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The Role of Digital Information Use on Student Performance and Collaboration in Marginal Universities

Ransome Epie Bawack^{a,*}, Jean Robert Kala Kamdjoug^b

^a TBS Business School Research Centre, Toulouse 1 Capitole University, 1 Place Alphonse Jourdain - CS 66810, 31068 Toulouse Cedex 7, France, ransome.bawack@tsm-education.fr

^b Catholic University of Central Africa, Nkolbisson, 11628 Yaoundé, Cameroun

Abstract

Using technology to facilitate learning in universities and other higher education institutions (HEIs) has become common practice due to its ability to reduce barriers related to time and space in traditional learning environments. However, current literature mostly focuses on the use of the technology and not on the use of the information it conveys. Also, very few studies focus on technology adoption in universities and HEIs in developing countries, especially those in Africa. Thus, we propose a model that explains the changing information behaviors of students in this digital age and the effect this has on their learning outcomes. We collected questionnaire data from 303 students and analyzed the data using structural equation modelling partial least squares (SEM-PLS). We found that our proposed model explains 60.2% of student satisfaction, 24.2% of academic performance, 24.1% of information sharing, and 19.8% of their information exchange behavior. This study confirms that the use of digital information and its antecedent factors have significant effects on the college experience of students. This has several implications for information systems research and practice, especially in the design and assessment of technology use in learning environments.

Keywords: information seeking; information need; information source; information use; digital literacy.

Declarations of interest: none.

1. Introduction

Using technology to facilitate learning in universities and other higher education institutions (HEIs) has become common practice due to its ability to reduce barriers related to time and space in traditional learning environments (Henrie, Halverson, & Graham, 2015; Sweeney & Oram, 1992). Thus, several studies have investigated factors that influence the adoption, continuance, and use of such technologies, as well as their effect on learning outcomes and student engagement (Panigrahi, Srivastava, & Sharma, 2018). They reveal that several personal and environmental factors need to be assessed to obtain expected outcomes and engagement goals. Some researchers have conducted studies to determine how to best use technology to engage millennial students in meaningful and effective learning experiences despite the challenges involved. Thus far, they have linked educational outcomes and performances to behavioral, emotional, cognitive (Henrie et al., 2015), physical (Rashid & Asghar, 2016), applied, social, and reflective engagement (Gebre, Saroyan, & Bracewell, 2014). The results obtained vary significantly depending on the context, social practices, and the global flow of information. Thus, changes in student engagement associated with information technology (IT) may not be the same between continents, countries, and even universities in the same country. However, existing literature on the topic is limited in context and focus.

Contextually, very few studies focus on technology adoption in universities and HEIs in developing countries, especially those in Africa. In developed countries, for example, most universities are using technology to provide a more valuable learning experience to their students through their digital devices (Gould, 2012a). Online access to academic databases and research material is a natural part of most universities in developed countries. This is not the same reality in many universities in developing countries although university students also own at least one digital device (Snyder & Prinsloo, 2007). Many of the universities there do not provide their students with the information-seeking capabilities and reliable sources of information they need to effectively use digital information to improve their learning experiences. Access to international academic databases and reliable sources of scholarly information is still perceived as a luxury in several universities in developing countries. In this study, we refer to such universities as “marginal” because this phenomenon poses a social identity threat to students from universities in developing countries. It undermines the legitimacy of the university and the academic competency of the students. This is reflected in the poor international rankings of universities from developing countries, especially those in Africa, and justifies why students from such universities find it hard to get admissions into top-ranking institutions.

For HEIs in developing countries to gain recognition and improve the social identity of its students in the global spheres, they have to go beyond technology infrastructure and focus on the quality of information the students use during the learning process. Information technologies often convey so much unreliable information and are major agents of distraction thereby affecting student engagement in their studies (McCoy, 2013). Teachers have expressed concerns about the ability of their students to evaluate and use the information they find electronically (Urquhart et al., 2005). Thus, what good is the technology if the information it conveys is not used or usable in a way that improves learning outcomes or/and student engagement? We argue that digital information use is what affects the learning outcomes and enhances collaboration between students, not the technology itself. If the

students are not provided with reliable digital information sources and the skills to find relevant information they need and can use, their academic performance and learning experience through technology will be affected negatively.

This is an important topic because a systematic review of publications from 1984 to 2016 shows that there is a significant shortage of scientific publications in the context of HEI, especially in the field of information systems (IS) and management (Pinho, Franco, & Mendes, 2018). The few studies conducted on the topic focus on the impacts of IT on student engagement, satisfaction, and performance and not on the information behavior of the students. Students experience changes in information behavior and get distracted by technology, whether in developing or developed countries. Thus, there is a need for frameworks that model the complexity of information behavior in this technology age. Moreover, this study is even more critical for universities and HEIs in developing countries, especially those that spend a lot of their resources on IT infrastructure and staff training without considering the information use behaviors of their students.

In this paper, we propose a conceptual model based on a general model of information behavior proposed by Ohtoshi and Gottschalg-Duque (2016). In the context of marginal universities, we empirically assess our proposed model to show how digital information and its antecedents can influence student collaboration, satisfaction, and academic performance. We found that despite the limited resources available in marginal universities, the use of digital information has a strong direct effect on students' academic performance, satisfaction, and collaboration behaviors. Based on these findings, we discuss several implications for research and practice and demonstrate that this original model offers a fertile landscape for expansion in IS research. These findings are critical for designing information systems that fit the information needs of students and support information management in HEI. This could help managers of HEI improve the learning experiences of their students, improve their competitiveness in the job market, and boost the overall ranking of the universities.

In the next section, we present a literature review of digital information use and information behavior. After that, we present the theoretical foundations of our work and present the methodology used to validate our hypotheses. We then present and discuss our results as well as the limitations of our study and suggestions for future research.

2. Literature Review

2.1. Digital Information Use in Universities and HEIs

Even though it is a popular topic of discussion, there is limited empirical evidence to support the factors that influence the use of digital information by millennial students in HEI given that most studies focus on the technology itself (Pinho et al., 2018). For example, undergraduate students in Australia show that technology is an essential element of learning in contemporary universities. Students tend to engage more in learning practices when they use their own devices like laptops and smartphones to access the internet, learning platforms, and library resources. The students can hardly imagine their university experience without these technologies (Henderson, Selwyn, Finger, & Aston, 2015). In Saudi Arabia, the use of technology was also found to have a positive influence on student engagement and self-directed learning although it had no significant impact on their academic

performance (Rashid & Asghar, 2016). That wasn't the case in the USA where students use their devices extensively and view them as important to their academic success. They see technology as a positive force in helping them engage with their instructor, with other students for collaboration and communication, and with their course contents (Gould, 2012b).

Over 90% of the universities in the USA provide educational technology services to both faculty staff and students (Gregory, 2011). Several other authors have addressed this issue in the context of other universities in developed countries (Bryson, 2016; Johnson et al., 2016; Owen, 2014) and have obtained similar results. The results emphasize the improvement of campus infrastructure and educational technology services because of their potential to increase engagement and academic performances. For example, autonomy and practical aspects of learning are also found to drive student engagement, satisfaction, and performance (Papworth, 2016). Thus, providing students with access to digital information resources could provide them with the autonomy and practical experience they need to be more engaged in the learning process. This is because they could take advantage of the remote accessibility, flexibility, and technologically appropriateness of digital information (Johnston, Barton, Williams-Pritchard, & Todorovic, 2018). Nevertheless, the type of technology used may influence student engagement and attitude towards learning. For example, mobile technology has been found to increase collaborative learning but decreases engagement during lessons (Heflin, Shewmaker, & Nguyen, 2017). However, other technologies like laptops may increase student engagement or at least facilitate its development (Gunuc & Kuzu, 2015).

We see that the extant literature focuses on the effects of technology use on student engagement, satisfaction, and performance, but not on the information it mediates. Also, this review brings us to the conclusion that research on student engagement in marginal universities, especially in the context of developing countries is very rare. Thus, a study focusing on such universities will make significant contributions to literature by providing new arguments for discussions on student engagement and performance in higher education.

Our research seeks to fill this gap in the extant literature, especially on student performance, satisfaction, and collaboration (information sharing and exchange). In this study, we argue that students use technology to access information from multiple sources worldwide, and it is the use of digital information that drives collaboration, satisfaction, and academic performance. Therefore, the best campus infrastructure and educational technology services will not drive these learning experiences if they do not provide students with useful information for their studies. Thus, understanding student information behavior could be used to determine the technological ecosystems needed to drive student engagement in HEIs.

2.2. Information behavior and organizational management

Information is a key part of corporate strategy, especially when it comes to its use in making strategic decisions and managing costs (Papazov & Mihaylova, 2015). That is why organizational competitiveness depends on the ability of managers to promptly detect environmental changes and quickly readjust their behavior (Razhivina, Yakimovich, Korshunov, Tyurin, & Zagoruiko, 2016). Nevertheless, managers do not seem to pay attention to the changes that occur in information behaviors, limiting the ability of information systems to meet up with the evolving needs of

information users. Information behavior refers to why and how humans need, seek, and use information (Campbell, 2013). As information behaviors evolve, information systems and current information practices need to be configured for each other to improve engagement, satisfaction, and performance (Runaas et al., 2017). Defining clear and targeted benefits that meet the information needs of users will considerably increase the chances of successfully implementing good information systems and ensure their effective use in driving engagement, satisfaction, and performance (Marnewick, 2016). People spend so much time searching for information on the internet which turns out almost 50% of the time to be unreliable or unsatisfactory (Elliott, Bartel, Simonson, & Roukis, 2015). Understanding information needs could enable information systems to provide information sources that reflect the quality values of an organization (Leon, Neştian, & Nica, 2015). This could go a long way to influence information sharing behavior and increase satisfaction and performance by saving time and cost (Weng, Lu, Wang, Megahed, & Martinez, 2018).

HEIs stand to enjoy these same benefits of understanding the information behaviors of their students. Worldwide, HEIs recognize the need to incorporate technology into the teaching and learning experiences of their students because of their ability to drive innovation and inventive projects (Mahdi, Sukarman, & Yok, 2015). However, many of them do not know exactly how to go about it or the extent to which certain factors affect these experiences. Understanding the information behavior of students is one way that can lead to outcome-based decision-making, and serve as starting points for managers to foster the use of quality information by students (Kroll, 2015). Managers of HEIs need student information behavior models that emphasize collaborative learning through information sharing and exchange (Sun, Jiang, Hwang, & Shin, 2018) using technologies and information systems designed to influence such behavior. These models will help identify intentions and preferences towards specific technologies or information systems that could enable students to use information that increases their satisfaction, engagement, and academic performances.

Boosting academic performance and student engagement influences the competitiveness of students in the job market (Pinto & Ramalheira, 2017) and the overall ranking of HEIs. They also have significant relationships with university-industry partnerships and academic innovation performance (M. H. Huang & Chen, 2017). However, it is the timely availability of relevant and reliable information that makes all the difference for students and not the technology. IT essentially conveys information which is what affects knowledge sharing and scholarly performance (Ghabban, Selamat, & Ibrahim, 2018). An essential part of every information system is the information it carries and how it connects the users, processes, and organizations. Thus, for HEIs to propose comprehensive information systems that meet the needs of students in contemporary universities, they need to understand factors that motivate students to use digital information for learning purposes. Therefore, one of our contributions to literature is to propose a model that could help managers of HEIs understand the changing information behavior of students.

3. Theoretical Background and Hypotheses Development

3.1. Theoretical background - the Ohtoshi-Gottschalg-Duque model

Information behavior has mostly been studied in the field of information and documentation science (Choo, Detlor, & Turnbull, 2000; Leckie, Pettigrew, & Sylvain, 1996; Wilson, 1999, 2006). The models proposed in this field are difficult to compare in great detail given their differences in context, vocabulary, emphasis, and age. Also, most existing models focus on information seeking (Campbell, 2013), paying relatively less attention to information need, information use, and user satisfaction. This raised the issue of a single model capable of describing the whole cycle of information need, seeking, and use especially in contemporary settings. Given that people's information habits have been transformed by technologies like the internet, laptops, and smartphones, models, and frameworks need to be proposed to capture these changing behaviors. They need to be adapted to reflect new trends and explain new forms of information behavior which could not be explained using previous models. A general model of information behavior (GMIB) based on semantic models was proposed by Ohtoshi and Gottschalg-Duque (2016) to meet this need. The model strives to capture all facets of current information behavior that could help predict user choices and decisions.

