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Technology as a Double-Edged Sword: From Behavior Prediction with UTAUT to Students' Outcomes Considering Personal Characteristics

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Abstract

Aim/Purpose	We aim to bring a better understanding of technology use in the educational context. More specifically, we investigate the determinants of webinar acceptance by university students and the effects of this acceptance on students' outcomes in the presence of personal characteristics such as anxiety, attitude, computer self-efficacy, and autonomy.
Background	According to literature in information systems, understanding the determinants of technology use and their effect on outcomes can help ensure their effective deployment, which might yield productivity payoffs.
Methodology	Data collection with an online quantitative questionnaire yielded to 377 valid responses from students enrolled in an undergraduate management information systems course. SPSS software allowed obtaining descriptive statistics and Smart-PLS was used for validity and hypotheses testing.
Contribution	Previous studies assessed either the determinants of technology use or the effect of their use on students' outcomes, and often omitted to assess the role of personal characteristics. This research fulfills the gap about the scarcity of studies that link goals to intentions and behavior, while considering personal cognitive characteristics.
Findings	Results showed that performance expectancy, social influence, facilitating conditions, and voluntariness of use explained the behavioral intention and webinar usage. Some of these relationships were direct and others were moderated. Satisfaction was the only student outcome affected by the use of webinars. Anxiety, attitude, and autonomy are the personal characteristics that exerted direct and moderating effects on the relationships between the main variables of the research model.

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Recommendations for Practitioners	Results gave rise to interesting managerial recommendations for adopting technologies in universities. Among them, teachers are encouraged to promote the webinars' advantages and to exert less pressure on students to use webinars.
Recommendation for Researchers	On the theoretical side, we brought a holistic view of the use of technologies in higher education by linking goals to intentions and behavior, and integrating personal cognitive characteristics into the same model. Results allowed enriching the literature about technology adoption in the educational context.
Future Research	Future research should follow closely the results of studies on generation Z to find better explanatory variables of technology adoption. We also propose to consider new variables from the updated technology acceptance models to further understand the derteminants of technology use by students.

Keywords webinar, UTAUT, students' outcomes, personal characteristics, Smart-PLS

INTRODUCTION

Kambouchner, Meirieu, Stiegeler, Gautier, and Vergne (2012) defended the idea that the petty-minded attitude toward the use of technologies in the educational system have to be rejected because we live in a digital area. Philosophers Vilém Flusser and Bernard Stiegel share the same techno-centric view in that they consider technologies used in our everyday lives more than simply means. Their broader vision recognizes technologies as "the kind of beings we are" (Vlieghe, 2014). They believe that our minds should behave differently by adapting their operation to the use of technologies. However, philosopher Stiegel claims, "education should consist in preserving an existing frame of reference across the changing of generations" (Vlieghe, 2014). In the presence of these two conflicting ideas, the philosophical question that Vlieghe (2014) raised was, "whether the introduction of digital media in the educational sphere may—or may not—fundamentally alter the very meaning of education itself."

We support astronaut Neil Armstrong's idea he expressed when he walked on the moon and said, "That's one small step for man, one giant leap for mankind." Indeed, we are far from answering the issue of whether the digitization of education will lead to transformation within education or of education itself (Vlieghe, 2014). We believe we are better to go one-step at a time by trying first to understand the use of technologies in the educational context as they are invading almost all educational levels.

Vlieghe (2014) argued that most existing studies ask if replacing one technology with another may have positive or negative effects on education. The issue, then, is not whether technologies should or should not be used in education, but how they should be used to avoid a "generalized proletarization of the consumer," blindly following the herd of technology consumers (Vlieghe, 2014).

Vlieghe (2014)'s analogy is interesting in that he compared technologies to "pharmaka." Like medicines, technologies cure and poison at the same time. Saying that technologies are good or bad depends on the way in which they are used. The philosopher Agamben argued, "There is no correct use of technology." While Stiegler interpreted this assertion to mean that technology can only be used incorrectly, Vlieghe (2014) allots a more profound meaning to it by asserting, "Under present societal and cultural conditions, it is no longer possible to discern between correct and incorrect use." This last vision makes us free from the normative framework of good and bad uses. However, we deem it relevant to know what makes an individual use technologies and what the impact of that use is. According to Taylor & Todd (1995b), there is a pragmatic finality in understanding the determinants of use because they can help ensure effective deployment of technological resources. This usage can yield productivity payoffs from information technology investments (Davis, 1989).

In the educational context, many researchers studied the determinants of technology use and intention to use (Khechine, Lakhal, Bytha, & Pascot, 2013, 2014a, 2014b; Lakhal, Khechine, & Pascot, 2013). Other authors tried to understand the effect of technology use on students' outcomes such as learning (de Gara & Boora, 2006; Myers & Schiltz, 2012; Wang & Hsu, 2008), learning performance, and satisfaction (Khechine & Lakhal, 2015; Lakhal, Khechine, & Pascot, 2014). Personal characteristics such as autonomy (Khechine et al., 2013; Lakhal & Khechine, 2016; Lakhal et al., 2013; Roca & Gagné, 2008), anxiety (Bozionelos, 2004; Khechine & Lakhal, 2015; Mcilroy, Sadler, & Boojawon, 2007), attitude (Myers & Schiltz, 2012), and computer self-efficacy (Mcilroy et al., 2007) were integrated into models assessing either the determinants of use or the effect of use on students' outcomes. To our knowledge, no study brought a holistic view of technology use by simultaneously assessing the determinants of use, the effect of use on students' outcomes, and the role of personal characteristics of the users. Integrating all these elements in one model allows capturing the perceptions that may affect the acceptance of technology—perceptions that most of the adoption theories support—and the consequences of their concrete technology use while considering their personal cognitive characteristics. Adopting such a holistic view is a way of "implementing" Tate, Evermann, and Gable (2015) recommendations. Indeed, these authors suggested that new studies should fulfill the significant gap that characterizes TAM-related (Technology acceptance model) research (Bagozzi, 2007), and consequently UTAUT (Unified theory of use and acceptance of technology) research. This gap is about the scarcity of studies that link goals to intentions and behavior and that integrate personal cognitive characteristics.

In the research, we aim to bring a better understanding of the use of technologies in the educational context. More specifically, we investigate the determinants of technology acceptance by university students and the effects of this acceptance on students' outcomes in the presence of personal characteristics such as anxiety, attitude, computer self-efficacy, and autonomy. The specific technology under consideration here is webinars. Webinars are technologies that organizations and universities use to support online training and courses. They permit synchronous interactions between participants and asynchronous communication through videos, audios, images, whiteboards, and shared applications. Webinars enable students to follow the course in live from outside the classroom or to listen to the recordings later. These options are advantageous to busy students who are in the labor market or to foreign students unable to travel at a specific time to attend a classroom session (Khechine et al., 2014a).

The aim of this research is **threefold**:

- **The first aim** is to identify the determinants of webinar intention to use and effective use by students. We think it is important to know why students accept or reject a technology as it represents an important investment in an economic stringency climate. As stated earlier, understanding determinants of usage can help ensure an effective deployment of technologies (Taylor & Todd, 1995b), which may enhance productivity (Davis, 1989). The acceptance of a technology would be improved if we focus managerial efforts on these determinants.
- **The second aim** is to investigate the effect of webinar use on students' outcomes. These outcomes dissociate into two categories: an objective outcome (grades) and a subjective outcome (satisfaction). According to Venkatesh, Thong, and Xu (2016), research has mainly operationalized individual impact as performance. In the context of education, the impact of technology use cannot be limited to students' grades. It has to be extended to other outcomes that we look for when training students, such as satisfaction. The choice of satisfaction as an outcome variable is owing to the fact that user satisfaction is recognized from decades as a key metric of information systems success (DeLone & McLean, 1992).
- **The third aim** is to consider the influence of personal characteristics on webinar use and on students' outcomes. On one hand, the propensity of students to use a certain kind of technology is dependent on their personal intrinsic characteristics such as attitude, autonomy, anxiety, and computer self-efficacy (Khechine & Lakhal, 2015; Khechine et al., 2013; Lakhal et al., 2013). On the other hand, we think that student results are dependent not only upon technology use, but on many other factors derived from the environment of use. Because we are not able to control the

complex environmental factors, we focused on personal factors that could be influenced by this environment, which are students' personal characteristics.

The paper is organized as follows. In the literature review, we define blended learning and the webinar concept, we present some recent studies dealing with the use of webinars, and we introduce the theoretical framework of this research. Then, we define the research variables, describe the model and propose the hypotheses. Following that, we present the study context and the procedure we used to collect data. We present and discuss study results in four steps: 1) descriptive statistics; 2) reliability and validity; 3) hypotheses testing and interpretation; and 4) explained variances discussion. We end the paper with a conclusion where we summarize the findings, present contributions, debate limitations, and provide suggestions for future research.

LITERATURE REVIEW

The aim of this research is to investigate the determinants of webinar use by university students and the effects of this use on students' outcomes considering personal characteristics. Because webinar use is made in the context of blended learning, we deem it relevant to explain this concept and its different combinations. Webinars, and in particular Elluminate product, are also introduced in order to build a framework for better understanding the context of the study. The theoretical foundation of this study is the UTAUT model and it deserves to get familiar with before presenting the research model and hypotheses.

BLENDED LEARNING

In many universities around the world, the classroom courses have made room for online courses. Already in 2000, Volery and Lord (2000) asserted that introducing e-learning technologies to courses in universities is no longer an option but a requirement to respond to globalization. Quietly, educators began experimenting with several formulas of learning based totally or partially on information technologies. Among these formulas, blended learning attracted the interest of teachers and researchers in the fields of education and information technologies. Blended learning is a mixture of face-to-face instruction with computer-mediated instruction (Graham, 2006; Rooney, 2003; Young, 2002). Hijazi, Crowley, Smith, and Schaffer (2006) describe it as a leaning in which both face-to-face and distance learning methods are collaboratively used in an effort to provide students with the benefits of both delivery styles. The convergence of the technology-based distributed environments and the traditional face-to-face learning environment gave rise to different forms and combinations of blended learning (Duhaney, 2004). Graham (2006) and J-H. Wu, Tennyson, and Hsia (2010) described these combinations as processes where participants and trainers interact in e-learning and face-to-face learning scenarios. Four dimensions determine these scenarios (Graham, 2006): space (physical/face-to-face vs distributed), time (live/synchronous vs asynchronous), fidelity (rich/all senses vs text only), and humanness (high human/no machine vs no human/high machine). Khechine et al. (2014b) gave some examples of blended learning scenarios based on these dimensions. For instance, an online course that adds synchronous technology-based interactions with live chats becomes blended. In this case, the time dimension is changed. If we add audio broadcasting or recordings, the fidelity dimensions is affected. Integrating virtual communities or virtual messaging to this course makes the humanness dimension move.

Universities and organizations adopted blended leaning for education and training because of their potential advantages (Bitzer, Söllner, & Leimeister, 2016). Indeed, blended learning allows for mixing the strengths of synchronous face-to-face and asynchronous technology-based learning activities (Garrison & Kanuka, 2004). Blended instruction offers students the "best of both worlds": flexibility of online education, and social and instructor support commonly associated with face-to-face classes (Lloyd-Smith, 2010). However, instructors embark on blended-learning experiences while research has not shed enough light on the questions regarding students' willingness to accept blended technologies and the efficacy of this acceptance.

Elluminate as a Webinar

In blended learning, many technologies are used to let participants interact with each other synchronously or to get access to recorded face-to-face sessions. Some of these technologies are called webinars. A webinar is a web conferencing seminar where events and information can be shared with remote participants in real-time (O'Leary, 2013). Instead of a mere broadcast of information, the webinars enable rich, interactive, and participatory learning (Wyatt, 2006). Indeed, participants can exchange synchronously text-centric messages, view and record videos, and discuss with voice services. Other software and services can be associated with webinar sessions like software and screen sharing. The real time interaction fosters a social presence because participants can observe each other's reactions. This interaction makes participants constantly connected, actively engaged, and motivated for the course (Hrastinski, 2008; Kear, Chetwynd, Williams, & Donelan, 2012; Lee & McLoughlin, 2010). All webinar sessions can also be recorded for later viewing or listening, which also makes the webinar an asynchronous communication tool.

