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Modeling the Measurements of the Determinants of ICT Fluency and Evolution of Digital Divide Among Students in Developing Countries—East Africa Case Study

Jean-Pierre Niyigena [1,2], Qingshan Jiang [1,*], Djemel Ziou [1,3], Ruey-Shiang Shaw [4] and A S M Touhidul Hasan [5]

1 Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen 518055, China; jeanpierre@siat.ac.cn (J.-P.N.); djemel.ziou@usherbrooke.ca (D.Z.)
2 Shenzhen College of Advanced Technology, University of Chinese Academy of Sciences, Beijing 100049, China
3 Department of Computer Science, University of Sherbrooke, Sherbrooke, QC J1K2R1, Canada
4 Department of Information Management, Tamkang University, New Taipei 25137, Taiwan; rsshaw@mail.tku.edu.tw
5 Department of Computer Science and Engineering, University of Asia Pacific, Dhaka 1205, Bangladesh; touhid@uap-bd.edu
* Correspondence: qs.jiang@siat.ac.cn; Tel.: +86-0755-8639-2340

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Featured Application: This article creates a paradigm for future studies on measuring the determinants of ICT fluency and the evolution of the digital divide among higher education students in developing countries.

Abstract: During the last decade, information and communication technology has brought remarkable changes to the education style of developed countries, especially in the context of online learning materials accessibility. However, in developing nations such as the East African (EA) countries, university students may lack the necessary ICT training to take advantage of e-learning resources productively. Therefore, the comprehension of the key factors behind ICT fluency is a significant concern for this region and all the developing countries in general. This paper applies the Concentration Index and proposes a Logistic Regression based model to discover the key determinants of ICT fluency and to explore the evolution of the digital divide among EA students within the four years of undergraduate studies. To identify the principal determinants, data composing of 1237 participants is collected from three different universities in EA within a one year period. The experimental results indicate that the digital divide among students decreases quite fast from the first year to the fourth year. Regression computational findings show that the key determinants of ICT fluency are the student urban/rural origin, computer ownership, computer experience, class year, and major. The findings provide heuristic implications for developers, practitioners, and policy makers for an improved ICT environment implementation in EA and the developing nations in general.

Keywords: logistic regression; concentration index; digital divide; factors of ICT fluency; East Africa

1. Introduction

Information and Communication Technology (ICT) has become indispensable in the daily lives of many; it is transforming the way students are educated by supporting their learning and helping them to meet their informational needs by providing cost-effective education regardless of time and geographical boundaries [1,2]. At present, ICT usage has proliferated in many developed countries, owing to the fact of its potential to facilitate learning, even reduce poverty, foster growth, and increase the living standards. However, despite its achievement in developed countries, ICT still holds an enormous pledge for the future world generations in developing countries, especially in African nations, by promising a favorable education [3].

Numerous studies have shown that technology usage is not equal or proportionate all over the world. Sife [4] and Tabira [5] point out that there is a tangible digital divide in technology across the world where some factors (e.g., continent, country, personal income level or capacity, educational background, gender, and age), among students, specifically impact the access to and usage of online learning resources. In addition, given the pace at which technology has been adopted, several people in the developing countries have had little (or no formal) education or preparation on how to use it effectively. Many people have a limited understanding of the technologies they use and/or they are often underutilizing them. Even when in a group of people, all have access to technology, it is very likely that only a small portion may be able to use it fluently [6].

In developed countries, ICT skills significantly help the students to benefit from the distribution of education especially in the context of the higher education sector. However, in developing nations, numerous research indicate that most university students lack the necessary technology skills to take similar advantages and the digital divide is still an issue (EA as an example) [7–9]. On this account, an in-depth understanding of the determinants of ICT fluency and an investigation into the evolution of the digital divide are significant concerns for the EA and the developing countries in general.

In regard to ICT fluency and digital divide in EA, few studies have been conducted in the context of higher education, but no study predicted the determinants of technology fluency to understand better the influences of EA regional local characteristics on undergraduate students' technology skills. Most of the studies used, instead, empirical descriptive statistic methods that describe the undergraduate students' barriers and enablers to technology skills [10–13]. This paper claims that further studies are needed to understand the reality better and it steps forward by developing one model to study the determinants of ICT fluency and the other to explore the evolution of digital inequalities by class year (1st year to 4th year). The two models are assessed on EA undergraduate students considering the local characteristics.

The contribution of this article is to, by integrating individual local characteristics, achieve a better understanding of the determinants of ICT fluency among EA undergraduate students. Moreover, it documents the evolution of the digital divide among them, which is beneficial to educational practitioners and policy makers in getting insights into their role to play, thus, providing excellent ICT infrastructures, increasing Internet penetration, and motivating the students to adopt technology more.

1.1. Research Aims

Similarly to other developing nations, the EA countries are in the middle of fast technological change and a high percentage of the universities have access to the Internet. However, earlier studies have reported that learning technology is not well integrated within the relatively new higher education sector. This study takes EA students as a sample and develops a model incorporating the local factors to document the determinants of ICT fluency among undergraduate students in developing countries (RQ1). In Africa, the sub-Saharan region in particular, has been less covered in terms of digital divide studies while, according to the United Nations Development Program, this region ranks the least developed in the world in terms of educational attainment, life expectancy, and income [14]. Based on the students' class year aspect, this study investigates digital inequality evolution among EA students from the first year to the fourth year of undergraduate studies (RQ2).

- RQ1: What are the determinants of ICT fluency among developing countries undergraduate students from the 1st year to the 4th year?
- RQ2: How do digital inequalities evolve among students during these four years of undergraduate studies?

1.2. EA Context

In this paper, the words East Africa (EA) refer to East African Community (EAC), a region which is composed of six partner developing countries, including the United Republic of Tanzania, the Republics of Burundi, Kenya, Uganda, Rwanda, and South Sudan. The headquarters are located in Arusha, Tanzania [15].

With a land area of 1.82 million square kilometers and a combined gross domestic product of US$ 146 billion (EA Statistics for 2016), the EA realization bears great strategic and geopolitical significance and prospects for the renewed and reinvigorated EA. Today, EA is one of the fastest-growing regional economic blocs in the world [15]. At the beginning of the 2017-2018 academic year, there was a total of 84,000 university students enrolled in different EA states, of which 35% are female, and 65% are male [16].

The rest of this paper is organized as follows. In Section 2, we look into the recent research on ICT and the digital divide in EA and the developing countries in general. Section 3 reviews the problem definition and formulate the measurements. Section 4 describes the research setting which includes the dataset and the research hypothesis. Section 5 contains the computation models of ICT fluency and the digital divide proposed. Findings and discussions are presented in Sections 6 and 7, respectively. Limitations and future recommendations are discussed in Section 8. Finally, Section 9 provides concluding remarks and practical research implications.

2. Literature Review

This paper focuses on the determinants of ICT fluency, and the evolution of digital inequalities. In the following literature, earlier studies on ICT are mentioned, but the goal remains the same, which is just elaborating on practical dimensions of ICT fluency determinants and digital inequalities in developing countries. Specifically, this section covers the following topics: Factors influencing students' ICT fluency, digital divide concept and prior research, and online learning in EA. In this study, the words digital divide and digital inequality bear a similar meaning and they are used interchangeably.

2.1. Factors Affecting Students' ICT Fluency

The term ICT fluency refers to ICT skills, i.e., the level of proficiency and understanding in the concepts of Information and Communication Technologies [17]. According to the literature, factors such as gender, student urban/rural origin, class year, major, ICT educational experience, parent encouragement, and English language level often influence ICT fluency among students [18–23]. Table 1 contains the background research of factors affecting students' ICT fluency.

Table 1. Factors affecting students' Information and Communication Technology (ICT) fluency.

Factor	Background Research
Parent encouragement	Parents and family are the other vital factors that affect students' attitudes over computers. In the study of first-year students in Iran and Taiwan, respectively. C. Liu [21] and Zhan [24] found that access to computers with the help of parents helped students develop their computer skills and that students with educated parents expressed the tendency to have more knowledge and confidence over utilizing computers. Despite this, students' interest and confidence in computer work have decreased, especially for girls, who think their parents possess stereotyped views over computers. The previous study found that there are gender differences in the way parents encourage their children to use technology, indicating that parents are more protective of girls than boys. A study conducted by Alothman [18] on the use of the Internet and television in EA students revealed that parents minimize or limit the use of the Internet in their girls more than in sons.