Ontology-driven models are developed to capture the meaning of people's perception of an application domain. Such models could lead to improved conceptual models and help ensure they are indeed faithful representations of their application domain (Shanks, Tansley, & Weber, 2003). Thus, to employ them as conceptual modeling constructs, each construct has to be rigorously defined especially in the case of relationship constructs (Wand, Storey, & Weber, 1999). Also, ontology-driven models are found to be advantageous to apply when having to model some challenging facets of an application domain (Verdonck et al., 2019). The authors point out the model's ability to help understand people in different contexts based on a set of factors and characteristics which could be useful in modern data-driven business settings. This makes the model very interesting for IS researchers and practitioners because of its potential to foster the design and development of more personalized and insightful information systems.

According to the base model, an information user is an individual who has a profile defined by specific personality and demographic characteristics. In the context of this study, we are referring to university students. An information need is the recognition of the lack of adequate knowledge to meet the goals of an information user. This need is shaped by the characteristics of the information user. Information seeking is a conscious effort to fill our knowledge gap in response to an information need.

An information source refers to the origin of the information obtained after seeking to satisfy an information need. In this study, information sources are strictly digital and obtained only using digital technologies. Information use refers to the acts taken by the information user based on the information obtained from information sources. Specific to this study, we distinguish between information exchange and information sharing. Information exchange refers to discussions that involve exchanging ideas and knowledge. This is limited to exchange with classmates, lecturers, or closed workgroups in the context of this study.

Information sharing refers to the reciprocal dissemination of information among information users, without necessarily having to discuss it. This sharing could be done with anyone anywhere. Together, information sharing and information exchange evaluate the effect of information use on the student's engagement through collaboration and participation.

The education sector is one of those sectors that has been completely transformed by technology. E-learning facilities, e-libraries, media centers, and the internet have made many traditional information behaviors obsolete. Yet, models that capture these current trends are rare, let alone in the field of information systems. Therefore, we propose to use the Ohtoshi and Gottschalg-Duque (2016) model (henceforth OGD model) (Figure 1) as the theoretical foundation for the development of a contextualized conceptual model that can be used to understand the information behavior of students in HEIs in the digital age. This implies transforming an ontology-driven model into a conceptual model. In the next subsection, we explain the transformation guidelines used to arrive at our proposed conceptual model.

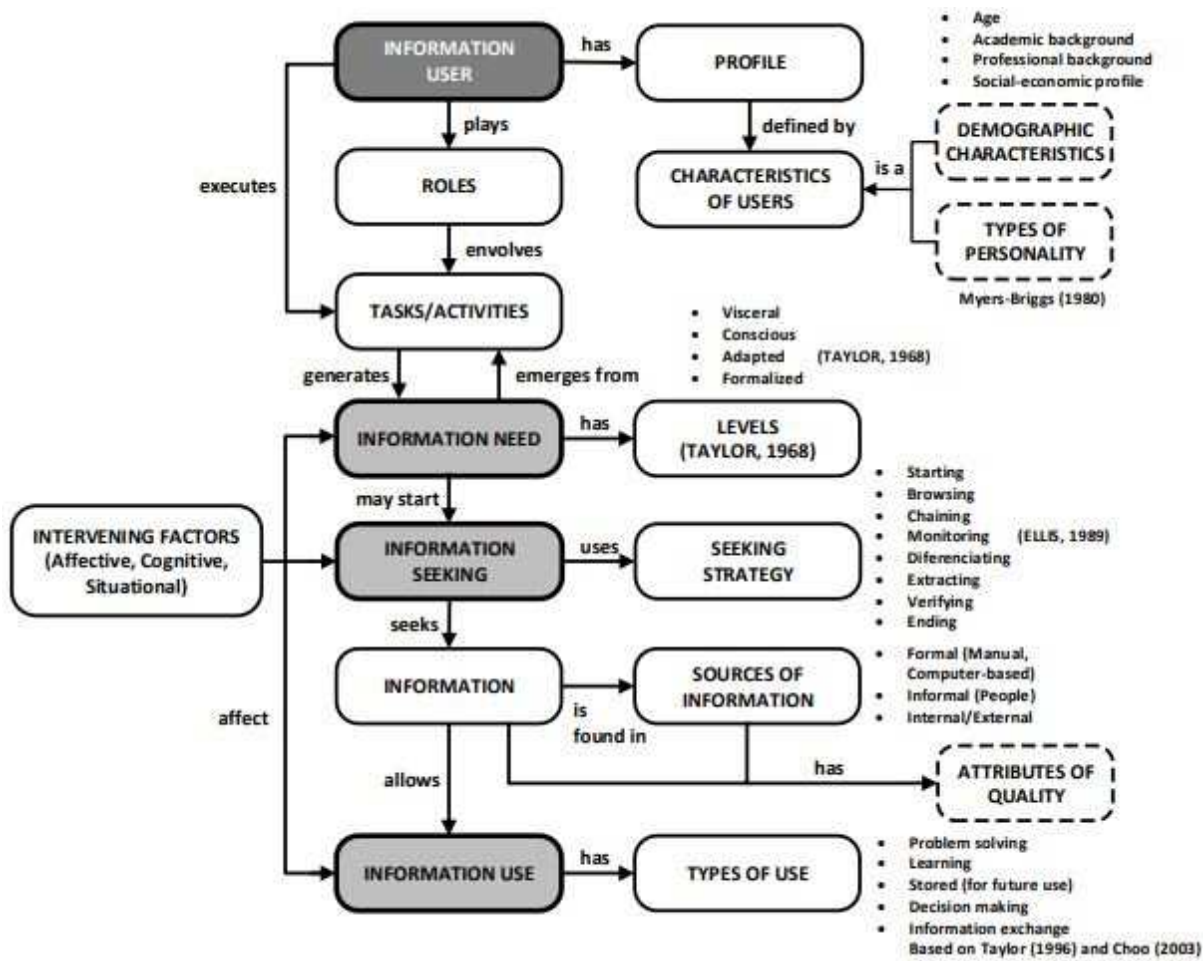


Figure 1. Ohtoshi and Gottschalg-Duque (2016 pg.2) Model of information Behavior

3.2. Transforming the OGD model into a conceptual model

There is a rising need for information models framed in terms of significant paths in a defined context (Beynon-Davies, 2018). To this end, ontologies have been found to facilitate the development of meta-theories and models that can be used to understand one or more contexts by providing an arrangement of constructs that lead to theoretical assumptions and propositions (Bostrom, Gupta, & Thomas, 2009). Ontologies have been used in designing systems and understanding behaviors in IS

research. For example, they have been used to assess the utility of natural disaster management websites (Chou, Zahedi, & Zhao, 2014), to understand market contexts, assess transaction risks (Li, Sun, Chen, Fung, & Wang, 2015), and evaluate IS use in healthcare (Maass & Varshney, 2012). However, when using ontologies for conceptual modeling, grammatical terms may affect the perceived ease of use and perceived usefulness of a construct which could affect the use of these constructs in real-life contexts (Recker, Rosemann, Green, & Indulska, 2011).

Evermann (2005) discussed the importance of conceptual semantics in guiding the transition from semantic (ontological) models to conceptual models. He describes ontologies as concepts and their relationships that reflect empirically observed realities. While examining the use of ontologies in IS research and applications, he showed that ontologies can provide strong empirical justification for the conceptual representation of knowledge and could be used to theorize about a given domain. He also shows how hypotheses based on ontologies like Bunge's ontology (M. Bunge, 1979; M. A. Bunge, 1977) have been empirically verified in a variety of application domains using conceptual modeling methods, confirming the ability of ontologies to conceptually represent existing realities or perceptions of reality. Evermann (2005, p. 155) put forth the following arguments on the correlation between conceptual structures and semantic models that were used to guide the development of our conceptual model:

- The construction or adoption of an ontology must be guided by empirical evidence of entities in the real or perceived world.
- Knowledge of the world is governed by our cognitive structures.
- Our cognitive structures must be based on our empirical knowledge of the world.
- Thus, the study of language can suggest relevant cognitive concepts.
- Knowledge representation language should reflect cognitive concepts, the terms in which we think about the real world.
- These concepts are empirically well-founded, and this empirical foundation provides support for these concepts.

Based on these guidelines, we adopted the OGD model and used it to develop a contextualized conceptual model to understand the information behaviors of students in HEIs in developing countries. The development of the OGD model was guided by empirical evidence of real-world perceptions of peoples' information behaviors in terms of their information need, seeking, and use behaviors as represented by the well-established models that led to their comprehensive model. Information need, seeking, use, sources, sharing, exchange, and user, are all cognitive concepts that are easy to understand and relate to the real world. They are also familiar concepts in academic research and clearly defined during the development of the semantic model. Therefore, we conclude that the model meets the criteria to be adapted for conceptual modeling practices.

To provide empirical support for our proposed conceptual model, we also adopted the following guidelines from Evermann (2005):

- Find direct empirical evidence that determines how well an ontology expresses concepts and relationships in the real or perceived world.
- Relationships between concepts should be socially accepted in the context of the study.

- Deductive arguments can be used if the ontology adopted is built upon an empirically well-founded basis.
- Predictive arguments made base on ontological considerations should be based on an ontologically clear language that leads to a better understanding of the represented domain.

These guidelines influenced our research assumptions, hypotheses, and methodology. We made sure that in designing our conceptual model, we hypothesized only on concepts that made sense in real-life and on relationships that made sense in the context of our study (see Table 1). Our hypotheses were a mix of deductive and predictive arguments depending on the ontological clarity of the language used when translated to reflect reality through the conceptual model. In the subsection that follows, we develop the hypotheses derived from the OGD model that led to our proposed conceptual model.

Table 1. Transition from the original semantic model to the proposed contextualized conceptual model

Original Semantic Model (Ohtoshi & Gottschalg-Duque, 2016)	Propose model adaptations
Information user executes tasks that generate information needs	H1: Information user affects information need
Information need may start from information seeking	H2: Information need affects information seeking
Information users use information differently due to basic differences in the way individuals prefer to use their perception and judgment.	H3: Information user affects information use
Information need affects information use	H4: Information need affects information use
Information seeking affects information use	H5: Information seeking affects information use
Information is found in information sources, which have attributes of quality, and allows information use	H6s: Information source affects information use
Information use has different types of uses.	Information use has different outcomes: H7: Information use affects Academic performance. H8: Information use affects (digital) Information exchange. H9: Information use affects Information sharing. H10: Information use affects user satisfaction.
Differences in user profiles result in individual differences in perceptions and judgment on how or if information is used.	Hypothesis 11 (H11a-g): information user profile moderates the relationship between information user and information use.

3.3. Hypotheses development

The information user is the main concept of the OGD model. Every user has a profile that is defined by individual characteristics that shape their information needs. These individual characteristics include

personality and other specificities like age, professional background, socio-economic status, and academic background. The information user plays roles that involve performing tasks or activities that they need to execute. Executing these tasks involves acquiring the information thereby generating information needs.

In the context of HEIs, students are information users who perform regular academic and learning tasks that involve attending lessons, doing assignments and projects, taking part in examinations, and even doing some self-learning. Performing these tasks involves acquiring the information needed to complete their knowledge and understanding of the subject of interest thereby generating information needs. However, students need to understand the nature of information need to be able to identify the best way to meet their information needs (Nazari, 2016). For students to understand the nature of information need, they need to actively take part in the learning process through due diligence. This will help them know the kinds of resources they need to enhance their learning experiences which they can then communicate to their administration to obtain relevant content at the right time in the right format. This could help bridge the gap between the information provided by the institution and what the students find relevant, attractive, and resourceful (Fong, Au, Lam, & Chiu, 2020). Today, students mostly use e-resources to meet their information needs for academic tasks (El-Maamiry & Amour El-Maamiry, 2017). However, for students to appreciate the relevance of the e-resources provided to them by their institutions, they must first understand their own information needs. Therefore, we hypothesize that:

Hypothesis 1 (H1): information user affects information need.