Mostly, webinars are used for educational presentations, business meetings, or trainings. The main advantages of webinars are the avoidance of travel fees and the flexibility of the time and the place of use. They also allow for access to distant skills with low costs, as they require only an Internet connection for participants. The deployment of webinars began in the early 1990s thanks to video web-conferencing capabilities. A decade later, businesses and higher education institutions introduced webinars in their daily activities (Zoumenou et al., 2015).

A number of literatures have reported many experiences of webinar use. For instance, the Illinois Library Association introduced webinars using Elluminate software for employee training (Wyatt, 2006). Most of the participants enjoyed the webinar experience and asserted that webinars were a good tool for professional development. In the educational context, college students whose mission was to "teach" their class on the subject of their choice also used Elluminate (Wang & Hsu, 2008). Students enrolled in this graduate-level course at a Northeastern University in the United States of America (USA) have appreciated the tools that the webinar offered such as whiteboards and polls. They were also pleased by the rich and interactive dialogue that occurred, thanks to synchronous communication. Discussions were promoted by the intervention of shy students because they enjoyed anonymity. Technical problems were the most cited disadvantages by students. Medical college students in Japan used Skype as a webinar system to organize real-time video-audio seminars with a geographically distant American medical educator. Excluding technical problems, participants indicated that they took great advantages from webinars as supplementary material to their clinical training (Stein, Shibata, Bautista, & Tokuda, 2010). Another webinar system, Adobe Acrobat Connect Pro, was tested in an undergraduate chemistry and biochemistry seminar course at Andrews University in Michigan (Hamstra, Kemsley, Murray, & Randall, 2011). Most students were excited by the use of the webinar system and appreciated its use by confirming that the remote presenter had a strong presence. They admitted that both the presentation technology and the seminar content were well-received compared to traditional "in-person" presentations. They also reported an increased grasp of the course's content.

Blackboard is a company that offers online collaborative solutions to institutions (see Blackboard website www.blackboard.com). One of its products, Elluminate, is a tool that enhances visual pedagogical practices in the classroom. It is a user-friendly software designed as a web conferencing solution for learning. It does not require software download on the desktop of the user. Many tools are available within Elluminate: vocal discussions using microphones, video discussions, text chatting, writing, drawing and pasting images on a shared whiteboard, viewing and sharing documents and screens, using emotion icons, and raising hands if students have a question (Michael, 2012). Some studies reported research results about Elluminate. Among them, Michael (2012) collected the opinions of students and teachers who used the software. The objective of her study was to understand student and staff experiences with online learning at higher education using Elluminate. The main advantages identified by Michael (2012) of using Elluminate were flexibility, convenience, and cost reduction. Flexibility refers to the ability for teachers to maintain their teaching duties in their original country and to respond to overseas teaching responsibilities. Convenience was materialized by the ability of students to logon to the course at times that were convenient for them. In contrast to regular face-to-face classes where a number of students withdraw due to work, family, or other obligations, the convenience may contribute to reducing student dropout. Cost reduction was achieved by decreasing travel expenses (e.g., petrol, parking, airfares) for students and teachers. Teacher replacement costs to ensure classes on remote campuses were also avoided because instructors could deliver course content from the main campus. The reduction of a student's carbon footprint may lead to a reduction in waste and energy consumption, which ultimately represents another example of cost reduction.

In the light of these studies, we can learn that blended instruction offers students the "best of both worlds": flexibility of online education, and social and instructor support commonly associated with face-to-face classes (Lloyd-Smith, 2010). However, most instructors tout the advantages of blended software without questioning their acceptance by students and their efficacy. In the information systems field, we all recognize that the acceptance of a technology is a guarantor of its use and success. Despite this, to our knowledge, questions about student's willingness to accept blended technologies and the efficacy of their use were not investigated well enough. To fill this gap, we propose to answer three research questions. 1) What are the determinants of the intention to use Elluminate and of its effective use by students? 2) Does the use of Elluminate have an impact on students' outcomes, specifically grades and satisfaction? 3) Do personal characteristics such as anxiety and autonomy have an effect on the intention to use or the effective use of Elluminate, and on students' outcomes?

UTAUT Model as a Theoretical Foundation

One of the main streams of management information systems research is understanding individual acceptance and use of technologies (Benbasat & Barki, 2007; Venkatesh, Davis, & Morris, 2007). Oye, A.Iahad, and Ab.Rahim (2012 as cited in Samaradiwakara & Gunawardena, 2014) argued that "technology is of little value, unless it is accepted and used". It is therefore important to investigate how to promote use and to determine what hinders the acceptance and usage of technologies in order to provide managers with the best recommendations.

During the last six decades, many theories were designed to measure the acceptance of technologies at both the individual and organizational levels. Among them, the unified theory of acceptance and use of technology (UTAUT), proposed by Venkatesh, Morris, Davis, and Davis (2003), was considered by many authors (Al-Shafi & Weerakkody, 2010; Alawadhi & Morris, 2008) as the best predictive model in the acceptance literature. The UTAUT model is the result of a synthesis of eight theories of technology acceptance, diffusion, and use, usually employed in the management information systems field (theory of reasoned action of Fishbein and Ajzen (1975); technology acceptance model of Davis (1989); motivational model of Davis, Bagozzi, and Warshaw (1992); theory of planned behavior of Ajzen (1991); combined theory of planned behavior/technology acceptance model of Taylor and Todd (1995a); model of personal computer utilization of Thompson, Higgins, and Howell (1991); diffusion of innovation theory of Rogers (1995); and social cognitive theory of Compeau and Higgins (1995)). Venkatesh et al. (2003) designed the UTAUT model to obtain a more exhaustive understanding and prediction of users' behavior that previous models could not achieve individually (Khechine, Ndjambou, & Lakhal, 2016).

The UTAUT model contains six main variables: four independent variables that are performance expectancy, effort expectancy, social influence, and facilitating conditions, and two dependent variables that are behavioral intention and usage behavior. The moderating variables of the UTAUT model are gender, age, experience, and voluntariness of use. These variables moderate the relationship between the independent and the dependent variables (Venkatesh et al., 2003).

The UTAUT model was originally developed to explain employee technology acceptance and use (Venkatesh, Thong, & Xu, 2012). It was applied to many contexts such as health and education. Later, it was extended to the UTAUT2 model that was destined to explain consumer acceptance and use of technologies. For this purpose, three independent variables were added to the original UTAUT model: hedonic motivation (the fun or pleasure derived from using a technology), price value (consumers' cognitive tradeoff between the perceived benefits of the technology and the monetary cost for using it), and habit (self-reported perception that the behavior is automatic) (Venkatesh et al., 2012). Because we are not in a context of a hedonic use, we adopted the original UTAUT model that we adapted to blended learning technology users.

RESEARCH MODEL AND HYPOTHESES

In this section, we present the research variables of the UTAUT model. According to Venkatesh et al. (2012), the addition of new variables to theories that focus on a specific context can be helpful to expand the theoretical horizons of these theories. In accordance with Venkatesh et al. (2012) suggestion, we explain how we embedded outcome and the personal characteristics variables to the original UTAUT model in the context of blended learning.

RESEARCH VARIABLES

In recent years, we observed an increasing interest in applying the UTAUT model to the educational context. For instance, Donaldson (2011) used it to understand the determinants of students' acceptance and use of mobile technologies for learning in the USA. Sun and Jeyaraj (2013) used the UTAUT model to evaluate the adoption of a Blackboard system by Chinese students. Khechine et al. (2014b) chose the UTAUT model to find factors that explained the acceptance of a webinar system in a blended learning course by students in Canada. Maduku (2015) used the UTAUT model to identify factors that affect the intention to use e-books by students in South African institutions of higher learning. Ho, Chou, and Fang (2016) experimented the UTAUT model to evaluate the adoption of podcasts for language learning in Taiwan and China. We are aware that the UTAUT is a very popular model in the information systems literature since the early 2000s. It was usually and largely employed to identify the determinants of technology use. However, it was not enough employed to explore beyond this use for evaluating the outcomes of technology adoption, especially in higher education. In this research, we contribute to fill this gap by extending the original UTAUT model to students' outcomes.

Over the years, many variables related to individual personal characteristics were added to the original UTAUT model for a better understanding of technology acceptance by students. For instance, Ima, Kimb, and Hanc (2008) integrated into the UTAUT model the perceived risk of decisions made by students that used three kinds of technologies in undergraduate and graduate courses in a university in northeastern US. Lakhal et al. (2013) added autonomy as an explaining factor of the intention of undergraduate business students in Canada to use a webinar technology. Olatubosun, Olusoga, and Shemi (2014) integrated self-efficacy, attitude toward using the technology, and anxiety to the UTAUT model to evaluate the readiness of Nigerian students to use an e-learning system. Lwoga and Komba (2015) have shown that self-efficacy had a significant effect on the behavioral intention and the effective use of web-based learning management systems in Tanzania. Barnett, Pearson, Pearson, and Kellermanns (2015) integrated the personality traits of the Big Five model to the UTAUT model to predict the intention to use and the effective use of a custom-designed web-based course management system by students in the US.

As seen in Figure 1 (below), 10 of the tested model's 16 variables belonged to the UTAUT model of Venkatesh et al. (2003). Testing the relationships between these variables allows answering the first research question. Except for age and gender, the operational definitions of these variables are as follows (Khechine et al., 2016).

- Performance expectancy (PE): the degree to which an individual believes that using the system will help him or her to attain gains in job performance (Venkatesh et al., 2003) (p. 447);
- Effort expectancy (EE): the degree of ease associated with the use of the system (Venkatesh et al., 2003) (p. 450);
- Social influence (SI): the degree to which an individual perceives that important others believe he or she should use the new system (Venkatesh et al., 2003) (p. 451);
- Facilitating conditions (FC): the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system (Venkatesh et al., 2003) (p. 453).
- Behavioral intention (BI): the willingness of respondents to use the system, often measured with a three-item scale (Davis, 1989).
- Use behavior (UB): participants' self-report of the degree of using the system (the number of times they log into the system or the period spent on it).
- Experience: the opportunity for an individual to use a technology. It is often measured with the time spent from the initial use of this technology, such as a computer (Kim & Malhotra, 2005; Venkatesh et al., 2003).
- Voluntariness of use: the degree to which use of the innovation is perceived as being voluntary, or of free will (Moore & Benbasat, 1991) (p. 195).

We added the following variables that allowed integrating personal characteristics into the UTAUT model in order to answer the second research question:

- Anxiety: anxious or emotional reaction when it regards to performing a behavior (Venkatesh et al., 2003).
- Attitude: an individual's negative or positive feelings about performing the target behavior (Fishbein & Ajzen, 1975). In this research, attitude refers to students' feelings about the technology in use.
- Autonomy: the action of taking responsibility for and control of his/her learning (Fillion, 2005).
- Computer self-efficacy: judgment of one's ability to use a technology (Compeau & Higgins, 1995) – in this case a computer – to accomplish a particular job or task (Venkatesh et al., 2003).

For the third research question, we measured students' outcomes with these two variables:

- Performance: the value of the knowledge acquired from studying and completing assignments. Course grades were the objective measure used to assess students' performance.
- Satisfaction: a set of elements nurturing the sense of well-being experienced by students in a course, from both technological and pedagogical sides (Hobbs & Osburn, 1989).

Hypotheses and Research Model

Testing the UTAUT model allowed confirming the influence of performance expectancy, effort expectancy, and social influence on behavioral intention to use a technology with an explained variance of 77 percent. Behavioral intention and facilitating conditions determine technology use with an explained variance of 52 percent. These results were obtained in longitudinal field studies of employees' acceptance of technology (Venkatesh et al., 2016). In the original UTAUT model, age, gender, experience and voluntariness of use were found to moderate various UTAUT relationships (Venkatesh et al., 2003). However, subsequent research has scarcely considered the moderation effects of individual differences of the original UTAUT. Venkatesh et al. (2016) considered this finding both surprising and disappointing because passing over all possible boundary conditions could jeopardize the generalizability of UTAUT. Thus, we deem it necessary to include the moderating variables while testing the UTAUT model.

