DEVELOPING A STUDENT SUPPORT SYSTEM THROUGH LEARNING ANALYTICS FOR UNDERGRADUATES AT THE UNIVERSITY OF THE PHILIPPINES OPEN UNIVERSITY

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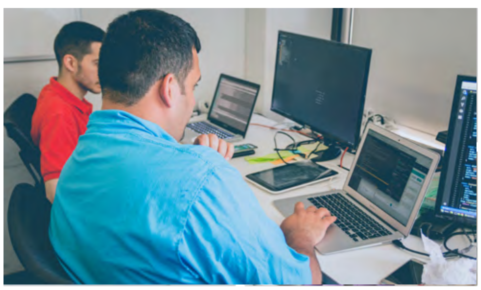
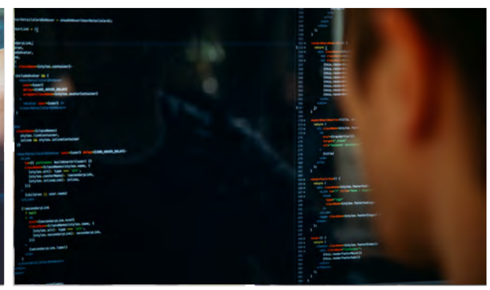
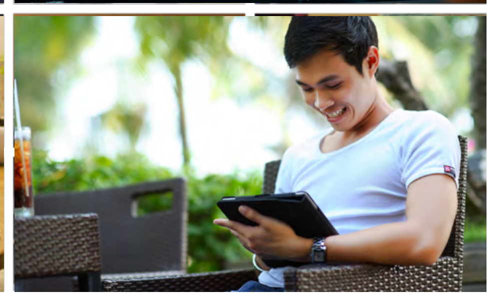
DIGITAL LEARNING FOR DEVELOPMENT

Developing a Student Support System Through Learning Analytics for Undergraduates at the University of the Philippines Open University





Charisse T. Reyes

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TABLES AND FIGURES

CONTENTS

PREFACE

Learning analytics provides educators with the necessary information to make decisions about their teaching and learning practices at the university, programme, or course level. These informed decisions are more likely to meet the individual learning needs of the students, and hence, more likely to enhance the quality of the learning experiences for the students. The University of the Philippines Open University (UPOU) has been providing quality access to higher education through its distance education programmes. One such programme is the Associate in Arts (AA) programme. Similar to other distance education programmes, the AA programme has a very diverse intake of students with respect to academic background, readiness for online learning, and other demographic differences. This sub-project examines how the characteristics and experiences of the students affect their successful completed by the AA programme. By examining these characteristics and experiences, the AA programme is more likely to address the individual learning needs of the students. The researchers have proposed a student learning support system based on the key findings of this study.

This study was conducted under the Digital Learning for Development (DL4D) project of the Foundation for Information Technology Education and Development (FIT-ED) of the Philippines. As part of the Information Networks in Asia and Sub-Saharan Africa (INASSA) program of the International Development Research Centre (IDRC) of Canada and the Department for International Development (DFID) of the United Kingdom, DL4D aims to improve educational systems in developing countries in Asia through testing digital learning innovations and scaling proven ones.

Cher Ping Lim
DL4D Network Lead

ABSTRACT

Through learning analytics, this study identified various factors affecting students' success in the Associate in Arts (AA) program of the University of the Philippines Open University (UPOU). Data from various sources were obtained for the analysis of demographic information, previous academic experiences, learner readiness for distance education, and students' learning behavior. Based on the analysis of their demographic information, it was found that students' age, gender, civil status, occupation and location are factors influencing their completion of the program. Completion of the Distance Education Readiness module before beginning the AA program has also been found to have a positive impact on program completion. Moreover, prior academic experiences gained by the students before entering the AA program, such as previous enrollments in other universities or colleges, has also been found to have a positive impact on the students' success in the program. While in the program, academic factors such as a student's enrollment of required and prescribed courses and activities in the learning management system (i.e., MyPortal) have been found to contribute significantly to a student's success. A statistical model that can predict the probability of a student's success in the AA program based on their demographic characteristics and completion of the Distance Education Readiness Module was obtained in this study.

A key aspect of this study is the proposal for the development of a student support system based on the characteristics and attributes of learners as well as their academic behaviors. This student support system aims to promote the students' success in the AA program.