The OGD model explains that for the information users to meet their information needs, they may start the information seeking process. This involves searching for the information required to meet the information needs of the user. Information seeking implies using different strategies like that proposed by Ellis (1989) to find the information needed to complete the required task of activity. Information needed can be found in both formal/informal and internal/external sources.

In the context of HEIs, information seeking is an essential part of the learning process. Students are constantly required to search for information that can help them do assignments, prepare for examinations, and complete/expand their knowledge on a given topic. Consequently, they need to learn information seeking strategies that would enable them to obtain the information they need from the most relevant sources. Students often use strategies like heuristic search, phrase queries (Marchionini, 1989), starting, browsing, differentiating, and extracting (Baro, Onyenania, & Osaheni, 2010) to search the internet despite how unreliable and incomplete the information often is (Walraven, Brand-Gruwel, & Boshuizen, 2009). However, it also provides easy access to much information on every topic making it a great source of information for students, especially when the student wants to acquire a general understanding of a topic. Nevertheless, when students need access to more academically verified facts, they may need to search within reliable academic databases. Although some institutions have access to such databases, some studies face difficulties in choosing the best databases for their information need (El-Maamiry & Amour El-Maamiry, 2017). Therefore, we hypothesize that:

Hypothesis 2 (H2): information need affects information seeking behavior.

The next four hypotheses concern the antecedents of information use. The OGD model explains that, firstly, information users use information differently due to basic differences in the way individuals prefer to use their perception and judgment.

In the context of HEIs, students need to have the skills and competencies to be able to use digital information for their learning activities. Also, their perceptions of a great learning experience as well as their desire for more autonomy and control over their learning process could influence their information use behaviors (Fernández-Ramos, 2019). In addition to the fact that such autonomy is a growing trend among university students, they are more likely to use the digital information if it fits their tasks (F. O. Omotayo & Haliru, 2020). Therefore, we hypothesize that:

Hypothesis 3 (H3): information user affects information use.

Secondly, the OGD model reveals an intertwined relationship between information need, information seeking, and information use as information need and information seeking behaviors are what lead users to the information they possess and choose to use (or not to use).

In HEIs, students adopt search strategies that are adapted to their information needs and use the resulting information that most accurately provides the information they need for their tasks (Rieh & Rieh, 2005). For information to meet user needs and thereby increase the chances of being used, it should be organized in a relevant and concise manner (Lehmann & Heagy, 2014). Thus, if students have good information seeking strategies, they are more likely to find the information they need quickly and easily. Consequently, if they find the information they need reported in a concise and precise manner, it could influence their decision to use it. On the other hand, if students do not need the information provided, they may not seek this information and may eventually never use it. This interrelation between information need and information seeking led us to the following hypotheses:

Hypothesis (H4): information need affects information use.

Hypothesis (H5): information seeking affects information use.

Thirdly, information is found in information sources, which have attributes of quality and determine information use.

In the real-world context of HEIs, this could be translated as trust in the sources of information affects the use of the information for academic purposes. As mentioned above, the internet is a significantly unreliable source of information because anyone can publish unverified data as facts on the internet. Therefore, in academic settings, information obtained from sources like academic databases or institutional repositories are more likely to be used by students because they will be regarded as high-quality information sources. Studies also show that university students find commercial social media apps to be an important source of information that institutions can use to channel relevant information and provide library services (Guo & Huang, 2020). Therefore, we hypothesize that:

Hypothesis 6 (H6): Information source affects information use.

The next four hypotheses concern the outcomes of digital information use in our context of study. The OGD model suggests that information is mainly used for problem-solving, learning, storage, decision-making, and information exchange. In the context of HEIs, students use information for the same reasons as well. However, what matters in the real world is not the type of use but rather the outcome of information use.

We revealed through the literature review that academic performance, student satisfaction, and collaboration (behavioral engagement through information sharing and exchange) are the expected outcomes of student engagement. However, most studies have focused on the technology like mobile social networks (Cao, Masood, Luqman, & Ali, 2018) and the internet, paying little attention to the use of the information they carry. In our review, we argued that although students use technology to access information from multiple sources worldwide, it is the use of digital information that drives collaboration, satisfaction, and academic performance. For example, the use of the internet by university students has proven to increase their perceptions of learning and engagement (Cheung & Huang, 2005). We argue that it is the use of information from the internet and not the internet itself that creates this effect because if the information sought by the user is not useful, it may rather negatively affect their learning experience and academic performance (Zhu, Chen, Chen, & Chern, 2011). Therefore, we hypothesize that:

Hypothesis 7 (H7): information use affects academic performance.

In the same light, students perceive the use of technology as a tool that increases their engagement with their course work through collaboration in the form of information exchange and feedback (Gould, 2012a). However, they find that exchanging information relevant to their studies helps them learn better and provide mutual support for each other (Lyu, Huang, & Hu, 2019). Therefore, we hypothesize that:

Hypothesis 8 (H8): information use affects information exchange.

Also, an essential part of student collaboration is information sharing. If information is found useful, it is often shared with colleagues or classmates to help them solve similar problems, learn something new, or make decisions. Such information sharing is sometimes supported by pre-discussion notes which are used to help the student remember useful information before work sessions (Zhou, Xiao, Liu, & Chen, 2018). Also, it is common practice today for students to share information they deem useful through their social media class groups. At the same time, they may not share information they do not use unless they feel it might be useful for someone else. Therefore, we hypothesize that:

Hypothesis 9 (H9): information use affects information sharing.

Furthermore, studies show that providing students with useful and quality information influences their satisfaction with a course (Park, Yoo, Kim, & Lee, 2018; Xu & Du, 2019). Also, information quality is found to influence student satisfaction. Therefore, the more students use the information they are provided with, the more satisfied they are likely to be with their experience at the university. Therefore, we hypothesize that:

Hypothesis (H10): information use affects user satisfaction.

Finally, the OGD model suggests that the profile of the information user influences their use of information. This is because differences in profiles result in individual differences in perceptions and judgment on how or if information is used. This suggests a moderating effect between information user and information use. Characteristics that make up user profiles include age, gender, work experience, field of study (domain), level of education, revenue, and personality types as defined by Myers & Myers (2010). In the context of HEIs in developing countries, age, gender, and university affiliation were found to influence the information behaviors and needed to be considered when designing information systems to ensure the optimal use of information by users (Donkor & Nwagwu, 2019). Thus, students affiliated with universities that provide them with access to academic databases and/or free or affordable internet services are more likely to use digital information than their peers without access.

The level of education and field of study could also influence the use of digital information. Generally, it is observed that in developing countries, students are expected to use more reliable sources of information as they climb the academic ladder. Undergraduates, for example, may use internet sources like Wikipedia and YouTube to complete class assignments and projects. However, once the students get to graduate-level studies, they are expected to use more academically-reliable sources like academic journal publications and reputable news bulletins to support their arguments. Furthermore, the use of digital information seems to vary with the field of study. It is observed in the region that students from science-oriented fields like medicine and engineering use more digital information than those from art-oriented fields like history and literature.

As concerns digital access in developing countries, the cost of internet services remains a major obstacle for students (van Deursen & van Dijk, 2015). Consequently, students who cannot afford internet services or access to academic databases will not be able to use information from such sources. Moreover, many institutions in those countries, especially in the African region do not purchase access to such platforms for their students making the use of such information practically impossible for them. Personality traits have been found to influence learning behaviors, especially concerning the compulsive use and motivation to use technology for information and learning (Klobas, McGill, Moghavvemi, & Paramanathan, 2018). Based on such studies, we argue that the information user's personality could affect their motivation to use digital information for learning purposes. All these arguments justify the possibility based on the OGD model that the user profile has a moderating effect on information user and information use. Therefore, we hypothesize that:

Hypothesis 11 (H11a-g): information user profile (age, gender, work experience, field of study (domain), level of education, revenue, and personality type) moderates the relationship between information user and information use.

Based on the guidelines from Evermann (2005), we were able to support each hypothesis in our contextualized conceptual model through the extant literature and facts collected on the field. Figure 2 presents the diagrammatic representation of our proposed contextualized conceptual model. In the next section, we describe the methodology used to test the proposed model.

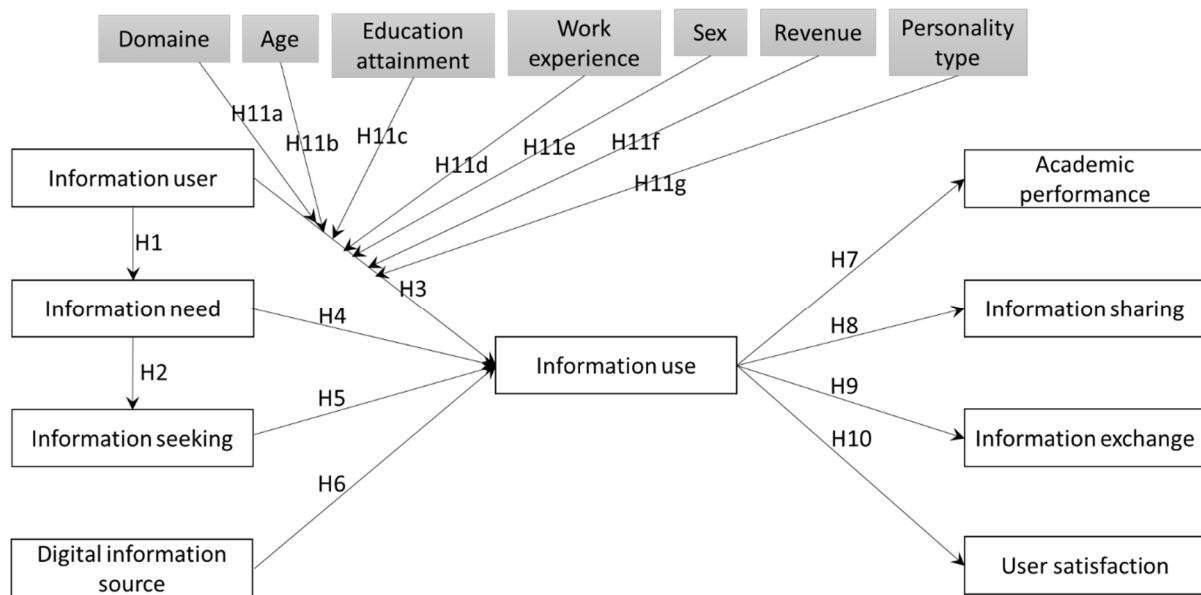


Figure 2. Proposed contextualized conceptual model for digital information behavior (based on Ohtoshi & Gottschalg-Duque, 2016)

4. Methodology

Our goal is to verify the hypotheses we derived from the OGD model. To this end, our methodology was guided by research done by Case (2002) who proposed methods for studying information behaviors.

4.1. Instrument development and validation

Case (2002) suggests and shows how different methods can be used to collect data that could help explain the information behaviors of users. Among the methods proposed, we found focus groups to be the most effective for our study because it gave us the possibility to capture the real opinions of the students in context thereby ensuring high face validity of our data. Nevertheless, this method alone is weak because it reflects the opinion of a specific group of people in a given setting and at a particular time. Thus, it was recommended that focus groups should be combined with other data collection methods to limit this weakness. Consequently, we complemented our findings from the focus groups with a survey.