Furthermore, we followed Hong, Chan, Thong, Chasalow, and Dhillon (2014)'s guidelines to "contextualize" the original UTAUT model. Hong et al. (2014) suggested as a first guideline to ground on a general theory. This is what we made by choosing the UTAUT model which we applied to study technology adoption in the blended learning field. They also recommended evaluating the context in order to identify context-specific factors. As this research was made in a university context, we deemed it relevant to take into account students' personal characteristics, as they are the main actors of technology adoption and acceptance. We therefore added to the original UTAUT model personal characteristics variables (anxiety, autonomy, attitude, and computer-self efficacy) as direct and moderating variables.We also considered outcome variables (satisfaction and performance) as dependent variables in order to fulfill the gap about the scarcity of studies that link goals to intentions and behavior, as suggested by Tate et al. (2015).

In the next paragraphs, we set the hypotheses tested in this research. We begin with both the direct and the moderated relationships of the original UTAUT model. We then explain the additional hypotheses incorporated into the original model. All relationships are depicted in Figure 1.

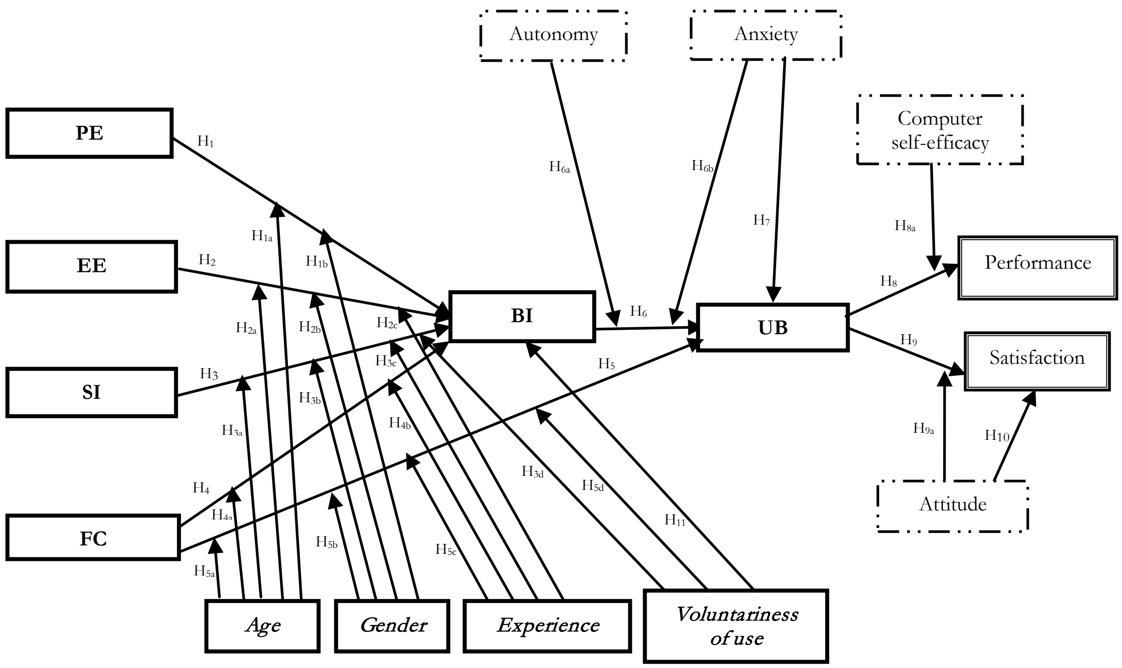

Figure legend:

- In bold: Main UTAUT variables (PE, EE, SI, and FC as independent variables; BI and UB as dependent variables).
- In bold and Italic: Moderating UTAUT variables.
- Dashed outlined: Personal characteristics variables.
- Double outlined: Outcome variables.

Figure 1. Research model

Performance expectancy was considered the strongest predictor of behavioral intention (Venkatesh et al., 2003). Most of the time, its relationship with the intention to use the technology or the system was positive (AbuShanab, Pearson, & Setterstrom, 2010; Eckhardt, Laumer, & Weitzel, 2009; Khechine et al., 2014b; Venkatesh et al., 2003). In the case of Elluminate, we think that students would be more inclined to plan for the use of this technology when they expect it to bring them help for better performing. We propose then to test the following hypothesis:

H_1: **Performance expectancy** will positively influence behavioral intention to use webinars.

According to some research results (Bandyopadhyay & Fraccastoro, 2007; Venkatesh et al., 2003), age and gender moderate the relationship between performance expectancy and behavioral intention. The effect is stronger for young people (Khechine et al., 2014b; Lu, Yu, & Liu, 2009), and especially for men (Venkatesh & Morris, 2000). For Elluminate, we tested the following hypotheses:

> H_{1a}: **Age** will moderate the effect of performance expectancy on behavioral intention to use webinars, such that the effect will be stronger among younger students.
>
> H_{1b}: **Gender** will moderate the effect of performance expectancy on behavioral intention to use webinars, such that the effect will be stronger among male students.

Users accustomed to a technology will perceive its use as easier (Venkatesh et al., 2003). In this study, the technology in use is Elluminate. It is known to be a user-friendly software. Based on the results obtained by Khechine et al. (2014b) that confirmed a positive relationship between effort expectancy and behavioral intention, we expect that the degree of ease needed to use this webinar system will stimulate the intention of students to use it. We propose to test the following hypothesis:

H_2: **Effort expectancy** will positively influence behavioral intention to use webinars.

Based on the assumptions that the effect of effort expectancy on behavioral intention is more salient for older people (Venkatesh et al., 2003), that women are more worried about ease of use (Cheng, Yu, Huang, Yu, & Yu, 2011; Venkatesh & Morris, 2000), and that more effort is needed for people with relatively little experience (Venkatesh et al., 2003), we propose to test the following three hypotheses:

> H_{2a}: **Age** will moderate the effect of effort expectancy on behavioral intention to use webinars, such that the effect will be stronger among younger students.
>
> H_{2b}: **Gender** will moderate the effect of effort expectancy on behavioral intention to use webinars, such that the effect will be stronger among female students.
>
> H_{2c}: **Experience** will moderate the effect of effort expectancy on behavioral intention to use webinars, such that the effect will be stronger among students with little experience with a computer.

The UTAUT as well as previous models (e.g., theory of planned behavior with subjective norms) have shown that social influence has a positive effect on the behavioral intention to use the technology (AbuShanab et al., 2010; Eckhardt et al., 2009; San Martin & Herrero, 2012; Venkatesh et al., 2003). As we live in a "social network" world where personal image is important, we think that others' opinion like students, teachers, friends, and family members is important for technology adoption. Relying on the results of Khechine et al. (2014b) that confirmed this effect for webinar use, we made the following assumption concerning Elluminate:

H_3: **Social influence** will positively influence behavioral intention to use webinars.

Previous studies found that age moderates the link between social influence and behavioral intention (Lu et al., 2009; Venkatesh et al., 2003). According to Venkatesh et al. (2003), the effect of social influence was more salient for older people. Gender also was proven to moderate the relationship between social influence and behavioral intention (Bandyopadhyay & Fraccastoro, 2007; Venkatesh et al., 2003). The effect of social influence is more salient for women (Cheng et al., 2011; Venkatesh & Morris, 2000). The effect of social influence on behavioral intention is moderated by experience and voluntariness of use such that the effect is more salient for users with limited technology experience and who were under conditions of mandatory use (Venkatesh et al., 2003). In the light of these assertions, we propose to test the following hypotheses:

> H_{3a}: **Age** will moderate the effect of social influence on behavioral intention to use webinars, such that the effect will be stronger among older students.

H_{3b}: **Gender** will moderate the effect of social influence on behavioral intention to use webinars, such that the effect will be stronger among female students.

H_{3c}: **Experience** will moderate the effect of social influence on behavioral intention to use webinars, such that the effect will be stronger among students with little experience with a computer.

H_{3d}: **Voluntariness of use** will moderate the effect of social influence on behavioral intention to use webinars, such that the effect will be stronger among students in mandatory settings.

In studying the factors associated with the use of learning technologies by higher education faculty, Buchanan, Sainter, and Saunders (2013) concluded that whatever the acceptance model used, it has to consider facilitating or inhibiting conditions variable as a determinant of use and the intention to use. Even though Venkatesh et al. (2003) did not test the relationship between facilitating conditions and behavioral intention, we propose to integrate the corresponding hypothesis into our model. Indeed, this relationship was tested in the UTAUT2 model (Venkatesh et al., 2012) and was found as significant and positive. The UTAUT2 model was tested in a consumer context where authors followed the general model of the theory of planned behavior and linked facilitating conditions to both behavioral intention and behavior. In the context of Elluminate use, we consider students as consumers because they pay for the educational services provided. Thus, we propose to test the following hypothesis:

H_4: **Facilitating conditions** will positively influence behavioral intention to use webinars.

While testing UTAUT2, Venkatesh et al. (2012) found that the effect of facilitating conditions on behavioral intention is more pronounced for older users. Older people see availability of resources, knowledge, and support very important for accepting a new technology. We suppose this importance can be explained by their unfamiliarity with technology. Therefore, we assume that it could fade with the acquisition of experience in using the technology. The moderating effects of age and experience are expressed by the following hypothesis:

H_{4a}: **Age** will moderate the effect of facilitating conditions on behavioral intention to use webinars, such that the effect will be stronger among older students.

H_{4b}: **Experience** will moderate the effect of facilitating conditions on behavioral intention to use webinars, such that the effect will be stronger among students with little experience with a computer.

In Buchanan et al. (2013), authors invite future research to focus on the effect of facilitating conditions on behavior and to examine if this effect is direct or mediated by behavioral intention. Venkatesh et al. (2003) asserted that the empirical results of previous studies indicate that facilitating conditions do have a direct influence on usage. For instance, the theory of planned behavior allowed proving that facilitating conditions were modeled as a direct antecedent of usage. In the context of webinar use, we propose to test the following hypothesis:

H_5: **Facilitating conditions** will positively influence use behavior of webinars.

According to Venkatesh et al. (2003), the relationship between facilitating conditions and use behavior is moderated by age and experience such that the effect is more salient for older users with increasing experience. For Elluminate use, we propose to test the following hypothesis:

H_{5a}: **Age** will moderate the effect of facilitating conditions on use behavior of webinars, such that the effect will be stronger among older students.

H_{5c}: **Experience** will moderate the effect of facilitating conditions on use behavior of webinars, such that the effect will be stronger among students with little experience with a computer.

Venkatesh et al. (2003) deduced that men tend to rely less on facilitating conditions when using technologies and women rely more on supporting factors. Thus, for webinar use, we propose to test the moderating effect of gender on the relationship between facilitating conditions and usage behavior with hypothesis H_{5b}.

> H_{5b}: **Gender** will moderate the effect of facilitating conditions on use behavior of webinars, such that the effect will be stronger among female students.

J. Wu and Lederer (2009) categorized research on voluntariness of use into two main streams. The first focuses on the moderating role of voluntariness in the context of information system use. The second examines the direct impact of voluntariness on technology adoption and use. Most research of the first stream adopted voluntariness as a moderating variable between behavioral intention and its antecedents. Hartwick and Barki (1994) are among the few researchers who considered voluntariness as a moderating variable between use behavior and its explanatory variables. They found that user participation and involvement were important predictors of attitudes, norms, intentions, and use for the voluntary group. We expect that facilitating conditions will behave similarly in that its effect on behavioral use will be moderated by voluntariness of use. We believe that in the absence of pressure for mandatory use of any system, assistance is more openly accepted and even more actively sought. For webinar use, we think the availability of facilitating conditions will make students willing to use Elluminate when they feel that they are in a voluntary setting.

> H_{5d}: **Voluntariness of use** will moderate the effect of facilitating conditions on use behavior of webinars, such that the effect will be stronger among students in voluntary settings.

According to Venkatesh et al. (2003), behavioral intention will have an influence on usage. A meta-analysis of Khechine et al. (2016) confirmed this result, asserting that even though the impact of behavioral intention on use behavior was classified as medium, the positive association between behavioral intention and use was confirmed. As previous literature concurs with Khechine et al. (2016), supporting that intention is an antecedent of action, we propose to test the following hypothesis because we think that intention may often lead to a real use:

H_6: **Behavioral intention** will positively influence use behavior of webinars.