Table 1. *Cont.*

Factor	Background Research
Gender	The researchers found a continuing dissimilarity among females and males in their anxiety levels associated with using ICT in EA universities. While most students described themselves as confident or very confident with ICT, at least 17% of females compared to 25% of males reported being apprehensive or very apprehensive about using ICT as after the first year of their college studies [5,25]. Braten and Stromso [20] study also unveils the evidence that ICT usage varies by gender. For example, females report that they use computers predominantly for communication, while males say they use it for entertainment. The use of ICT for school work is higher among males than among females. In addition to usage, confidence levels associated with ICT also vary by gender. Males tend to rate their ICT fluency higher than females. Researchers have found large gaps between the reality and perception of students' fluency with ICT in developing countries [22,23]. Most undergraduate students report that they have excellent technology skills. Similarly, faculty and administrators often expect students to be fluent with technology [22,23]. However, Sakellariou [19] found that college students do not generally perform at perceived levels. They contend that many college students graduate without the technical skills necessary to be successful in the workplace because of weak ICT education.
Student urban/rural origin	The literacy rate in urban Africa is higher than in rural areas [26]. In urban areas, the population without a formal education is between 16% and 18%, and everyone among them can read and write. However, it is estimated that half of the rural population does not obtain any formal education. Rural schools and their teachers have very little experience [26]. As a result, most rural residents lack the skills to use standard software packages since they have no digital learning in schools. Moreover, there are cultural differences between rural and urban areas, which can affect the acceptance of the technology. Many EA cities have several people with different origins. This differs from the villages and small towns, which have many families with traditional conservative traditions [27].
Class year	In a progress report on the study, Alothman [18] identified two factors that influenced the California State University (CSU) students' information competence. First, breadth and depth responses were related to student class year. That is, students' skills and knowledge increased throughout their college career. This reinforced the important role that education plays in developing information competency. Second, there was a relationship between breadth and depth scores and race/ethnicity with Asians underperforming Whites, Hispanics, and African Americans, respectively. Researchers concluded this underperformance, in part, was related to a language barrier since English was a second language for many of the Asian students.
ICT educational experience	Previous studies revealed that computer anxiety is associated with computer experience [28]. Past experience with computers reduces anxiety and increases self-confidence when utilizing them. A research of 70 Turkish students stated that students with over four years of computer experience are more self-confident in using computer software and other digital equipment than those with less previous experience [29]. Research by Korobili [30] indicates that the level of anxiety of Greek students over computers changes according to their computer experience and how often they use computers. The researchers revealed that students who owned computers since high school, as well as who use them regularly, have less anxiety over computers. Bakers and Schmidt conducted research of 184 students in the Netherlands to study the evolution of computer anxiety [31]. They found that enjoying a computer for the first time, when the user feels in control, is associated with upcoming computer experience, which is also associated with subsequent lower anxiety levels.

Table 1. *Cont.*

Factor	Background Research
Major	Educators have recognized that students' ICT skills and needs also vary by major/discipline [12]. While most colleges and universities have ICT courses designed for non-majors, a number of them offer discipline/major-specific courses. For example, the Computer Science Department at the University of Furman offers separate sections of its information literacy course for four different majors: art, business, education, and the natural sciences [5]. They find that these specific sections enable discipline specific needs to be addressed while still covering the essential ICT concepts.
English language level	International students may find language barriers when using technology, as many computer programs utilize English and can be expressed in an unusual way. Therefore, before a student uses technology to complete his/her homework, he/she must first learn the basics of the language used in that software [5]. Rizvi [12] conducted research on English language skills as an influence on students' attitudes. Students having a better knowledge of the English language claimed to have more positive attitudes towards computers. N. Li [32] compared the opinions of Chinese and British students on the Internet; some Chinese students said they did not want to utilize the Internet because many websites were in the English language, and they have no cultural interchange because of language barriers.

2.2. Digital Divide Concept and Prior Research

After the release of the reports of "Falling Through the Net" [33,34], the phenomenon of the digital divide began to gain attention among governments and researchers [35]. Although, several researchers associated its denomination with Larry Junior, the US Assistant Secretary for Information and Communication, however, the real origin of the "digital divide" denomination is still unknown [36,37].

At first, the digital divide was understood as a gap between those who could access ICT and those who could not [38]. It was, therefore, suggested that solving the problem of the digital divide is just accommodating access to ICT. Ignoring that access is only the first step, and there is no guarantee of continued use [39,40]. However, when the researchers began to go beyond the access differences, the original definition declined and the concept of the digital divide was extended [38]. At present, understanding this subject requires not only to integrate the disproportions relating to access to ICT but also the different ways of using it [36].

In 2005, Jan van Dijk [41] conducted research that illustrated that the digital divide is far from closed in the world and it was still widening in developing countries. Moreover, he contended that the digital divide is deepening in developed countries for the reason that the physical access gap had ceased widening. Another study by Hargittai [42] concluded that in order to bridge the digital divide universally, the necessary online skills should be achieved by focusing policy not only on improving access but also investing in training. As an example, he stated that although there has been a rapid increase in the number of public schools offering Internet access during the years 2000 in USA, the support for the necessary training and staffing had lagged at the moment.

Several studies on the digital divide have taken into account the digital divide at the global level. Brandtzaeg [43] and Labrianidis [44] investigated the digital divide across the countries of the European Union and concluded that digital inequality reflects the social-economic differences between the Member States. Antonio and Tuffley [35] conducted a cross-national survey on the distribution of personal computers and the Internet, revealing that the distribution of these technologies was at a very low level in the developing countries. Apart from global digital inequalities, a country can also present a domestic digital divide, that is, differences between regions or groups of its people. During the Antonio and Tuffley [35] research process, the first study investigated into personal computers and internet distribution in the demographic and socioeconomic context, based on the following factors: age, gender, ethnicity, education, income, and geography. It was concluded that inequalities in access are mainly due to differences in the levels of education and income. However, later, some researchers started to put their attention on user behavior once access has been provided. As for access, income and education eventually remained the significant predictors of the use of ICT.

Researchers have also shown that some models of technology adoption can be used to understand the digital divide. Hsieh, Rai, and Keil [37] partitioned the theory of planned behavior (TPB) to get insight into the user adoption of ICT in the social-economically advantaged groups and the not advantaged. The authors suggested that various factors influence the intention of continued use for the two groups, where hedonic outcomes and attitude possessed a more significant influence on the not advantaged groups. Niehaves and Plattfaut [45] compared two theories, namely the unified theory of acceptance and use of technology (UTAUT) and the model of adoption of technology in households (MATH). In the aspect of the digital divide related to age in the acceptance of the Internet by the elderly, MATH and UTAUT could both describe Internet acceptance. However, UTAUT was more likely feasible while MATH showed a more significant explanation.

Recently, the debate on the digital divide focused on other factor elements, namely the skills for using ICT and digital inclusion—defined as a way to empower people through ICTs [46]. However, the existing digital divide due to differential access to ICT tools, low digital literacy, and lack of sustainable usage is the greatest hindrance to digital inclusion. Upadhyaya [46] conducted a study aimed at finding a suitable location-specific strategy to bridge the digital divide in India. His study revealed that the problem and solution for the local communities are different with respect to access, skills, and usage of ICT. Therefore, he concluded that there is no suitable overall digital inclusion strategy for the whole developing world, which is on the way to becoming tech savvy. Van Dijk [38,41] conducted a study that revealed that the digital divide is composed of four categories of access: skills, physical, motivational, and usage. He concluded that the first three are the essential condition for the actual ICT use. Ferro, Helbig, and Gil-Ga's [47] research claimed that the impact of ICT literacy on Internet use is more influential than age, income, and owning a home personal computer. According to these authors, ICT literacy is considered as a factor of the digital divide.

Researchers have also explored the digital divide in developing countries such as the African nations. For example, Bornman [48] used technology acceptance model (TAM) to study the difference in adoption and usage of Internet in Southern Africa (SA) and concluded that social and economic history influence technology exposure. Brown and Licker [49] assert that individual internet use in SA is much lower compared with other developing nations such as South Asian countries. Igbo and Imo [50] reported that relating to the e-government, Nigeria had a multidimensional digital divide. Another study revealed that income has been shown to be the main driver of the household Internet [51].

The literature demonstrates that the digital divide is both a complex and broader topic, it does not just only imply technology access, as a matter of fact, it can be considered as a multidimensional subject that requires a comprehensive analysis of the social, psychological, and cultural factors that underlie it.

2.3. Online Learning in EA

This subsection attempts to describe the difference between e-learning and online learning, the latter's current state in EA and other developing countries in general. It also talks about Synchronous Online Interactive Education (SOIE), its understanding and current state in developing countries.

Online learning refers to getting the learning experience by using the Internet. The learners must use some techniques such as online talking software tools to get this studying experience. However, e-learning refers to a form of learning where the students take a course from the teacher without physically visiting an actual classroom with him. Both of them (students and teachers) communicate and learn the courses online even if they are on the same premise. Mostly, e-learning is performed in a classroom or an online setting [52].

From the last decade, the EA higher education sector continued to narrow the gap between online courses and the long-established face-to-face course style. Awidi and Cooper [9] indicate that despite the scarcity of infrastructure, the number of students taking online courses has continued to increase since 2010. Wanstreet [53] mentions that there are a few differences between online learning and face-to-face teaching style environments. She stated that the constructivist online learning environment could reproduce the same interactions of learner-to-learner, teacher–learner, and learner with the course content. In a survey conducted by Rizvi et al. [12] in EA, students responded that the performance of online courses relies on improving dialogue, writing, and critical thinking in a way that is not available in many face-to-face classrooms. For those who are often quiet and shy students, compared to the more extroverted and outgoing students who lead the classroom conversations, face-to-face teaching is hard to make the students feel comfortable and perform well. Unlike participation in a large classroom, online discussion allows them to talk freely, without literally talking in front of a peer group.

Martin, Wang, and Sadaf [54] found SOIE as an effective online learning method. SOIE differs from face-to-face instruction and asynchronous online learning because it contains bidirectional real-time video/audio components. Martin et al. [54] also stated that 86% of instructors agreed or strongly agreed that social interactions from SOIE are productive and the dynamic learning feature, active discussion, immediate feedback, and a personal familiarity that the learner can only get through that real-time interaction are significantly meaningful. Moreover, their research revealed that the "good" experience depends largely on the ease of use of the technology, the degree of skills, and the ready-to-use teachers. Continuance of participation in discussions and detailed expectations facilitate the student's comprehension of their role in leading the course [55].

When asked about the efficacy of the SOIE, the students point out that the teacher's effectiveness in real-time synchronization courses depends more on the teacher's help rather than the design of the course or program. Martin et al.'s [54] study also indicates that the students' evaluations of courses using the SOIE method are positive. The most convincing and compelling evidence was revealed during their research that appeared in the students' assessment. Specifically, of the levels 1–5, where one (1) is the lowest and five (5) is the highest, the average of the overall experience given by the students is 4.24. Students, in particular, singled out that learning by using the SOIE method encourages the students–teachers contact, and strengthens the cooperation among the students as SOIE positive attributes. Currently, many developing countries do not accommodate the necessary infrastructures to take advantage of learning by using SOIE.