For the focus group interviews, we observed and took notes that helped us uncover the underlying opinions and motivations influencing digital information behaviors of students in the context of our study – marginal universities in developing countries. The interviews were conducted by the authors, one acting as a facilitator and the other as an observer. The focus group was made up of 10 master’s degree students (3 from social sciences, 3 from hard sciences, 3 from arts & literature fields, and 1 from theology). The participants were students from different universities in Cameroon who came to participate in a seminar at the Catholic University of Central Africa, Yaoundé, Cameroon. The participants volunteered to take part in our one-hour focus group session during which they were incited to discuss their digital information behavior in terms of need, seeking, and use, as well as its

impact on their engagement as university students. The participants enthusiastically participated in this activity because, at the time, the government of Cameroon had just decided to offer 500,000 mini laptops to university students in Cameroon to support their digital information needs. However, there was a huge divide among the students because some believed the government would have rather made internet services more affordable for students and purchased access to academic databases that students can access free of charge. Thus, participants saw this study as an opportunity to express their needs and expectations as university students. The focus group was centered around five general questions:

- What kind of information or e-resources do you need as a university student?
- How/where do you obtain the information you need?
- How do you use the information you obtain from these sources?
- What do you think should be done to satisfy your information needs?
- What difference do you expect these changes to make in your university experience?

Participants were allowed to give their personal opinions directly or react to the opinions of other participants. Based on our observations and notes, we were able to validate the relevance of every concept in our model and predict the veracity of our proposed hypotheses. Nevertheless, as proposed by the methodology we adopted, we had to complement these findings by sampling a wider population which we did using a survey.

After searching in the literature on the way the concepts in our model were measured, we found no existing scales adapted to our study. This seemed logical because this is the first study that attempts to conceptualize these concepts as we do. Thus, we used our focus group notes and our understanding of the context from extant literature to develop measurement scales that reflect the reality of our constructs in the context of the study. We tested our measurement instrument using a seven-point Likert scale questionnaire in two stages. First, we pretested the instrument with 18 management & information systems students who were asked to comment on the clarity and understandability of each item relative to its construct. This led us to rephrase and eliminate some items. Secondly, we conducted a pilot test with 30 random university students to assess the validity and reliability of our constructs which we did. After validating our instrument (see Appendix A), we proceeded to the full data collection stage to validate our findings.

4.2. Data collection phase

We determined the minimum sample size for this study using the power analysis with the help of G*Power 3.1.9.2 software (Perugini, Gallucci, & Costantini, 2018). We selected an effect size of 0.0625, alpha of 0.05, and a power of 0.95, giving an acceptable sample size of 119 for this study. We collected data from 339 students in a developing country, namely Cameroon, between May 2018 to September 2018. The questionnaires were addressed to students from three marginal universities in Cameroon namely the Catholic University for Central Africa, the University of Yaoundé I, and the University of Yaoundé II. The questionnaires were distributed both electronically via google forms and paper-based from campus to campus. We hired independent consultants to collect the paper-based data on the field, after giving them a full day of training. Each day, we verified the data collected for consistency

and validity until the end of the process. They were also given incentives to use in motivating students to take part in the study. In total, we obtained 303 valid responses that were used in the data analysis. The structure of the respondents is an adequate representation of Cameroon's student population as presented in Table 2.

Table 2. Demographic profile of participants

Sample	No. of categories	Category	Frequency per category	Rel. Frequency per category (%)
Age (years)	5	Unknown	23	7.59
		15-20	81	26.73
		21-25	142	46.86
		26-30	50	16.50
		31-35	7	2.31
Sex (gender)	3	Unknown	17	5.61
		Male	131	43.23
		Female	155	51.16
Field of study (Domain of Study)	5	Unknown	32	10.56
		Social sciences	46	15.18
		Pure sciences	41	13.53
		Arts & Literature	33	10.89
		Others	151	49.83
Level of education (Educational attainment)	5	Unknown	13	4.29
		Higher National Diploma or lower	26	8.58
		Bachelor	205	67.66
		Master's	52	17.16
		Higher than a Master's degree	7	2.31
Work experience (years)	6	Unknown	35	11.55
		None	154	50.83
		<1	49	16.17
		1-2	54	17.82
		3-5	7	2.31
		>5	4	1.32
Revenue / Allowance (in XAF)	6	Unknown	115	37.95
		<=15000	80	26.40
		15001-30000	68	22.44
		30001-45000	22	7.26
		45001-60000	13	4.29

		>60000	5	1.65
Personality type	9	Unknown	26	8.58
		Extravert	89	29.37
		Introvert	79	26.07
		Sensitive	31	10.23
		Thinker	26	8.58
		Emotional	8	2.64
		Judging	28	9.24
		Intuitive	6	1.98
		Perceptive	10	3.30

4.3. Data analysis phase

Among the data analysis techniques proposed by Case (2002), we found statistical analysis most suitable for our study. We specifically used partial least squares structural equation modeling (PLS-SEM), a technique that has been widely used and approved in the field of information systems and technology (L. Huang, Zhang, & Liu, 2017; Ifinedo, 2016; Leguina, 2015). We used XLSTAT version 2014.5.03 and SmartPLS version 3.2.8 to analyze the data. XLSTAT was used to obtain the descriptive statistics, item loadings, and eigenvalues, while SmartPLS was used to measure the model assessment and determine the corresponding structural equations. We chose PLS because the proposed research model is based on a model that is not fully established. We developed our model by altering the original model and adding concepts from existing literature. PLS is best suited because it will help us better understand the relationship between the model and the data, by explaining the variation in dependent variables caused by the independent variables (Petter, 2018).

The data analysis was conducted in two stages: measurement model assessment, and structural model assessment. During the first stage, we verified the unidimensional nature of each latent construct to make sure all items per construct measured the same underlying idea. A construct was considered unidimensional if the first eigenvalue was greater than one while the others were smaller, and all item loadings were greater than 0.6 (Vinzi, Trinchera, & Amato, 2010). Next, we assessed the construct reliability and validity to determine the internal consistency or homogeneity of the measurement model. To verify the convergent validity of the model, we accepted constructs that had Average Variance Extracted (AVE) values at 0.5 or higher. We also approved constructs with composite reliabilities greater or equal to 0.6. To verify homogeneity, we accepted constructs that had both Cronbach's alpha and Dillon-Goldstein's rho values greater or equal to 0.7 (Vinzi et al., 2010). To assess the discriminant validity of the model, we used the Fornell-Larcker Criterion (Venturini & Mehmetoglu, 2019).

During the structural model assessment stage, we, first of all, evaluated the validity of relationships between constructs suggested in the hypothesis. This was done based on the significance of path coefficients, determined through their p-values. Conventionally, the valid p-values are $p < 0.05$, $p < 0.01$ and $p < 0.001$ (Dahiru, 2011). Next, we assessed the fitness of the model based on the data used in this study. We decided to accept the model if the standardized root mean square residual (SRMR)

value is less than or equal to 0.08. We chose this criterion because it is a well-established approximate model fit criterion implemented for PLS path modeling (Henseler, Hubona, & Ray, 2016). Finally, we used R Square values to determine the proportion of variance in the dependent variables that can be explained by the independent variables. R Square values with the minimum cutoffs of 0.67, 0.33, and 0.19 were considered “substantial”, “moderate” and “weak” respectively (Chin, 1998). We also tested the effects of the moderating variables on the relationship between the information user and information use. We used bootstrapping to determine if they have any significant direct or indirect effects on the model. We bootstrapped using 500 subsamples, two-tailed with a significance level of 0.05.

5. Results

5.1. Measurement model assessment

After running the measurement model in XLSTAT and SmartPLS, we obtained the item loadings and eigenvalues presented in Table 2. We can see that all loadings are greater than 0.6 and all first eigenvalues are greater than one, confirming the unidimensional nature of every latent construct block of items. We were able to confirm the convergent validity of the model by the fact that all AVE values were greater than 0.5, and all composite reliability values were above 0.6. Seven constructs were proven to be fully reliable because their Cronbach's alpha and D.G. rho values were all above the 0.7 thresholds. However, *information exchange* had a low Cronbach's alpha of 0.687, while information seeking had bad Cronbach's alpha and D.G. rho values. Nevertheless, we maintained them throughout the rest of the analysis given that they were internally valid, and they had good AVE and composite reliability values. Thus, although these constructs are questionable (Montshiwa & Moroke, 2014), they are not unacceptable at this point given the other measurement results, as presented in Table 2.

Table 3. Assessment of the measurement model

Construct	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Academic performance	0.760	0.800	0.860	0.674
Information exchange	0.687	0.742	0.804	0.513
Information need	0.772	0.784	0.846	0.525
Information seeking	0.669	0.683	0.799	0.501
Information sharing	0.865	0.871	0.903	0.650
Information sources	0.791	0.795	0.857	0.548
Information use	0.817	0.819	0.873	0.579
Information user	0.812	0.830	0.864	0.560
User satisfaction	0.809	0.820	0.862	0.511

The discriminant validity of the model was confirmed by the Fornell-Larcker Criterion given the AVE of each latent constructs are higher than the squared correlations with all other latent constructs. The square roots of the AVEs are shown by the bolded numbers in the matrix diagonals as presented in Table 3.

Table 4. Discriminant Validity using Fornell-Larcker Criterion

Constructs	AP	DIE	IN	IS	ISH	DIS	IUS	IU	USAT
AP	0.821								
DIE	0.267	0.716							
IN	0.254	0.49	0.725						
IS	0.188	0.503	0.57	0.708					
ISH	0.301	0.362	0.249	0.322	0.806				
DIS	0.441	0.408	0.359	0.474	0.522	0.74			
IUS	0.492	0.445	0.483	0.41	0.491	0.588	0.761		
IU	0.22	0.356	0.554	0.262	0.208	0.242	0.314	0.748	
USAT	0.512	0.415	0.398	0.433	0.573	0.632	0.776	0.258	0.715

5.2. Structural model evaluation

Given that the outer model estimations are reliable and valid, we present the results of the inner path model estimates. The results of the structural model are presented in Figure 3 and summarized in Tables 4. The results show that all the hypotheses of this study are supported with very strong significance except H3 and H5.

Table 5. Structural modelling results

Hypothesis	Path coefficient	P -values	Result
H1: Information user -> Information need	0.554****	0	Supported
H2: Information need -> Information seeking	0.57****	0	Supported
H3: Information user -> Information use	0.04	0.458	Unsupported
H4: Information need -> Information use	0.284***	0.001	Supported
H5: Information seeking -> Information use	0.015	0.866	Unsupported
H6: Information sources -> Information use	0.469****	0	Supported
H7: Information use -> Academic performance	0.492****	0	Supported
H8: Information use -> Information exchange	0.445****	0	Supported
H9: Information use -> Information sharing	0.491****	0	Supported
H10: Information use -> User satisfaction	0.776****	0	Supported

Note: $p < 0.001$ ***; $p < 0.000001$ *****

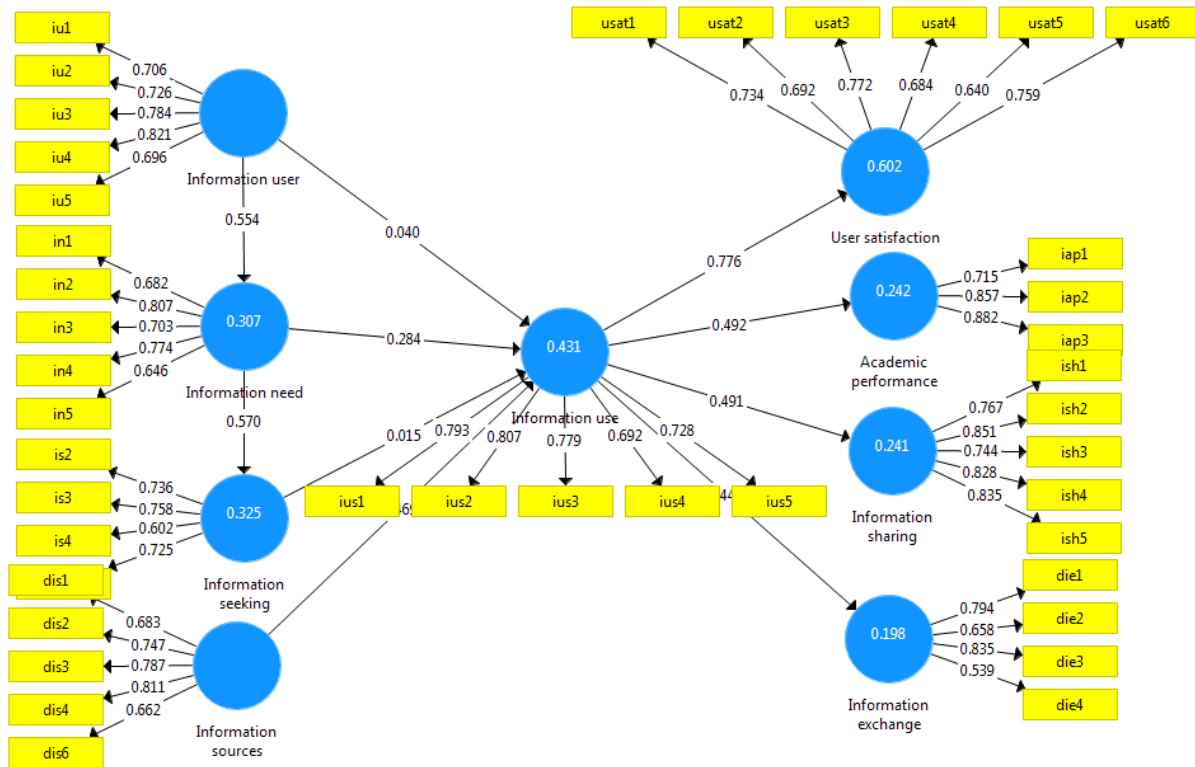


Figure 3. Results of the structural model

H11 was not supported as well because the moderating variables had no significant effect on the model. Nevertheless, at a significance level of 0.1, domain of study had a direct significant effect. Age, sex, work experience, educational attainment, revenue, and personality type did not moderate the relationship between information user and information user even at low significance levels.