Keywords: *distance education, learning analytics, undergraduate program, success and completion rate*

I. INTRODUCTION

In 2011, the University of the Philippines Open University (UPOU) Faculty of Education started offering a revised curriculum for the Associate in Arts (AA) program; a 60-unit liberal arts program at the undergraduate level. The AA program is offered online and through a full distance education mode. Within the program curriculum, there are 45 units of General Education courses, 15 units of additional required courses, 8 units of Physical Education, and 6 units of National Service Training Program (NSTP) courses. A student who enrolls in a maximum of 12 units per academic term can complete the program in five trimesters or 1.5 years.

Since 2011, a total of 249 students have been admitted to the AA program. Of this number, only 39 students (16%) have completed the program as of the end of the 1st trimester AY2015-2016. The low program completion rate has motivated and is the focus of this study. While several studies have established low retention and persistence in higher education, only a few studies have identified factors that significantly contribute to a learner's persistence in distance education. Moreover, there are few published studies on the persistence of distance education by learners in the Philippines, particularly in the undergraduate programs.

Using learning analytics, this study aimed to determine the characteristics of successful learners and the factors that affect program completion at the undergraduate level. More specifically, by developing a learning analytics tool based on existing information about AA students, the investigators aimed to predict the probability of student completion of the AA program. The information obtained through this study will allow program administrators to understand and determine the pertinent factors that promote and hinder student completion of the AA program.

II. OBJECTIVES

The general aim of this research is to identify the factors that affect student completion of the AA program, by employing a learning analytics tool. Specifically, this study aims to:

(a) utilize learning analytics to determine the major factors that affect the completion of undergraduate courses based on the students' demographic information, enrolment pattern, and learning behavior;
(b) trace a possible learning trajectory for students using a learning analytics tool; and
(c) propose an intervention mechanism to provide support to students in their completion of their undergraduate courses.

The study addresses the following research questions:

1. What are the characteristics and attributes of successful learners and their milestones in the AA program?
2. Are there course-related factors that positively affect program completion by a learner?
3. Are there pre-university attributes that significantly contribute to the success of the learner in the program?
4. Can learners' success be predicted through a learning analytics tool?
5. What student support system can be proposed to promote learners' success in the AA program?

III. REVIEW OF LITERATURE

3.1 Persistence and drop-out from distance education

Distance education (DE) is defined by Moore (1973) (as cited in Keegan, 1980) as the "family of instructional methods in which the teaching behaviours are executed apart from the learning behaviours". Communication between the learner and the teacher in this educational mode is technology-mediated, including through "print, electronic, or mechanical or other devices" (Moore, 1973; as cited in Keegan, 1980). The use of technology in the execution of the teaching and learning processes enables the provision of instruction to "great numbers of students at the same time wherever they live" (Peters, 1973; as cited in Keegan, 1980).

DE programs are popular, especially among adult learners, (Meister, 2002; Moore & Kearsely, 2005) as it makes it possible for those with family, employment, and other responsibilities to achieve further educational goals and update their professional knowledge and skills without having to physically attend classes at a university.

However, even as enrollment in DE programs continues to increase, student attrition is a major concern for institutions offering DE. Studies on persistence and dropout in distance education have been focused on proposing models to explain the trends in persistence and attrition in DE. Many of these studies have employed Tinto's longitudinal model of dropout (1975) that was originally proposed for four-year residential university settings. The model described persistence and dropout as follows:

> a longitudinal process of interactions between the individual and the academic and social systems of the college during which a person's experiences in those systems (as measured by his normative and structural integration) continually modify his goal and institutional commitments in ways which lead to persistence and/or to varying forms of dropout. (pp. 89–125)

Tinto's model concludes that the higher the integration of the learner into the academic and social systems of the college, the greater their commitment will be to the institution and to the goal of completing the college degree. The model shows that each learner enters college with a set of demographic attributes, pre-college experiences, and family background that directly or indirectly affects their performance in college. These background characteristics and attributes further impact the "development of the educational expectations and commitments the individual brings with him into the college environment" (Tinto, 1975).

One of the goals of learning analytics is to construct appropriate interventions.

Bean and Metzner's (1985) also proposed a model on persistence and attrition of non-traditional undergraduate students on the basis of student-institution ''fit''. The model identifies four factors that affect persistence, namely:

(a) academic variables (i.e., study habits, advising, course availability, program fit)
(b) background and defining variables (i.e., age, residence status, educational goals, ethnicity, prior GPA)
(c) environmental variables (i.e., finances, employment information, family responsibilities, outside encouragement, opportunity to transfer)
(d) academic (i.e., GPA while at college) and psychological (i.e., utility, stress, satisfaction, commitment) outcomes

Sweet (1986) applied Tinto's model in a DE setting, modifying the framework by including, as a variable, a telephone tutoring system used as a means to enhance social integration in the DE system. In another study, Rovai (2003) integrated the models proposed by Tinto (1975) and Bean and Metzner's (1985) into a composite model emphasizing two prior-to-admission factors (i.e., student characteristics and student skills) and two after-admission factors (i.e., external factors and internal factors). According to Rovai, this model can be used by DE program administrators to identify students with a tendency to drop out. The model also puts emphasis on areas where an intervention can be made to increase persistence.