Many authors focused on the relevance of autonomy in the user's acceptance of technology (Lakhal et al., 2013; Roca & Gagné, 2008; Sorebo, Halvari, Gulli, & Kristiansen, 2009), especially in the educational context. However, no one studied its possible role as a moderating variable between the intention to use a technology and its effective use. We think that because autonomy is often considered as a fuel of motivation (Sorebo et al., 2009), this incentive may make potential systems' users more willing to use them. This argument is supported by Johns (2006) who asserted that limited autonomy constrains behavior. Thus, for users who have the intention to use a system, autonomy may stimulate behavior.

In the meta-analysis of Powell (2013), many studies considered anxiety as either a direct or an indirect factor that could explain individual acceptance and use of information technologies. However, it was never considered as a moderating variable of the relationship between the intention to use a technology and its effective use. According to Celik (2011), the evaluation of consumer acceptance of technologies could not relinquish the users' affective responses, such as anxiety. Even if users have the will to make a behavior, their anxious attitude may make them reluctant to take action.

Based on these arguments, we postulate the following two hypotheses concerning the moderating roles of autonomy and anxiety:

> H_{6a}: **Autonomy** will moderate the effect of behavioral intention on use behavior of webinars, such that the effect will be stronger among autonomous students.

> H_{6b}: **Anxiety** will moderate the effect of behavioral intention on use behavior of webinars, such that the effect will be stronger among less anxious students.

Venkatesh et al. (2003) considered that computer anxiety did not play any role in the UTAUT model. However, according to Powell (2013), anxiety is a negative affective response of end users toward new technologies that has received a great attention in technology adoption studies. His assumption relies on a meta-analysis of 276 studies that showed how anxiety influences individual acceptance of information technologies. The difference of visions between Venkatesh et al. and Powell is probably due to the definition of the variable "anxiety." In our research setting, as in Powell's meta-analysis, anxiety refers to a broader definition of this personal characteristic because it is not limited to fear of technologies as stipulated by Venkatesh et al. (2003). Moreover, these latter researchers did not give a great importance to anxiety because the UTAUT was originally formulated and cross-validated in organizational contexts. Employees' cognitive and behavioral responses toward a new technology are known to be better predictors of the use than anxiety (Venkatesh et al., 2012). However, in the consumer context, the affective responses of the users (e.g., enjoyment, fun, fear, and anxiety) should not be overlooked in evaluating consumer acceptance of technologies (Celik, 2011). Beaudry and Pinsonneault (2010) reported that psychology research confirmed that anxiety makes users physically avoid the stressor (Duhachek, 2005) or engage in exit strategies (Lazarus & Folkman, 1984). Research in the organizational behavior field reported the same conclusions. Anxiety was thus considered as the reason why people distanced themselves from their jobs (Hackett & Bycio, 1996), reduced the necessary effort to cope with the situation, and relinquished any attempt to attain goal behavior (Carver, Scheier, & Weintraub, 1989; Yi & Baumgartner, 2004). For webinar use, we propose the following hypothesis to test the direct effect of anxiety on use behavior:

H_7: **Anxiety** will negatively influence use behavior of webinars.

According to Khechine and Lakhal (2015), webinar use has had a negative effect on students' performance. They explained this result was from a lack of concentration when technical problems with the system occurred and from the absence of visual contact with the professor. They also admitted that students did other activities while listening (eating breakfast or folding laundry), which distracted them. Kwak, Menezes, and Sherwood (2015) found the same results and concluded that face-to-face students obtained better scores than both online and blended learning students. This is particularly true in the case of cumulative learning. Because we are in the context of webinar use where there is no visual contact between the participants and where the learning is cumulative, we think that technology, as a double-edged sword, could have a harmful effect on students' results. We propose to test the following hypothesis:

H_8: **Use behavior** will negatively influence students' performance.

Venkatesh et al. (2003) did not find a significant relationship between computer self-efficacy and behavioral intention to use technology because computer self-efficacy was captured by an effort expectancy variable. However, Compeau and Higgins (1995) stated that self-efficacy plays an important role in shaping individuals' feelings and behaviors. In this research, we did not consider computer self-efficacy as an independent variable like in Venkatesh et al. (2003), but a moderating one between use behavior and performance. We previously supposed that the use of the technology would have a negative impact on students' performance. We explained this assumption by the lack of concentration experienced by the students using technology. This lack will certainly be accentuated for individuals who do not master the technology because they will spend time trying to resolve technical difficulties instead of assimilating course material. This situation will make them lose their train of thought, which will probably undermine their performance. Thus, we think students who are fluent in using Elluminate will better perform in the course. The hypothesis that moderates the relationship between use behavior and performance is:

> H_{8a}: **Computer self-efficacy** will moderate the effect of use behavior on students' performance, such that the effect will be stronger for students who are less confident in their ability to use a computer.

Studies like Fillion (2005), Lakhal, Khechine, and Pascot (2007), and Khechine, Lakhal, and Pascot (2009) observed a better satisfaction among groups of students using information and communication technologies in online courses compared to students in face-to-face courses. Khechine et al. (Khechine et al., 2009) explained this result with the course setting. Because the course was online and its technology usage – podcasts in this case – was not compulsory, students who listened to recorded sessions thought that they had an advantage over those who did not. This belief materialized because they had access to more details about the course content whenever and wherever they need them. This situation made the students more confident about the efficacy of their learning, and thus more satisfied with the course (Bongey, Cizadlo, & Kalnbach, 2006; Janossy, 2007). In this study, we are in a context of an online course where the use of the technology is optional. For the ninth hypothesis, we think students who use Elluminate will be more satisfied with the course than those who do not.

H_9: **Use behavior** will positively influence students' satisfaction.

We think that the effect of use behavior on students' satisfaction could be moderated by the personal characteristics of the users. In respect to attitude, C-Y Lee, Tsao, and Chang (2015) asserted that this variable had a direct and positive influence on satisfaction. Their results meant that a person who has a positive attitude toward a technology would be satisfied with that technology regardless of the intensity of its use. However, we postulated in H9 that satisfaction might vary according to the variation of use behavior. Hence, in support to this hypothesis, we would take account of the intensity of use by positioning attitude as a moderating variable between behavioral use and satisfaction. We believe that students who use webinars will be more satisfied when they have a good attitude. Even if to our knowledge no literature reported attempts of testing the moderating role attitude on the relationship between use behavior and satisfaction, we propose to the following hypothesis:

> H_{9a}: **Attitude** will moderate the effect of use behavior on students' satisfaction, such that the effect will be stronger for students who have a good attitude toward the technology.

The original UTAUT model did not include attitude as an independent variable for evaluating technology acceptance. However, TAM built a strong foundation of measuring attitude toward technology applications (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989). In TAM and TPB (Theory of planned behavior) models, attitude was often considered as a strong and significant antecedent of the intention to use and the effective use of a technology. However, Venkatesh et al. (2003) concluded, "the attitudinal constructs are significant only when specific cognitions—in this case, constructs related to performance and effort expectancies—are not included in the model." They considered and proved through empirical results that the relationship between attitude toward a technology and the intention to use it is spurious. Because our model considers performance expectancy and effort expectancy as potential determinants of the intention to use and of the use of the technology, we will not test the effect of attitude on these two last variables. However, we suspect a relationship between attitude and satisfaction. Indeed, we think that satisfaction of the course is a student result that may be better for students who have a good attitude toward using a technology in the course. C-Y Lee et al. (2015) suggested that users' attitude significantly and positively influences customer satisfaction of using life insurers' app services. Therefore, we propose to test the hypothesis below:

H_{10}: **Attitude** will positively influence students' satisfaction.

Voluntariness of use was, most of the time, considered as a moderating variable of the relationships between the independent variables of the UTAUT model and behavioral intention (Venkatesh et al., 2003). Some research tried to test its direct effect on use behavior. For instance, Moore and Benbasat (1996) found a significant, though negative, relationship between voluntariness of use and usage of personal workstations. Agarwal and Prasad (1997) found a significant relationship between the perceived voluntariness of use and the current usage. Moreover, Anderson, Schwager, and Kerns (2006) found that voluntariness of tablet PC use positively affects the use behavior. However, Anderson et al. (2006) agreed with Venkatesh et al. (2003) that, as a direct determinant, voluntariness of use has a small influence on usage, which makes us less willing to deepen this influence. Nonetheless, to our knowledge, voluntariness of use was seldom tested as a direct determinant of behavioral intention. Agarwal and Prasad (1997) did this, but did not find a significant relationship between perceived voluntariness and the intention of usage. Karahanna, Straub, and Chervany (1999) are also among the few researchers to examine the direct relationship between voluntariness of use and intention to use. They concluded that perceived voluntariness is a significant determinant of intention to use Windows software for current users, but not for potential adopters. As our sample is made of current users of Elluminate, we think voluntariness of use may have a direct effect on intention, such that the perception of a voluntary setting will contribute to increase behavioral intention. Thus, the last hypothesis is:

H_{11}: **Voluntariness of use** will positively influence behavior intention to use Elluminate.

Research Design

The study setting and the measurement instrument used for data collection are explained in the following subsections.

Study Setting

This study was conducted in a business School at Laval University in Quebec where most online courses have switched to the blended learning formula using Elluminate software. Elluminate is a web conferencing software developed by Elluminate Inc. company and acquired later by Blackboard Inc. Elluminate software allows schools to hold virtual classes and businesses to hold virtual meetings. Classes and meeting are broadcasted live and recorded for later listening or visioning. Some features of Elluminate software are chat rooms, quizzing and polling, emoticons, a whiteboard, application sharing, and file transfer. These features are presented in the screenshot of Elluminate interface in Appendix A.

In the online version of these courses, course material was available only online on a homemade learning management system (LMS). The LMS allows instructors to make content – such as documents and web pages – available to students for each course session. The only interactive tools used in the LMS are discussion boards and mail systems. Therefore, the LMS does not allow live broadcasting or session recording. Enrolled students log into the course website through the LMS to download readings, instructor PowerPoint presentations, and instructions for homework. Homework can be upload in online deposit boxes or made with automatic online choice questions. Students interact with others and with the instructor via online – asynchronous – forums. Exams are however made in class at the main school campus or at distant brick-and-mortar exam centers.

The use of Elluminate allowed transforming these online courses into blended ones. Indeed, instructors also organized weekly classroom sessions. These classroom sessions of one to two hours were dedicated to explain the course material available online and to answer students' questions. For these classroom sessions, an appointment was made by the instructors with students each week to ask them to come to school or to connect online to Elluminate on a scheduled time. Students that are able to come to school did not need to connect to Elluminate because of their physical presence. Students that can't come to school, but are available on the scheduled time, connected live to Elluminate. They see instructors' presentation on their computer screens and listen to what the instructors say in the classroom and to what it is discussed in class with present students. In addition to the audio and the visual presentations, distant users were able to write their questions on a chat window that the instructors and the students in the classroom can read and answer live. The instructors can use other functionalities of Elluminate, such as permitting the participants to use their own microphones to ask questions and sharing the computer screen to show a demo or a video. These sessions were also recorded for later listening by all students and especially by those that were not able to be live connected.

As so, because the use of Elluminate was voluntary, students had four choices in these blended courses: 1) to follow the course exclusively online using only the website (asynchronous learning); 2) to follow the course online using the website and to attend physical classroom sessions (asynchronous and synchronous learning); 3) to follow the course online using the website and to listen to the live broadcasted sessions with Elluminate (asynchronous and synchronous learning); or 4) to follow the course online using the website and to listen to the recorded sessions with Elluminate (asynchronous learning).

We asked 436 students enrolled in a compulsory undergraduate course in management information systems to participate in our study. Students belonged to all business concentrations: accounting, finance, management, information systems, and marketing. Data collection began three weeks before the exams and lasted five weeks. Students' participation was voluntary but they were encouraged by some incentives in the form of gift certificates and extra credit for the course. Aside from the first message sent by electronic mail to invite students to fill out the questionnaire, three reminder messages were distributed over the weeks following the initial email.

Questionnaire

The online questionnaire used for this study was made of 68 items and required nearly 20 minutes to complete. The questionnaire began with an introduction aimed at explaining the research objective and ensuring students of their confidentiality. Except for age, gender, and behavioral use, all items were rated on a seven-point Likert-type scale (from strongly disagree to strongly agree). Thirty-six items were obtained from the original UTAUT questionnaire (Venkatesh et al., 2003), but were adapted to the specific settings of this study (8 items for performance expectancy, 4 for effort expectancy, 7 for social influence, 5 for facilitating conditions, 2 for use behavior, 3 for the behavioral intention, 4 for voluntariness of use, and 1 item for each age, gender, and experience with a computer). The items that we retained after checking for reliability of the main UTAUT variables are in Appendix B.