Overall, the Goodness of fit of the model is acceptable given that it has an SRMR of 0.078. The results of the R Square values are presented in Table 5. We observe that this model best explains student satisfaction and information use.

Table 6. R Square values

Construct	R Square	R Square Adjusted	Result
User satisfaction	0.602	0.601	Moderate
Information use	0.431	0.424	Moderate
Information seeking	0.325	0.323	Weak
Information need	0.307	0.304	Weak

Academic performance	0.242	0.24	Weak
Information sharing	0.241	0.239	Weak
Information exchange	0.198	0.196	Weak

6. Discussion

The objective of this study is to understand the information behavior of students in HEIs in developing countries and its effect on their learning experiences and outcomes in terms of academic performance, satisfaction, and collaboration. To do so, we conceptualized information behaviors by transforming an ontology-driven model on information behavior into a contextualized conceptual model that shows relationships between antecedents and outcomes of the use of digital information. Specifically, we show how (i) information users, information need, information seeking, and information sources affect the use of digital information by students, and how (ii) the use of digital information influences the academic performance, collaboration, and satisfaction of students in marginal universities. Our findings strongly support the fact that the information need and information source highly affect the information use behavior of students. Although information seeking behavior does not influence their information use behavior, information seeking behavior is affected by the information need of the student. Meanwhile, the information use behavior of students was found to strongly affect the academic performance, collaboration, and satisfaction of students in HEIs in developing countries.

In the real-world context of HEIs, these findings are logical, including our findings that information user and information seeking behaviors do not influence information use behavior. First, the information user is the subject of the study and not a concept and our results confirm that it cannot be conceptualized like the other concepts in the semantic model. Rather, it is the demographic characteristics and personality traits of the information user that could be conceptualized and tested directly on information use behaviors rather than as moderators as we did in this study. Secondly, information seeking is described as a conscious effort to fill our knowledge gap in response to an information need. This could imply that no matter how good the user's seeking strategy is, what matters is the source of the information obtained and therefore has no direct effect itself on information use. This could explain the strong influence of information source on information use. However, the fact that information seeking behavior is affected by the information need of the student confirms that students adopt different seeking strategies depending on their information needs.

Our findings are strongly tied to current discussions on digital information literacy in HEIs. When compared to the extant literature, we find that our results are relevant in the context of HEIs in developed countries as well. Irrespective of the region of the world or university, digital information literacy is essential for students in HEIs. Unfortunately, these are skills that are not taught to students in some HEIs even in developed countries (Guzmán-Simón, García-Jiménez, & López-Cobo, 2017; Polizzi, 2020). Today, it is a popular belief that millennials and younger generations "naturally master" the use of digital information. Contrary to this belief, Çoklar, Yaman, & Yurdakul (2017) show that information seeking competencies are strongly correlated with digital information literacy and weakly

correlated with digital nativity. Our study supports suggestions that in this digital age flooded with information that is easily accessible through search engines, it is critical to teach students how to find and use digital information and related resources effectively (Desilets, Larson, Filkins, & DeJonghe, 2017; Sieber, Anthoney, Barker, & Roberts, 2017). This includes training them on how to clearly define their information needs, use appropriate information seeking strategies (like designing effective search strings), and finding the right sources of digital information. This requires developing students' abilities to evaluate digital content through reflections on the origins, context, and digital environment in which the information is found.

At the level of outcomes, our findings also tend to support several studies on the effect of digital information on student satisfaction, performance, and collaboration. Recent studies show that providing students with online lectures and assignments tends to yield significantly better student performance as it gives them the ability to prepare for courses ahead of time. This way, the lecturer can dedicate more time in class enriching the understanding of the students and discussing issues of concern rather than spending time on things they could simply read by themselves (Nakos & Whiting, 2018). Also, our study supports arguments for the need to develop methodologies and taxonomic systems that could help synthesize and analyze digital information sources during collaboration. Students who use this approach are found to perform better than those who do not (Kiili & Leu, 2019). Furthermore, our study provides more evidence to the fact that using digital information can help improve students' communication, collaboration, teamwork skills, responsibility for their learning outcomes (Blau, Shamir-Inbal, & Avdiel, 2020), and learning autonomy (Ting, 2015).

Although our results show the central role of digital information use on the academic performance, collaboration, and satisfaction of students in HEIs, it also reveals the limitations and challenges faced by students in marginal universities. For students to enjoy the benefits of using digital information in their learning processes, our results have highlighted the importance of the students to be able to (i) identify their information needs (ii) develop the skills needed to acquire the information they need, and (iii) obtain the information needed from the most reliable sources. In addition to barriers related to digital information literacy which is a worldwide phenomenon as discussed above, marginal universities, especially in the African region, suffer highly from the digital divide. Khalid & Pedersen (2016) show that the concept of digital divide in HEIs includes social exclusion, digital exclusion, and accessibility.

Regarding social exclusion, like in many universities in developing countries, universities in Cameroon are full of students between the ages of 15 and 25 most of whom have no professional experience and highly financially dependent on their parents or sponsors. Given that most participants have a monthly allowance of about 15,000 francs CFA (about 23 EUR; 26 USD) or less, it is hard for them to keep up with the expenses. With 1 GB per day of 4G data costing about 10,000 francs (about 15 EUR; 17 USD) per month in Cameroon, this is practically unaffordable for most students in such universities. This situation is not limited to Cameroon. Findings from South Africa also confirm the effect of such social inequalities on the internet use of students (Oyedemi, 2015).

Digital exclusion is also a major concern as most of the HEIs in Cameroon do not provide free on-campus internet services for its students although the teachers expect the students to use information

obtained online to complete and submit class assignments. Even when they provide paid internet services, they are slow and unreliable which was also shown to be the case in Nigeria (B. O. Omotayo, 2006). This systematically excludes many students from accessing internet-based sources of information. Also, most HEIs in Cameroon do not have access to academic databases like Business Source Complete, Web of Science, or ScienceDirect. Yet, students are often expected to do research that is publishable at the international level. Thus, students are bound to rely on open source material and Google Scholar to conduct their research which again leads to issues regarding the lack of training on how to identify reliable sources of information on those platforms. With such limitations, students in marginal universities cannot compete with students in universities that provide a stable access to reliable digital information and related resources.

In Cameroon, the government has invested about 75 Billion francs CFA (about 114,336,763 Eur; 129,873,663 USD) to purchase 500,000 mini laptops for its university students (Marshall, 2016). This is meant to boost their academic performance and the competitiveness of universities in Cameroon through greater access to digital information. However, the students cannot make the most of this generosity because the universities do not have the required information system in terms of information access and technological infrastructure. Most of the students already own at least one digital device (a computer or a smartphone). Thus, an additional device isn't much help to the students in terms of contribution to their university experience. Our findings show that providing the students with digital information literacy training and a stable access to reliable digital information sources will have a more positive effect on the academic experiences of the students and more appreciation for the government's efforts.

The bottom line of our study is that the issues of digital information use and literacy are common to HEIs in both developed and developing countries. Nevertheless, the environment in which the HEI operates makes all the difference. Specifically, accessibility, digital exclusion, and social exclusion make it such that developed and developing countries do not experience issues related to digital information use in the same way and thus need to address these issues differently. This study makes several theoretical contributions to research and has several implications for practice regarding information management and information systems in HEIs in developing countries especially in the African region.

6.1. Theoretical contributions

Our research contributes to the limited amount of studies on information management in HEIs (Arapaci, 2019; Masa'deh, Shannak, Maqableh, & Tarhini, 2017; Pinho et al., 2018). Specifically, we use concepts on information behavior to explain the impact of digital information use on the experience of students in marginal universities. By showing the effect of digital information use on student performance, satisfaction, and collaboration, we contribute to the body of knowledge on digital information literacy, student engagement, and academic performance in the context of marginal universities, especially in the African region (Snyder & Prinsloo, 2007). By relating digital information use behaviors to learning outcomes, we also enrich discussions on the quality of HEIs in developing countries, especially regarding universities in Africa (Darley & Luethge, 2019; Idowu, 2019).

In IS research, information behaviors are mostly studied separately. For example, information seeking (Allen, Ball, & Jeff Smith, 2011; Garg, Smith, & Telang, 2011), information sharing (Fadel, Meservy, & Jensen, 2015), and information need (Appan & Browne, 2012) behaviors are each studied separately. While this helps researchers understand each behavior separately, there was no evidence about relationships between them. Moreover, there are no well-established constructs in IS literature to measure these concepts. By analyzing these behaviors through the lens of the OGD model, we contribute to IS research by conceptualizing these behaviors and developing an instrument that can be used to measure each of them. The OGD model was developed based on well-established information behavior models (Choo et al., 2000; Leckie et al., 1996; Wilson, 1999, 2006) thereby providing a solid theoretical foundation of our work. Thus, our instrument can be used to complement or as an alternative to other instruments that may be used to capture and measure these information behaviors.

Developing the measurement instrument involved transforming an ontology-driven model into a conceptual model. There are several debates around the ability of ontology-based models to support contextual explanations to IS phenomena (Avgerou, 2019; Burton-Jones, Recker, Indulska, Green, & Weber, 2017) and its utility as a foundation for conceptual modeling (Allen & March, 2012; Shanks, Tansley, Nuredini, Tobin, & Weber, 2008). In addition to being used as a foundation for conceptual modeling, the OGD model enabled us to contextually explain digital information use using the traditions of behavioral conceptual modeling. The validation of our measurement instrument through this study contributes to this debate by showing the ability of ontology-based models to support the conceptualization of existing or perceptions of reality. Moreover, our formulation of Evermann's (2005) work as guidelines for transforming ontology-driven models to conceptual models contributes an approach that can be leveraged by other researchers attempting similar studies.

6.2. Implications for practice

This study informs the top management of HEIs and policymakers of the central role of digital information on student engagement and performance. In a bid to improve the quality and global competitiveness of HEIs in developing countries, these stakeholders have been advised to increase vocational and technical training, increase budgetary allocations, and ensure policy implementation (Idowu, 2019). In enforcing these strategies, they must consider the information behaviors and trends of the students to obtain the best results.