3.2 Learning analytics and student support in undergraduate DE programs

Recently, there has been a growing interest among various organizations across industries in utilizing data from various sources to "provide decision makers with information that can help determine the best course of action" (Educase, 2011). This approach has been taken up by post-secondary and higher education for "the objective of supporting the achievement of specific learning goals" (Cooper, 2012). The approach, known as Learning Analytics (LA), is defined by the Society for Learning Analytics Research (SoLAR, 2011) as "the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (p. 4). Learning Analytics is often used interchangeably with the term "academic analytics" (AA) but Long and Siemens (2011) distinguish between the two terms, thus:

> Academic analytics reflects the role of data analysis at an institutional level, whereas learning analytics centers on the learning process, which includes analyzing the relationship between learner, content, institution, and educator (Long & Siemens, 2011).

Ferguson (2012) identifies three key factors that drive the development of learning analytics. The first arises from the technical challenge of extracting valuable information from a large amount of learner-related data that have become available especially with educational institutions' use of virtual learning environments (VLEs) or learning management systems (LMSs). The second factor is the educational challenge of optimizing opportunities for online learning. While online learning offers significant benefits to both the learner and the teacher, there are also considerable challenges related to it. The third factor is the political challenge for educational institutions to measure, demonstrate, and improve the performance of learners as governments aim to uplift the educational attainment of the population. The above-mentioned factors involve three different interest groups — the learner and teacher, the educational institution, and the government. Shifts in the balance between factors and interest groups require "analytics work on different scales and at different granularities" (Ferguson, 2012).

Since the rise of big data and learning analytics have been a result of the proliferation of online learning, a number of researchers employ learning analytics to make use of, manage, and analyze data for the improvement of the academic performance of online learners. Fritz (2011) presents a case study of using online course activity data of successful students to increase the self-awareness of underperforming students. Although the study does not conclude that this learning analytics tool affects the behavior of underperforming students, the increase in usage of the tool has initiated further research to determine whether it can be used to change self-awareness, behavior, and academic performance. Another study by Fournier, Kop, and Sitlia (2011) investigated the use of learning analytics tools in a 10-week massive open online course (MOOC) on Personal Learning Environments, Networks, and Knowledge (PLENK, 2010) to determine the benefits and challenges of using tools and methodologies in analyzing data gathered from online learning environments. The study concluded that learning analytics "can be powerful in giving meaning to interactions and actions in a learning environment" to a MOOC. Macfadyen and Dawson (2010) employed learning analytics in fully online undergraduate courses in biology to determine which LMS-based activities predict student success. This study determined that LMS-based activities such as forum posts, mail messages, and assessments can be predictors of student achievement — i.e., they can serve as an early warning system for educators, with 70% accuracy in predicting at-risk students.

One of the goals of learning analytics is to construct appropriate interventions. According to Brown (2011) (as cited in Harmelen & Workman, 2012), enabling appropriate interventions "at the individual, course, department, or institutional level" is the reason for doing learning analytics. Learning analytics has the potential to determine "what is working and what is not at a much finer level of granularity than ever before, even while a course is in progress" (Brown, 2011; as cited in Harmelen & Workman, 2012). But beyond enabling assessment of what learners have done and prediction of what they will do, learning analytics enables the development of intervention systems to improve the quality of teaching and learning. As Long and Siemens (2011) assert, "[a]nalytics in education must be transformative, altering existing teaching, learning, and assessment processes, academic work, and administration".

One example of an intervention based on learning analytics is the development of a suitable student support system to improve academic performance. Some universities and colleges in the United Kingdom have employed learning analytics for student support systems that track student performance and these educational institutions have implemented interventions that improve student success. While it may be too early to conclude whether these interventions are effective, there is already a "clear view of the key factors that [influence] student success" which drives priorities in the strategic planning process (Sclater, 2014). Universities in the United States have also utilized learning analytics tools to provide student support in the form of academic tracking, models for advising and retention, alert systems for academic issues and successes, and knowledge-building and prediction of student success (Dietz-Uhler & Hurn, 2013).