We then asked students to report the number of times they used Elluminate to listen to live or recorded sessions. The other 32 items allowed measuring the personal characteristics of the students and the outcome satisfaction. We adopted the six items of autonomy, and the three items of anxiety from Fillion (2005). The four items of attitude toward technology and the four items of computer self-efficacy were tested in Venkatesh et al. (2003). Regarding outcomes, we adapted the fifteen items of satisfaction from Fillion (2005) and obtained the students' final grades in the course from the teacher with students' permission.

Results

In this section, we first present descriptive statistics. We then verify item loadings, measurement instruments reliability, and convergent and discriminant validities. Hypothesis testing results are then explained and discussed, and the explained variance of the dependent variables is commented.

Descriptive Statistics

Of the population of 436 students enrolled in the course, 415 students responded to our call for participating in the study, which led to a response rate of 95%. However, 37 of the students did not provide their names or identification numbers. Hence, we were not able to find their final grades to measure the performance variable, which reduced our sample to 378 students. With one invalid response, our final sample consisted of 377 responses.

SPSS software was used for descriptive statistics. As can be seen in Table 1, there are almost 10% more male than female students. Most of the respondents are under 25 years old (91.7% in Table 2). Ninety-two percent (92%) are enrolled in the course with a full-time status (Table 3). Table 4 shows that accounting and finance are the leading concentrations.

Concerning experience with technology, Table 5 shows that more than 90% of the students have at least 5 years of experience with using computers, which suggests their relative familiarity with technology. As the course was online, 42.2% of the students did not attend any classroom sessions (Table 6). However, as can be seen in Table 9, more than half of the students (59.6%) used Elluminate 10 to 12 times, whether the sessions were live or recorded. This result may suggest that most students choose to listen either to the live sessions or to the recorded ones, but seldom to both. The results shown in Tables 7 and 8 confirm this finding, because the greater percentages related to Elluminate use are at the extremities. For instance, 19.1% of the students did not listen to any recorded sessions, whereas 19.6% listened to 10 live sessions. On the other hand, 20.7% of the respondents listened to 10 recorded sessions, whereas 23.3% did not use Elluminate for any live sessions.

Table 1. Gender

Gender	Frequency	Percent (%)
Male	207	54.9
Female	170	45.1
Total	377	100

Table 2. Age

Years	Frequency	Percent (%)
15 to 20	166	44
21 to 25	180	47.7
26 to 30	16	4.2
31 to 35	8	2.1
36 to 40	2	0.5
41 and up	5	1.3
Total	377	100

Table 3. Registration status

Status	Frequency	Percent (%)
Part time	30	8
Full time	347	92
Total	377	100

Table 4. Concentrations

Concentration	Frequency	Percent (%)
Accounting	88	23.3
Finance	83	22
Management	35	9.3
Human resources	25	6.6
Operational research	13	3.4
Marketing	38	10.1
Management information systems	20	5.3
Other	75	19.9
Total	377	100

Table 5. Experience in using computer

Computer use (years)	Frequency	Percent (%)
Less than 1	8	2.1
1 to 2	7	1.9
2 to 3	14	3.7
3 to 4	8	2.1
5 and up	340	90.2
Total	377	100

Table 6. In-class presence

Number of sessions	Frequency	Percent (%)
0	159	42.2
1	59	15.6
2	30	8
3	15	4
4	11	2.9
5	10	2.7
6	10	2.7
7	9	2.4
8	9	2.4
9	8	2.1
10	57	15.1
Total	377	100

Table 7. Listening to recorded sessions with Elluminate

Number of sessions	Frequency	Percent (%)
0	72	19.1
1	63	16.7
2	36	9.5
3	24	6.4
4	17	4.5
5	20	5.3
6	15	4
7	23	6.1
8	18	4.8
9	11	2.9
10	78	20.7
Total	377	100

Table 8. Listening to live sessions with Elluminate

Number of sessions	Frequency	Percent (%)
0	88	23.3
1	38	10.1
2	44	11.7
3	27	7.2
4	28	7.4
5	19	5
6	12	3.2
7	10	2.7
8	11	2.9
9	26	6.9
10	74	19.6
Total	377	100

Table 9. Total Elluminate use

Number of sessions	Frequency	Percent (%)	Number of sessions	Frequency	Percent (%)
0	19	5	11	56	14.9
1	12	3.2	12	40	10.6
2	16	4.2	13	7	1.9
3	10	2.7	14	6	1.6
4	15	4	15	4	1.1
5	11	2.9	16	2	0.5
6	11	2.9	17	3	0.8
7	16	4.2	18	4	1.1
8	23	6.1	20	3	0.8
9	20	5.3	Total	377	100
10	99	26.3			

Item Loadings and Reliability

Because all endogenous variables were validated in previous studies, we have assessed the validity of their measurement instruments with confirmatory factor analysis (CFA). CFA allowed us to remove unreliable items that had weak loading values. Table 10 shows item loadings after eliminating two questions from the "Social influence" variable, three from "Facilitating conditions," one from "Computer self-efficacy," two from "Voluntariness of use," one from "Autonomy," and six from "Satisfaction." We consider the "loss" of the six items of satisfaction positive because five of them were directly related to satisfaction about the technological support of Elluminate during the course. Thus, we avoid possible confusion with the measure of attitude toward the system. The remaining items of satisfaction focus on the students' satisfaction with the course content and the knowledge acquired as well as their satisfaction with the conduct of the course. All the remaining items have significant and strong loading values, exceeding 0.7 as recommended by Hair, Anderson, Tatham, and Black (1995).

Once again, we used SPSS software to test the internal consistency with Cronbach's Alpha. The values of Alphas for the measurement instruments of the eleven latent variables are shown in Table 10. Reliability coefficients were satisfactory because they correspond to what was recommended by Nunnally (1978) and Martínez-López, Gázquez-Abad, and Carlos Sousa (2013), except for "Voluntariness of use" (α = 0.691, slightly under the recommended 0.70). However, we later considered this variable reliable, because its composite reliability was satisfactory (CR = 0.861 in Table 10) as was its AVE (average variance extracted was equal to 0.757 in Table 11).

Internal consistency was assessed one more time by composite reliability when we ran data analysis using Smart-PLS software. As can be seen in Table 10, the measurement instruments of the endogenous variables fulfilled the recommended level of composite reliability with coefficient values exceeding the recommended 0.7 (Gerbing & Anderson, 1988), except for the "Computer self-efficacy" variable. The "Computer self-efficacy" variable was then retrieved from the model because of its low composite reliability (CR = 0.604 in Table 10) and AVE (less than 0.5) (Martínez-López et al., 2013). Therefore, hypothesis H8a was not considered for subsequent analysis of the structural model.

Table 10. Item loadings, Cronbach's Alpha, and composite reliability

Variables	Items	Loadings	Variables	Items	Loadings
Performance expectancy	α = .953/CR = .960		Effort expectancy	α = .895/CR = .925	
	PE1	.848		EE1	.888
	PE2	.870		EE2	.861
	PE3	.862		EE3	.890
	PE4	.916		EE4	.856
	PE5	.888	Facilitating conditions	α = .834 / CR = .924	
	PE6	.912		FC1	.927
	PE7	.855		FC2	.927
	PE8	.790			
Social influence	α = .851/CR = .890		Behavioral intention	α = .949/CR = .967	
	SI1	.794		BI1	.948
	SI2	.809		BI2	.959
	SI5	.800		BI3	.951
	SI6	.796			
	SI7	.764			
Voluntariness of use	α = .691/CR = .861		Autonomy	α = .851/CR = .884	
	Vu1	.875		Aut1	.804
	Vu2	.875		Aut2	.825
Anxiety	α = .906/CR = .941			Aut3	.837
	Anx1	.905		Aut5	.787
	Anx2	.931		Aut6	.738
	Anx3	.918			

Variables	Items	Loadings	Variables	Items	Loadings
Computer self-efficacy	α = .750/CR = .604		Satisfaction	α = .942/CR = .950	
	CSE2	.769		Satis1	.881
	CSE3	.832		Satis2	.812
	CSE4	.851		Satis3	.824
Attitude	α = .889/CR = .923			Satis5	.758
	ATUT1	.787		Satis6	.730
	ATUT2	.881		Satis7	.860
	ATUT3	.885		Satis13	.840
	ATUT4	.910		Satis14	.885
				Satis15	.840

α : Cronbach's Alpha
CR: Composite reliability (Rho)

Convergent and Discriminant Validity

Convergent validity was assessed using the AVE measure. As suggested by Chin (1998), AVEs have to be greater than 0.5 in order to assert that items, which theoretically measure the same variable, are correlated. We can see in Table 11 that, after retrieving the "Computer self-efficacy" variable, all the AVEs were satisfactory as they were 0.75 or above, which ensures the convergent validity of our measurement instruments.

To ensure discriminant validity, items that theoretically belong to different variables must not be related. This condition is validated when the square roots of the AVEs are greater than the other correlations (Fornell & Larcker, 1981). Table 11 presents the correlation matrix for the latent variables. The diagonal elements represent the square roots of the AVE, and the off-diagonal elements are between-variable correlation values. For all endogenous variables, the square roots of AVEs were greater than all other correlations. Indeed, each variable shares greater variance with its own block of measures (in the diagonal) than with the other variables representing a different block of measures, hence providing evidence for the discriminant validity of the scales.

Table 11. Convergent and discriminant validity

	AVE	1	2	3	4	5	6	7	8	9	10
1. Anxiety	.84	**.92**									
2. Attitude	.75	-.06	**.87**								
3. Autonomy	.61	-.21	.16	**.78**							
4. BI	.91	-.03	.65	.04	**.95**						
5. EE	.76	-.34	.38	.28	.22	**.87**					
6. FC	.86	-.38	.26	.25	.16	.55	**.93**				
7. PE	.75	-.06	.78	.18	.57	.39	.21	**.87**			
8. SI	.62	.18	.53	.09	.37	.17	.15	.50	**.79**		
9. Satisfaction	.68	-.02	.57	.18	.37	.29	.18	.49	.38	**.83**	
10. Voluntariness of use	.75	.04	.11	.02	.08	.05	.07	.08	.04	.05	**.87**

NB. Diagonal elements are square roots of AVEs and off-diagonal elements are correlations.

Hypotheses Testing and discussion

As can be seen in Table 12, 8 out of 29 hypotheses were confirmed (in bold characters) and for one hypothesis (***H₉***), the path coefficient was significant, but not positive as expected (in bold and italic characters).

