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CHATBOT AS A LEARNING ASSISTANT: FACTORS INFLUENCING ADOPTION AND RECOMMENDATION

Caio Lemos Moraes

Dissertation presented as partial requirement for obtaining the Master's degree in Information Management

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by

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ABSTRACT

Soon, it is expected that artificial intelligence (AI) may replace many jobs whose work is based in repetitive tasks. Considering the role that this technology will play in our lives over the next few years, it would be interesting to take advantage of its potential now and use it as a transformation agent in the educational system. This study aims to evaluate the main drivers for adoption and recommendation of chatbots as a learning assistant to students in higher education. The research uses an innovative model based on gamification affordance, support construct from the students control model, and performance expectance, hedonic motivation, and behavioural intention to adopt constructs from the well-known UTAUT2 model. The model was empirically assessed using structural equation modelling (SEM) based on 302 responses from an online survey conducted in a South American country, Brazil. Support and hedonic motivation were found to be the most significant drivers for behaviour intention to adopt a chatbot. To explain the antecedents of the intention to recommend a chatbot, support and behavioural intention to adopt were the most important drivers found. For scholars, this research brings new material for further exploration of individual drivers for technology adoption and recommendation. For practitioners, knowing the main drivers for adoption and recommendation of a chatbot enables them to develop a technology with higher chances of absorption in the market.

KEYWORDS

Chatbot; Gamification; Mobile learning; Personal Learning Environment.

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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
UTAUT2	Unified Theory of Acceptance and Use of Technology
MOOC	Massive Open Online Course
PLE	Personal Learning Environment
SEM	Structural equation modelling
AVE	Average variance extracted
HTMT	Heterotrait-monotrait ratio
VIF	Variance inflation factor

1. INTRODUCTION

Artificial intelligence (AI) has the potential to drastically change our society in the near future. Eventually, AI will replace jobs that mainly involve repetitive tasks while creating opportunities in areas that require more social, interpersonal, and creativity skills (Makridakis, 2017). At the same time, AI demonstrates potential to be applied to education. It can enhance learners' experiences to respond to the future needs that AI itself will create (Bates, Cobo, Mariño, & Wheeler, 2020).

Learning involves emotional and personal traits that should be addressed when using technology to enhance learners experience (Garrison, 2007). Through chatbots, AI can play an important role supporting the communication and emotional aspects of the learning process, delivering a more personal experience to each individual (Bates et al., 2020).

Chatbots are gaining more space in the educational sector. Fadhil and Villafiorita (2017) presented promising findings indicating its use as a framework for gamification of learning. As presented by Markopoulos et. al (2015), the use of gamification in education can have a positive impact because it can increase intrinsic motivation, collaboration, and engagement among learners.

There are few studies done about chatbot adoption in the learning segment, but there are even fewer studies regarding the topic in a South American country, Brazil when compared to European countries and the United States. Moreover, the studies regarding chatbot adoption for education started very recently, such as Boeding (2020) and Sandu and Gide (2019). Nonetheless, most of the articles about gamification in education focus on different information systems, such as Massive Open Online Course (MOOC) and web 2.0 technologies. Hence, there is a lack of studies using chatbots as a framework for gamification of learning.

Learning using a chatbot means that students are proactively defining their learning preferences, and to help in this end, this research will assess the support construct from a pedagogy-driven model proposed by E. Rahimi, Van Den Berg, and Veen (2015a). Combining it with constructs from UTAUT2 from Venkatesh, Thong, and Xu (2012a), and gamification affordance from Suh, Cheung, Ahuja, and Wagner (2017), the proposed model will propose a holistic way to explore the main factors that may influence chatbot adoption and recommendation.

Consequently, this research contributes to the scarce literature in this field by offering a unique model. To the best of our knowledge, there is no research assessing the intention to recommend chatbots in the education sector. The construct is relevant to the education sector because users can influence the visibility of the technology. A greater audience would be reached, which could bring more customers. Finally, as the technology was recently adopted in the educational sector, there is still a lack of studies on chatbot as a learning assistant. Hence, this study may add valuable knowledge to chatbot developers and the educational industry to develop market strategies to achieve better results in the educational market.

2. LITERATURE REVIEW

2.1. Chatbots Applied in Education

Artificial intelligence is a broad term, since intelligence is also a complex concept. Russell and Norvig (2009) have found that the main textbooks about the subject defines the term in dimensions that concern how machines could mimic human thinking, and also how it could go beyond by maximizing its performance using previous acquired knowledge.

AI has great potential to be applied in the educational environment. One of the most well-known examples is the Georgia Tech AI teaching assistant named Jill Watson. In response to the highly demanded computer science online classes, it was developed an AI virtual assistant, able to answer frequently asked questions, given human teachers more time to invest in deeper discussions with students (Goel & Polepeddi, 2016). In 2020, due to the success of Jill Watson, Georgia tech develop a system which professors can easily create their own virtual teaching assistant (Georgia Tech, 2020). A virtual assistant is a software agent that can be programmed to help humans to perform specific daily activities such as making phone calls, control other devices, schedule activities, and so on (Joshi, 2018).

Virtual assistants have been used as pedagogical agents since early 1970. A more humanlike experience would be more powerful, because developing a more personal relationship is extremely important for pedagogical purposes (Bickmore, 2003). Chatbots have demonstrated a great potential to become human tutors, responding to the need of a closer relationship to the learner. In our study they are considered virtual assistants specially designed to engage in a humanlike conversation (Colace et al., 2018). As Tarouco, Silveira, and Krassmann (2018) have stated, as well as virtual assistants, they are permanently available and are able to perform automated tasks to help students to search for content and work collaboratively.

Recent studies have shown how chatbots can significantly help learners to organize themselves to study more efficiently and excel their capabilities as shown to help health learning professionals (Corral, 2021). Smutny and Schreiberova (2020) have studied educational chatbots in the Facebook Messenger platform and has shown how much the chatbots can vary in how much personalization it might have, and how much this field can still grow.

Chatbots were also to be a promising asset psychoeducation, making these processes more enjoyable and effective (Vaidyam, Wisniewski, Halamka, Kashavan, & Torous, 2019). Still on the health and education domains, chatbots were promising on helping users to learn how to change their behaviour with its features of interactive education and self-monitoring of behaviour change progress (Kennedy et al., 2012).

2.2. Students Control Model for Online Learning

Technology has never grown so fast (Chace, 2020), and as it grows people's ability to react to technology changes also needs to increase. Online learning can be a good option to keep up to date with the market demands, and educational chatbots can be helpful in this matter (Griol, Molina, & de Miguel, 2014; Shawar & Atwell, 2003). In general, e-learning is cheaper, more flexible and has more variety of options than traditional learning, but it also requires more self-discipline (Job, 2019). As stated by Lung-Guang (2019) the biggest challenge faced for online learners is self-discipline. It is very common for students to get distracted by other content on the Internet, which will jeopardize their learning experience (Henderikx, Kreijns, Castaño Muñoz, & Kalz, 2019). For this reason, it is important to tackle this issue with appropriate tools and strategies to mitigate any threats to the use of chatbots for online learning.

Proposed by Rahimi, Van Den Berg, and Veen (2015a), Student's Control Model, also called of pedagogy-driven model, aims to facilitate students' engagement in building their own learning environment. It does so by empowering the individuals with tools and resources, which leads to a greater feeling of ownership over their Personal Learning Environments (PLEs). Attwell (2007) states that PLEs are systems that empower students to manage and control their own learning process, by providing spaces they can, individually, control, manage, explore, and share ideas.

To successfully achieve a better PLE Rahimi, Van Den Berg, and Veen (2015), proposed a model to integrate Web 2.0 into educational practices in order to assist students to construct their own learning environment. Rahimi et al. (2015) established three dimensions to support student's control over educational process: capability, support, and autonomy.

In our research we will focus on the support dimension to evaluate how it would impact on the chatbot acceptance and recommendation. Support is defined as the extent in which the students have enough resources to learn. Resources includes learning materials, professor's guides, and a supportive environment with experts and other learners where they can look for help in their learning path (Ebrahim Rahimi, Van Den Berg, et al., 2015). Support also refers to how the communication is mediated, such as printed, computer, face-to-face, etc. In PLEs, due to the distance, the technology chosen plays an important role in the student´s control (Garrison & Baynton, 1987).

2.3. Gamified Learning Environments

It has never been so difficult to make students interested in classes as today. As presented by Bhat (2017), between 2003 and 2011 there was a 35% increase of attention-deficit/hyperactivity disorder in children between 4 to 17 years old in the United States. One theory discusses that the overuse of technology is exposes children to a heightened stimulation for long periods of time, while other activities, such as reading, might look much less may attractive and stimulating.

Gamification refers to the approach that applies the game design elements in non-game contexts (Deterding, Khaled, Nacke, & Dixon, 2011). Its main objective is to increase engagement (Kapp, 2012; Villagrasa, Fonseca, Redondo, & Duran, 2014). Therefore, gamified systems could be helpful to keep students interested in learning. This explains why gamification is mostly applied for educational purposes (De-Marcos, Garcia-Lopez, & Garcia-Cabot, 2016).