IV. CONCEPTUAL FRAMEWORK OF THE STUDY

This study adopted Rovai's (2003) composite model based on his synthesis of the models of Tinto (1975) and Bean & Metzner (1985), and the 3P Model of Biggs and Moore (1993) (as cited in Nemanich, Banks, & Vera, 2009). Rovai's composite model identifies two pre-admission factors (i.e., student characteristics and student skills) and two after-admission factors (i.e., external factors and internal factors) that affect a student's decision to persist in an online distance education environment, while the 3P Model identifies the presage (i.e., the characteristics of learners prior to engagement in learning) and how they contribute to the process (i.e., the students' learning experience) to yield the product (i.e., the learning outcome).

This study looked into pre-admission (prior to admission) factors and the predominant factors while the learners are in the AA program (after admission) that have an apparent effect on the student's persistence, or lack of persistence (i.e., attrition), in the AA program. The combined Rovai model and 3P Model provided a framework to determine the characteristics of learners and to identify the factors that contribute to their successful completion of the AA program. These models may also be employed to identify the possible areas where an intervention can be proposed in terms of a student support system for the purpose of increasing learner persistence in the program and consequently decreasing learner attrition.

In addition, the study applied the Learning Analytics Cycle presented by Clow (2012), which has four components (see Figure 1):

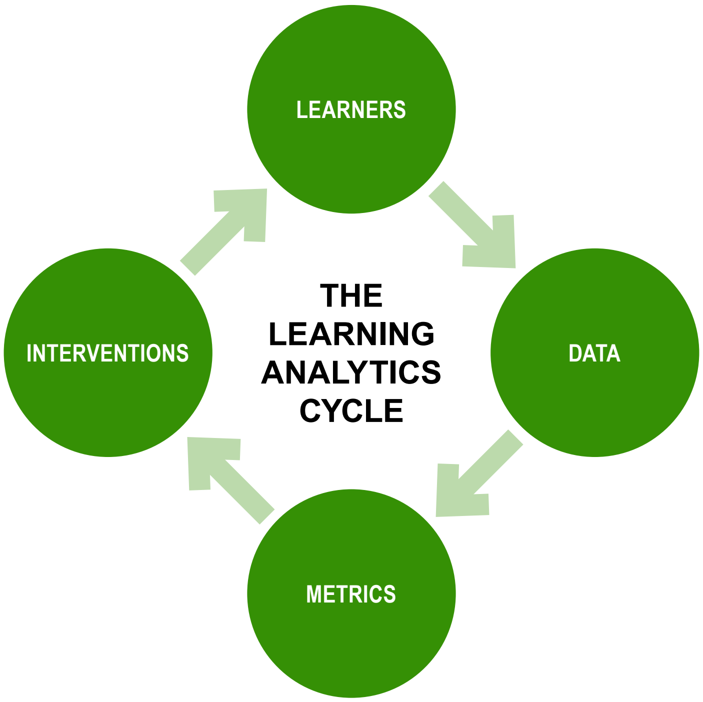

Figure 1. The learning analytics cycle (Clow, 2012)

The cycle begins with the learners who may be students enrolled in a course in a University, participants of a massive open online course (MOOC) or a research conference, or casual learners browsing an open educational resource (OER). From these learners, data, such as demographic information and activities in a Learning Management System (LMS), will be gathered and generated. The next step is to process the data collected into a metrics or analytics that provides some understanding of the learning process. This step is the "heart of most learning analytics projects" since the resulting metrics or analytics provides information such as predictions, a list of at-risk students, comparisons of assessment performance with benchmarks, aggregations, and the like that can be the basis for decision-making and/or intervention. The last step that completes the learning cycle is the use of the metrics or analytics to drive one or more interventions that will have an effect on learners. An example of such intervention is the development of a tutorial system for students with a high risk of dropping out. It should be noted that an intervention does not need to reach the learners from whom the data were generated or gathered. It may involve only the teachers or school administrators who make decisions that will affect current or future learners.

Figure 2 shows the combination of Rovai's composite model (2003), the 3P Model (Biggs & Moore, 1993), and the learning analytics cycle (Clow, 2012) that was employed in this study.