3. Problem Definition and Measurements

The current measurement models of the digital divide and ICT skills among students were designed firstly by focusing on developed countries. Later, the models were adopted as cross-national and their assessment results have always been integrated into the authentic contexts that reflect the real students' experiences in whatever nation those models are applied in [56]. However, in any assessment of a measurement model, the goal should be to provide the real experience from the participants and the context should reflect the familiar situations that they are accustomed to. So far, it is unclear to what extent the models designed for the developed countries' contexts maintain authenticity when they are implemented in developing (low or middle-income) nations [56]. It is of value to point out that the students in those countries may have different experiences. Similarly, this is a problem that can arise when assessing any group of individuals with a socioeconomic life that is different from the others (e.g., minority groups) within any country. As an example, in 2013, the IEA International Computer and Information Literacy Study (ICILS) conducted an ICT skills assessment, the results revealed that, for Thailand and Turkey, the only countries that were assessed with lower ICT development, high school students in the first year have a very low level of ICT skills compared to all other countries that participated in the assessment [57]. In low-income countries, technology access tools at school are insufficient, making it often impossible for students to rely on school computers. Therefore, cross-national measurement models may lead to inadequate conclusions and there is a need for models that integrate developing countries' local and regional contexts. Such models could achieve cross-group (e.g., gender in socioeconomic groups), cross-country, and over-time digital divide and ICT skills comparisons [56].

Referring to the previous study, commonly used methods to find the most influential variables and to study the digital divide are Logistic Regression (LR) and Concentration Index (CI), respectively [13,15,16,58]. This paper follows a similar approach to investigate the determinants of technology fluency among the EA undergraduate students by class year (1st year to 4th year) using an LR based model [11,12]. Moreover, it uses CI to model the evolution of digital inequalities [13]. A combination of LR and CI in the presence of binary variables is known to perform a better analysis of key factors and to explicitly explore the variations of inequalities among individuals [59–62].

3.1. Inequality Measurements CI and C_N

The Concentration Index (CI) is a statistical measure commonly used as a measurement of inequality. A CI of zero expresses perfect equality, where all values are the same (e.g., where every student has the same ICT fluency, that is, no digital inequality). A CI of 1 (or 100%) expresses maximal inequality among values (e.g., for a large number of students, where only one student is ICT fluent, the CI will be very nearly one). In order to formulate the CI, we assume that the change in the independent variables can explain interpersonal variations between the dependent variables. Under this assumption, the CI can be acquired using a linear regression model linking the variables y and x by developing Equation (1) as follows [63]:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \boldsymbol{\alpha} + Z \begin{bmatrix} \varnothing_1 \\ \varnothing_2 \\ \vdots \\ \varnothing_l \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix} \tag{1}$$

where the observation matrix $Z = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1l} \\ x_{21} & x_{22} & \cdots & x_{2l} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nl} \end{bmatrix}$.

Equivalently, for the p^{th} student, the above equation can be rewritten as Equation (2):

$$y_p = \alpha_p + \sum_{q=1}^{l} \phi_q x_{pq} + \varepsilon_p \tag{2}$$

where p = 1, ... , n; q = 1, ... , l; $\boldsymbol{\phi} = (\phi_1, \ldots, \phi_l)'$, and $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_n)'$ are the regression coefficients; $\boldsymbol{y} = (y_1, \ldots, y_n)'$, and $\boldsymbol{\varepsilon} = (\varepsilon_1, \ldots, \varepsilon_n)'$ is the error term. Given the matrix Z, ϕ and α can be estimated using existing algorithms such as the least square method [64].

We will now derive the C_q and the concentration index for the q^{th} variable, where the related observations are $x_q = (x_{1q}, \ldots, x_{nq})$ such that $x_{1q} \leq \ldots \leq x_{nq}$. Let us consider that the components of $\boldsymbol{y}$ are also ranked from lowest to highest. The Cq index is a similarity measure between $\boldsymbol{y}$ and x_q defined as the normalized and shifted inner product as Equation (3) [65,66]:

$$C_q = \frac{2}{n\mu} \sum_{p=1}^{n} y_p x_{pq} - 1 \tag{3}$$

where μ is the mean of y components and $q = 1, \ldots, l$. Given the regression parameters ϕ_p, the arithmetic mean $\overline{x}_q$ of x_q, the CI is the weighted sum of C_q up to some additive term as Equation (4) [63,67].

$$CI = \sum_{q=1}^{l} \left(\frac{\phi_q \overline{x}_q}{\mu} \right) C_q + \frac{G_\varepsilon}{\mu} \tag{4}$$

The second term on the right is the generalized concentration index for ε_p. It compensates the case where the CI cannot be explained by the observation x. It is calculated as:

$$G_\varepsilon = \frac{2}{n}\sum_{p=1}^{n} \varepsilon_p R_p,$$

The CI takes its values in the interval [−1, +1], −1 means inequality favoring the worse off and +1 means inequality favoring the better off. Let us consider $R_p = p/n$ the normalized rank of p^{th} sample. There are many ways to calculate the Concentration Index for need C_N, one of them is by Equation (5) [66]:

$$C_N = \frac{2}{n\mu}\sum_{p=1}^{n} y_p R_p - 1 \tag{5}$$

The CI for C_N takes its values in [−1, +1], −1 means inequality favoring the worse off and +1 means inequality favoring the better off.

3.2. Horizontal Inequality (HI)

Given a capacity s, we define $L(s)$ the resources available for him/her and $L_N(s)$ the required resources for his/her. The resources can be online resources utilization (ORU), number of computers, and Internet access. The *HI* index at s is the difference between $L_N(s)$ and $L(s)$. The deficit happens if what is required is greater than what is available as it is the case illustrated in Figure 1.

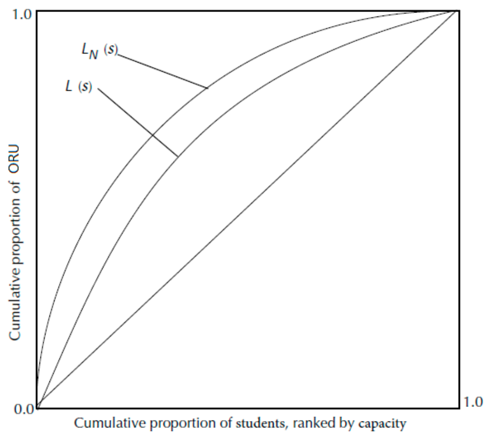

Figure 1. Concentration curves with L_N and L as a function of the capacity $s \in [0,1]$. Only s the diagonal line represents the cases where $L(s) = L_N(s)$.

In order to define a global *HI* measure, we used marginalization with regards to s as in Equation (6) [63]:

$$HI = 2\int_0^1 [L_N(s) - L(s)]ds = CI - C_N \tag{6}$$

The *HI* takes its values in the interval [−1, +1], −1 means inequality favoring the worse off and +1 means inequality favoring the better off.

3.3. ICT Fluency Determinants (IFE)

The goal was to estimate the IFE and to realize the interpretation in order to dress useful conclusions related to its determinants among different groups of students. To make the interpretation easier, we proposed a formalism allowing the estimation of their probabilities. Several methods could be used including Logistic Regression (LR) and Support Vector Machine (SVM) [68]. In this paper, LR was used since it outperforms SVM [59]. The Logistic Regression (LR) was used for the estimation of IFE for each student. To make the interpretation easier, we also estimated the probability for each student. In order to formulate the LR, we assumed that $x_{i1},\ x_{i2},\ldots,x_{il}$. Under this assumption, similar to Equation (2) the regression model linking the variables can be written as Equation (7):

$$y_i = \alpha + \sum_{q=1}^{l} \phi_q x_{iq} + \varepsilon_i \tag{7}$$

where $y_i = IFE_i + \varepsilon_i$, $i = 1, \ldots, n$, with n the total number of the participants, and l the total number of all considered variables.

Let us now deal with the probability. The IFE_i of a given student is associated with a binary variable t where it is one (1) if the IFE_i value is high and 0 otherwise. It follows that conditioned probability is given by Equation (8):

$$P_i = P(t = 1|y_i) = \frac{e^{y_i}}{1 + e^{y_i}} = \frac{e^{IFE_i}}{1 + e^{IFE_i}} \tag{8}$$

The probabilities P_i are used to categorize students' technology skills.

4. Research Setting

4.1. Dataset and Variables

The data were collected during the summer of 2019, through an online survey, from three universities located in EA countries—Kenyatta University (KU) in Kenya, University of Dar es Salaam (UDSM) in Tanzania, and University of Burundi (UB) in Burundi. Participants consist of a total of 1237 undergraduate students from seven different majors. Of the participants, 734 are males and 503 are females. By class year, the sample includes 477 freshmen, 407 sophomores, 195 juniors, and 158 seniors. Table 2 illustrates the sample variable parameters and the total number of all the students.

Table 2. East African (EA) universities students' data variables by class year, 2019.