Table 12. Structural model results

Hypotheses	Independent variables	Dependent variables							
		Behavioral intention R^2 =.3796		Performance R^2 = .0067		Satisfaction R^2 = .3457		Use behavior R^2 = .1178	
		β	t	β	t	β	t	β	t
H_1	**PE**	**.328**	**1.437***						
H_2	EE	.216	.487						
H_3	SI	.545	1.21						
H_4 – H_5	FC	- .388	.976					- .180	.476
H_6	BI							.001	.01
H_7	**Anxiety**							**- .266**	**1.567***
H_8 – ***H_9***	***Use behavior***			.107	1.084	***-.404***	***2.611******		
H_{10}	**Attitude**					**.305**	**2.994*****		
H_{11}	**Voluntariness of use**	**.192**	**1.337***						
H_{1a}	PE * Age	-.067	.276						
H_{2a}	EE * Age	.34	.752						
H_{3a}	SI * Age	-.107	.586						
H_{4a} – **H_{5a}**	**FC * Age**	.122	.248					**.832**	**1.610***
H_{1b}	PE * Gender	.264	.985						
H_{2b}	EE * Gender	-.073	.285						
H_{3b}	SI * Gender	-.276	1.053						
H_{4b} – H_{5c}	FC * Experience	.592	1.071					.151	.363
H_{5b}	FC * Gender							-.117	.318
H_{2c}	EE * Experience	-.451	.807						
H_{3c}	SI * Experience	-.022	.061						
H_{3d}	**SI * Voluntariness**	**-.243**	**1.332***						
H_{5d}	FC * Voluntariness							-.053	.257
H_{6a}	**BI * Autonomy**							**.107**	**1.605***
H_{6b}	BI * Anxiety							.192	1
H_{8a}	Use behavior * Computer self-efficacy			Not tested					
H_{9a}	**Use behavior * Attitude**					**0.535**	**3.053*****		

β : Path coefficient
t : t-statistic for significance
* t-value > 1.28 for confidence interval = 90%
** t-value > 1.65 for confidence interval = 95%
*** t-value > 2.33 for confidence interval = 99%

The first hypothesis that was confirmed is **H_1**, which stated that performance expectancy (PE) will positively affect behavioral intention to use Elluminate (BI). The relationship between these two variables was significant ($t = 1.437$, $p < 0.1$) and positive ($\beta = 0.328$). This result was supported by Khechine et al. (2013, 2014b), Venkatesh et al. (2003), and Al-Gahtani, Hubona, and Wang (2007), and it was explained in Khechine et al. (2014b) by the young age of the students. In our sample, too, 91.7% of the respondents were 25 years old or younger (see Table 2). Most of them did not start a professional career with the skills acquired from their study programs. Performance is therefore one of the most important concerns for them, because job hiring depends a lot on their academic record. Undergraduate students who aim for graduate studies have the same concern. We think that they consider Elluminate to be a technology that could support them in reaching their performance objectives. Khechine et al. (2013) considered performance expectancy useful for academics and administrators in promoting the use of webinars in higher education. This would make the students more willing to use webinars. We agree with Khechine et al.'s proposal, but we suggest using caution with regard to "selling" the technology to students. Indeed, as can be seen in Table 12, H8 was rejected, meaning that webinar use did not lead to a better performance when measured by grades ($t = 1.084 < 1.28$, $p < 0.1$).

The effect of social influence (SI) on behavioral intention to use Elluminate (BI) was not significant ($\beta = 0.545$, $t = 1.21$). This result corroborates the literature review of Williams, Rana, and Dwivedi (2015) with regard to UTAUT. They reported that 29 studies out of the 115 that tested this direct relationship found it nonsignificant. However, the effect of SI on BI, when moderated by voluntariness of use, was significant and negative. Indeed, hypothesis $\mathbf{H_{3d}}$ was confirmed with a path coefficient of $\beta = -0.243$ ($t = 1.332$, $p < 0.1$). This result means that when a student's influential people (family, friends, colleagues, etc.) are in favor of using Elluminate, his or her behavioral intention will decline when he or she perceives the use of the system as voluntary. Hence, the predictive power of SI on BI is weakened in a mandatory setting. According to Moore and Benbasat (1991), even if there are "voluntary" adopters of some technologies, because adoption is not strictly mandatory, some adopters may feel a degree of compulsion due to the influence of their social network. The perception of voluntariness of use often plays the role of a suppressor variable that interferes to weaken the relationship between two variables (here, SI and BI) (Rosenberg, 1968). The question that arises here is as follows: Why is the negative effect of SI on BI stronger in a voluntary setting? According to Venkatesh et al. (2003), the role of social influence on technology acceptance is complex and varies across contexts. For instance, Hartwick and Barki (1994) asserted that reliance on others' opinions is significant only in mandatory settings, especially in the early stages of experience. In our case, students oppose more to others' opinion when they perceive the setting as voluntary. The only valuable explanation for this result is generation Z, to which most of the students in our sample belong (between 15 and 25 years, as can be seen in Table 2). Generation Z is not only made of "digital natives" like generation Y; it was also born and has grown in the age of Web 2.0 technologies (Prabhjot, 2014). Even if there is not yet enough scientific evidence on the behavior of generation Z, some argue that, according to their observations, severity and strict orders can scare away individuals from generation Z. Indeed, one of the characteristics of this generation is that it is more "self-directed" than previous generations (Igel & Urquhart, 2012). Hence, people from this generation oppose others' opinions whenever they have the opportunity to do so. In the context of voluntariness of use, students belonging to generation Z found this opportunity—which is voluntariness—to escape others' influence who are in favor to Elluminate use.

Age moderates the relationship between facilitating conditions and use behavior, thus confirming hypothesis $\mathbf{H_{5a}}$ ($\beta = 0.832$, $t = 1.610$, $p < 0.1$). This result means that facilitating conditions may lead to an effective use of Elluminate, and the effect of facilitating conditions is more salient for older students. The original UTAUT model of Venkatesh et al. (2003) and its successor, UTAUT2 (Venkatesh et al., 2012), allowed the same results to be obtained, but with older workers. Facilitation conditions are resources that are available to support students in using Elluminate, and they are often more valuable to older students, who are less likely to be able to adapt quickly to new technologies.

Although most of the research on technology acceptance has found that behavioral intention is an antecedent of action (Khechine et al., 2016), our results showed that the relationship between behavioral intention and use behavior is significant only when moderated by autonomy. Studies that have tested the moderated relationship between intention and use are scarce. Celik (2016)'s is among the rare studies that have found that the effect of intentions on usage is significant only when moderated by other variables like age or experience. In our study, autonomy was the moderating variable of the relationship between intention and use. This result confirms hypothesis **H$_{6a}$** ($\beta = 0.107$, $t = 1.605$, $p < 0.1$), which means that the intention to use Elluminate may lead to the effective use of this technology for more autonomous students. Sorebo et al. (2009) asserted that autonomy leads to intrinsic motivation. This motivation may make students who have the intention to use Elluminate more willing to use it. This is especially true given that limited autonomy constrains behavior (Johns, 2006).

Most studies that have measured anxiety have assessed its variance with respect to the use of technology. For instance, Lakhal et al. (2007) and Khechine et al. (2009) tested the effect of the educational use of podcast systems on student outcomes like anxiety. These studies relied on the idea that "the flexibility and other benefits of asynchronous learning management systems remain a foundational component of the emerging model as a stress reliever" (Main & Dziekan, 2012). However, neither of them found a significant empirical relationship between the use of technology and anxiety. More recently, researchers have focused their efforts on the opposite relationship between these two variables, trying to elucidate the effect of anxiety on the intention to use or the actual use of technologies. A meta-analysis by Powell (Powell, 2013) confirmed the existence of studies that found a direct relationship between anxiety and the individual intention to use information technologies. Celik (2016) integrated anxiety as an independent variable into the UTAUT model. Celik's results indicated that anxiety exerts a negative direct influence on behavioral intention to shop online. However, studies that have confirmed the direct effect of anxiety on usage behavior are few. Barcy and Barcy (2008) explained this scarcity with regard to the assumption of Venkatesh et al. (2003) that anxiety is a long-standing determinant of an individual's response to the introduction of new technologies, with reduced impact over time. Indeed, Venkatesh et al. (2003) estimated that anxiety loses its effect as determinant of usage after 6 months of technology use. In the case of our sample, students used Elluminate for 4 months, which suggests that anxiety can still be considered a determinant of usage. Indeed, our results confirmed that anxiety has a negative effect on usage behavior, which supports hypothesis **H$_7$** ($\beta = -0.266$, $t = 1.567^*$, $p < 0.1$). This result is consistent with Bozionelos (2004) and Mcilroy et al. (2007) findings that anxiety makes users less inclined to use technology. Barbeite and Weiss (2003) also found that anxiety reflected aversion to Internet use. The negative relationship between anxiety and technology use was observed by Mcilroy et al. (2007) in a university setting. They affirmed that students with a high level of anxiety might be less likely to use the range of facilities provided for them. They explained this result by pointing to the general feeling of rejection in the presence of difficulty or novelty. Indeed, according to Rachman (1998), people with high anxiety use avoidance as a coping strategy for anxiety-inducing situations. As suggested by Venkatesh et al. (2003), once accustomed to the technology, the level of anxiety decreases, which will lead to increased use.

Even though hypothesis ***H$_9$*** was not confirmed, we want to expand on the significance of the relationship between use behavior and satisfaction. Unlike what we have supposed, this relationship was negative ($\beta = -0.404$, $t = 2.611^{***}$, $p < 0.01$), meaning that more students use Elluminate, the less satisfied they are with the course. This relationship is strong, because the t-value is greater than 1.96 for a confidence interval of 99%. This result allows us to consider technology as a "double-edged sword" because usually, students that use it expect obtaining practical contributions like convenience. However, the negative relationship for hypothesis ***H$_9$*** showed the opposite in that the use of the technology made students less satisfied. This result is surprising, because most previous research found a positive relationship between these two variables. For instance, Fillion (2005), Lakhal et al. (2007), and Khechine et al. (2009) observed an increase in satisfaction among groups of students using technology. The measure of satisfaction in these research papers was composed of three factors: satisfaction with the course content and knowledge, satisfaction with the conduct of the course, and satisfaction with the technological support. However, the results of our factorial analysis allowed us to keep only the two first factors for hypotheses testing. Indeed, five of the six items that were removed from the satisfaction measurement instrument had to do with technological support. Moreover, the qualitative data collected from the respondents indicated that most of the students did not encounter technological problems, which suggests that they did not use the available technological support. We collected qualitative data through open-ended questions that we asked the students at the end of the questionnaire. These questions dealt with the reasons they were willing to use Elluminate, the difficulties that they encountered while using Elluminate, and how Elluminate helped them learn better. Thus, the absence of the factor related to technological support may explain the difference between our results and those of previous studies. The question that needs answering now is why the relationship between Elluminate use and satisfaction was negative. Students' responses to qualitative questions suggest a possible explanation for this result. According to their comments, the students attributed their lack of satisfaction with the course content and delivery to the use of Elluminate. For instance, students admitted that the meetings were soporific, that it was difficult to maintain concentration at home, that they were unable to follow the course content when the teacher wrote on the blackboard, that they had difficulty managing their time, and that they were unable to take notes on the presentation shared with the teacher. Therefore, the students saw webinars as a technology that not only widened the gap between them and the others involved in the course, but also prevented them from reaching their learning objectives, which explains why hypothesis $\boldsymbol{H_9}$ was significant but negative.

The strong relationship between the attitude and satisfaction variables ($\beta = 0.305$, $t = 2.994$***, $p < 0.01$) confirmed hypothesis $\mathbf{H_{10}}$. This means that students who have a positive attitude toward Elluminate are more satisfied with the course content, the knowledge acquired, and the conduct of the course. This result is consistent with previous research that has confirmed a positive relationship between attitude and satisfaction (Chan et al., 2010). More recently, C-Y Lee et al. (2015) found that consumers of an insurance application were more satisfied with the application service when their evaluation of that application was higher. They concluded that attitude toward using a technology positively influences customer satisfaction.

Hypothesis $\mathbf{H_{9a}}$ was also supported in that a positive attitude toward Elluminate made the relationship between use behavior and satisfaction positive and strong ($\beta = 0.535$, $t = 3.053$***, $p < 0.01$). This result means that attitude moderates the effect of using webinars on students' satisfaction, and this positive effect is stronger for students who have a positive attitude toward Elluminate.

Finally, hypothesis $\mathbf{H_{11}}$ was supported ($\beta = 0.192$, $t = 1.337$*, $p < 0.1$), meaning that voluntary use of Elluminate has a positive effect on the intention to use it. This result is consistent with Karahanna et al. (1999) study, which concluded that voluntary use is a significant determinant of intention for current users. Two similarities between our study and that of Karahanna et al. (1999) made our results mutually corroborating. First, the significance of the relationship between voluntariness of use and intention was obtained for current users but not for future adopters. Second, factorial analysis gave the same result for the two studies with regard to the voluntariness of use variable. Indeed, the same two items were used to measure voluntariness in both studies. In our study, these two items are "My teacher does not require me to adopt Elluminate" and "Although it might be helpful, adopting Elluminate is certainly not compulsory in my course". Answering these items allowed students to determine whether use of the technology should be mandatory or voluntary.