Fadhil and Villafiorita (2017) used a chatbot game to create an engaging social relationship with children to teach them about healthy lifestyle. The authors have obtained promising results, showing that the chatbot game outperformed the paper base version. The systematic review of the literature made by Subhash and Cudney (2018) on gamified learning in higher education found that it can increase student engagement, performance and improve student attitude. The research states that students expressed to feel more motivated and that they have enjoyed the gamified experience.

Suh, Cheung, Ahuja, and Wagner (2017), identified four gamification affordances: rewards, status, competition, and self-expression. These affordances are considered to be the main elements that influence the user engagement in a gamified information system environment.

Rewards is the affordance which enables users to be rewarded for completing predefined tasks, also perceived as a feedback from their performance (Suh et al., 2017). Status affordance refers to the capability that individuals can increase their level by completing predefined milestones (Suh et al., 2017). Suh et al. (2017) defines competition as the affordance that enables users to compare their achievements with others, and it is considered one of the most important characteristics of gaming. Finally, self-expression refers to how users can express themselves, such as their personal characteristics or any kind of interests.

3. RESEARCH MODEL

It was found that gamification is a great topic of interest for researchers in the educational segment, but, as previously mentioned, there is a lack of studies using chatbots to create a gamified environment. Thus, based on the gamification affordance model from Suh et al., (2017), the constructs: competition affordance, status affordance, and rewards affordance, were selected to evaluate the influence of game elements towards the adoption and recommendation of a chatbot.

Socialization and knowledge sharing between peers is very important for learning. Therefore the model proposed in this research will assess how it may influence technology adoption and recommendation with the support construct from the students control model from E. Rahimi, Van Den Berg, et al. (2015a). Performance expectancy and hedonic motivation from Venkatesh, Thong, and Xu (2012b), are well known constructs to assess technology adoption, yet they were not extensively studied for chatbot adoption. Nonetheless, both constructs were found to be the most significant when deciding to adopt a technology (Venkatesh et al., 2012b), and therefore we included them in our model. Finally, the last construct selected is behavioural intention to adopt. It is an important construct because previous research has shown that the intention to adopt a new technology is directly related to the intention to recommend it (Oliveira, Thomas, Baptista, & Campos, 2016).

Accordingly, it was developed a conceptual model that combines constructs from gamification affordance, students' control, and the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2). The conceptual model is presented in Fig. 1.

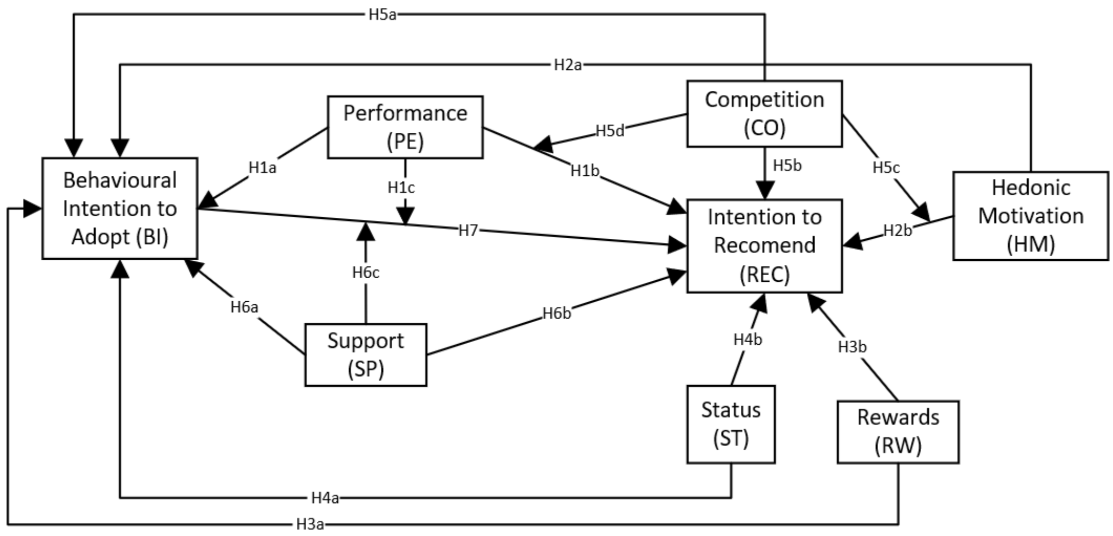


Figure 1 - Research model

Ebrahim Rahimi, Van Den Berg, et al. (2015) proposed the students' control model considering a broad range of functionalities that could store and display information in such a way that a chatbot is not designed to. A chatbot is understood in our study as a way to interact with the users helping to share information. Therefore, support is chosen from the students control model, while autonomy and capability would require a technology capable of gathering and displaying information in a structured manner. Similarly, self-expression affordance, from the gamification affordance model was not included in the proposed model. The construct is related to game elements that helps to describe the uniqueness of the character in the game, such as trophies and badges (Suh et al., 2017). Since this research is target to chatbot usage, it will not focus on self-expression affordance due to the chatbot graphical limitations.

3.1. PERFORMANCE EXPECTANCY (PE)

The performance expectancy construct is defined as the degree to which the user believes that adopting a technology will positively impact their performance (Venkatesh, Thong, & Xu, 2016). The construct is expected to be a strong predictor for behavioural intention (Venkatesh, Morris, Davis, & Davis, 2003). Performance expectancy plays an important role in motivating learners to use and accept learning system (Almaiah, Alamri, & Al-Rahmi, 2019), and therefore, motivated learners that uses chatbots could be a better promoter of the technology among its classmates. Performance expectancy was also found to be a driver for recommending the experience of using on online platforms (Loureiro, Cavallero, & Miranda, 2018). Having in consideration these factors, we hypothesize that:

H1a. Performance expectancy (PE) will positively affect behavioural intention to adopt (BI) a chatbot as a learning assistant.

H1b. Performance expectancy (PE) will positively affect intention to recommend (REC) a chatbot as a learning assistant.

H1c. Performance expectancy (PE) will positively moderate the effect of intention to adopt (BI) on behavioural intention to recommend (REC) in such a way that the relationship will be stronger among people who value more the performance expectancy.

3.2. HEDONIC MOTIVATION (HM)

Hedonic motivation refers to the degree which the user enjoys using the information system (Venkatesh et al., 2012). Insufficient satisfaction and enjoyment can jeopardize the adoption of a new technology system (Davis, Bagozzi, & Warshaw, 1992). Hedonic motivation was shown to be the second strongest construct in mobile learning adoption among higher education students in Malaysia (Moorthy, Yee, T'ing, & Kumaran, 2019), a positive indicator of gamified learning environment (Oluwajana, Idowu, Nat, Vanduhe, & Fadiya, 2019), and one of the drivers to share positive feelings about a service (K. H. Yoo & Gretzel, 2008). Considering these factors, we hypothesize that:

H2a. Hedonic motivation (HM) will positively affect behavioural intention to adopt (BI) a chatbot as a learning assistant.

H2b. Hedonic motivation (HM) will positively affect intention to recommend (REC) a chatbot as a learning assistant.

3.3. GAMIFICATION AFFORDANCE

A reward system is an important aspect for a satisfying game experience because it creates a cycle of achieving goals and being rewarded for it (Pluralsight, 2015). Ortega-Arranz et al. (2019) have found that on MOOCs tasks involving rewards had more participation of students. When humans are exposed to a rewarding stimulus nerve cells of the brain releases dopamine causing a pleasure experience (Wise, 1998). A pleasant experience leads to a higher chance of technology adoption and recommendation (Teixeira & Mendes, 2019). Rewards are also important to stimulate word of mouth (Kuester & Benkenstein, 2014). As the chatbot gamified experience will enable a reward system, we hypothesize that:

H3a. Rewards affordance (RW) will positively affect behavioural intention to adopt (BI) a chatbot as a learning assistant.

H3b. Rewards affordance (RW) will positively affect intention to recommend (REC) a chatbot as a learning assistant.

All elements of game mechanics drive to the status dynamic, in such a way that the primary motivation is to achieve the highest level (Bunchball, 2010). Hence, users are encourage to pursue the next challenge creating a sense of self-progress (Suh, Wagner, & Liu, 2015), promoting a pleasant and arousal experience that encourages sharing positive feelings about the experience (Huang, Ali, & Liao, 2017). The consequence is a pleasant chatbot gamified experience. Therefore, we hypothesize that:

H4a. Status affordance (ST) will positively affect behavioural intention to adopt (BI) a chatbot as a learning assistant.

H4b. Status affordance (ST) will positively affect intention to recommend (REC) a chatbot as a learning assistant.

Competition drives users to challenge each other to achieve the highest score in activities (Deterding, Dixon, Khaled, & Nacke, 2011). The competition element was shown to significantly improve learning and motivation among students (Cagiltay, Ozcelik, & Ozcelik, 2015). Competition might also stimulate more communication and interaction (Bakhanova, Garcia, Raffe, & Voinov, 2020), which can result in a better experience that is related to spreading word of mouth (Huang et al., 2017). Considering the competition element of the gamified chatbot, and its potential to promote an enjoyable way of learning, we hypothesize that:

H5a. Competition affordance (CO) will positively affect behavioural intention to adopt (BI) a chatbot as a learning assistant.