Variable	Unit	1st Year	2nd Year	3rd Year	4th Year	Total
Total Students	n	12,021	9741	8014	6984	36,760
	(%)	32.70	26.50	21.80	19.00	100.00
Sample	***n***	**477**	**407**	**195**	**158**	**1237**
	(%)	**38.60**	**32.90**	**15.8**	**12.70**	**100.00**
Gender						
Male	(%)	58.66	59.41	62.90	60.51	94,235
Female	(%)	41.34	40.59	37.10	39.49	61,525
Age						
18–25	(%)	98.01	94.23	90.59	89.89	93.18
25–30	(%)	1.97	3.35	6.01	7.58	4.73
>30	(%)	0.02	2.42	3.40	2.53	2.10
Major (number of students)						
Humanities and Social Sciences	n	92	83	74	62	308
Education and External Studies	n	61	55	47	41	204
Architecture and Engineering	n	41	37	32	27	137
Health Sciences	n	30	27	23	20	100
Environmental and Geographical Sciences	n	56	51	43	38	188
Science and Mathematics	n	51	38	33	29	150
Food Technology, Nutrition and Bio-engineering	n	45	41	35	30	150

Table 2. *Cont.*

Variable	Unit	1st Year	2nd Year	3rd Year	4th Year	Total
Prior technology experience	%	11	42	70	98	55.25
Introduction to computers	*n*	47	232	288	421	987
Desktop applications (word processing, spreadsheets, presentations, etc.)	*n*	41	201	249	365	856
Windows or other operating systems	*n*	33	160	199	291	682
Internet or World Wide Web	*n*	29	142	177	258	606
Research, library, or information science	*n*	28	135	168	245	575
Email	*n*	24	117	146	213	500
Programming	*n*	16	78	97	141	332
Number of computers (per class year)	(%)	2.06	40.47	60.92	79.20	45.66
Students by class year	(%)	38.60	32.90	15.80	12.70	100.00
PC property						
Owners	(%)	4.25	12.00	18.01	29.82	16.02
No owners	(%)	95.75	88.00	82.99	70.18	83.8
Class year size	*n*	477.00	407.00	195.00	158.00	1237
Student origin						
Urban	(%)	35.82	32.26	31.14	30.22	32.36
Rural	(%)	64.18	67.74	68.86	69.78	67.70
Internet access						
Yes	(%)	37.92	55.20	69.81	85.54	62.12
No	(%)	62.08	44.8	30.19	14.46	37.88
Personal computer						
Yes	(%)	2.96	9.19	17.83	23.03	13.25
No	(%)	97.04	90.81	83.17	77.97	76.75
Parents						
Educational attainment	years	6.63	7.05	7.28	7.58	7.12
Family size	*n*	3.81	3.70	3.60	3.50	3.66
Income per capita	US$	297.47	348.15	377.57	415.64	357.46
Employment status						
Employed	%	95.25	96.24	96.57	96.86	96.20
Unemployed	%	0.10	0.06	0.06	0.06	0.07
Retired	%	4.75	3.76	3.43	3.14	3.80

Note: This sample is collected from 1237 students of three EA universities (KU, UDSM, and UB), summer 2019.

4.2. Research Hypothesis

The hypothesis of the study refers to ICT determinants and the evolution of digital inequality. It considers that ICT fluency among EA undergraduates is represented by the proxy variables of ICT usage and ICT access (computer ownership and Internet connection). The other hypothesis is that it occurs significant increases in technology fluency among EA students along the four years of undergraduate studies, mainly due to an increasing level of education and training on computer knowledge.

In the context of the inequality investigation, the assumption is that digital divide determinants among the students are related to two dimensions; individuals' characteristics (gender, age, location, family size, parent education, income, and employment status) and external factors (computer property, English language, major, students class year, and class year size).

The assumption that a student's rural/urban origin can be a good proxy for digital illiteracy among the EA students is based on Louw [69] and Brannstrom [39]. This is because the low ICT infrastructures and poor educational level in EA rural areas are still a challenge to be overcome, and digital illiteracy is just one piece of illiteracy.

5. ICT Fluency and the Digital Divide

We proposed one measure for ICT fluency, the other for the digital divide (CI and HI). For ICT fluency, we developed a logistic regression model to estimate the probability of fluency for each student. The probabilities will be used in order to define classes of students according to their ICT skills. For CI and HI, we used a linear regression model. These measures lead to the experimental research procedure represented in Figure 2. A combination of LR and CI in the presence of binary variables is known to perform a better analysis of key factors and to explicitly explore the variations of inequalities among individuals [59–62].

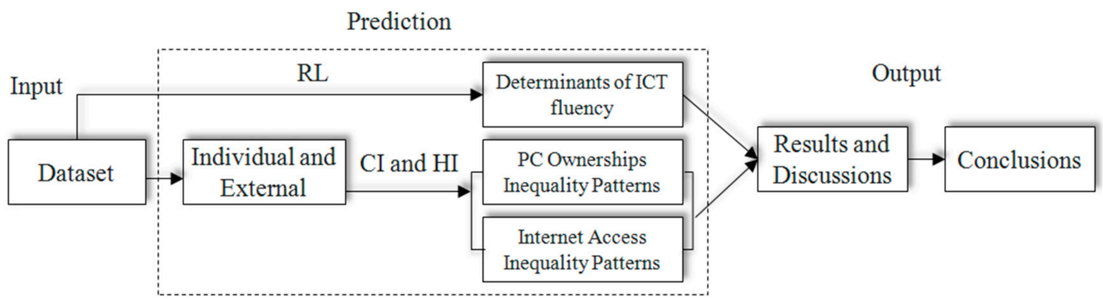

Figure 2. Data analysis and computation procedure.

5.1. Determinants of ICT Fluency

To estimate the ICT fluency (IFE) using Equation (7), we supposed that the total number of all considered variables (proxy variables of ICT usage and ICT access) were $x_{i1} = gender_i$, $x_{i2} = age_i$, $x_{i3} = classYear_i$, $x_{i4} = computerProperty_i$, $x_{i5} = computerAttitudes_i$, $x_{i6} = EnglishLanguage_i$, and $x_{i7} = location_i$. For all students, the coefficients $\boldsymbol{\phi} = (\phi_1, \ldots, \phi_l)'$ and $\boldsymbol{\alpha}$ are estimated by using the data in Table 2. In the computation, n = 1237 and l = 7. The model's parameters maximizing the likelihood are estimated according to variance–covariance matrices [70]. SPSS 25.0 and AMOS 20.0 are the software used for the computations [71].

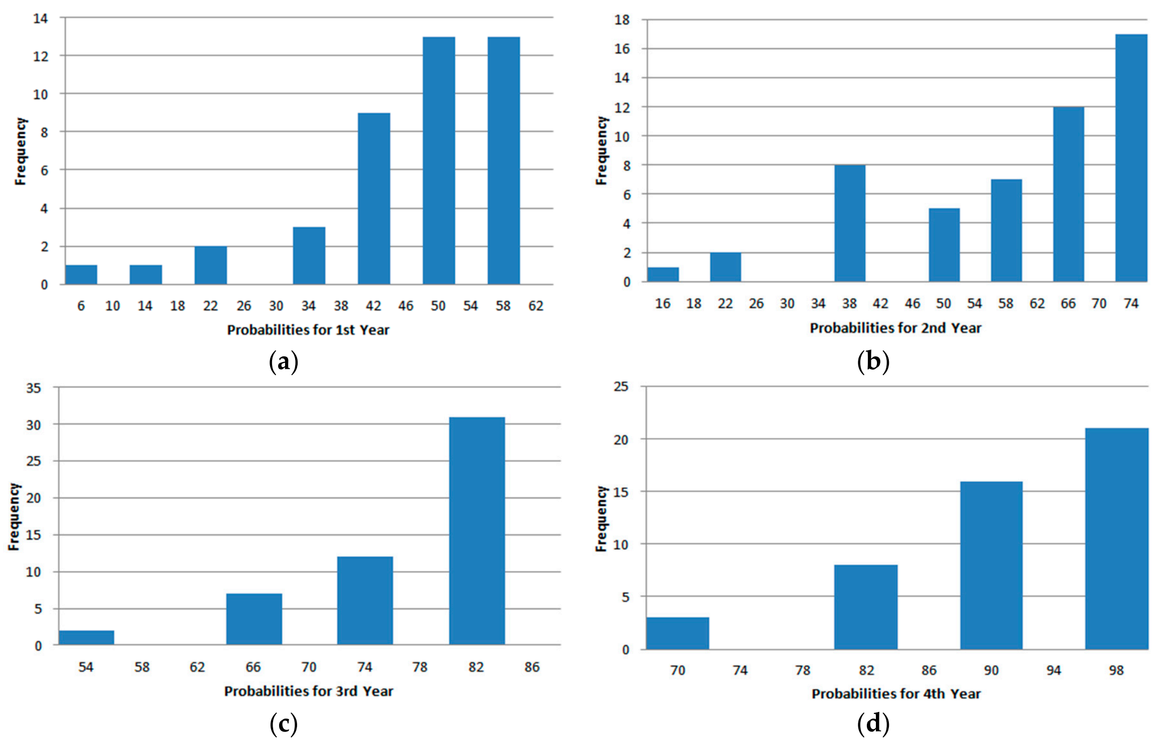

Figure 3. Illustrations resulting to the binning of the probabilities: (**a**) probabilities of ICT fluency for the 1st year; (**b**) probabilities of ICT fluency for the 2nd year; (**c**) probabilities of ICT fluency for the 3rd year; and (**d**) probabilities of ICT fluency for the 4th year.

