads to similar results, except the following. First, rankings are less significant for both types of institutions at the graduate level, which is consistent with our conjecture that the effect of TML on the quality of education (\( \frac{d_{C16}}{d_{C17}} \)) would be larger for graduate students. Second, state population density (i.e., location flexibility of TML) is more negatively significant for master’s institutions at the graduate level than the undergraduate level. This may be due to the increased opportunity cost of education for graduate students of such institutions. In short, we find strong support for Hypothesis 4 and conclude that the asynchronous nature of TML is more popular for graduate level courses. This result is in line with both Zhang et al. [35] who suggest time flexibility as an important benefit of TML and with the views of industry experts who argue that TML programs are geared mainly toward the adult learners. “It is the older student who is driving the market,” says Raymond Boggs, vice president of education research for International Data Corp., a technology research firm based in Framingham, MA. According to Andy DiPaolo, executive director of Stanford University’s Center for Professional Development, most of the online education is targeted to adults [7]. This study confirms and quantifies this statement.

5. Discussion and conclusions

Past IS research has primarily focused on the comparison of TML and non-TML environments but largely ignored the program and university levels of analysis [2]. We take the discussion to a different level by examining the extent of TML adoption among U.S. higher education institutions, and observe that a number of institutional and student characteristics drive adoption patterns.

Although TML has been diffusing at a rapid rate in the U.S., we find that certain types of institutions and programs are in a better position to take advantage of this new form of instructional delivery. For example, we find that top universities use TML less than their lower ranked counterparts, potentially due to the difficulty involved in improving their already well-established degree offerings through Web interfaces. Universities at the lower end of the ranking spectrum, on the other hand, are less likely to face such challenges. Note that this result also implies that top universities will benefit relatively more from future improvements in TML technology. Schell [33] points out a faculty incentive issue not considered here; he argues that faculty at schools with a doctoral program do not have an interest in developing online courses since doing so does not contribute to their promotion and tenure. The relative importance of research compared to teaching and the associated incentive structure in place at top schools may present another reason for their relatively limited adoption.

Our results confirm that offering graduate degrees with TML makes more economic sense than offering undergraduate ones. Universities throughout the U.S. employ TML more at the graduate level, a result that highlights the significance of time flexibility of TML in driving adoption. Further, universities in sparsely populated states that rely on a commuting student body are strongly advised to consider utilizing the opportunities enabled by TML. This would allow such institutions to increase the value of their degree offerings as perceived by their students since they will have to travel less to achieve their educational objectives.

In addition to researchers of TML, we expect the results of this study to be of value to academic administrators at public and private institutions who face the problem of designing a hybrid degree. Our framework provides a list of important issues to consider: What is the quality of your education on campus? Can you offer some of the classes from a distance using IT without sacrificing much from quality, and at what cost? What are the characteristics of your student body, and how much would they value the time and location flexibilities of TML? A rigorous treatment of these questions will help academic administrators design hybrid programs that would benefit both their institutions and their students.
Our dataset contains information about only accredited, not-for-profit institutions, which have traditionally provided the mainstream higher education with their overwhelming presence in the sector. The analytical framework applies to for-profit institutions as well because maximizing the net value to students using technology allows them to charge a higher tuition and thereby maximize profit (assuming the size of the institutions are fixed). Therefore, we would obtain similar hypotheses for for-profit institutions, and testing these hypotheses in this particular context is a potential direction for future research. Also, we admit that state population density is not the most precise measure for the location effect of TML adoption. The use of more precise measures would enhance future investigations in this area.

Given TML’s record rate of growth as reported by Sloan-C foundation [3], we expect the mainstream higher education institutions to embrace TML even further in the near future, a development that will have far-reaching implications for all stakeholders. For example, prospective students will have many more opportunities to choose from as universities compete to offer new courses and degrees through TML. In that environment, it will be imperative for students to pay close attention to the credentials of these degree programs as well as institutions that offer them. Adult learners will need to check the value of an online degree compared to a traditional one for their employer before they invest their time and money. Employers, on the other hand, will need to investigate the quality of online degree offerings since they will soon be evaluating such credentials more frequently as they recruit new hires. They will also need to update their policies about the kinds of online education they endorse and support for their employees. We suspect that these will be difficult tasks given the rate of change in TML in terms of technology, pedagogy, and subject area.

Administrators of higher education institutions are likely to be under pressure to expand their educational offerings through TML. One of the primary concerns of these institutions in this process will be maintaining the level of educational quality. Therefore, in order to make the right investments, administrators will need to examine the TML literature about the success factors as well as the available technologies that best support a thriving learning environment. They will also need to make the appropriate changes in faculty’s incentives so that the additional effort necessary to teach well-designed online courses will not be viewed as a burden. Finally, most faculty will eventually be expected to teach using online tools and resources, if not courses completely delivered online. Therefore, we as instructors need to understand the different needs of students taking online courses and equip ourselves with pedagogical tools that reportedly work. Online education is here to stay; the institutions that deliver it best will be the winners in this century.

References

[8] J. Braun, Do your homework: it’s easy to find online M.B.A. programs these days; it’s harder to find one that is right for you, The Wall Street Journal (in press) October 20, 2003.


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