H5b. Competition affordance (CO) will positively affect intention to recommend (REC) a chatbot as a learning assistant.

Gamified environments have demonstrated an increased engagement of learners, which resulted in better individual performance (W. Wu, Tzamos, Daskalakis, Weinberg, & Kaashoek, 2015). Zainuddin, Shujahat, Haruna, & Chu (2020) have shown that quiz competitions can motivate students to compete in the classroom, leading to better student performance in class. Consequently, students interested in raising their performance or in competing with each other will be more engaged and interested in using chatbots for educational purposes. Therefore, we hypothesize that:

H5c. Competition affordance (CO) moderates hedonic motivation (HM) and intention to recommend (REC) in such a way that the relationship will be stronger among people who are more competitive.

H5d. Competition affordance (CO) moderates performance expectancy (PE) and intention to recommend (REC) in such a way that the relationship will be stronger among people who are more competitive.

3.4. Support (SP)

The lack of support makes students feel unmotivated and isolated leading to problematic academic behaviours (Ford & Roby, 2013). Support can improve scholars help-seeking skills and enhance their engagement in the learning process improving their learning skills (Roll, Aleven, McLaren, & Koedinger, 2011). The learning outcomes can be tied to students engagement, which relates the quality and quantity of their involvement with learning activities (Krause & Coates, 2008). The engagement is shown to increase the number of users that write positive reviews that may influence others (J. Wu, Fan, & Zhao, 2018). Chatbots have the potential to create a supportive environment increasing student's interest and motivation (Tarouco et al., 2018). Therefore, we hypothesize that:

H6a. Support (SP) will positively affect behavioural intention to adopt (BI) a chatbot as a learning assistant.

H6b. Support (SP) will positively affect behavioural intention to recommend (REC) a chatbot as a learning assistant.

Since students will seek help during its learning process, autonomy also impacts support, but it does not necessary mean that they need to give up of their control (Garrison & Baynton, 1987). Therefore, we hypothesize that:

H6c. Support (SP) moderates behavioural intention to adopt (BI) and behavioural intention to recommend (REC) in such a way that the relationship will be stronger among people who feel that have more support (SP).

3.5. Behavioural intention to adopt (BI)

The act of recommending a technology to others is considered a post-adoption behaviour, and it is repeatedly been ignored by researchers that prefer to emphasize their studies on use (Lancelot Miltgen, Popovič, & Oliveira, 2013). Users that demonstrate more interest to adopt a new technology also have shown a greater chance to become adopters (Leong, Hew, Tan, & Ooi, 2013), thereafter more willing to recommend the technology to others (Lancelot Miltgen et al., 2013). Students tend to recommend more when they see that they can also gain when more students join the technology (Greenacre, Freeman, Cong, & Chapman, 2014). Chatbots are a promising technology to be applied to improve students' learning goals (Colace et al., 2018). Therefore, we hypothesize that:

H7. Behavioural intention to adopt (BI) will positively affect behavioural intention to recommend (REC) a chatbot for educational purposes.

4. RESEARCH METHODOLOGY

4.1. MEASUREMENT

Based on the research model, an English-language questionnaire was created and reviewed for content validity by a group of information systems academics. The questionnaire contains four sections: UTAUT2 data constructs (Performance Expectancy, Hedonic Motivation and Behavioural intention), Gamification Affordance constructs (Rewards, Competition and Status), Students Control construct (Support) questions and finally, general information and demographic characteristics. The items and scales for the UTAUT2 constructs were adapted from Venkatesh et al. (2003; 2012a), the Support construct from Rahimi et al. (2015a), and Gamification Affordance constructs from Suh et al. (2017). Each item was measured on a seven-point Likert scale whose answer choice ranges from "strongly disagree" (1) to "strongly agree" (7). Age was measured in years, and gender was coded using a 0 (women) or 1 (men). The items for all constructs are included in Appendix A. The initial questionnaire was translated into Portuguese because data collection takes place in Brazil. The questionnaire was revised by a Brazilian academic in order to adapt it to the characteristics of the local Portuguese language. Finally, the questionnaire was translated back into English, to ensure the consistency of its content (Brislin, 1970).

4.2. DATA COLLECTION

As claimed by Venkatesh et al. (2003), studies of technology acceptance have been widely developed using survey research. Therefore, it was designed as an online survey instrument with the revised Portuguese version of the questionnaire hosted by, SurveyMonkey, one of the main service providers for research papers and data collection.

The target population comprised individual adults that are students attending a higher education degree or that have attended one in the past 3 years. Due to the target population, an e-mail list of students from several Brazilian universities was collected and used exclusively for this purpose. The link to the online questionnaire was also shared on social networks specifically in university discussion group pages.

The survey was pilot tested with 25 participants within the target population who were not included in the final sample. The pilot showed confirmed that scales were valid and reliable. After the period of 16 weeks that started in late May 2020, a total of 597 people has visited the survey, 302 replied to it, representing a 50,6% response rate. 55.3% of the respondents were female and 44.7% male, most of them aged between 18 and 34 years with and education level up to the master's degree, while a small group of 3% with doctor degree, as illustrated by table 1.

Sample (n=302)								
Age			**Gender**			**Education**		
18-24	98	32.5%	Female	167	55.3%	Bachelor's degree	180	59.6%
25-34	124	41.1%	Male	135	44.7%	Professional degree	72	23.8%
35-44	46	15.2%				Master's degree	41	13.6%
45-54	24	7.9%				Doctor degree	9	3.0%
55-64	10	3.3%						

Table 1 – Demographic data of responses

5. ANALYSIS AND RESULTS

Structural equation modelling (SEM) was used to test and assess the theoretical causal relationships. SEM is a statistical method used in explanatory research to evaluate the qualitative causal relationship of a model (Byrne, 2013). The research model was estimated with partial least squares (PLS-SEM), which is a variance-based method, with SmartPLS 3 software (Ringle, C.M., Wend, S., Becker, 2015). This method presents some important advantages and it is capable to be applied in many research approaches (Henseler, Ringle, & Sinkovics, 2009), and for studying complex models with great number of constructs (Chin, 1998). The dimension of the sample is more than 10 times greater than the maximum number of paths directed to a construct (Gefen & Straub, 2005), hence PLS-SEM is suitable for estimation. This technique has minimal restrictions when it comes to residual distributions and sample sizes compared to other SEM such as covariance-based techniques (Chin, 1998).

5.1. MEASUREMENT MODEL

The measurement model was estimated based on construct reliability, indicator reliability, convergent validity, and discriminant validity. Table 2 presents that all constructs have composite reliability above 0.7, which is a strong indicator that the constructs are reliable (Straub, 1989).

The criteria for indicator reliability is that loading should be higher than 0.7 and loadings below 0.4 should be eliminated (Churchill, 1979). The loadings presented on this research are higher than 0.7 and are statistically significant at 0.01, suggesting a good indicator reliability of the instrument.

Average variance extracted (AVE) was the method used to test the convergence validity. All the constructs had a value above the minimal acceptable value of 0.50, meaning the latent variable explains more than half of the variance of its indicators (Fornell & Larcker, 1981; Hair, Sarstedt, Ringle, & Mena, 2012; Henseler et al., 2009).

The discriminant validity of the constructs was evaluated with Fornell-Larcker, cross-loadings, and heterotrait-monotrait ratio (HTMT) criteria. The first criterion states that the square root of AVE should be greater than the correlations between the construct (Fornell & Larcker, 1981). The second criterion requires that the loading of each indicator should be greater than all cross-loadings (Chin, 1998; Götz, Liehr-Gobbers, & Krafft, 2010; Grégoire & Fisher, 2006). The square roots of AVEs (diagonal elements) presented on table 2 are higher than the correlation between each pair of constructs (off-diagonal elements). The patterns of loading are greater than cross-loading as shown on table 3.

Construct	Mean	SD	CR	CA	PE	HM	RW	ST	CO	AT	SP	BI	REC
PE	5.52	1.43	0.96	0.95	**0.92**								
HM	5.49	1.67	0.97	0.96	0.80	**0.96**							
Rewards	5.48	1.69	0.97	0.96	0.53	0.54	**0.96**						
Status	3.82	1.79	0.96	0.93	0.35	0.38	0.55	**0.94**					
Competition	4.89	1.72	0.92	0.87	0.36	0.42	0.64	0.68	**0.89**				
Support	5.40	1.48	0.96	0.95	0.74	0.77	0.53	0.45	0.44	0.84	**0.90**		
BI	4.63	1.89	0.97	0.96	0.71	0.74	0.59	0.51	0.45	0.78	0.72	**0.93**	
Recommend	5.80	1.38	0.89	0.74	0.64	0.70	0.57	0.37	0.40	0.71	0.73	0.76	**0.89**

Table 2 – Descriptive statistics, correlation, composite reliability (CR), and average variance extracted (AVE).