As aforementioned, the probabilities P_i issued from Equation (8) are used to categorize students' technology skills. That is, the probabilities are binned with an interval of four values. The length of the interval is chosen in order to balance between the homogeneity of the groups and their numbers of students. Figure 3 contains the illustrations resulting to the binning of the probabilities. The computation procedure pursues the following Algorithm 1:

Algorithm 1 Students ICT fluency probability

Input: observation matrix Z
Output: ***Probabilities***

1. Estimate the coefficients in Equation (7)
2. ***For*** all students ***do***
3. Compute probabilities in Equation (8)
4. ***end for***

5.2. Measuring Digital Inequality

The objective is to study the digital inequalities related to internal and external factors. We define the observation *matrix M* for internal variables where a row is formed by the values $m_{p1} = gender_p$, $m_{p2} = age_p$, $m_{p3} = location_p$, $m_{p4} = familySize_p$, $m_{p5} = parentEducation_p$, $m_{p5} = income_p$, and $m_{p7} = employmentStatus_p$. Similarly, we define another *matrix W* for external variables where a row is formed by the values $w_{p1} = computerProperty_p$, $w_{p2} = EnglishLanguage_p$, $w_{p3} = major_p$, and $w_{p4} = studentsClassYear_p$. The splitting of variables into two groups makes explicit personal features and other features in the model. Unless the personal and external variables are completely independent, the effect of the internals on digital inequality indexes can be correlated to the effect of the external and vice-versa. We carry out the independence test between the two groups of variables and we find a no significant correlation between them as presented in Tables 3–6. Following Equation (2), using the above described variables, a linear regression model can be rewritten as Equation (9):

$$y_p = \alpha + \sum_{q=1}^{a} \phi_q M_{pq} + \sum_{q=1}^{b} \theta_q W_{pq} + \varepsilon_p \tag{9}$$

where p = 1, … , n; $\phi = (\phi_1, \ldots, \phi_a)'$, $\theta = (\theta_1, \ldots, \theta_b)'$, and α is the regression coefficient; $y = (y_1, \ldots, y_n)'$, and $\varepsilon = (\varepsilon_1, \ldots, \varepsilon_n)'$ is the error term. In the computation, ϕ, θ, and α estimated using a = 7, b = 4, and n = 1237.

Let us measure the Concentration Index (CI) in order to analyze the online resources access inequality patterns among students in every year. We assumed that online resources access inequality could be described by computer property and internet access. Rewriting Equation (4), we obtained Equation (10):

$$CI = \sum_{q=1}^{a} \left(\frac{\varnothing_q \overline{M}_q}{\mu} \right) C_q + \sum_{q=1}^{b} \left(\frac{\theta_q \overline{W}_q}{\mu} \right) B_q + \frac{G_\varepsilon}{\mu} \tag{10}$$

where $\overline{M}_q$ and $\overline{W}_q$ are the arithmetic means of the entries of matrix $\boldsymbol{M}$ and $\boldsymbol{W}$; that is $\overline{M}_q = \left(m_{1q} + m_{2q} + \ldots + m_{aq} \right)/a$ and $\overline{W}_q = \left(w_{1q} + w_{2q} + \ldots + w_{bq} \right)/b$, respectively; Cq and Bq are the concentration indexes related to the first a students and the last b students; and G_ε/μ is the generalized concentration index for ε_p. It compensates the case where the *CI* cannot be explained by the observation $\boldsymbol{M}$ and $\boldsymbol{W}$ such as [−1,0]. According to Equation (6), Horizontal Inequality (HI) becomes Equations (11) and (12):

$$HI = CI - C_N \tag{11}$$

$$= \sum_{q=1}^{a} \left(\frac{\varnothing_q \overline{M}_q}{\mu} \right) C_q + \sum_{q=1}^{b} \left(\frac{\theta_q \overline{W}_q}{\mu} \right) B_q + \frac{G_\varepsilon}{\mu} - \frac{2}{n\mu} \sum_{p=1}^{n} y_p R_p + 1 \tag{12}$$

Table 3. Correlation between variables characteristics of Matrix M and W for the 1st year.

N = 477	Gender	Age	Location	ClassYear	Major	PC_Owners	Educ_Att	Family_Size	IncomePerCap	EmplStatus
Gender	1	0.003	−0.087	−0.014	−0.084	−0.043	−0.006	−0.194 *	−0.180 *	0.027
		(0.976)	(0.341)	(0.881)	(0.357)	(0.637)	(0.948)	(0.032)	(0.046)	(0.765)
Age	0.003	1	0.027	0.047	−0.062	−0.058	0.027	0.062	−0.015	0.023
	(0.976)		(0.765)	(0.609)	(0.497)	(0.527)	(0.763)	(0.493)	(0.868)	(0.797)
Location	−0.087	0.027	1	0.047	−0.092	−0.104	−0.003	0.089	0.102	0.178 *
	(0.341)	(0.765)		(0.604)	(0.312)	(0.251)	(0.976)	(0.329)	(0.262)	(0.049)
ClassYear	−0.014	0.047	0.047	1	0.008	−0.024	−0.062	0.004	0.087	0.160
	(0.881)	(0.609)	(0.604)		(0.928)	(0.796)	(0.497)	(0.966)	(0.338)	(0.078)
Major	−0.084	−0.062	−0.092	0.008	1	−0.233 **	−0.027	0.000	0.020	0.006
	(0.357)	(0.497)	(0.312)	(0.928)		(0.009)	(0.769)	(0.998)	(0.824)	(0.948)
PC_Owners	−0.043	−0.058	−0.104	−0.024	−0.233 **	1	−0.013	−0.022	0.043	−0.032
	(0.637)	(0.527)	(0.251)	(0.796)	(0.009)		(0.887)	(0.811)	(0.635)	(0.724)
Educ_Att	−0.006	0.027	−0.003	−0.062	−0.027	−0.013	1	−0.071	0.173	−0.128
	(0.948)	(0.763)	(0.976)	(0.497)	(0.769)	(0.887)		(0.435)	(0.055)	(0.159)
Family_Size	−0.194 *	0.062	0.089	0.004	0.000	0.022	0.071	1	−0.028	0.126
	(0.032)	(0.493)	(0.329)	(0.966)	(0.998)	(0.811)	(0.435)		(0.757)	(0.163)
IncomePerCap	−0.180 *	−0.015	0.102	0.087	0.020	0.043	0.173	−0.028	1	−0.032
	(0.046)	(0.868)	(0.262)	(0.338)	(0.824)	(0.635)	(0.055)	(0.757)		(0.729)
EmplStatus	0.027	0.023	0.178 *	0.160	0.006	−0.032	−0.128	0.126	−0.032	1
	(0.765)	(0.797)	(0.049)	(0.078)	(0.948)	(0.724)	(0.159)	(0.163)	(0.729)	

Note: Educ_Att = Educational attainment, Family_Size = Family Size, IncomePerCap = Income Per Capita, EmplStatus = Employment Status; *. Correlation is significant at the 0.05 level (2-tailed); **. Correlation is significant at the 0.01 level (2-tailed).

Table 4. Correlation between variables characteristics of Matrix M and W for the 2nd year.

N = 407	Gender	Age	Location	ClassYear	Major	PC_Owners	Educ_Att	Family_Size	IncomePerCap	EmplStatus
Gender	1	0.031	0.201 *	−0.016	−0.058	0.135	−0.112	−0.139	−0.194 *	0.008
		(0.734)	(0.026)	(0.857)	(0.527)	(0.137)	(0.217)	(0.124)	(0.032)	(0.931)
Age	0.031	1	−0.017	0.013	−0.020	0.150	0.045	0.050	0.149	−0.081
	(0.734)		(0.855)	(0.883)	(0.825)	(0.097)	(0.620)	(0.579)	(0.100)	(0.371)
Location	0.201 *	−0.017	1	0.116	−0.103	0.010	−0.062	0.107	0.056	−0.045
	(0.026)	(0.855)		(0.203)	(0.255)	(0.910)	(0.497)	(0.239)	(0.539)	(0.619)
ClassYear	−0.016	0.013	0.116	1	−0.112	0.107	0.044	0.168	−0.117	−0.098
	(0.857)	(0.883)	(0.203)		(0.216)	(0.240)	(0.628)	(0.063)	(0.199)	(0.283)
Major	−0.058	−0.020	−0.103	−0.112	1	−0.055	−0.121	0.065	0.016	−0.092
	(0.527)	(0.825)	(0.255)	(0.216)		(0.544)	(0.181)	(0.473)	(0.860)	(0.312)
PC_Owners	0.135	0.150	0.010	0.107	−0.055	1	−0.014	−0.048	0.145	0.009
	(0.137)	(0.097)	(0.910)	(0.240)	(0.544)		(0.881)	(0.597)	(0.110)	(0.926)
Educ_Att	−0.112	0.045	−0.062	0.044	−0.121	−0.014	1	−0.065	0.119	0.152
	(0.217)	(0.620)	(0.497)	(0.628)	(0.181)	(0.881)		(0.476)	(0.190)	(0.094)
Family_Size	−0.139	0.050	0.107	0.168	0.065	0.048	0.065	1	0.117	−0.225 *
	(0.124)	(0.579)	(0.239)	(0.063)	(0.473)	(0.597)	(0.476)		(0.199)	(0.012)
IncomePerCap	−0.194 *	0.149	0.056	−0.117	0.016	0.145	0.119	0.117	1	0.047
	(0.032)	(0.100)	(0.539)	(0.199)	(0.860)	(0.110)	(0.190)	(0.199)		(0.604)
EmplStatus	0.008	−0.081	−0.045	−0.098	−0.092	0.009	0.152	−0.225 *	0.047	1
	(0.931)	(0.371)	(0.619)	(0.283)	(0.312)	(0.926)	(0.094)	(0.012)	(0.604)	

*. Correlation is significant at the 0.05 level (2-tailed).

Table 5. Correlation between variables characteristics of Matrix M and W for the 3rd year.