Digital information literacy must become an integral part of higher education curricula. Our study supports that all students in HEIs need to take courses on digital information literacy irrespective of their field of study. These courses should train students on how to (i) identify and formulate their information needs, (ii) develop information seeking competencies, (iii) identify relevant sources of information, and (iv) assess information quality. These courses should be taught both at undergraduate and graduate levels because each level has its own information needs which may require different information seeking strategies and different sources. Students also need to be taught how to use information effectively. Given the high impact digital information use could have on their learning experiences and outcomes, training the students on how to use the information obtained digitally is very important for the overall quality of the institution. If students use digital information

effectively their academic performance will be positively impacted thereby increasing their employability (Pinto & Ramalheira, 2017). Also, using digital information effectively can lead to better research and publications in reputable academic journals. Given that employability and academic publications are part of many HEI ranking systems worldwide, an institution that trains its study on how to use digital information effectively is likely to improve its international status and the social identity of its students.

In addition to training, the leadership of HEIs also needs to ensure that students have access to reliable digital information sources both internally and externally. These include internal resources like institutional repositories and external resources like academic databases. Eventually, this implies providing the infrastructure (campus networks and internet) needed for the students to be able to access these resources preferably anywhere (or at least on campus) and at any time. This will give students the possibility to have their learning autonomy and increase their sense of responsibility towards their learning outcomes. Information systems should also be developed that lecturers can use to provide lectures and assignments for students as well as facilitate student collaborations. By developing an information culture in institutions, such platforms will serve as sources of reliable information for students and lecturers and an exciting learning experience for everyone.

Of course, setting up such an infrastructure (access to databases, campus networks, internet...) and promoting a rich information culture requires significant investments that are not always easy to obtain. Therefore, institutions and policymakers must plan their scarce resources wisely to maximize the positive impact of their investments. To do so, platforms can be created through which leaders of HEIs can monitor the information needs of their students before making investments. For example, in Cameroon, if a simple survey was conducted regarding the needs of university students, it is very unlikely that the government would have spent 75 Billion francs CFA (about 114,336,763 EUR; 129,873,663 USD) to buy 500,000 mini laptops for its university students (Marshall, 2016). Given the negative reaction from the students, they certainly would have preferred that the government invested this money in providing them with other facilities. Therefore, it is important to investigate the information needs of students before making such huge investments in the future.

Understanding these implications and implementing the corresponding recommendations implies making policies that affect HEIs at the institutional and national levels, just like the decision to improve the quality of HEIs. At the institutional levels, top management needs to ensure that they understand the information needs of the students well enough to design the right training curricula, design an adequate information system, secure the right budget, and enforce strong information cultures in their institutions. At the national level, improving the quality and global competitiveness of HEIs should be part of the country's national strategy. This way, budget allocations will be made every year to support the HEIs in their effort to achieve this goal. The harmonization of higher education in Africa (Hahn & Teferra, 2017) is an example of international initiatives that are also trying to support institutions and countries to improve the standards of HEIs in the African region. Participating in joint initiatives like this could help boost the ability of marginal universities to meet the digital information needs of their students and eventually improve the quality of students graduating from such institutions.

6.3. Limitations and future research directions

We used the OGD model to develop and validate a conceptual model for information behavior. However, the OGD model still gives room for further investigations in the real world. For example, the OGD model shows that affective, cognitive, and situational factors could affect information need, seeking, and use behaviors. A future research direction that can complement our conceptual model is to conceptualize and validate such relationships in a real-world context. Furthermore, researchers could investigate the direct effects of demographic characteristics and personality traits on the information behaviors of users as suggested by the OGD model rather than as moderators as we did in this study.

Also, our theoretical development was limited to findings from Cameroon. Although we backed our findings with literature from other developing countries like Nigeria, South Africa, Kenya, and Uganda, empirical studies still need to validate our theory and measurement instrument in other developing countries. Also, more studies could be conducted to evaluate the generalizability of our findings by testing our model in HEIs located in developed country contexts. Furthermore, future research can also leverage our theoretical lens to complement other theories that can help explain the outcomes of information use better. Finally, our model can be adapted to investigate other contexts where the information behaviors of users are important like in healthcare and financial services.

Conclusions

In this study, we conceptualized the digital information behaviors of users and tested their effect on the learning experiences of students in marginal universities. By conceptualizing relationships between information need, information seeking, information sources, and information use, we demonstrated the central role of digital information use on student performance, collaboration, and satisfaction. Our study contributes to theory by increasing the body of knowledge on information management in HEIs, digital information literacy, and information behaviors of information system users. Methodologically, it contributes to current debates on using ontology-based models as theoretical foundations for conceptual modeling. Practically, this study contributes to highlighting the central role of digital information on student performance, engagement, collaboration, and the improvement of the quality of HEIs in developing countries, especially in the African region.

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References

Allen, G. N., Ball, N. L., & Jeff Smith, H. (2011). Information systems research behaviors: What are the normative standards? *MIS Quarterly: Management Information Systems*, 35(3), 533–551. <https://doi.org/10.2307/23042795>

- Allen, G. N., & March, S. T. (2012). A research note on representing part-whole relations in conceptual modeling. *MIS Quarterly: Management Information Systems*, 36(3), 945–964. <https://doi.org/10.2307/41703488>
- Appan, & Browne. (2012). The Impact of Analyst-Induced Misinformation on The Requirements Elicitation Process. *MIS Quarterly*, 36(1), 85. <https://doi.org/10.2307/41410407>
- Arpaci, I. (2019). A hybrid modeling approach for predicting the educational use of mobile cloud computing services in higher education. *Computers in Human Behavior*, 90, 181–187. <https://doi.org/10.1016/j.chb.2018.09.005>
- Avgerou, C. (2019). Contextual explanation: Alternative approaches and persistent challenges. *MIS Quarterly: Management Information Systems*, 43(3), 977–1006. <https://doi.org/10.25300/MISQ/2019/13990>
- Baro, E. E., Onyenania, G. O., & Osaheni, O. (2010). Information seeking behaviour of undergraduate students in the humanities in three universities in Nigeria. *South African Journal of Libraries and Information Science*, 76(2), 109–117. <https://doi.org/10.7553/76-2-74>
- Beynon-Davies, P. (2018). Declarations of significance: Exploring the pragmatic nature of information models. *Information Systems Journal*, 28(4), 612–633. <https://doi.org/10.1111/isj.12148>
- Blau, I., Shamir-Inbal, T., & Avdiel, O. (2020). How does the pedagogical design of a technology-enhanced collaborative academic course promote digital literacies, self-regulation, and perceived learning of students? *Internet and Higher Education*, 45, 100722. <https://doi.org/10.1016/j.iheduc.2019.100722>
- Bostrom, R., Gupta, S., & Thomas, D. (2009). A meta-theory for understanding information systems within sociotechnical systems. *Journal of Management Information Systems*, 26(1), 17–48. <https://doi.org/10.2753/MIS0742-1222260102>
- Bryson, C. (2016). Engagement through partnership: students as partners in learning and teaching in higher education. *International Journal for Academic Development*, Vol. 21, pp. 84–86. <https://doi.org/10.1080/1360144x.2016.1124966>
- Bunge, M. (1979). *Ontology II: A World of Systems*, vol. 4. New York, NY: D. Reidel Publishing Co., Inc.
- Bunge, M. A. (1977). *Treatise on Basic Philosophy - Ontology I: The Furniture of the World* (Vol. 3). <https://doi.org/10.1007/978-94-010-9924-0>
- Burton-Jones, A., Recker, J., Indulska, M., Green, P., & Weber, R. (2017). Assessing representation theory with a framework for pursuing success and failure. *MIS Quarterly: Management Information Systems*, 41(4), 1307–1333. <https://doi.org/10.25300/MISQ/2017/41.4.13>
- Campbell, P. (2013). Looking for Information: A Survey of Research on Information Seeking, Needs, and Behavior (3rd ed.). In *Library Management* (Vol. 34). <https://doi.org/10.1108/01435121311310941>
- Cao, X., Masood, A., Luqman, A., & Ali, A. (2018). Excessive use of mobile social networking sites and poor academic performance: Antecedents and consequences from stressor-strain-outcome perspective. *Computers in Human Behavior*, 85, 163–174. <https://doi.org/10.1016/j.chb.2018.03.023>
- Cheung, W., & Huang, W. (2005). Proposing a framework to assess Internet usage in university education: An empirical investigation from a student's perspective. *British Journal of Educational Technology*, 36(2), 237–253. <https://doi.org/10.1111/j.1467-8535.2005.00455.x>
- Chin, W. W. (1998). The partial least squares approach for structural equation modeling. *Modern Methods for Business Research*, 295(2), 295–336.
- Choo, C. W., Detlor, B., & Turnbull, D. (2000). Web work : information seeking and knowledge work on the World Wide Web. In *Information science and knowledge management volume 1* (Vol. 1). <https://doi.org/10.1007/978-94-015-9405-9>
- Chou, C. H., Zahedi, F. M., & Zhao, H. (2014). Ontology-based evaluation of natural disaster management websites: A multistakeholder perspective. *MIS Quarterly: Management Information Systems*, 38(4), 997–1016. <https://doi.org/10.25300/misq/2014/38.4.03>
- Çoklar, A. N., Yaman, N. D., & Yurdakul, I. K. (2017). Information literacy and digital nativity as

- determinants of online information search strategies. *Computers in Human Behavior*, 70, 1–9. <https://doi.org/10.1016/j.chb.2016.12.050>
- Dahiru, T. (2011). P-Value, a true test of statistical significance? a cautionary note. *Annals of Ibadan Postgraduate Medicine*, 6(1), 21–26. <https://doi.org/10.4314/aipm.v6i1.64038>
- Darley, W. K., & Luethge, D. J. (2019). Management and business education in Africa: A post-colonial perspective of international accreditation. *Academy of Management Learning and Education*, 18(1), 99–111. <https://doi.org/10.5465/amle.2016.0086>
- Desilets, M. R., Larson, C. M., Filkins, M. M., & DeJonghe, J. (2017). Forging Connections in Digital Spaces: Teaching Information Literacy Skills Through Engaging Online Activities. In T. Maddison & M. B. T.-D. L. Kumaran (Eds.), *Distributed Learning: Pedagogy and Technology in Online Information Literacy Instruction* (pp. 205–219). <https://doi.org/10.1016/B978-0-08-100598-9.00011-8>
- Donkor, A. B., & Nwagwu, W. E. (2019). Personal factors and personal information activities behaviors of faculty in selected universities in Ghana. *Library and Information Science Research*, 41(4), 100985. <https://doi.org/10.1016/j.lisr.2019.100985>
- El-Maamiry, A. A., & Amour El-Maamiry, A. (2017). The Information-Seeking Behaviour of Students: A Case of University of Dubai. *Information & Technology Global Journal of Computer Science and Technology*, 17(1), 0–6. Retrieved from https://globaljournals.org/GJCST_Volume17/1-The-Information-Seeking-Behaviour.pdf
- Elliott, A. D., Bartel, A. F. P., Simonson, D., & Roukis, T. S. (2015). Is the Internet a Reliable Source of Information for Patients Seeking Total Ankle Replacement? *Journal of Foot and Ankle Surgery*, 54(3), 378–381. <https://doi.org/10.1053/j.jfas.2014.08.012>
- Ellis, D. (1989). A behavioural model for information retrieval system design. *Journal of Information Science*, 15(4–5), 237–247. <https://doi.org/10.1177/102831538901500406>
- Evermann, J. (2005). Towards a cognitive foundation for knowledge representation. *Information Systems Journal*, 15(2), 147–178. <https://doi.org/10.1111/j.1365-2575.2005.00193.x>
- Fadel, K. J., Meservy, T. O., & Jensen, M. L. (2015). Exploring knowledge filtering processes in electronic networks of practice. *Journal of Management Information Systems*, 31(4), 158–181. <https://doi.org/10.1080/07421222.2014.1001262>
- Fernández-Ramos, A. (2019). Online information literacy instruction in Mexican university libraries: The librarians' point of view. *Journal of Academic Librarianship*, 45(3), 242–251. <https://doi.org/10.1016/j.acalib.2019.03.008>
- Fong, K. C. H., Au, C. H., Lam, E. T. H., & Chiu, D. K. W. (2020). Social network services for academic libraries: A study based on social capital and social proof. *Journal of Academic Librarianship*, 46(1), 102091. <https://doi.org/10.1016/j.acalib.2019.102091>
- Garg, R., Smith, M. D., & Telang, R. (2011). Measuring information diffusion in an online community. *Journal of Management Information Systems*, 28(2), 11–38. <https://doi.org/10.2753/MISO742-1222280202>
- Gaston, N. (2013). Looking for Information: A Survey of Research on Information Seeking, Needs, and Behaviour (3rd ed.). *The Electronic Library*, 31(6), 813–814. <https://doi.org/10.1108/EL-05-2013-0086>
- Gebre, E., Saroyan, A., & Bracewell, R. (2014). Students' engagement in technology rich classrooms and its relationship to professors' conceptions of effective teaching. *British Journal of Educational Technology*, 45(1), 83–96. <https://doi.org/10.1111/bjet.12001>
- Ghabban, F., Selamat, A., & Ibrahim, R. (2018). New model for encouraging academic staff in Saudi universities to use IT for knowledge sharing to improve scholarly publication performance. *Technology in Society*, 55, 92–99. <https://doi.org/10.1016/j.techsoc.2018.07.001>
- Gould, R. (2012a). ECAR Study of Undergraduate Students and Information Technology 2013. In *C2C Digital Magazine* (Vol. 1). 2018.
- Gould, R. (2012b). ECAR Study of Undergraduate Students and Information Technology 2013. In *C2C Digital Magazine* (Vol. 1). 2017.
- Gregory, D. E. (2011). Review of “Student engagement in higher education: Theoretical perspectives