Construct	ITEM	PE	HM	RW	ST	CO	AT	SP	BI	REC
Performance Expectancy	PE1	**0.907**	0.736	0.482	0.267	0.298	0.625	0.654	0.623	0.603
	PE2	**0.929**	0.710	0.508	0.330	0.348	0.644	0.664	0.647	0.591
	PE3	**0.899**	0.689	0.468	0.299	0.297	0.657	0.682	0.652	0.582
	PE4	**0.937**	0.746	0.481	0.361	0.351	0.719	0.714	0.681	0.567
	PE5	**0.920**	0.772	0.496	0.365	0.362	0.692	0.689	0.664	0.587
Hedonic Motivation	HM1	0.747	**0.952**	0.523	0.347	0.399	0.740	0.748	0.695	0.678
	HM2	0.767	**0.971**	0.512	0.381	0.411	0.710	0.731	0.728	0.673
	HM3	0.777	**0.955**	0.528	0.375	0.398	0.720	0.739	0.703	0.668
Rewards	RW1	0.495	0.510	**0.962**	0.575	0.599	0.580	0.494	0.553	0.524
	RW2	0.525	0.526	**0.972**	0.528	0.619	0.614	0.518	0.565	0.547
	RW3	0.507	0.528	**0.949**	0.494	0.626	0.623	0.522	0.577	0.570
Status	ST1	0.348	0.382	0.581	**0.935**	0.682	0.508	0.438	0.489	0.363
	ST2	0.332	0.367	0.456	**0.936**	0.602	0.441	0.425	0.492	0.337
	ST3	0.311	0.326	0.516	**0.938**	0.618	0.427	0.407	0.459	0.351
Competition	CO1	0.384	0.439	0.626	0.636	**0.950**	0.523	0.444	0.467	0.415
	CO2	0.355	0.406	0.633	0.590	**0.925**	0.491	0.454	0.395	0.398
	CO3	0.176	0.230	0.407	0.603	**0.783**	0.320	0.221	0.300	0.193
	AT5	0.637	0.626	0.572	0.438	0.457	**0.896**	0.732	0.681	0.614
	AT6	0.633	0.654	0.577	0.462	0.455	**0.895**	0.715	0.747	0.652
Support	SP1	0.705	0.710	0.495	0.394	0.378	0.777	**0.921**	0.692	0.662
	SP2	0.638	0.696	0.462	0.431	0.431	0.740	**0.896**	0.638	0.622
	SP3	0.612	0.684	0.441	0.409	0.393	0.746	**0.891**	0.659	0.649
	SP4	0.682	0.712	0.522	0.340	0.329	0.760	**0.875**	0.640	0.672
	SP5	0.723	0.698	0.512	0.418	0.393	0.756	**0.911**	0.660	0.696
	SP6	0.622	0.641	0.429	0.448	0.445	0.752	**0.885**	0.605	0.597
Behavioural Intention	BI1	0.647	0.657	0.570	0.494	0.436	0.748	0.680	**0.944**	0.704
	BI2	0.674	0.734	0.541	0.476	0.413	0.751	0.695	**0.956**	0.728
	BI3	0.668	0.690	0.531	0.513	0.405	0.738	0.695	**0.943**	0.693
	BI4	0.664	0.671	0.458	0.444	0.341	0.627	0.622	**0.890**	0.679
	BI5	0.663	0.690	0.634	0.463	0.476	0.772	0.683	**0.925**	**0.751**
Intention to Recommend	REC1	0.651	0.663	0.523	0.404	0.376	0.669	0.672	0.786	**0.911**
	REC2	0.474	0.583	0.493	0.252	0.328	0.596	0.620	0.559	**0.872**

Table 3 – Loadings and cross-loadings.

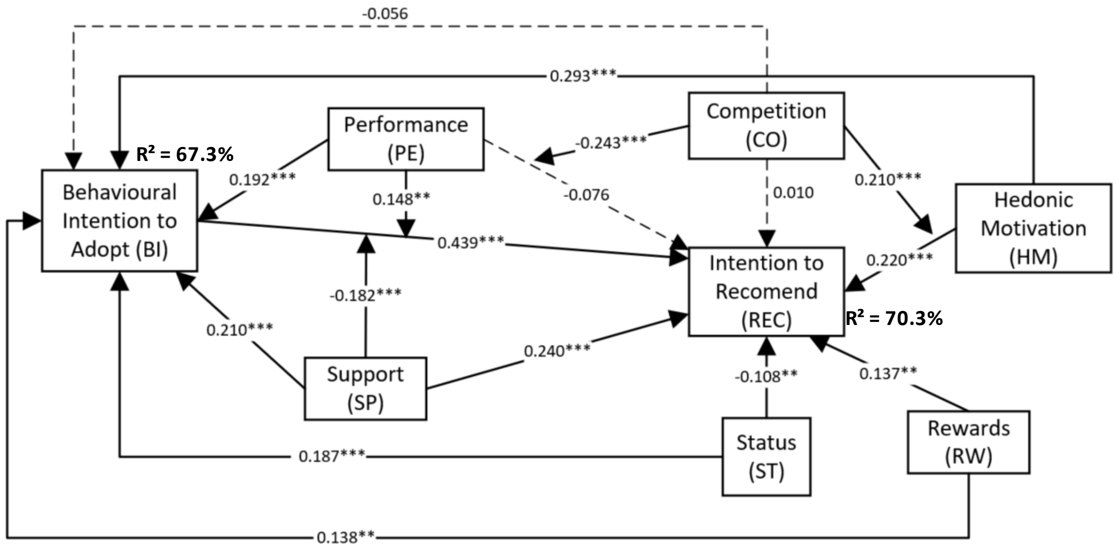
Finally, the discriminant validity criterion is accomplished if all HTMT ratios are below the threshold of 0.9 (Henseler et al., 2014). In Table 4, we see that all HTMT ratios scored below 0.9; Hence, the constructs' discriminant validity is confirmed. The measurement model results for construct reliability, indicator reliability, convergent validity, and discriminant validity meet the criteria indicating that the constructs are statistically distinct and can be used to test the structural model.

Constructs	PE	HM	RW	ST	CO	SP	BI	REC
Performance expectancy								
Hedonic motivation	**0,833**							
Rewards	0,554	**0,567**						
Status	0,374	0,406	**0,587**					
Competition	0,376	0,441	0,683	**0,762**				
Support	0,777	0,807	0,557	0,482	**0,462**			
Behavioural intention to adopt	0,743	0,770	0,611	0,542	0,475	**0,756**		
Intention to recommend	0,748	0,827	0,673	0,441	0,465	0,859	**0,889**	

Table 4 – Heterotrait-Monotrait Ratio (HTMT).

5.2. STRUCTURAL MODEL AND HYPOTHESES TESTING

The multicollinearity of all variables was tested using the variance inflation factor (VIF). All VIF are lower than the threshold of 5, meaning the model does not have a multicollinearity problem (Hair, Ringle, & Sarstedt, 2011). The structural model was estimated using R^2 measures and path coefficients' level of significance. The model results are displayed on fig. 2, as well as the path coefficients. The significance of the path coefficients was assessed using bootstrapping procedure with 5000 iterations of resampling (Chin, 1998).



Note: *** p < 0.01; ** p < 0.05; p < 0.10

Figure 2 - Research model with results

The model explains 67.3% of the variation in behavioural intention to adopt, with the following variables presenting a statistically significant relationship, namely performance expectancy ($\hat{\beta} = 0.192$; $p < 0.01$), hedonic motivation ($\hat{\beta} = 0.293$; $p < 0.01$), rewards ($\hat{\beta} = 0.138$; $p < 0.05$), status ($\hat{\beta} = 0.187$; $p < 0.01$), and support ($\hat{\beta} = 0.210$; $p < 0.01$). Respectively hypotheses H1a, H2a, H3a, H4a, H6a are confirmed. On the other hand, competition ($\hat{\beta} = -0.056$; $p > 0.10$) was found not statistically significant, therefore hypotheses H5a is not confirmed.

The variation in intention to recommend is explained by 70.3% through hedonic motivation ($\hat{\beta} = 0.220$; $p < 0.01$), rewards ($\hat{\beta} = 0.137$; $p < 0.05$), status ($\hat{\beta} = -0.108$; $p < 0.05$), support ($\hat{\beta} = 0.240$; $p < 0.01$), and behavioural intention to adopt ($\hat{\beta} = 0.439$; $p < 0.01$). Thus, hypotheses H2b, H3b, H4b, H6b, H7 are confirmed. However, performance expectancy ($\hat{\beta} = -0.076$; $p > 0.10$), competition ($\hat{\beta} = 0.010$; $p > 0.10$) are not statistically significant. Consequently, hypothesis H1b and H5b are not confirmed.

Finally, several statically significant moderation effect were found, namely performance in relationship between behavioural intention to adopt and intention to recommend ($\hat{\beta}$ = 0.148; $p < 0.05$), competition in relationship between hedonic motivation and intention to recommend ($\hat{\beta}$ = 0.210; $p < 0.01$), competition in relationship between performance expectancy and intention to recommend ($\hat{\beta}$ = -0.243; $p < 0.01$), and support in relationship between behavioural intention to adopt and intention to recommend ($\hat{\beta}$ = -0.182; $p < 0.01$). Thus, hypothesis H1c, H5c, H5d, and H6c are confirmed. The supported hypothesis are presented in table 5.