N = 195	Gender	Age	Location	ClassYear	Major	PC_Owners	Educ_Att	Family_Size	IncomePerCap	EmplStatus
Gender	1	0.007	−0.086	0.047	0.048	−0.043	−0.238 **	0.073	−0.036	0.047
		(0.939)	(0.342)	(0.605)	(0.597)	(0.638)	(0.008)	(0.421)	(0.691)	(0.608)
Age	0.007	1	0.193 *	−0.028	0.016	0.013	0.073	0.213 *	−0.193 *	0.023
	(0.939)		(0.033)	(0.762)	(0.859)	(0.883)	(0.424)	(0.018)	(0.032)	(0.804)
Location	−0.086	0.193 *	1	−0.119	0.047	0.062	−0.033	0.073	−0.042	−0.026
	(0.342)	(0.033)		(0.191)	(0.605)	(0.496)	(0.717)	(0.420)	(0.643)	(0.771)
ClassYear	0.047	−0.028	−0.119	1	0.017	0.033	0.021	0.109	−0.130	−0.031
	(0.605)	(0.762)	(0.191)		(0.851)	(0.717)	(0.817)	(0.230)	(0.153)	(0.731)
Major	0.048	0.016	0.047	0.017	1	−0.007	−0.078	0.152	0.020	0.034
	(0.597)	(0.859)	(0.605)	(0.851)		(0.936)	(0.392)	(0.093)	(0.827)	(0.706)
PC_Owners	−0.043	0.013	0.062	0.033	−0.007	1	0.096	0.203*	−0.023	−0.277 **
	(0.638)	(0.883)	(0.496)	(0.717)	(0.936)		(0.289)	(0.024)	(0.803)	(0.002)
Educ_Att	−0.238 **	0.073	−0.033	0.021	−0.078	0.096	1	−0.184 *	−0.080	0.050
	(0.008)	(0.424)	(0.717)	(0.817)	(0.392)	(0.289)		(0.042)	(0.381)	(0.581)
Family_Size	0.073	0.213 *	0.073	0.109	0.152	0.203 *	0.184	1	0.058	−0.173
	(0.421)	(0.018)	(0.420)	(0.230)	(0.093)	(0.024)	(0.042)		(0.528)	(0.056)
IncomePerCap	−0.036	−0.193 *	−0.042	−0.130	0.020	−0.023	−0.080	0.058	1	−0.001
	(0.691)	(0.032)	(0.643)	(0.153)	(0.827)	(0.803)	(0.381)	(0.528)		(0.992)
EmplStatus	0.047	0.023	−0.026	−0.031	0.034	−0.277 **	0.050	−0.173	−0.001	1
PC_Owners	(0.608)	(0.804)	(0.771)	(0.731)	(0.706)	(0.002)	(0.581)	(0.056)	(0.992)	

*. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed).

Table 6. Correlation between variables characteristics of Matrix M and W for the 4th year.

N = 158	Gender	Age	Location	ClassYear	Major	PC_Owners	Educ_Att	Family_Size	IncomePerCap	EmplStatus
Gender	1	−0.023	−0.057	−0.120	−0.022	0.080	−0.036	−0.008	−0.004	0.164
		(0.798)	(0.535)	(0.185)	(0.805)	(0.377)	(0.695)	(0.934)	(0.961)	(0.069)
Age	−0.023	1	0.016	−0.025	0.009	0.122	0.004	0.048	−0.024	−0.026
	(0.798)		(0.859)	(0.781)	(0.920)	(0.178)	(0.961)	(0.595)	(0.791)	(0.775)
Location	−0.057	0.016	1	−0.060	0.107	−0.068	−0.129	−0.056	−0.075	−0.068
	(0.535)	(0.859)		(0.511)	(0.237)	(0.452)	(0.156)	(0.539)	(0.407)	(0.456)
ClassYear	−0.120	−0.025	−0.060	1	0.002	−0.144	0.095	−0.091	−0.003	0.077
	(0.185)	(0.781)	(0.511)		(0.987)	(0.112)	(0.295)	(0.317)	(0.971)	(0.396)
Major	−0.022	0.009	0.107	0.002	1	0.086	−0.111	−0.104	0.070	−0.009
	(0.805)	(0.920)	(0.237)	(0.987)		(0.345)	(0.222)	(0.251)	(0.440)	(0.917)
PC_Owners	0.080	0.122	−0.068	−0.144	0.086	1	0.044	0.140	−0.004	0.042
	(0.377)	(0.178)	(0.452)	(0.112)	(0.345)		(0.628)	(0.124)	(0.961)	(0.647)
Educ_Att	−0.036	0.004	−0.129	0.095	−0.111	0.044	1	−0.030	−0.081	0.010
	(0.695)	(0.961)	(0.156)	(0.295)	(0.222)	(0.628)		(0.742)	(0.372)	(0.914)
Family_Size	−0.008	0.048	−0.056	0.091	−0.104	0.140	0.030	1	0.085	−0.133
	(0.934)	(0.595)	(0.539)	(0.317)	(0.251)	(0.124)	(0.742)		(0.350)	(0.142)
IncomePerCap	−0.004	−0.024	−0.075	−0.003	0.070	−0.004	−0.081	0.085	1	0.028
	(0.961)	(0.791)	(0.407)	(0.971)	(0.440)	(0.961)	(0.372)	(0.350)		(0.761)
EmplStatus	0.164	−0.026	−0.068	0.077	−0.009	0.042	0.010	−0.133	0.028	1
	(0.069)	(0.775)	(0.456)	(0.396)	(0.917)	(0.647)	(0.914)	(0.142)	(0.761)	

The Algorithm 2 for the computation of HI is:

Algorithm 2 Determinants inequality estimates

Input: observation matrix M and W
Output: ***CI***, ***HI***

1. Estimate the coefficients in Equation (9)
2. Estimate *CI* in Equation (10)
3. Compute *HI* in Equation (12)

6. Results Analysis

This section contains the data analysis and findings from the application of the two developed models. The models were evaluated on an undergraduate students' dataset in order to find out the determinants (influential variables) of ICT fluency among students from the 1st year to the 4th year (RQ1) and to study how the digital divide evolves along these four years (RQ2).

6.1. RQ1: Determinants of ICT Fluency

The assumption of the study was that ICT fluency among students is represented by proxy variables of ICT usage and ICT access (computer ownership and Internet connection); and increasing level of education and training on computer knowledge. In Table 7, logistic regression estimates of the determinants of Internet access indicate that, in general, computer experience, capacity levels, computer property, and class year proxy variables increase in probabilities from the 1st year to the 4th year. Apart from that, more significant changes (from negative to positive) are occurring, especially when referring to the likelihood of Internet access by the females and no PC owners students during the four years. For example, there is higher Internet access among 3rd and 4th years' students. The students from rural areas show a reduced likelihood of Internet access, more significant in the 1st year, which is possibly because of a lack of prior computer experience.

Table 7. Internet access logistic regression estimates for EA undergraduate students.

Dep. Variable	Variation of Determinants			
	1st Year	2nd Year	3rd Year	4th Year
Female	−0.080 *** (0.010)	−0.057 *** (0.008)	−0.008 *** (0.008)	0.048 *** (0.008)
Age >18	1.865 *** (0.031)	1.626 *** (0.032)	1.371 *** (0.033)	1.571 *** (0.034)
Age > 30	−0.632 *** (0.022)	−0.693 *** (0.025)	−0.737 *** (0.028)	−0.828 *** (0.037)
Computer owners	0.208 *** (0.026)	0.248 *** (0.026)	0.260 *** (0.027)	0.264 *** (0.029)
Computer experience	0.230 *** (0.013)	0.243 *** (0.013)	0.252 *** (0.013)	0.270 *** (0.014)
Class year size	0.229 *** (0.019)	0.225 *** (0.018)	0.197 *** (0.018)	0.166 *** (0.017)
No PC owners within class year	0.122 *** (0.032)	−0.197 *** (0.031)	−0.012 *** (0.031)	−0.116 *** (0.029)
PC owners within class year	−0.248 *** (0.032)	−0.364 *** (0.032)	−0.311 *** (0.032)	−0.256 *** (0.036)
Computer Attitude	0.985 *** (0.024)	0.994 *** (0.025)	1.044 *** (0.025)	1.248 *** (0.026)
Urban	−0.092 *** (0.046)	0.212 *** (0.047)	0.223 *** (0.048)	0.267 *** (0.049)
Rural	−1.295 *** (0.079)	−1.300 *** (0.057)	−1.440 *** (0.046)	−1.271 *** (0.043)
Parents				
Educational attainment	0.259 *** (0.003)	0.241 *** (0.002)	0.232 *** (0.002)	0.219 *** (0.002)
Family size	0.155 *** (0.007)	0.186 *** (0.006)	0.214 *** (0.007)	0.218 *** (0.008)
Income per capita	1.237 *** (0.015)	1.033 *** (0.013)	0.974 *** (0.014)	0.983 *** (0.014)
Employment status				
Employed	−0.081 ** (0.038)	0.256 *** (0.035)	0.212 *** (0.037)	0.201 *** (0.036)
Unemployed	1.318 *** (0.052)	1.555 *** (0.064)	1.581 *** (0.080)	1.530 *** (0.084)
Retired	−0.285 (0.233)	−0.565 ** (0.239)	−0.447 * (0.245)	−0.313 (0.214)
Constant	−10.621 *** (0.97)	−8.593 *** (0.098)	−7.590 *** (0.094)	−7.378 *** (0.095)
R^2	0.3861	0.4471	0.3525	0.3374
Observations	477	407	195	158

Note: (1) Observation standard errors in parentheses; (2) *** $p < 0.001$, ** $p < 0.01$, and * $p < 0.05$, the computations are performed using SPSS 25.0.

By examining empirical data in Table 2, there is evidence of improvements in Internet access from the 1st year to the 4th year: there are higher rates of computer owners, computer experience, and capacity in income among EA university students. Moreover, regarding the proxy variables of access to ICT, Internet access and PC property are increasing significantly.

Relating to the main determinants of computer property, similar effects like those observed for Internet access are identified. Higher capacity in income and prior computer experience, being urban as well, affect the likelihood of computer property in EA undergraduate students positively, as shown in Table 8. Moreover, from the 1st year to the 4th year, there is an increasing likelihood of computer ownership among the students that are no computer owners, but with higher prior computer experience (i.e., as they get in the 2nd, 3rd, and 4th year), while the effect of rural origin is declining.