- and practical approaches for diverse populations.” In *Journal of Student Affairs Research and Practice* (Vol. 46). <https://doi.org/10.2202/1949-6605.5042>
- Gunuc, S., & Kuzu, A. (2015). Confirmation of Campus-Class-Technology Model in student engagement: A path analysis. *Computers in Human Behavior*, 48, 114–125. <https://doi.org/10.1016/j.chb.2015.01.041>
- Guo, J., & Huang, J. (2020). Information literacy education in WeChat environment at academic libraries in China. *Journal of Academic Librarianship*, 46(1), 102073. <https://doi.org/10.1016/j.acalib.2019.102073>
- Guzmán-Simón, F., García-Jiménez, E., & López-Cobo, I. (2017). Undergraduate students’ perspectives on digital competence and academic literacy in a Spanish University. *Computers in Human Behavior*, 74, 196–204. <https://doi.org/10.1016/j.chb.2017.04.040>
- Hahn, K., & Teferra, D. (2017). Africa: Harmonization and Tuning: Integrating Africa: International Higher Education, Fall 2012, Number 69. In *Understanding Global Higher Education* (pp. 45–48). Brill Sense.
- Heflin, H., Shewmaker, J., & Nguyen, J. (2017). Impact of mobile technology on student attitudes, engagement, and learning. *Computers and Education*, 107, 91–99. <https://doi.org/10.1016/j.compedu.2017.01.006>
- Henderson, M., Selwyn, N., Finger, G., & Aston, R. (2015). Students’ everyday engagement with digital technology in university: exploring patterns of use and ‘usefulness.’ *Journal of Higher Education Policy and Management*, 37(3), 308–319. <https://doi.org/10.1080/1360080X.2015.1034424>
- Henrie, C. R., Halverson, L. R., & Graham, C. R. (2015). Measuring student engagement in technology-mediated learning: A review. *Computers and Education*, 90, 36–53. <https://doi.org/10.1016/j.compedu.2015.09.005>
- Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management and Data Systems*, 116(1), 2–20. <https://doi.org/10.1108/IMDS-09-2015-0382>
- Huang, L., Zhang, J., & Liu, Y. (2017). Antecedents of student MOOC revisit intention: Moderation effect of course difficulty. *International Journal of Information Management*, 37(2), 84–91. <https://doi.org/10.1016/j.ijinfomgt.2016.12.002>
- Huang, M. H., & Chen, D. Z. (2017). How can academic innovation performance in university–industry collaboration be improved? *Technological Forecasting and Social Change*, 123, 210–215. <https://doi.org/10.1016/j.techfore.2016.03.024>
- Idowu, H. A. (2019). Benchmarking global best practices for improving higher education quality in Africa. In *Quality management implementation in higher education: Practices, models, and case studies* (pp. 72–90). <https://doi.org/10.4018/978-1-5225-9829-9.ch004>
- Ifinedo, P. (2016). Applying uses and gratifications theory and social influence processes to understand students’ pervasive adoption of social networking sites: Perspectives from the Americas. *International Journal of Information Management*, 36(2), 192–206. <https://doi.org/10.1016/j.ijinfomgt.2015.11.007>
- Isabel Myers, P. M. (2010). Gifts Differing: Understanding Personality Type. In *Nicholas Brealey Publishing*. <https://doi.org/10.1525/jung.1.1981.2.3.18>
- Johnson, L., Adams Becker, S., Cummins, M., Estrada, V., Freeman, A., & Hall, C. (2016). Horizon Report - 2016 Higher Education Edition. In *NMC Horizon Report*. <https://doi.org/ISBN 978-0-9968527-5-3>
- Johnston, A. N., Barton, M. J., Williams-Pritchard, G. A., & Todorovic, M. (2018). Youtube for millennial nursing students; using internet technology to support student engagement with bioscience. *Nurse Education in Practice*, 31, 151–155. <https://doi.org/10.1016/j.nepr.2018.06.002>
- Khalid, M. S., & Pedersen, M. J. L. (2016). Digital Exclusion in Higher Education Contexts: A Systematic Literature Review. *Procedia - Social and Behavioral Sciences*, 228, 614–621. <https://doi.org/10.1016/j.sbspro.2016.07.094>
- Kiili, C., & Leu, D. J. (2019). Exploring the collaborative synthesis of information during online

- reading. *Computers in Human Behavior*, 95, 146–157. <https://doi.org/10.1016/j.chb.2019.01.033>
- Klobas, J. E., McGill, T. J., Moghavvemi, S., & Paramanathan, T. (2018). Compulsive YouTube usage: A comparison of use motivation and personality effects. *Computers in Human Behavior*, 87, 129–139. <https://doi.org/10.1016/j.chb.2018.05.038>
- Kroll, A. (2015). Explaining the Use of Performance Information by Public Managers: A Planned-Behavior Approach. *American Review of Public Administration*, 45(2), 201–215. <https://doi.org/10.1177/0275074013486180>
- Leckie, G. J., Pettigrew, K. E., & Sylvain, C. (1996). Modeling the information seeking of professionals: A general model derived from research on engineers, health care professionals, and lawyers. *Library Quarterly*, 66(2), 161–193. <https://doi.org/10.1086/602864>
- Leguina, A. (2015). A primer on partial least squares structural equation modeling (PLS-SEM). In *International Journal of Research & Method in Education* (Vol. 38). <https://doi.org/10.1080/1743727x.2015.1005806>
- Lehmann, C. M., & Heagy, C. D. (2014). Organizing information into useful management reports: Short cases to illustrate reporting principles and coding. *Journal of Accounting Education*, 32(2), 130–145. <https://doi.org/10.1016/j.jaccedu.2014.03.001>
- Leon, R.-D., Neştian, A.-Ş., & Nica, P. (2015). The Impact of Information Sources on the Quality Values Promoted in the Romanian Universities. *Procedia Economics and Finance*, 20, 342–349. [https://doi.org/10.1016/s2212-5671\(15\)00082-9](https://doi.org/10.1016/s2212-5671(15)00082-9)
- Li, X., Sun, S. X., Chen, K., Fung, T., & Wang, H. (2015). Design Theory for Market Surveillance Systems. *Journal of Management Information Systems*, 32(2), 278–313. <https://doi.org/10.1080/07421222.2015.1063312>
- Lyu, J., Huang, H., & Hu, L. (2019). Leisure education and social capital: The case of university programmes for older adults in China. *Journal of Hospitality, Leisure, Sport and Tourism Education*, 25, 100207. <https://doi.org/10.1016/j.jhlste.2019.100207>
- Maass, W., & Varshney, U. (2012). Design and evaluation of Ubiquitous Information Systems and use in healthcare. *Decision Support Systems*, 54(1), 597–609. <https://doi.org/10.1016/j.dss.2012.08.007>
- Mahdi, R., Sukarman, S. S., & Yok, M. C. K. (2015). Fostering Creativity through Innovation Engagement in Science and Technology Education: Case Study of Universiti Teknologi MARA Students. *Procedia - Social and Behavioral Sciences*, 167, 256–260. <https://doi.org/10.1016/j.sbspro.2014.12.671>
- Marchionini, G. (1989). Information-seeking strategies of novices using a full-text electronic encyclopedia. *Journal of the American Society for Information Science*, 40(1), 54–66. [https://doi.org/10.1002/\(SICI\)1097-4571\(198901\)40:1<54::AID-ASI6>3.0.CO;2-R](https://doi.org/10.1002/(SICI)1097-4571(198901)40:1<54::AID-ASI6>3.0.CO;2-R)
- Marnewick, C. (2016). Benefits of information system projects: The tale of two countries. *International Journal of Project Management*, 34(4), 748–760. <https://doi.org/10.1016/j.ijproman.2015.03.016>
- Marshall, J. (2016). Accusations of state corruption over Chinese computers. Retrieved December 12, 2019, from University World News website: <https://www.universityworldnews.com/post.php?story=20160811155300316>
- Masa'deh, R., Shannak, R., Maqableh, M., & Tarhini, A. (2017). The impact of knowledge management on job performance in higher education: The case of the University of Jordan. *Journal of Enterprise Information Management*, 30(2), 244–262. <https://doi.org/10.1108/JEIM-09-2015-0087>
- McCoy, B. R. (2013). Digital Distractions In The Classroom: Student Classroom Use of Digital Devices for Non-Class Related Purposes. *Journal of Media Education*, 4(4), 5–12. Retrieved from <http://en.calameo.com/read/000091789af53ca4e647f>
- Montshiwa, V. T., & Muroke, N. D. (2014). Assessment of the reliability and validity of student-lecturer evaluation questionnaire: A case of North West University. *Mediterranean Journal of Social Sciences*, 5(14), 352–364. <https://doi.org/10.5901/mjss.2014.v5n14p352>