Explained Variance Discussion

The explained variance R^2 of the dependent variable behavioral intention is 37.96%. Performance expectancy and voluntariness of use are the direct determinants of intention. Social influence has an indirect effect on behavioral intention because voluntariness of use moderated the relationship between the two variables. The original model of Venkatesh et al. (2003) obtained an explained variance for behavioral intention of about 0.69, considering the direct and the indirect effects of the independent variables. We think that we lost a part of the explained variance of behavioral intention because we did not capture the effect of effort expectancy. Further statistical analysis has shown that students did not have varying opinions about the effort expected for using Elluminate. Indeed, about 85% of the respondents agreed that Elluminate was easy to use and that they had the right skills to use it (with a low variance of 1.384 and a standard deviation of 1.17 for effort expectancy). As we have argued previously, most students in our sample belong to generation Z, which has grown in the age of the Web 2.0 technologies. Therefore, the need to invest effort in learning to operate a user-friendly technology like Elluminate is almost nonexistent. Moreover, the sociodemographic variables of age, gender, and experience did not play a primary role in moderating variables like they did in Venkatesh et al. (2016)'s research. According to Samaradiwakara and Gunawardena (2014), moderators can play a significant role in the explanatory ability of a model. As we have seen in Tables 2 and 5, most of the students in the sample are under 25 years and have at least 5 years' experience with computers. A certain kind of homogeneity of the sample with regard to age and experience may have inhibited the possible effects of these moderators. It is, however, more difficult to explain why gender did not play a moderating role. The sample was almost equally split between male and female. Considering that most of them belong to generation Z, their behavior and expectancies seem not to differ based on gender. Only more in-depth research on generation Z can confirm this assumption.

The relative weakness of the explained variance of behavioral intention suggests the existence of other explanatory variables. However, we must be careful about the delicate balance between the parsimony of a model that tests few predictors and that model's contribution to understanding (Taylor & Todd, 1995b). It is obvious that a parsimonious model with a good explanatory power is ideal. We think that, for the time being, a certain degree of parsimony must be sacrificed in order to obtain a complete understanding of technology acceptance among the new generation of users of Web 2.0 technology. We recommend future research to address this particular concern.

In our study, use behavior was explained by behavioral intention only when the relationship was moderated by autonomy. The other two variables that explained use behavior were anxiety and facilitating conditions – but only when moderated by age. Compared to the original UTAUT study (Venkatesh et al., 2003), in which the explained variance R^2 of the dependent variable use behavior ranged from 40% to 42%, the explained variance obtained in this study was weak ($R^2 = 0.1178$). Even though we can consider that the endogenous variables have adequate nomological validity because $R^2 > 0.10$ (McKenna, Tuunanen, & Gardner, 2013), we have to linger on this result. We can explain it by our inability to capture the direct effect of behavioral intention on use. Indeed, most researchers have stated that the best determinant of use is intention. The source of the weakness of the explained variance probably lies in the measurement instrument of the variable use behavior. Indeed, our respondents self-reported their use of Elluminate. Venkatesh et al. (2003), however, measured the actual usage behavior by the duration of use via system logs. According to Barnett et al. (2015), prior research in information systems has recognized that actual behavior and perceived or self-reported behavior are not necessarily interchangeable. They claimed that self-reporting usage for complex systems may be difficult. In their literature review about the UTAUT model, Williams et al. (2015) placed self-reported usage seventh in a list of acknowledged limitations in studies that have used UTAUT. Thus, measuring actual use by system logs may be a more reliable method for capturing usage behavior. In this context, Barnett et al. (2015) have dared to assess whether the UTAUT has the same predictive validity for both actual and perceived usage behavior. As a result, they observed almost the same explained variance of the original UTAUT model either for actual use or for perceived use. However, the explained variance of actual use improved a lot when they added the explanatory variables from the personality traits model (conscientiousness, extraversion, agreeableness, openness, and neuroticism) to the original model. However, adding the determinants from the personality trait model did not offer a better explanation of the variance in the perceived use variable. In their investigation, Barnett et al. (2015) found that actual use and perceived use were poorly correlated, and thus not closely related. They explained this result by referring to Straub, Limayem, and Karahanna-Evaristo (1995), who considered that users are poor estimators of their own behavior, because individuals present many differences in their information-processing capabilities. This result supports the assumption that actual use and perceived use do not capture the same variable, though this assumption has yet to be confirmed.

Use behavior and attitude were the explanatory variables for the dependent variable satisfaction, and they were able to explain 34.57% of its variance. We deem this level of variance explanation acceptable because the R^2 was greater than 0.10 (McKenna et al., 2013). We wonder if other variables can explain satisfaction better. Scarce are the studies that have evaluated satisfaction after the use of technology. Among them, Maillet, Mathieu, and Sicotte (2015) found that PE, EE, FC, UB, and compatibility with an electronic patient record system were the variables that explained satisfaction ($R^2 = 0.52$). The authors measured satisfaction with regard to the system only. Chan et al. (2010) were able to explain users' satisfaction with PE, EE, and FC ($R^2 = 0.30$). Like Maillet et al. (2015), they measured users' satisfaction with the system itself. Moreover, they did not measure the behavioral use of the system, because respondents did not frequently use the system. Welch, Hinnant, and Moon (2005) found that government website use is positively associated with e-government satisfaction and website satisfaction. Once again, the variable that these authors measured here is satisfaction with the use of the technology and not satisfaction with the services offered. Because we did not aim to evaluate satisfaction with the system itself, we do not think that the explanatory variables of Chan et al. (2010), Maillet et al. (2015), and Welch et al. (2005) can help us explain the variance in satisfaction. Only future research can investigate other avenues for better explaining students' satisfaction with the pedagogical impact of webinar use.

CONCLUSION

As a conclusion, we highlight the main results of the study and we present the theoretical and practical contributions of the research. We then discuss about limitations and propose future research avenues.

RESULTS AND CONTRIBUTIONS

Hypothesis testing results are summarized in Table 13. These results allowed to answer the three research objectives:

1. The first objective was to identify the determinants of the intention to use and the effective use of a webinar system by students. We found that performance expectancy and voluntariness of use were the direct determinants of intention to use the webinar ($\mathbf{H_1}$ and $\mathbf{H_{11}}$). Concerning performance expectancy, we adhere to the idea that webinars could provide students with either psychological support, which makes them believe that they better perform, or practical support, which helps them stay organized in managing the course content. Therefore, when introducing technologies in higher education, students' performance in terms of grades should not be the "selling argument" of university managers. For voluntariness of use, we address our managerial recommendation to the teachers. We think that it is better to exert less pressure on students to use Elluminate, because the feeling that use is voluntary may increase their intention to use it. Teachers can emphasize the usefulness of the technology, but they have to let students have a sense of freedom concerning the use of webinars.

   Results also show that social influence was moderated by voluntariness of use in its relationship with behavioral intention ($\mathbf{H_{3d}}$). As we said in the hypotheses testing and discussion subsection about $\mathbf{H_{3d}}$ hypothesis, our sample was made of students of generation Z and this generation oppose more to others' opinion when they perceive the setting as voluntary. As a managerial recommendation, we think that university managers do not have to focus on the influence of others when they want to promote the use of Elluminate or any other webinar technology. Instead, they are better off channeling their marketing strategy based on the needs and the behavior of generation Z. However, it will take a long time to elucidate these needs and behaviors, but this is a problem for another time.

   Effective use was explained by facilitating conditions when moderated by age ($\mathbf{H_{5a}}$), and it was explained by behavioral intention when moderated by autonomy ($\mathbf{H_{6a}}$) and negatively influenced by anxiety (**H$_7$**). Concerning the moderating effect of age, managers can use this result for their segmentation strategy to encourage students to use Elluminate. They can focus on affording human, informational, and technological resources to older students in order provide the best conditions of technology use. These resources can take the form of a user manual, an online FAQ, discussion forums, training sessions, or personal support that is available seven days a week. For the moderating effect of autonomy, we recommend investigating students' self-initiative, judgment, and time management abilities before investing time and effort to make them adopt webinars. For the direct and negative effect of anxiety on use behavior, we recommend teachers and university managers to work on alleviating students' anxiety. They will undoubtly be deceived by the use of webinars if they aim to employ them for less than 6 months because during this period, anxiety is higher and may inhibit their adoption. Holding information and training sessions about the technologies that students will use in future courses can be an effective solution to reduce their level of anxiety. Also, universities have to encourage interpersonal relationships between students and instructors and to offer the necessary human and organizational support that lower anxiety. Although we are aware of the budgetary pressures facing the field of education, we think it is useless to invest in technologies if institutions do not simultaneously provide the necessary conditions to encourage students to use them wisely.

2. The second objective of this study was to investigate the effect of webinar use on students' outcomes. These outcomes were objective outcomes measured by grades as well as subjective outcomes measured by students' satisfaction. Satisfaction covered the pedagogical aspects of the course (form and content). Use behavior did not have any effect on students' grades. However, we observed a negative direct effect of use behavior on satisfaction (***H$_9$***). We ask managers to be careful about delivering a blended course using any kind of technology, because some subtleties in the course content and delivery, if not fixed, may make "customers" unsatisfied. The economic and financial consequences of such a dissatisfaction can be disappointing. For instance, we propose that the instructor writes on the interactive board of the webinar system instead of writing on the classroom blackboard. We encourage instructors to make the meetings more motivating, to maintain the concentration of distant students by diversifying the pedagogical activities, to interact more actively with distant students, and to add more breaks. We also recommend using a software that allows students to take notes on the presentation shared by the teacher. Teachers can also give advice to students on how to manage their time while using the technology. Even if these actions may seem small, they can make a big difference.

   The effect of use behavior on satisfaction becomes positive when attitude moderated the relationship between the two variables (**H$_{9a}$**). Once again, our recommendation is to "bet" on the right technology—that is, the technology that stimulates a positive attitude, making students more satisfied with the course. We also found that attitude has a direct positive effect on satisfaction (**H$_{10}$**). We recommend that university teachers and managers work on finding strategies to help students develop a positive attitude toward the technology. They have to show students the advantages of webinars and help them take full advantage of the technology to improve their learning. The advancement of technology is not expected to stop, and future generations of students are increasingly relying on technology. Therefore, future generations of students will be more and more difficult to please. Consequently, strategies cannot be limited to changing teachers' practices, providing information sessions, and answering questions about the technology. Universities also have to make an informed choice about which technology best matches their students' needs and inspires a positive attitude toward it.

   The results obtained from the second aim allowed us bridge the gap reported by Venkatesh et al. (Venkatesh et al., 2016), who observed that researchers have examined outcome mechanisms less frequently than other types of extensions (e.g., moderating variables). Indeed, the authors identified only two studies (Sun, Bhattacherjee, & Ma, 2009; Xiong, Qureshi, & Najjar, 2013) that examined new performance-based outcomes (respectively, individual performance and economic development). According to Sun et al. (2009), most usage models have been criticized because they consider usage as an end in itself (the last dependent variable) rather than as an intermediate variable for assessing user performance. However, the aim of investing in information technologies is to improve the outcomes of users. By evaluating the outcomes, we can know whether the investments made in technologies are successful or not. Managers and decision-makers can then take the right actions about extending the use of these technologies or rejecting their adoption.

3. The third objective was to study the influence of personal characteristics on students' intention to use or effective use of the webinar technology and on students' outcomes. We found that autonomy, anxiety, and attitude played direct and moderating roles in explaining the dependent variables (**H_{6a}** and **H_7**, **H_{9a}**, and **H_{10}**). We removed the computer self-efficacy variable from the model because of its low reliability and convergent validity values. We deemed it important to consider personal characteristics while studying technology use and its impact because we are trying to understand human behavior. It is obvious that human beings are not devoid of feelings. We think that it would be wrong to assess human behavior by ignoring emotional and cognitive states. Our results have provided some insights by showing that behavioral intention may lead to effective use only for autonomous students. This effective use decreases for anxious students. A positive attitude may lead to greater satisfaction with the course and may reinforce the effect of use on satisfaction. As we said earlier, teachers and university managers have to boost the autonomy of students and to help them control their anxiety if they want them to use webinar technologies. Because satisfaction depends on students' personal attitude toward a technology, we recommend that teachers should strengthen students' perception that participating in a webinar is enjoyable and can make learning activities more interesting. Once again, teachers have to work on the course content and on the delivery of the course materials to help their students adapt to the technology that is being used.