	Independent variable	Dependent Variable	Moderator	Conclusion
H1a	Performance Expectancy (PE)	Behavioural intention to adopt (BI)	n.a.	supported
H1b	Performance Expectancy (PE)	Behavioural Intention to Recommend (REC)	n.a.	not supported
H1c	Performance Expectancy (PE) * Behavioural intention to adopt (BI)	Behavioural Intention to Recommend (REC)	Performance Expectancy (PE)	supported
H2a	Hedonic Motivation (HM)	Behavioural intention to adopt (BI)	n.a.	supported
H2b	Hedonic Motivation (HM)	Behavioural Intention to Recommend (REC)	n.a.	supported
H3a	Rewards (RW)	Behavioural intention to adopt (BI)	n.a.	supported
H3b	Rewards (RW)	Behavioural Intention to Recommend (REC)	n.a.	supported
H4a	Status (ST)	Behavioural intention to adopt (BI)	n.a.	supported
H4b	Status (ST)	Behavioural Intention to Recommend (REC)	n.a.	supported
H5a	Competition (CO)	Behavioural intention to adopt (BI)	n.a.	not supported
H5b	Competition (CO)	Behavioural Intention to Recommend (REC)	n.a.	not supported
H5c	Competition (CO) * Hedonic Motivation (HM)	Behavioural Intention to Recommend (REC)	Competition (CO)	supported
H5d	Competition (CO) * Performance Expectancy (PE)	Behavioural Intention to Recommend (REC)	Competition (CO)	supported
H6a	Support (SP)	Behavioural intention to adopt (BI)	n.a.	supported
H6b	Support (SP)	Behavioural Intention to Recommend (REC)	n.a.	supported
H6c	Support (SP) * Behavioural intention to adopt (BI)	Behavioural Intention to Recommend (REC)	Support (SP)	supported
H7	Behavioural Intention to Adopt (BI)	Behavioural Intention to Recommend (REC)	n.a.	supported

Table 5 – Conclusions for hypothesis

6. DISCUSSION

This research corroborates the previous studies that show that when the students have more control over their learning strategies (Koehler & Mishra, 2006; E. Rahimi, Van den Berg, & Veen, 2013; Valtonen et al., 2012), and perceive that the technology might improve their performance and enable a more pleasant experience (Markopoulos et al., 2015; Tsay, Kofinas, & Luo, 2018) will increase the behavioural intention to adopt the technology (Almaiah et al., 2019; J. Wu et al., 2018). This also positively affects the behavioural intention to recommend the chatbot to others (Huang et al., 2017; Kuester & Benkenstein, 2014; Loureiro et al., 2018).

The research supported the positive effect that performance expectancy has on the behavioural intention to adopt, as earlier studies have suggested (Almaiah et al., 2019), but it was not able to explain the intention to recommend the technology. Hedonic motivation was found to be an important driver for behavioural intention to adopt as well as for the intention to recommend, as expected according to previous studies (Moorthy et al., 2019; Oluwajana et al., 2019; S. J. Yoo & Han, 2013).

The empirical results showed that rewards is significant to predict the behavioural intention to adopt, as previously presented by Ortega-Arranz et al. (2019). Rewards was also found valid to explain the intention to recommend, as previous research identified (Kuester & Benkenstein, 2014; Teixeira & Mendes, 2019). Similarly, status was valid to predict behavioural intention to adopt but acted as a negative driver when it comes to the intention to recommend. It implies that those who value status more, might not be willing to recommend as much those who do not value status that much. Status can be related with how unique a user perceives himself (Latter, Phau, & Marchegiani, 2012), hence recommending the chatbot could impact on their status. The study results failed to validate the direct role of competition to predict both behavioural intention to adopt and to recommend. The support construct was shown to be valid to predict behavioural intention to adopt as well as to predict intention to recommend, aligned with some previous studies (Krause & Coates, 2008; Roll et al., 2011).

As displayed in Fig.3a the moderation effect of performance expectancy on the relationship between behavioural intention to adopt and intention to recommend has been shown to be stronger among those with high levels of performance expectancy than for people with low levels. Fig 3b shows that the competition moderator presents a stronger influence of high hedonic motivation on intention to recommend when the user is more competitive.

The slope on Fig 3c implies that the relationship between behavioural intention to adopt and intention to recommend is weaker for learners with higher levels of support than for learners with lower levels of support. Finally, Fig 3d illustrates that the competition moderator presents a stronger impact of high performance expectancy among those learners with lower competition. This is interesting because comparing fig. 3b and 3d, we can interpret that students want to see competition as a fun moment to learn. They expect it to be a pleasant experience in their learning path. When students face competition as a way to improve their performance, it may be perceived as not so interesting. They do not seem to want to compete with the direct goal of performing better on learning, they want to compete believing that the activity will be an amusing way to learn.

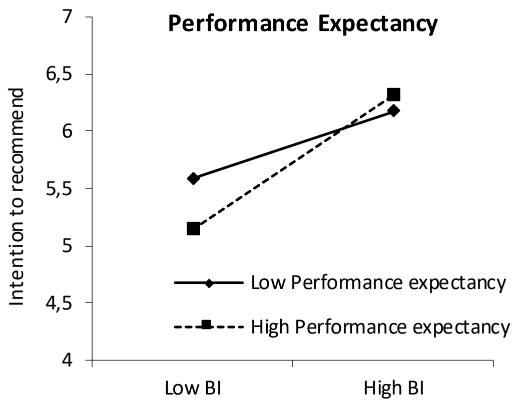


Figure 3a - Moderation effect of performance expectancy on behavioral intention to adopt over intention to recommend

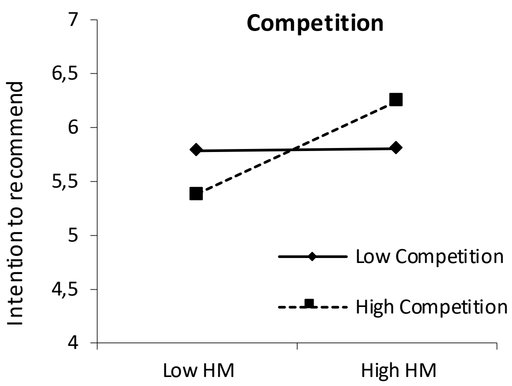


Figure 3b - Moderation effect of competition on hedonic motivation over intention to recommend

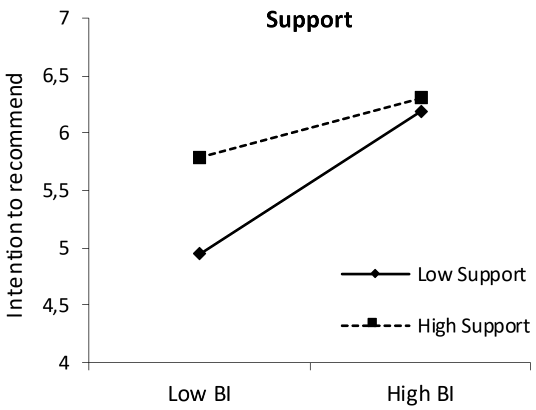


Figure 3c - Moderation effect of support on behavioral intention to adopt over intention to recommend

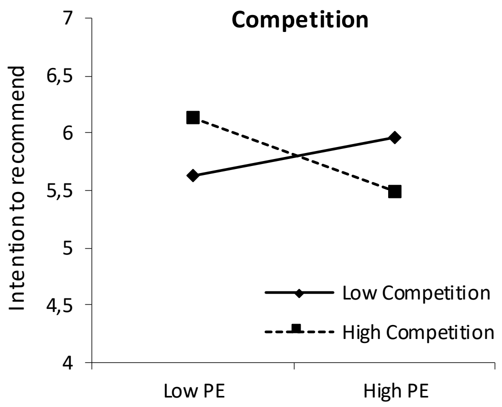


Figure 3d - Moderation effect of competition on performance expectancy over intention to recommend

Regarding possible particularities of the sample, in 2018 Brazil was the 8th country in the world on the number of websites with chatbot per 1000 persons (Goboomtown, 2019). It is likely that users from the sample have had some type of contact with one or more chatbots in their lives, and that the past experiences might play a role on their expectations with a chatbot as a learning assistant.

6.1. THEORETICAL IMPLICATIONS

Our research provides several contributions for the literature. First, as mentioned in the literature review, the field of chatbot adoption for higher education is relatively new. Therefore, the research on the topic is still scarce, especially when it comes to Brazil. Second, this study combines three distinguish models introducing moderators to achieve a broader view of the main drivers regarding chatbot in higher education adoption and recommendation. Third, as previously discussed, researchers have focused their attention on gamification in education applying other technologies rather than chatbots. Hence, this research adds more knowledge to enable a more effective study of the subject.

For researchers this study provides more material for analysis of individual models of technology adoption and recommendation. The model should be proved in a wide variety of demographic factors, such as different age groups, countries, and cultural backgrounds, to investigate in which extent these factors may contribute to the model.