- Nakos, G., & Whiting, A. (2018). The role of frequent short exams in improving student performance in hybrid global business classes. *Journal of Education for Business*, 93(2), 51–57. <https://doi.org/10.1080/08832323.2017.1417231>
- Nazari, M. (2016). The actuality of determining information need in geographic information systems and science (GIS): A context-to-concept approach. *Library and Information Science Research*, 38(2), 133–147. <https://doi.org/10.1016/j.lisr.2016.04.005>
- Ohtoshi, P. H., & Gottschalg-Duque, C. (2016). A new model of information behavior based on semantic modeling. *Proceedings of the Association for Information Science and Technology*, 53(1), 1–5. <https://doi.org/10.1002/pr2.2016.14505301081>
- Omotayo, B. O. (2006). A survey of Internet access and usage among undergraduates in an African university. *International Information and Library Review*, 38(4), 215–224. <https://doi.org/10.1016/j.iilr.2003.10.016>
- Omotayo, F. O., & Haliru, A. R. (2020). Perception of task-technology fit of digital library among undergraduates in selected universities in Nigeria. *Journal of Academic Librarianship*, 46(1), 102097. <https://doi.org/10.1016/j.acalib.2019.102097>
- Owen, J. E. (2014). Teaching Naked: How Moving Technology Out of Your College Classroom Will Improve Student Learning by José Antonio Bowen. In *Journal of College Student Development* (Vol. 55). <https://doi.org/10.1353/csd.2014.0071>
- Oyedemi, T. (2015). Participation, citizenship and internet use among South African youth. *Telematics and Informatics*, 32(1), 11–22. <https://doi.org/10.1016/j.tele.2014.08.002>
- Panigrahi, R., Srivastava, P. R., & Sharma, D. (2018). Online learning: Adoption, continuance, and learning outcome—A review of literature. *International Journal of Information Management*, 43, 1–14. <https://doi.org/10.1016/j.ijinfomgt.2018.05.005>
- Papazov, E., & Mihaylova, L. (2015). Organization of Management Accounting Information in the Context of Corporate Strategy. *Procedia - Social and Behavioral Sciences*, 213, 309–313. <https://doi.org/10.1016/j.sbspro.2015.11.543>
- Papworth, R. (2016). a Multi-Disciplinary, Social Constructivist Approach To Promoting Student Engagement, Retention and Achievement in Higher Education. *Dialogue (1311-9206)*, (3), 52–68. Retrieved from <http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=119027799&site=bsi-live>
- Park, S. H., Yoo, H., Kim, K. B., & Lee, T. J. (2018). Perceptions of university students of ‘tourism-focused English’ as a second language: The case of Korean universities. *Journal of Hospitality, Leisure, Sport and Tourism Education*, 23, 59–69. <https://doi.org/10.1016/j.jhlste.2018.05.001>
- Perugini, M., Gallucci, M., & Costantini, G. (2018). A Practical Primer To Power Analysis for Simple Experimental Designs. *International Review of Social Psychology*, 31(1). <https://doi.org/10.5334/irsp.181>
- Petter, S. (2018). “Haters Gonna Hate”: PLS and Information Systems Research. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems*, 49(2), 10–13. <https://doi.org/10.1145/3229335.3229337>
- Pinho, C., Franco, M., & Mendes, L. (2018). Web portals as tools to support information management in higher education institutions: A systematic literature review. *International Journal of Information Management*, 41, 80–92. <https://doi.org/10.1016/j.ijinfomgt.2018.04.002>
- Pinto, L. H., & Ramalheira, D. C. (2017). Perceived employability of business graduates: The effect of academic performance and extracurricular activities. *Journal of Vocational Behavior*, 99, 165–178. <https://doi.org/10.1016/j.jvb.2017.01.005>
- Polizzi, G. (2020). Digital literacy and the national curriculum for England: Learning from how the experts engage with and evaluate online content. *Computers and Education*, 152, 103859. <https://doi.org/10.1016/j.compedu.2020.103859>
- Rashid, T., & Asghar, H. M. (2016). Technology use, self-directed learning, student engagement and academic performance: Examining the interrelations. *Computers in Human Behavior*, 63, 604–612. <https://doi.org/10.1016/j.chb.2016.05.084>
- Razhivina, M., Yakimovich, B., Korshunov, A., Tyurin, I., & Zagoruiko, I. (2016). Features of

- information support processes integration of organization and management in the RF machine-building complex. *Procedia Engineering*, 149, 421–424. <https://doi.org/10.1016/j.proeng.2016.06.687>
- Recker, J., Rosemann, M., Green, P., & Indulska, M. (2011). Do ontological deficiencies in modeling grammars matter? *MIS Quarterly: Management Information Systems*, 35(1), 57–79. <https://doi.org/10.2307/23043489>
- Rieh, H. Y., & Rieh, S. Y. (2005). Web searching across languages: Preference and behavior of bilingual academic users in Korea. *Library and Information Science Research*, 27(2), 249–263. <https://doi.org/10.1016/j.lisr.2005.01.006>
- Runaas, L., Hanauer, D., Maher, M., Bischoff, E., Fauer, A., Hoang, T., ... Choi, S. W. (2017). BMT Roadmap: A User-Centered Design Health Information Technology Tool to Promote Patient-Centered Care in Pediatric Hematopoietic Cell Transplantation. *Biology of Blood and Marrow Transplantation*, 23(5), 813–819. <https://doi.org/10.1016/j.bbmt.2017.01.080>
- Shanks, G., Tansley, E., Nuredini, J., Tobin, D., & Weber, R. (2008). Representing part-whole relations in conceptual modeling: An empirical evaluation. *MIS Quarterly: Management Information Systems*, 32(3), 553–573. <https://doi.org/10.2307/25148856>
- Shanks, G., Tansley, E., & Weber, R. (2003). Using ontology to validate conceptual models. *Communications of the ACM*, 46(10), 85–89. <https://doi.org/10.1145/944217.944244>
- Sieber, V., Anthoney, J., Barker, H., & Roberts, E. (2017). Information Literacy in a Digital Age: Embedding Information Literacy in the Curriculum. In D. Baker & W. B. T.-T. E. of W. Evans (Eds.), *The End of Wisdom?: The Future of Libraries in a Digital Age* (pp. 135–140). <https://doi.org/10.1016/B978-0-08-100142-4.00015-4>
- Snyder, I., & Prinsloo, M. (2007). Young people's engagement with digital literacies in marginal contexts in a globalised world. *Language and Education*, 21(3), 171–179. <https://doi.org/10.2167/le745.0>
- Sun, Y., Jiang, H., Hwang, Y., & Shin, D. (2018). Why should I share? An answer from personal information management and organizational citizenship behavior perspectives. *Computers in Human Behavior*, 87, 146–154. <https://doi.org/10.1016/j.chb.2018.05.034>
- Sweeney, M. T., & Oram, I. (1992). Information technology for management education: The benefits and barriers. *International Journal of Information Management*, 12(4), 294–309. [https://doi.org/10.1016/0268-4012\(92\)90036-P](https://doi.org/10.1016/0268-4012(92)90036-P)
- Ting, Y. L. (2015). Tapping into students' digital literacy and designing negotiated learning to promote learner autonomy. *Internet and Higher Education*, 26, 25–32. <https://doi.org/10.1016/j.iheduc.2015.04.004>
- Urquhart, C., Thomas, R., Spink, S., Fenton, R., Yeoman, A., Lonsdale, R., ... Rowley, J. (2005). Student use of electronic information services in further education. *International Journal of Information Management*, 25(4), 347–362. <https://doi.org/10.1016/j.ijinfomgt.2005.04.006>
- van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2015). Toward a Multifaceted Model of Internet Access for Understanding Digital Divides: An Empirical Investigation. *Information Society*, 31(5), 379–391. <https://doi.org/10.1080/01972243.2015.1069770>
- Venturini, S., & Mehmetoglu, M. (2019). Plssem: A stata package for structural equation modeling with partial least squares. *Journal of Statistical Software*, 88(1). <https://doi.org/10.18637/jss.v088.i08>
- Verdonck, M., Gailly, F., Pergl, R., Guizzardi, G., Martins, B., & Pastor, O. (2019). Comparing traditional conceptual modeling with ontology-driven conceptual modeling: An empirical study. *Information Systems*, 81, 92–103. <https://doi.org/10.1016/j.is.2018.11.009>
- Vinzi, V. E., Trinchera, L., & Amato, S. (2010). PLS Path Modeling: From Foundations to Recent Developments and Open Issues for Model Assessment and Improvement. In *Handbook of Partial Least Squares* (pp. 47–82). https://doi.org/10.1007/978-3-540-32827-8_3
- Walraven, A., Brand-Gruwel, S., & Boshuizen, H. P. A. (2009). How students evaluate information and sources when searching the World Wide Web for information. *Computers and Education*, 52(1), 234–246. <https://doi.org/10.1016/j.compedu.2008.08.003>

- Wand, Y., Storey, V. C., & Weber, R. (1999). An Ontological Analysis of the Relationship Construct in Conceptual Modeling. *ACM Transactions on Database Systems*, 24(4), 494–528. <https://doi.org/10.1145/331983.331989>
- Weng, B., Lu, L., Wang, X., Megahed, F. M., & Martinez, W. (2018). Predicting short-term stock prices using ensemble methods and online data sources. *Expert Systems with Applications*, 112, 258–273. <https://doi.org/10.1016/j.eswa.2018.06.016>
- Wilson, T. D. (1999). Models in information behaviour research. *Journal of Documentation*, 55(3), 249–270. <https://doi.org/10.1108/EUM0000000007145>
- Wilson, T. D. (2006). On user studies and information needs. *Journal of Documentation*, 62(6), 658–670. <https://doi.org/10.1108/00220410610714895>
- Xu, F., & Du, J. T. (2019). Examining differences and similarities between graduate and undergraduate students' user satisfaction with digital libraries. *Journal of Academic Librarianship*, 45(6), 102072. <https://doi.org/10.1016/j.acalib.2019.102072>
- Zhou, H., Xiao, L., Liu, Y., & Chen, X. (2018). The effect of prediscussion note-taking in hidden profile tasks. *Journal of the Association for Information Science and Technology*, 69(4), 566–577. <https://doi.org/10.1002/asi.23976>
- Zhu, Y. Q., Chen, L. Y., Chen, H. G., & Chern, C. C. (2011). How does Internet information seeking help academic performance? - The moderating and mediating roles of academic self-efficacy. *Computers and Education*, 57(4), 2476–2484. <https://doi.org/10.1016/j.compedu.2011.07.006>

Appendix A: Measurement instrument - Questionnaire

INFORMATION USER (IU)	
IU1	I attend all my classes at the university
IU2	I copy all my notes and print out all my handouts
IU3	I do all my assignments and deliver them on time
IU4	I take an active part in group assignments and class presentations
IU5	I often do extra reading to improve or complete my knowledge in my field of study
INFORMATION NEED (IN)	
IN1	I often look for information online when I have a problem to solve
IN2	I often seek information online I need to complete my knowledge on a course
IN3	I often look for information online when I have an assignment or class presentation to do
IN4	I often search for information online to update my notes
IN5	I seek information online mostly for general knowledge purposes
IN6	I often seek information online when my instinct tells me to do it
IN7	I am mainly looking for information online when I have to do it to succeed in an exam
INFORMATION SEEKING (IS)	
IS1	I use the Internet through my laptop and smartphone to seek relevant information online
IS2	I search for specific or well-known sources when I search for information on the Internet
IS3	I have strategies that I use to search for information using digital technologies
IS4	I mainly use semi-structured research when I consult information online
IS5	I often look for information online using precise search techniques
IS6	I mainly looking for information online when I am employed by a classmate or a teacher
DIGITAL INFORMATION EXCHANGE (DIE)	
DIE1	I use digital technologies to exchange information with friends and classmates
DIE2	I often use digital technologies to send my homework to teachers
DIE3	I often use digital technologies to collaborate on group work and homework with my classmates
DIE4	I often use digital technologies for distance learning purposes
DIE5	I belong to several online groups where we exchange on school work
DIE6	I use digital technology to exchange only with people who are looking for similar information
DIE7	I use digital technology to interact with people who may be interested in similar information
DIGITAL INFORMATION SOURCES (DIS)	
DIS1	I often check the accuracy of information obtained from digital information sources
DIS2	I know how to filter the amount of information obtained from digital information sources
DIS3	I can selectively identify relevant documents in a digital information source
DIS4	I know it when I have the information I need from digital information sources
DIS5	I often trust the information I get from digital information sources
DIS6	I often download information obtained from digital sources
DIS7	I find the information obtained from digital sources easy to use
INFORMATION SHARING (ISH)	
ISH1	I often share information obtained after a work session with my peers using digital technologies
ISH2	I like to share information obtained after a work session with my peers using digital technologies
ISH3	I like to share information obtained using digital technologies only if I am satisfied
ISH4	My satisfaction with information determines my enthusiasm to share information
ISH5	My satisfaction with the quality of the work done using digital technologies determines my enthusiasm to share information
INFORMATION USE (IUS)	
IUS1	I use the information I obtained using technology to solve the problems I face with school work
IUS2	Information obtained using technology makes it easier for me to understand my lessons
IUS3	I often store the information I have obtained using digital technologies for future use

IUS4	Information obtained online often helps me make better decisions during school projects
IUS5	I use information obtained online to improve my ideas during group work
USER SATISFACTION (USAT)	
USAT1	I am often satisfied when using information I obtain from digital resources
USAT2	I am often satisfied with the information I obtain using my information seeking strategies
USAT3	I have a better experience when using digital information during work sessions
USAT4	I am often satisfied with the quality of the information I get from digital information sources
USAT5	I often share the information I am satisfied with using digital technologies
USAT6	I often use the information I'm satisfied with, obtained using digital technologies
ACADEMIC PERFORMANCE (IAP)	
IAP1	I perform better in courses where I relied more on digital information resources
IAP2	My academic performance has increased since I started using information obtained digitally
IAP3	I think my performance in school will improve if I use digitally-obtained information to learn more often