Table 8. Computer property logistic regression estimates for undergraduate students.

Dep. Variable	Variation of Determinants			
	1st Year	2nd Year	3rd Year	4th Year
Female	−0.235 *** (0.014)	−0.086 *** (0.013)	−0.020 *** (0.014)	0.023 * (0.015)
Age >18	−0.513 *** (0.022)	−0.902 *** (0.021)	−1.165 *** (0.022)	−1.160 *** (0.021)
Age > 30	−1.08 *** (0.027)	−1.003 *** (0.025)	−0.976 *** (0.026)	−0.963 *** (0.025)
Computer owners	0.074 *** (0.016)	0.058 *** (0.017)	0.044 *** (0.018)	0.015 *** (0.018)
Computer experience	0.157 *** (0.005)	0.156 *** (0.005)	0.160 *** (0.007)	0.174 *** (0.008)
Class year size	−0.085 *** (0.007)	−0.090 *** (0.007)	−0.110 *** (0.008)	−0.119 *** (0.008)
No PC owners within class year	0.192 *** (0.016)	0.295 *** (0.018)	0.371 *** (0.020)	0.397 *** (0.021)
PC owners within class year	−0.252 *** (0.020)	−0.336 *** (0.020)	−0.430 *** (0.023)	−0.466 *** (0.023)
Computer Attitude	0.771 *** (0.013)	0.717 *** (0.013)	0.617 *** (0.014)	0.625 *** (0.014)
Urban area	0.203 *** (0.042)	−0.005 *** (0.043)	0.107 *** (0.043)	0.134 *** (0.047)
Rural area	−0.706 *** (0.033)	−0.758 *** (0.033)	−0.906 *** (0.034)	−0.915 *** (0.036)
Parents				
Educational attainment	0.154 *** (0.002)	0.153 *** (0.002)	0.157 *** (0.002)	0.171 *** (0.002)
Family size	−0.082 *** (0.004)	−0.087 *** (0.004)	−0.107 *** (0.005)	−0.116 *** (0.005)
Income per capita	0.768 *** (0.010)	0.714 *** (0.010)	0.614 *** (0.011)	0.622 *** (0.011)
Employment status				
Employed	0.200 *** (0.030)	−0.002 (0.033)	0.104 *** (0.039)	0.131 *** (0.044)
Unemployed	0.443 *** (0.045)	0.216 *** (0.054)	0.040 (0.071)	0.152 * (0.078)
Retired	0.086 (0.180)	−0.003 (0.224)	−0.081 (0.243)	0.161 (0.229)
Constant	−4.379 *** (0.064)	−3.555 *** (0.072)	−2.410 *** (0.075)	−2.115 *** (0.085)
R^2	0.2803	0.2742	0.283	0.275
Observations	477	407	195	158

Note: (1) Observation standard errors in parentheses; (2) *** $p < 0.001$, ** $p < 0.01$, and * $p < 0.05$, the computations are performed using SPSS 25.0.

Contrariwise, we found evidence of declining influences for some determinants (e.g., class year and being female) of computer property. However, the likelihood of having a computer increased among the EA undergraduate students in general, as presented in Table 8, possibly due to the reduction of the number of students per class year, the increase of computer experience, capacity in income, and computer utility on students daily tasks, from the 1st to the 4th year.

The estimates of computer ownership show another significant evidence worth being highlighted relating to the barriers of ICT access due to the capacity, computer experience, and possibly, restraints of the electronic tools for specific uses (e.g., Internet access), particularly among the 1st-year students. During the 4th year, the results in Table 8 indicate that the likelihood of computer ownership increased. However, it was decreasing with a negative effect on the variable of being from rural and increasing with a positive effect on the variable of computer experience. This evidence indicates that computer utilization among EA undergraduate students might take into account higher complexity compared to Internet access.

Prior computer experience, considered among the major dimensions of technology utilization, significantly continued to increases along the four years as found in Table 8. Therefore, access to

ICT can be ameliorated by accommodating more computer training among EA students. However, it is essential to highlight that the number of students in a class is also an important determinant of technology inequalities. That is, even though the determinants of inequality coefficients were evaluated according to the capacity of utilization, the number of students in a class has been declining from the 1st year to the 4th year as well, which increases the number of computers per class, thus reducing inequalities. In addition, geographic location (urban/rural origin) shows an increasing tendency as a determinant of inequalities on both computer property and Internet access. The results show that, based on regional location, there are still significant ICT infrastructure differences between EA rural and urban areas, especially Internet access.

Figure 4 depicts the evolution of the concentration curves of Internet access and computer property among the EA undergraduate students. From the 1st to the 4th year, the inequalities in PC ownership decrease very sharp in comparison to the inequalities relating to Internet access.

According to the estimates of inequalities evolution in computer property and Internet access in Figure 4, the digital divide reduces from the 1st year to the 4th year, mainly because of the convergence in technology access due to the acquisition of more computers and reduction of the number of students in classrooms.

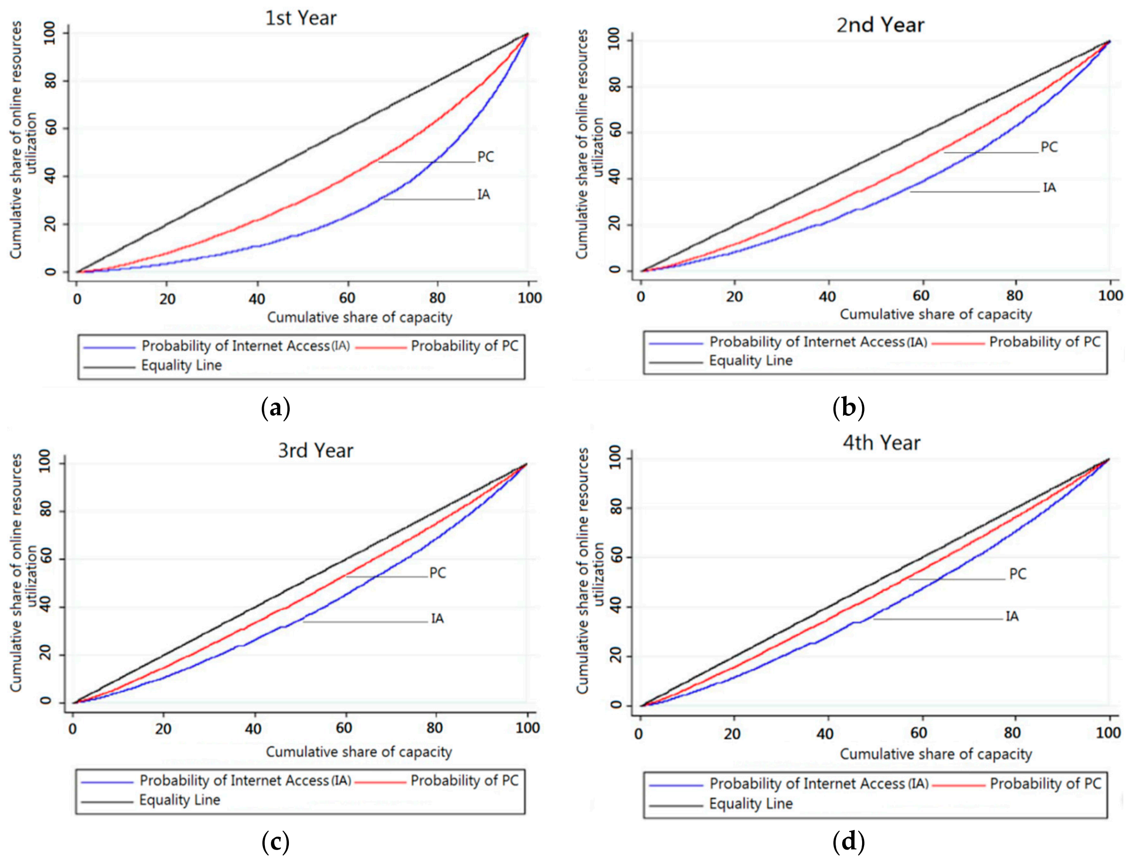

Figure 4. Evolution of the concentration curves of Internet access and computer property: (**a**) cumulative share of 1st-year students ranked by capacity; (**b**) cumulative share of 2nd-year students ranked by capacity; (**c**) cumulative share of 3rd-year students ranked by capacity; and (**d**) cumulative share of 4th-year students ranked by capacity.

6.2. RQ2: Digital Inequalities Evolution

The hint to understanding the interpretation of the model developed for studying the evolution of inequalities is that its meaning presents some similarities with the Gini coefficient, and its function follows the rules of the Lorenz Curves [72]. For the Horizontal Inequality (HI), apart from one's own characteristics (internal factors) that might restrain the students' technology usage, the HI includes the indicators of inequalities relating to external factors. In Table 4, the Horizontal Inequality (HI) and the Concentration Indexes (CIs) show that the inequality decreased both on computer property and Internet access from the 1st year to the 4th year. In seniors, computer ownership attained a significantly lower value of inequality (4th year CI = 7%) as compared with Internet access (4th year CI = 16%).

As shown by the differences between HI and CI, there was evidence of the convergence of inequality coefficients for computer ownership between senior (4th year) students and other students; which indicates that computer property among EA undergraduate students was more limited by external factors than internal factors as Table 9 illustrates.

Table 9. Evolution of the Concentration Index (CI) and Horizontal Inequality (HI).