6.2. PRACTICAL IMPLICATIONS

From the presented research it is possible to identify important considerations for educational institutions that want to make available chatbots for educational purposes. The findings suggest that students want to have better tools to learn, study, communicate with each other and share knowledge.

The chatbot needs to provide a pleasant experience to the learners. Gamified learning environment was found to be one important concept to be considered when creating a pleasant learning experience (Oluwajana et al., 2019). In this sense, the chatbot can be a channel that enables an effective educational that stimulates the engagement of the learners in activities related to the study object (Fadhil & Villafiorita, 2017). In order to obtain a successful chatbot embedded with game elements, the research indicate that status and rewards are important factors, while competition is not directly important. A good gamification strategy could be the one where the students are stimulated to participate in reward-base activities and obtain better status by doing so. The process should not be focused on winners and losers, but in a pursuit for better rewards and therefore better status.

Students have seen in the chatbot a great opportunity to increase their control over the study strategies they want to follow. It is important for the learners to be able to personalize the way they study. It is also important that the chatbot enables an easy way to share knowledge between the classmates and professors. Students should feel that the chatbot will facilitate their access to knowledge and therefore improving their performance in school.

Companies and educational institutions interested on investing in chatbots should have in consideration current work findings to explore different strategies to design and develop a chatbot with higher success chances to be adopted and recommended in the market. Finally, our study allows developers to implement AI assistants capable of enriching the educational environment, transforming the learning process into something more pleasant for the students, with higher levels of adoption and intention to recommend the technology among learners.

6.3. LIMITATIONS AND FUTURE RESEARCH

Technology is evolving extremely fast, and the network infrastructure of each country may play a big role on how the learners would respond to adoption and recommendation of the chatbot. The data for this study was based on a sample from a single country, Brazil, and specific from people with high education degree. Future studies might consider assessing samples from countries, learners with different educational levels, and different demographic characteristics.

There are possibly other moderated factors that might play significant role in the study such as cultural moderators. Future research may extend the academic comprehension of behavioural intention to adopt and intention to recommend by adding cultural specific constructs. Chatbots have visual graphical limitations, and they are not designed to present information in a structured manner. Therefore, it is possible that other technologies might be able to explore more constructs from the three models referenced, such as self-expression from gamification affordance and capability from student's control.

7. CONCLUSIONS

Chatbots are increasingly present in our lives. As technology evolves, the chatbots get closer to a natural humanlike conversation, which will bring many benefits for different segments of society. Due to the extensive use of technology by young people, education will be highly influenced by the next technology breakthroughs in natural language processing. Chatbots are an innovative option to enable a new way of studying. This study has combined support from students control with constructs from the gamification affordance, and constructs from UTAUT2 models. This is the first time that these models were combined in a single study to provide a broader view of the chatbot usage in the educational context.

The presented findings from the proposed model demonstrate its strong explanatory power in predicting consumer intention to adopt a chatbot as a learning assistant and their intention to recommend the technology. The results reveal positive statistically significant influence of the performance expectancy, hedonic motivation, rewards, status, and support over the behavioural intention to adopt the chatbot. Additionally, it was confirmed that hedonic motivation, rewards, support, and behavioural intention to adopt have a positive effect on the intention to recommend the use of the technology, while status produces a negative influence. Behavioural intention to adopt was the main driver for intention to recommend.

It was confirmed the moderation effect of performance expectancy between behavioural intention to adopt and intention to recommend. Competition appears to have moderation effect between hedonic motivation and intention to recommend, as well as between performance expectancy and intention to recommend. Finally, support was hound to have a moderation effect between behavioural intention to adopt and intention to recommend.

To conclude, the findings contribute for the theory and for the practice with valuable insights endorsing the initiatives related to the creation, maintenance, and support of a chatbot as a learning assistant in higher educational levels. For scholars this research brings new material for further exploration of individual drivers for technology adoption and recommendation. For practitioners, knowing the main drivers for adoption and recommendation of a chatbot enables a more data-driven decision on how to invest in the development of digital assistants, applications and information systems that may achieve high levels of acceptance.

8. REFERENCES

Almaiah, M. A., Alamri, M. M., & Al-Rahmi, W. (2019). Applying the UTAUT Model to Explain the Students' Acceptance of Mobile Learning System in Higher Education. *IEEE Access*, *7*(December), 174673–174686. https://doi.org/10.1109/ACCESS.2019.2957206

Attwell, G. (2007). Personal Learning Environments - the future of eLearning ? *Elearning Papers*, *2*(January), 1–8. Retrieved from http://www.elearningeuropa.info/files/media/media11561.pdf

Bakhanova, E., Garcia, J. A., Raffe, W. L., & Voinov, A. (2020). Targeting social learning and engagement: What serious games and gamification can offer to participatory modeling. *Environmental Modelling & Software*, *134*, 104846. https://doi.org/10.1016/j.envsoft.2020.104846

Bates, T., Cobo, C., Mariño, O., & Wheeler, S. (2020). Can artificial intelligence transform higher education? *International Journal of Educational Technology in Higher Education*, *17*(1). https://doi.org/10.1186/s41239-020-00218-x

Bhat, J. (2017). Attention Spans in the Age of Technology | NAMI: National Alliance on Mental Illness. Retrieved December 10, 2020, from National Alliance on Mental Illness website: https://www.nami.org/Blogs/NAMI-Blog/August-2017/Attention-Spans-in-the-Age-of-Technology

Bickmore, T. (2003). Relational agents: Effecting change through human-computer relationships. *SciencesNew York*, *PhD Thesis*(March), 284. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.7.1474&rep=rep1&type=pdf%5Cnhttp://www.ccis.northeastern.edu/home/bickmore/bickmore-thesis.pdf

Boeding, J. A. (2020). How Ai-Powered Chatbots Are Being Adopted and Used By Higher Education Institutions To Improve the Student Experience By Scaling Professional Staff. *Repositorio UPENN*, 179. Retrieved from https://repository.upenn.edu/dissertations/AAI28000542/

Brislin, R. W. (1970). Back-Translation for Cross-Cultural Research. *Journal of Cross-Cultural Psychology*, *1*(3), 185–216. https://doi.org/10.1177/135910457000100301

Bunchball. (2010). *Gamification 101: An Introduction to the Use of Game*. (October). https://doi.org/10.1016/j.compedu.2012.12.020

Byrne, B. M. (2013). *Structural Equation Modeling With EQS*. https://doi.org/10.4324/9780203726532

Cagiltay, N. E., Ozcelik, E., & Ozcelik, N. S. (2015). The effect of competition on learning in games. *Computers and Education*, *87*, 35–41. https://doi.org/10.1016/j.compedu.2015.04.001

Chace, C. (2020). Change Has Never Been This Fast. It Will Never Be This Slow Again. Retrieved December 1, 2020, from https://www.forbes.com/sites/cognitiveworld/2020/12/31/change-has-never-been-this-fast-it-will-never-be-this-slow-again/?sh=3b529c636429

Chin, W. W. (1998). The partial least squares approach to structural equation modelling. In Marcoulides G. A. (Ed.). *Modern Methods for Business Research*, *295*(2), 295–336.

Churchill, G. A. (1979). A Paradigm for Developing Better Measures of Marketing Constructs. *Journal of Marketing Research*, *16*(1), 64. https://doi.org/10.2307/3150876

Colace, F., De Santo, M., Lombardi, M., Pascale, F., Pietrosanto, A., & Lemma, S. (2018). Chatbot for e-learning: A case of study. *International Journal of Mechanical Engineering and Robotics Research*, *7*(5), 528–533. https://doi.org/10.18178/ijmerr.7.5.528-533

Corral, J. (2021). Artificially intelligent chatbots for health professions education. In *Digital Innovations in Healthcare Education and Training* (pp. 127–135). https://doi.org/10.1016/b978-0-12-813144-2.00008-8

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and Intrinsic Motivation to Use Computers in the Workplace'. In *Journal of Applied Social Psychology* (Vol. 22).

De-Marcos, L., Garcia-Lopez, E., & Garcia-Cabot, A. (2016). On the effectiveness of game-like and social approaches in learning: Comparing educational gaming, gamification & social networking. *Computers and Education*, *95*, 99–113. https://doi.org/10.1016/j.compedu.2015.12.008

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness: Defining "gamification." *Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments, MindTrek 2011*, (September), 9–15. https://doi.org/10.1145/2181037.2181040

Deterding, S., Khaled, R., Nacke, L. E., & Dixon, D. (2011). *Gamification: Toward a Definition*.

Fadhil, A., & Villafiorita, A. (2017). An adaptive learning with gamification & conversational UIs: The rise of CiboPoliBot. *UMAP 2017 - Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization*, 408–412. https://doi.org/10.1145/3099023.3099112

Ford, V. B., & Roby, D. E. (2013). Why do high school students lack motivation in the classroom? *Global Education Journal*, (2), 101–114.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39. https://doi.org/10.2307/3151312

Garrison, D. R. (2007). Online community of inquiry review: Social, cognitive, and teaching presence issues. *Journal of Asynchronous Learning Networks*, *11*(1), 62–72.