Table 13. Summary of the hypothesis testing results

Hypotheses	Independent variables	Dependent variables	Moderating variables	Hypothesis results
H_1	**Performance expectancy**	**Behavioral intention**		**Confirmed**
H_2	Effort expectancy	Behavioral intention		Not confirmed
H_3	Social influence	Behavioral intention		Not confirmed
H_4	Facilitating conditions	Behavioral intention		Not confirmed
H_5	Facilitating conditions	Use behavior		Not confirmed
H_6	Behavioral intention	Use behavior		Not confirmed
H_7	**Anxiety**	**Use behavior**		**Confirmed**
H_8	Use behavior	Performance		Not confirmed
H_9	*Use behavior*	*Satisfaction*		*No confirmed, but a significant β*
H_{10}	**Attitude**	**Satisfaction**		**Confirmed**
H_{11}	**Voluntariness of use**	**Behavioral intention**		**Confirmed**
H_{1a}	Performance expectancy	Behavioral intention	Age	Not confirmed
H_{2a}	Effort expectancy	Behavioral intention	Age	Not confirmed
H_{3a}	Social influence	Behavioral intention	Age	Not confirmed
H_{4a}	Facilitating conditions	Behavioral intention	Age	Not confirmed
H_{5a}	**Facilitating conditions**	**Use behavior**	**Age**	**Confirmed**
H_{1b}	Performance expectancy	Behavioral intention	Gender	Not confirmed
H_{2b}	Effort expectancy	Behavioral intention	Gender	Not confirmed

Hypotheses	Independent variables	Dependent variables	Moderating variables	Hypothesis results
H_{3b}	Social influence	Behavioral intention	Gender	Not confirmed
H_{4b}	Facilitating conditions	Behavioral intention	Experience	Not confirmed
H_{5c}	Facilitating conditions	Use behavior	Experience	Not confirmed
H_{5b}	Facilitating conditions	Use behavior	Gender	Not confirmed
H_{2c}	Effort expectancy	Behavioral intention	Experience	Not confirmed
H_{3c}	Social influence	Behavioral intention	Experience	Not confirmed
H_{3d}	**Social influence**	**Behavioral intention**	**Voluntariness**	**Confirmed**
H_{5d}	Facilitating conditions	Use behavior	Voluntariness	Not confirmed
H_{6a}	**Behavioral intention**	**Use behavior**	**Autonomy**	**Confirmed**
H_{6b}	Behavioral intention	Use behavior	Anxiety	Not confirmed
H_{8a}	Use behavior	Performance	Computer self-efficacy	Not tested
H_{9a}	**Use behavior**	**Satisfaction**	**Attitude**	**Confirmed**

We believe that addressing these three objectives simultaneously brought a holistic view of the acceptance of technology in the educational context. On the theoretical side, we contributed to the literature on information technology use and enriched the UTAUT model with variables that are relevant to the use of technology in the specific context of higher education as suggested by Hong et al. (2014). Our research allowed us to confirm the importance of considering students' personal characteristics in evaluating what determines the acceptance of technology. It also provided clues for future research, suggesting that managers and teachers should not expect the use of technology to improve rational outcomes like personal performance (e.g., grades). Our research permits us to infer that research should rather focus on technology's contributions, such as its promotion of psychological and emotional outcomes like the feeling of satisfaction.

In agreement with Vlieghe (2014), our final target was not to make judgments about correct or incorrect uses of webinars. Instead, we aim to take a small step on the long road to understanding whether the digitization of education will lead to transformation within education or transformation of education itself (Vlieghe, 2014). Because the use of the technology did not lead to the expected outcomes (less satisfaction), we are now confident that technology is a double-edged sword. To be effective, it must be carefully adapted to the context of use and to users' personal characteristics.

Limitations and Future Research

As with any research, this study has some limitations. The first one concerns the scales of the measurement instruments. We used the highest-loading items to evaluate reliability and validity and to test the hypotheses (loadings greater than 0.7). This choice is consistent with the recommendations in the psychometric literature, for example those made by Hair et al. (1995). However, what Venkatesh et al. (2003) called the "pruning" of the instruments is double-edged. Pruning certainly provides variables that are more robust, but it runs the risk of eliminating some facets from each variable, which threatens content validity. If we kept items with loadings higher than 0.5, we could recover nine of the fifteen items that were eliminated after the factorial analysis. Most of these items concern the variables of social influence and satisfaction. Future research should be more permissive in item loadings in order to capture more facets of these variables.

The second limitation is about the potential threat of "selection bias" of the respondents. We can think that students who did not use or like to use Elluminate have less motivation to take the survey, which compromises the objectivity of their answers. However, as we can see in Table 9, more than half of the sample (51.8% of the students) used Elluminate 10 to 12 times (live or recorded sessions), which minimizes the effect of this bias without however guaranteeing its absence.

The third limitation concerns the weakness of the explained variances of the dependent variables, especially for the use behavior variable ($R^2 = 0.1178$). We ascribed this limitation based on our inability to capture the direct effect of behavioral intention on use behavior. We argued that such a result could be attributed to the choice of the measurement instrument for use behavior. Self-reported usage is among the acknowledged limitations of studies that have used UTAUT (Williams et al., 2015). It is preferable that future research capture use behavior using the duration of system logs, as suggested by Venkatesh et al. (2003). To justify this choice, researchers can rely on the assertion that self-reporting usage for complex systems is not easy (Barnett, Kellermanns, Pearson, & Pearson, 2007) and can lack of accuracy. Moreover, the information systems field recognizes that perceived behavior and actual behavior may not lead to the same results (Barnett et al., 2007). We agree with this argument, because we noticed the same phenomenon concerning students' performance (self-reported versus objectively measured). Indeed, in our previous research, students thought that they performed better in their course when they used the technology (Khechine et al., 2009). However, this study has shown that technology use does not influence students' performance when assessed by grades.

Our sample was made up of a group of respondents who were more or less homogenous in terms of age and experience with technology, which made our results different from the previous research (e.g., social influence had a negative effect on behavioral intention when moderated by voluntariness of use). It is obvious that the educational field is now confronted with "customers" who have a lot of experience with technology. However, we are convinced that, in itself, this use is different for generation Z. The behaviors of individuals from generation Z are not only conditioned by their mastery of technology, but also by their bilateral relationship with technology. Indeed, their skills are not limited to exploiting technology; their skills also extend to "remodeling" technology to achieve their goals. Thus, the presence of generation Z raises several interesting issues to investigate in future research. In the field of education, future research should follow up on the results of studies on generation Z to be able to choose better explanatory variables and to interpret the results obtained more precisely.

The findings of this study indicate a need for further investigation of the variables that may explain the intention to use technology, the effective use of technology, and the effect of this use on students' outcomes. Venkatesh et al. (2012) proposed a new explanatory model of users' behavior that they called UTAUT2. In this model, they added three explanatory variables: hedonic motivation, price value, and habit. Future research should draw from this model to identify other explanatory factors of technology acceptance. The influence of "situatedness" on technology adoption is also interesting to explore. Indeed, Neufeld and Delcore (2018) argued that instructional context, settings of student work, and social and cultural contexts may affect students' adoption. As we said earlier, we suggest taking small, achievable steps rather than bold, more insecure steps to explain students' acceptance of technology and the effect of this acceptance on their outcomes. Maybe one day we will be able to answer Vlieghe (2014) question about "whether the introduction of digital media in the educational sphere may—or may not—fundamentally alter the very meaning of education itself."

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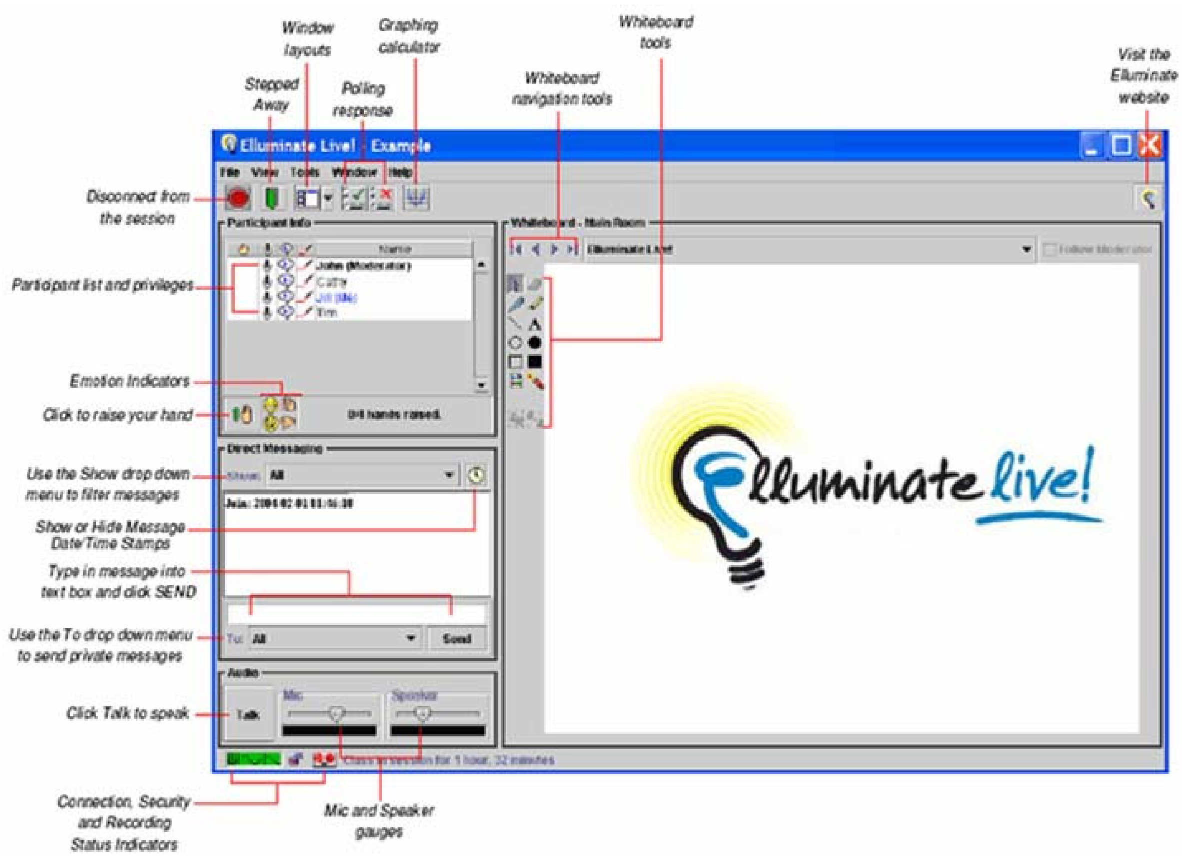
APPENDIX A

Elluminate software screenshot and main features



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APPENDIX B

Items of the main UTAUT variables after reliability checking

Behavioural intention (BI)

BI1: I intend to use Elluminate in future sessions
BI2: I predict I will use Elluminate in future sessions
BI3: I plan to use Elluminate in future sessions

Performance expectancy (PE)

PE1: Using Elluminate will improve my performance in the course
PE2: I'll find the system useful in my learning activities
PE3: Using Elluminate enables me to accomplish my learning activities more quickly
PE4: Using Elluminate improves the quality of my learning activities
PE5: Using Elluminate makes my learning activities easier
PE6: Using Elluminate enhances my effectiveness in my learning activities
PE7: Using Elluminate increases my productivity in my learning activities
PE8: If I use the system, I will increase my chances of getting higher marks on tests and exams

Effort expectancy (EE)

EE1: Learning to operate Elluminate will be easy for me
EE2: My interaction with Elluminate will be clear and understandable
EE3: It'll be easy for me to become skillful at using Elluminate
EE4: I'll find Elluminate easy to use

Social influence (SI)

SI1: People who influence my behaviour think I should use Elluminate
SI2: People who are important to me think I should use Elluminate
SI5: In my class, students who use Elluminate enjoy more prestige than those who do not
SI6: In my class, students who use Elluminate have a high profile
SI7: Using Elluminate is academically status-enhancing for students

Facilitating conditions (FC)

FC1: I have the resources necessary to use Elluminate
FC2: I have the knowledge necessary to use Elluminate

BIOGRAPHIES

Dr. Khechine is a full professor in the management information systems department of Laval University, Canada. She has an MBA in information technology and a Ph.D. in information systems. Her research interests mainly relate to the study of the acceptance and adoption of information technologies for eLearning and eHealth and the outcomes of this adoption. She publishes in journals and conferences that straddle the fields of information systems and education or health sciences.

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