	1st Year	2nd Year	3rd Year	4th Year
Internet access				
Full sample				
Concentration Index	46%	28%	19%	**16%**
Horizontal Inequality	32%	19%	13%	11%
No PC owners				
Concentration Index	62%	50%	38%	32%
Horizontal Inequality	43%	35%	26%	21%
Computer property				
Full sample				
Concentration Index	28%	17%	9%	**7%**
Horizontal Inequality	18%	10%	5%	3%
No PC owners				
Concentration Index	38%	26%	15%	12%
Horizontal Inequality	19%	14%	6%	4%

In Table 9, from the comparison of the inequality index levels of computer property and Internet access, the Internet access has higher concentration indexes because its determinants possess higher likelihoods than computer ownership as found in Figure 4. This result is evidence of the potentiality of promoting mass Internet access policy, that is, providing free wireless and broadband access on campus, which has been being implemented by certain universities in EA, based on examples from universities of developed countries.

The identified patterns of ICT convergence, in some cases identical to other countries [73], constitute the evidence of a decrease in the digital divide among the EA students during the four years of undergraduate studies, especially when referring to Internet access.

7. Discussions and Managerial Implications

This paper studied the determinants of ICT fluency and the evolution of technology inequalities among students from the 1st year to 4th year, using the two developed globally applicable models. The evaluation of the models is carried out on the undergraduate students' data from three East African (EA) universities (KU, UDSM, and UB), collected during the summer of 2019. The classification of the frequencies of students by ICT fluency indicated that the number of technology fluent students grow faster from the 1st year to the 4th year as shown by Figure 4. In every class year, the ICT fluent students can be categorized into two main groups that are the fluent group and the no fluent—which implies a digital divide, thus, the justification of the necessity of the investigations into the determinants of technology fluency in the region.

Regression computational findings show that the most significant proxy determinants of ICT fluency were the student urban/rural origin, computer ownership, class year, major, and prior computer experience. Surprisingly, gender was not a very significant predictor of ICT fluency among students, given that usually in EA, males and females possess different gender roles [39]. It might be that since the number of technology fluent students among the enrolling students (in the 1st year) was very reduced, both male and female students started the digital learning at university studies, which led to the insignificant gender differences along the four years of studies.

This study assumed that the inequality related to individual and external factors was the basis of the digital divide in utilizing available online resources. With that assumption, the digital divide evolution measured with inequality indexes indicates that: (i) computer experience or the lack of computer skills is the main barriers to online resources utilization and (ii) the capacity to purchase a personal computer (influenced by family income), as well as a big number of students in a class with an unmatched number of lab computers constitute the major barriers to accessing online resources.

The influence of external barriers to technology fluency was reducing from the 1st year to the 4th year. However, still, the effect of prior computer experience remained expressive in every part. Computer ownership rationalizes most of the inequalities in individual technology skills, this implies that the model shows evidence that the improvements in the capacity to buy a computer, accommodating more computer labs, and providing more computer usage training may be valuable strategies to decrease: (i) the digital divide among the students and (ii) the barriers associated with ICT fluency, an argument that was supported by Niyigena et al. [26] as well.

Although, the results confirm that senior students are highly involved in using the Internet, however, this is slightly in contrast with the recently reported growth on consuming ICT facilities in sub-Saharan Africa assigned to the need of the elimination of poverty in the region and to adopt globalization through the attainment of ICT equipment in the line with the common belief that ICT facilities are the main incentives to achieving the Millennium Development Goals by all the population in the world countries [74]. Additionally, the rankings of Economist Intelligence in 2015 about online readiness, which ranked East Africa as 63th, North Africa 48th, West Africa 60th, and Southern Africa 45th—evidence that East Africa needs to face the competition of broadband [75]. It has been proven that access is not utilization, even improving the access of technology infrastructure does not imply the effective usage of ICT facilities. Many ICT products are damaged due to dirt in offices and degrade the environment in sub-Saharan Africa, evidence that potential users are still not available even if the products have been acquired.

The report on the increasing number of people accessing technology in developing nations was based on the assertion that, at the moment, individuals obtained more access, particularly to mobile phones, rapidly than they accessed any other newly introduced technologies in history. Such growth reports probably did not consider the quality of accessed ICT facilities. In addition, they do not seem to capture the access quality, content adequacy, effective utilization, and cost of access [74]. In Figure 5, showing a comparison of the digital divide on access to the Internet across the world continents, the gap between the developing and developed world region on quality of access to the Internet and access to quality internet infrastructures is growing [76]. By the year 2000, some regions of the world (e.g., Africa and the Middle East) had very limited or no Internet at all; as a result, they appear to have a very significant growth in Figure 5. Moreover, the western countries and African countries Infostate gap, ranges from 9 to 225, putting sub-Saharan Africa countries and other developing countries on the bottom rung [77].

Based on the results from the evaluation of the developed models, government initiatives still have an immense role to play. For example, increasing Internet penetration and providing excellent ICT infrastructures would motivate students to become more fluent with ICT and makes them more willing to use online educational resources. Besides, in East Africa and other developing countries in general, mobile technology is improving quickly, outgrowing some of its important limitations related to Internet utilization. Therefore, considering that the objective of mass Internet access is to stimulate the dissemination of information, the adoption of public policies encouraging mobile Internet access and utilization can also improve the possibilities of access to online resources among EA students [78]. Mobile broadband effective access and utilization would provide access to online relevant information and educational resources while accessing from anywhere, at any time.

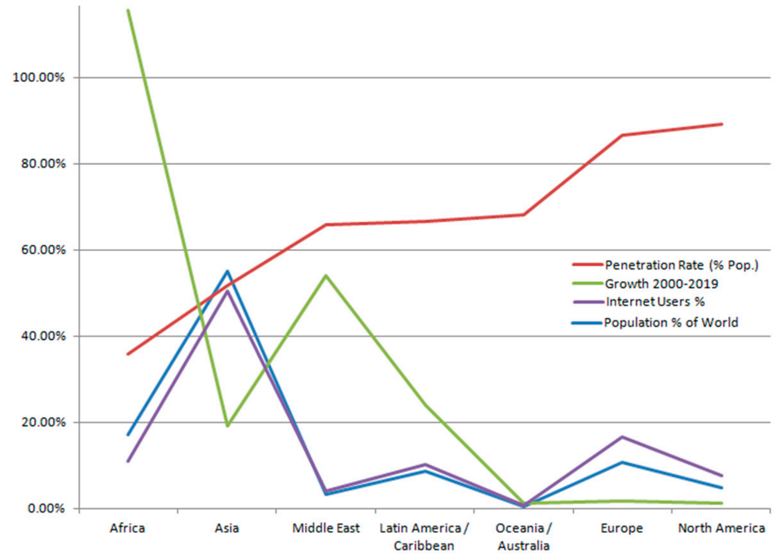

Figure 5. Comparison of current Internet usage between Africa and other continents by the year 2019.

8. Limitations and Future Recommendations

Although this study used thorough research procedures, there are some possible limitations that might be pointed out. First, the findings and implications from the two models' assessments were inferred from the African developing countries, specifically the East African nations. Thus, the generalizability of the findings should be treated with caution due to cross-cultural differences between developing countries. In regards to that, a longitudinal study that would include samples from a larger number of developing nations may find more exciting insights and enhance the generalizability of the study. Second, at odds with other studies that express ICT fluency and digital divide based on the students' ICT skills, this study did examine ICT fluency and digital divide based on the individuals' internal and external proxy variables that influence the students' online resources access. An investigation based on the socioeconomic status of the participants might serve to explore the in-depths of the digital divide while dividing the constructs into more small groups, for instance, one can study ICT fluency and digital divide based on cultural capital and level of wealth considering the urban and rural origin students.

Finally, since this study's data collection was performed by a cross-sectional method and the models' assessments are conducted at a single given moment, it must be noted that personal opinions may change over time. Hence, future research should consider assessing the models by conducting panel studies in order to continue deepening the understanding of the causal and relationships between the variables that are crucial for ICT fluency and evolution of digital inequality in developing countries.

9. Conclusions

The general aim of this paper was twofold. First, to investigate the determinants of ICT fluency, and second, to study the evolution of technology inequalities among the students from the developing countries. To achieve its goal, this study developed one measurement model based on logistic regression and the other based on the concentration index [63]. The two models are evaluated on data from East African undergraduate students. The findings indicate that computer ownership is the most significant determinant of ICT fluency throughout the four years of studies, whereas prior computer experience accounts as a major factor of inequality in technological skills along that study time. The impact of the barriers, relating to students' external characteristics (computer property, computer owners, English language, prior computer experience, and class year size), to technology usage declines as the EA undergraduate students go from the 1st year to the 4th year. Moreover, the evolution of the concentration curves of Internet access and computer property indicates that inequalities in computer property decrease very sharp in comparison to the inequalities of Internet access along with the studies.

The findings of this study provide insight into the determinants of ICT fluency and digital divide among the students from the developing countries and yield some advice to policymakers and regional practitioners for improving ICT fluency among university students. It is more productive to accommodate more computer labs to the students. This might be a valuable strategy to reduce technology inequalities as it could make the students have more access to computers. The findings of this study present some dissimilarities between the developing and the developed countries—most students from the developed countries can own personal computers while the evidence from this study shows that in EA, computer property, which is at a very low level in developing countries, is a major predictor of computer experience, thus a major determinant of ICT fluency and a very significant factor of digital divide. This challenge can be addressed as follows: as mobile technology is developing fast in most developing countries, specifically in EA [79,80], policymakers and regional practitioners should put forward the scheme to provide Internet infrastructures in rural areas, make wireless internet available in universities, design online learning resources access platform that are mobile users friendly and encourage the students to adopt online learning. This might reduce the digital divide while increasing ICT fluency among students.

Author Contributions: J.-P.N. and D.Z. conceptualized the model; J.-P.N. and Q.J. composed the experiments, conducted the experiments, and examined the data and contributed analysis tools; J.-P.N. and D.Z. wrote the manuscript. A.S.M.T.H. and R.-S.S. revised the manuscript. All authors have read and agreed to the published version of the manuscript.

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