Garrison, D. R., & Baynton, M. (1987). Beyond Independence in Distance Education: The Concept of Control. *American Journal of Distance Education*, *1*(3), 3–15. https://doi.org/10.1080/08923648709526593

Gefen, D., & Straub, D. (2005). A Practical Guide To Factorial Validity Using PLS-Graph: Tutorial And Annotated Example. *Communications of the Association for Information Systems*, *16*(July). https://doi.org/10.17705/1cais.01605

Georgia Tech. (2020). Jill Watson, an AI Pioneer in Education, Turns 4. Retrieved October 25, 2020, from https://ic.gatech.edu/news/631545/jill-watson-ai-pioneer-education-turns-4

Goboomtown. (2019). Chatbot Statistics: The 2018 State of Chatbots [New Study]. Retrieved July 17, 2021, from https://www.goboomtown.com/blog/chatbot-statistics-study

Goel, A. K., & Polepeddi, L. (2016). Jill Watson: A Virtual Teaching Assistant for Online Education. *Georgia Tech Library*, (Daniel 2012), 21. Retrieved from https://smartech.gatech.edu/handle/1853/59104

Götz, O., Liehr-Gobbers, K., & Krafft, M. (2010). Evaluation of Structural Equation Models Using the Partial Least Squares (PLS) Approach. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang

(Eds.), *Handbook of Partial Least Squares: Concepts, Methods and Applications* (pp. 691–711). https://doi.org/10.1007/978-3-540-32827-8_30

Greenacre, L., Freeman, L., Cong, K., & Chapman, T. (2014). Understanding and predicting student Word of Mouth. *International Journal of Educational Research*, *64*, 40–48. https://doi.org/10.1016/j.ijer.2013.10.006

Grégoire, Y., & Fisher, R. J. (2006). The effects of relationship quality on customer retaliation. *Marketing Letters*, *17*(1), 31–46. https://doi.org/10.1007/s11002-006-3796-4

Griol, D., Molina, J. M., & de Miguel, A. S. (2014). *The Geranium System: Multimodal Conversational Agents for E-learning*. https://doi.org/10.1007/978-3-319-07593-8_26

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a Silver Bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, *40*(3), 414–433. https://doi.org/10.1007/s11747-011-0261-6

Henderikx, M., Kreijns, K., Castaño Muñoz, J., & Kalz, M. (2019). Factors influencing the pursuit of personal learning goals in MOOCs. *Distance Education*, *40*(2), 187–204. https://doi.org/10.1080/01587919.2019.1600364

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). *The use of partial least squares path modeling in international marketing*. https://doi.org/10.1108/S1474-7979(2009)0000020014

Huang, M., Ali, R., & Liao, J. (2017). The effect of user experience in online games on word of mouth: A pleasure-arousal-dominance (PAD) model perspective. *Computers in Human Behavior*, *75*, 329–338. https://doi.org/10.1016/j.chb.2017.05.015

Job, K. (2019). 5 Benefits of Online Courses vs. A Traditional Classroom. Retrieved December 1, 2020, from https://online.illinois.edu/articles/online-learning/item/2019/10/22/5-benefits-of-online-courses-vs.-a-traditional-classroom

Joshi, N. (2018). Yes, Chatbots And Virtual Assistants Are Different! *Forbes*, p. 2. Retrieved from https://www.forbes.com/sites/cognitiveworld/2018/12/23/yes-chatbots-and-virtual-assistants-are-different/?sh=72dd0cb96d7d

Kankanhalli, Tan, & Wei. (2005). Contributing Knowledge to Electronic Knowledge Repositories: An Empirical Investigation. *MIS Quarterly*, *29*(1), 113. https://doi.org/10.2307/25148670

Kapp, K. M. (2012). *The gamification of learning and intruction: Game-based methods and strategies for training and education* (Pfeiffer, Ed.). San Francisco, CA, USA.

Kennedy, C. M., Powell, J., Payne, T. H., Ainsworth, J., Boyd, A., & Buchan, I. (2012). Active assistance technology for health-related behavior change: An interdisciplinary review. *Journal of Medical Internet Research*, *14*(3), 1–20. https://doi.org/10.2196/jmir.1893

Koehler, M. J., & Mishra, P. (2006). Technological Pedagogical Content Knowledge: A Framework for Teacher Knowledge PUNYA MISHRA. *Teachers College Record*, *108*(6), 1017–1054. Retrieved from http://one2oneheights.pbworks.com/f/MISHRA_PUNYA.pdf

Krause, K. L., & Coates, H. (2008). Students' engagement in first-year university. *Assessment and Evaluation in Higher Education*, *33*(5), 493–505. https://doi.org/10.1080/02602930701698892

Kuester, M., & Benkenstein, M. (2014). Turning dissatisfied into satisfied customers: How referral reward programs affect the referrer[U+05F3]s attitude and loyalty toward the recommended service provider. *Journal of Retailing and Consumer Services*, *21*(6), 897–904. https://doi.org/10.1016/j.jretconser.2014.07.005

Lancelot Miltgen, C., Popovič, A., & Oliveira, T. (2013). Determinants of end-user acceptance of biometrics: Integrating the “big 3” of technology acceptance with privacy context. *Decision Support Systems*, *56*(1), 103–114. https://doi.org/10.1016/j.dss.2013.05.010

Latter, C., Phau, I., & Marchegiani, C. (2012). The roles of consumers need for uniqueness and status consumption in haute couture luxury brands. *Journal of Global Fashion Marketing*, *1*(4), 206–214. https://doi.org/10.1080/20932685.2010.10593072

Lee, C. L., & Yang, H. J. (2011). Organization structure, competition and performance measurement systems and their joint effects on performance. *Management Accounting Research*, *22*(2), 84–104. https://doi.org/10.1016/j.mar.2010.10.003

Leong, L. Y., Hew, T. S., Tan, G. W. H., & Ooi, K. B. (2013). Predicting the determinants of the NFC-enabled mobile credit card acceptance: A neural networks approach. *Expert Systems with Applications*, *40*(14), 5604–5620. https://doi.org/10.1016/j.eswa.2013.04.018

Loureiro, S. M. C., Cavallero, L., & Miranda, F. J. (2018). Fashion brands on retail websites: Customer performance expectancy and e-word-of-mouth. *Journal of Retailing and Consumer Services*, *41*(June 2017), 131–141. https://doi.org/10.1016/j.jretconser.2017.12.005

Lung-Guang, N. (2019). Decision-making determinants of students participating in MOOCs: Merging the theory of planned behavior and self-regulated learning model. *Computers and Education*, *134*(October 2018), 50–62. https://doi.org/10.1016/j.compedu.2019.02.004

Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures*, *90*, 46–60. https://doi.org/10.1016/j.futures.2017.03.006

Markopoulos, A. P., Fragkou, A., Kasidiaris, P. D., & Davim, J. P. (2015). Gamification in engineering education and professional training. *International Journal of Mechanical Engineering Education*, *43*(2), 118–131. https://doi.org/10.1177/0306419015591324

Moorthy, K., Yee, T. T., T’ing, L. C., & Kumaran, V. V. (2019). Habit and hedonic motivation are the strongest influences in mobile learning behaviours among higher education students in Malaysia. *Australasian Journal of Educational Technology*, *35*(4), 174–191. https://doi.org/10.14742/ajet.4432

Oliveira, T., Thomas, M., Baptista, G., & Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Computers in Human Behavior*, *61*(2016), 404–414. https://doi.org/10.1016/j.chb.2016.03.030

Oluwajana, D., Idowu, A., Nat, M., Vanduhe, V., & Fadiya, S. (2019). The adoption of students’ hedonic motivation system model to gamified learning environment. *Journal of Theoretical and Applied Electronic Commerce Research*, *14*(3), 156–167. https://doi.org/10.4067/S0718-18762019000300109

Ortega-Arranz, A., Bote-Lorenzo, M. L., Asensio-Pérez, J. I., Martínez-Monés, A., Gómez-Sánchez, E., & Dimitriadis, Y. (2019). To reward and beyond: Analyzing the effect of reward-based strategies in a MOOC. *Computers and Education*, *142*(March), 103639. https://doi.org/10.1016/j.compedu.2019.103639

Pluralsight. (2015). Keep Your Players Engaged: Why Rewards and Medals Play a Key Factor in Your Game. Retrieved November 14, 2020, from https://www.pluralsight.com/blog/film-games/keep-players-engaged-rewards-medals-play-key-factor-game

Rahimi, E., Van den Berg, J., & Veen, W. (2013). Investigating teachers' perception about the educational benefits of Web 2.0 personal learning environments. *E-Learning Papers, (35), 2013*, (November), 1–13.

Rahimi, E., Van Den Berg, J., & Veen, W. (2015). Facilitating student-driven constructing of learning environments using Web 2.0 personal learning environments. *Computers and Education*, *81*, 235–246. https://doi.org/10.1016/j.compedu.2014.10.012

Rahimi, Ebrahim, van den Berg, J., & Veen, W. (2015). A learning model for enhancing the student's control in educational process using Web 2.0 personal learning environments. *British Journal of Educational Technology*, *46*(4), 780–792. https://doi.org/10.1111/bjet.12170

Rahimi, Ebrahim, Van Den Berg, J., & Veen, W. (2015). A learning model for enhancing the student's control in educational process using Web 2.0 personal learning environments. *British Journal of Educational Technology*, *46*(4), 780–792. https://doi.org/10.1111/bjet.12170

Ringle, C.M., Wend, S., Becker, J. M. (2015). *SmartPLS 3*. Retrieved from http://www.smartpls.com/

Roll, I., Aleven, V., McLaren, B. M., & Koedinger, K. R. (2011). Improving students' help-seeking skills using metacognitive feedback in an intelligent tutoring system. *Learning and Instruction*, *21*(2), 267–280. https://doi.org/10.1016/j.learninstruc.2010.07.004

Russell, S., & Norvig, P. (2009). *Artificial Intelligence: A Modern Approach* (3rd ed.). USA: Prentice Hall Press.

Sandu, N., & Gide, E. (2019). Adoption of AI-chatbots to enhance student learning experience in higher education in india. *2019 18th International Conference on Information Technology Based Higher Education and Training, ITHET 2019*, (January). https://doi.org/10.1109/ITHET46829.2019.8937382

Shawar, B., & Atwell, E. (2003). *Using dialogue corpora to train a chatbot*. (October 2014). https://doi.org/10.13140/2.1.1455.7122

Smutny, P., & Schreiberova, P. (2020). Chatbots for learning: A review of educational chatbots for the Facebook Messenger. *Computers and Education*, *151*(June 2019), 103862. https://doi.org/10.1016/j.compedu.2020.103862

Straub, D. W. (1989). Validating Instruments in MIS Research. *MIS Quarterly*, *13*(2), 147. https://doi.org/10.2307/248922

Subhash, S., & Cudney, E. A. (2018). Gamified learning in higher education: A systematic review of the literature. *Computers in Human Behavior*, *87*(February), 192–206. https://doi.org/10.1016/j.chb.2018.05.028

Suh, A., Cheung, C. M. K., Ahuja, M., & Wagner, C. (2017). Gamification in the Workplace: The Central Role of the Aesthetic Experience. *Journal of Management Information Systems*, *34*(1), 268–305. https://doi.org/10.1080/07421222.2017.1297642

Suh, A., Wagner, C., & Liu, L. (2015). The effects of game dynamics on user engagement in gamified systems. *Proceedings of the Annual Hawaii International Conference on System Sciences*, *2015-March*, 672–681. https://doi.org/10.1109/HICSS.2015.87

Tarouco, L. M. R., Silveira, C., & Krassmann, A. L. (2018). Collaborative learning with virtual entities. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *10924 LNCS*(January), 480–493. https://doi.org/10.1007/978-3-319-91743-6_35

Teixeira, T. S., & Mendes, R. (2019). How to Improve Your Company's Net Promoter Score. Retrieved November 14, 2020, from Harvard Business Review website: https://hbr.org/2019/10/how-to-improve-your-companys-net-promoter-score?registration=success

Tsay, C. H. H., Kofinas, A., & Luo, J. (2018). Enhancing student learning experience with technology-mediated gamification: An empirical study. *Computers and Education*, *121*(December 2017), 1–17. https://doi.org/10.1016/j.compedu.2018.01.009

Vaidyam, A. N., Wisniewski, H., Halamka, J. D., Kashavan, M. S., & Torous, J. B. (2019). Chatbots and Conversational Agents in Mental Health: A Review of the Psychiatric Landscape. *The Canadian Journal of Psychiatry*, *64*(7), 456–464. https://doi.org/10.1177/0706743719828977

Valtonen, T., Hacklin, S., Dillon, P., Vesisenaho, M., Kukkonen, J., & Hietanen, A. (2012). Perspectives on personal learning environments held by vocational students. *Computers and Education*, *58*(2), 732–739. https://doi.org/10.1016/j.compedu.2011.09.025

Venkatesh, V., Morris, M., Davis, G., & Davis, F. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425–478.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012a). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly: Management Information Systems*, *36*(1), 157–178. https://doi.org/10.2307/41410412

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012b). CONSUMER ACCEPTANCE AND USE OF INFORMATION TECHNOLOGY: EXTENDING THE UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY. *MIS Quarterly*, *36*(1), 157–178. Retrieved from https://pdfs.semanticscholar.org/6256/0e2001480fd1f22558ce4d34ac93776af3e6.pdf%0Ahttps://pdfs.semanticscholar.org/6256/0e2001480fd1f22558ce4d34ac93776af3e6.pdf?_ga=2.124539978.1994179764.1540339706-2125081534.1540339706

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems*, *17*(5), 328–376. https://doi.org/10.17705/1jais.00428

Villagrasa, S., Fonseca, D., Redondo, E., & Duran, J. (2014). Teaching case of gamification and visual technologies for education. *Journal of Cases on Information Technology*, *16*(4), 38–57. https://doi.org/10.4018/jcit.2014100104

Wise, R. A. (1998). Drug-activation of brain reward pathways. *Drug and Alcohol Dependence*, *51*(1–2), 13–22. https://doi.org/10.1016/S0376-8716(98)00063-5

Wu, J., Fan, S., & Zhao, J. L. (2018). Community engagement and online word of mouth: An empirical investigation. *Information and Management*, *55*(2), 258–270. https://doi.org/10.1016/j.im.2017.07.002

Wu, W., Tzamos, C., Daskalakis, C., Weinberg, M., & Kaashoek, N. (2015). Game theory based peer grading mechanisms for MOOCs. *L@S 2015 - 2nd ACM Conference on Learning at Scale*, 281–286. https://doi.org/10.1145/2724660.2728676

Yoo, K. H., & Gretzel, U. (2008). What Motivates Consumers to Write Online Travel Reviews?

Information Technology & Tourism, *10*(4), 283–295. https://doi.org/10.3727/109830508788403114

Yoo, S. J., & Han, S. H. (2013). The effect of the attitude towards e-learning: The employees' intention to use e-learning in the workplace. *International Journal on E-Learning: Corporate, Government, Healthcare, and Higher Education*, *12*(4), 425–438.

Youcheng, W., & Fesenmaier, D. R. (2003). Assessing Motivation of Contribution in Online Communities: An Empirical Investigation of an Online Travel Community. *Electronic Markets*, *13*(1), 33–45. https://doi.org/10.1080/1019678032000052934

Zainuddin, Z., Shujahat, M., Haruna, H., & Chu, S. K. W. (2020). The role of gamified e-quizzes on student learning and engagement: An interactive gamification solution for a formative assessment system. *Computers and Education*, *145*(October 2019), 103729. https://doi.org/10.1016/j.compedu.2019.103729

9. APPENDIX

Appendix A

Construct	Item	Adapted from
Performance Expectancy (PE)	PE1: I Find the chatbot useful in my daily life as student PE2: I think that using the chatbot would increase my chances of success as a student PE3: I think that using the chatbot would enable me to conduct my tasks more quickly PE4: I think that using the chatbot would increase my productivity PE5: I think that using the chatbot would improve my performance	Venkatesh et al. (2012)
Hedonic Motivation (HM)	HM1: I think that using the chatbot would be fun HM2: I think that using the chatbot would be enjoyable HM3: I think that using the chatbot would be very entertaining	Venkatesh et al. (2012)
Status (ST)	I think that the Chatbot would offer me the possibility to: ST1: Have a higher status than others ST2: Be regarded highly by others ST3: Try to increase my status	(Suh et al., 2017; Youcheng & Fesenmaier, 2003)
Rewards (RW)	I think that the Chatbot would offer me the possibility to: RW1: Obtain points as a reward for my studying activities RW2: Accumulate points I have gained RW3: Obtain more points if I try harder	(Kankanhalli, Tan, & Wei, 2005; Suh et al., 2017)
Competition (CO)	I think that the Chatbot would offer me the possibility to: CO1: Compete with others CO2: Compare my performance with others CO3: Threaten the status of others by my active participation	(Lee & Yang, 2011; Suh et al., 2017)

Construct	Item	Adapted from
Support (SP)	SP1: The chatbot helps me collaborate with my classmates, and teachers. SP2: The chatbot helps me share web resources and other content related with learning SP3: The chatbot allows me to support/ help others on using the technology SP4: The chatbot supports new ways of learning and interaction with others SP5: The chatbot allows additional opportunities to analyse and discuss class content with other students and teachers SP6: The chatbot promotes communication about technology with other students outside my class and with my family members	(E. Rahimi et al., 2015)
Behavioural Intention to adopt (BI)	BI1: I intent to use the chatbot in the next months BI2: I predict I would use the chatbot in the next months BI3: I plan to use the chatbot in the next months BI4: I will try to use the chatbot in my daily life BI5: Using the chatbot to help me with my studies is something that I would do	Venkatesh et al. (2012)
Intention to Recommend (REC)	REC1: I will recommend my friends to use the chatbot, if it is available REC2: If I have a good experience with the chatbot I will recommend friends to use it.	(Oliveira et al., 2016)