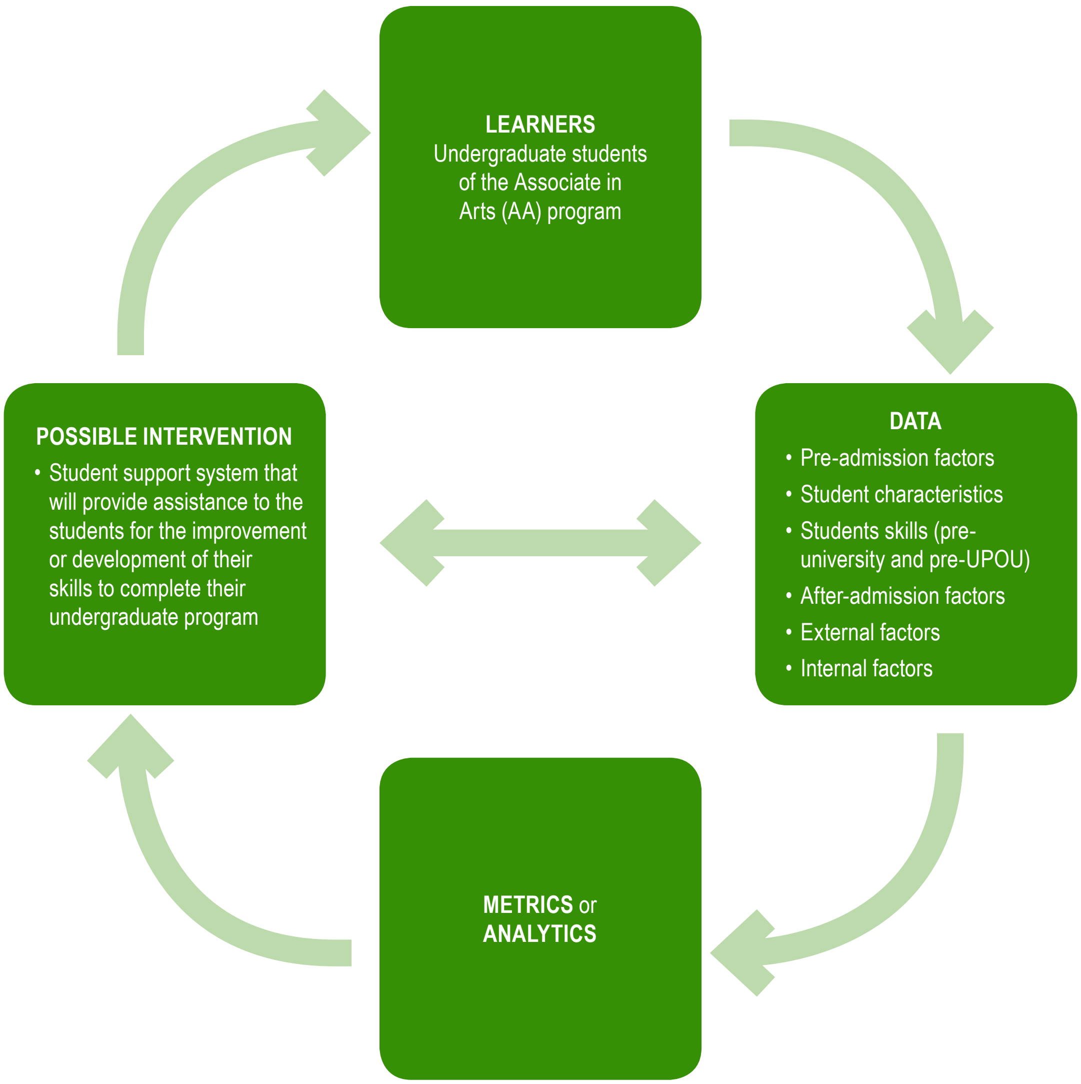

Figure 2. The conceptual framework employed in the study

V. METHODOLOGY

5.1 General methodology

This study had three phases. Phase 1 involved gathering and generating the AA students' demographic information, academic data, and data on their activities in UPOU's learning management system (LMS), MyPortal. These data were compiled in a database system specially designed to allow extraction of relevant information. Phase 2 employed learning analytics to identify the factors that promote completion of the undergraduate program. Phase 3 of the study was the design and development of a student support system based on the information obtained from the learning analytics. In the future, this student support system will serve as the intervening mechanism that will provide assistance to the students for the improvement or development of their skills to complete their undergraduate program.

5.2 The learning analytics for the study

By mining learner data — such as their demographic characteristics, pre-university and pre-UPOU academic history, learners' efforts as measured by their activity in the LMS (i.e., MyPortal), and general weighted average (GWA) in UPOU — and using a learning analytics tool, various factors that affect learner persistence — or student attrition — in the AA program were identified (Figure 3).

An initial survival analysis was conducted to determine the rate at which students' progress through the program and/or student attrition. Subsequently, factor analysis was conducted to determine the predominant attributes and characteristics of successful learners using the composite model presented by Rovai (2003). Based on the survival and factor analyses of available data and information, a statistical model was developed to measure the predicted success of a particular student. Finally, a student support system for high-risk students is proposed.

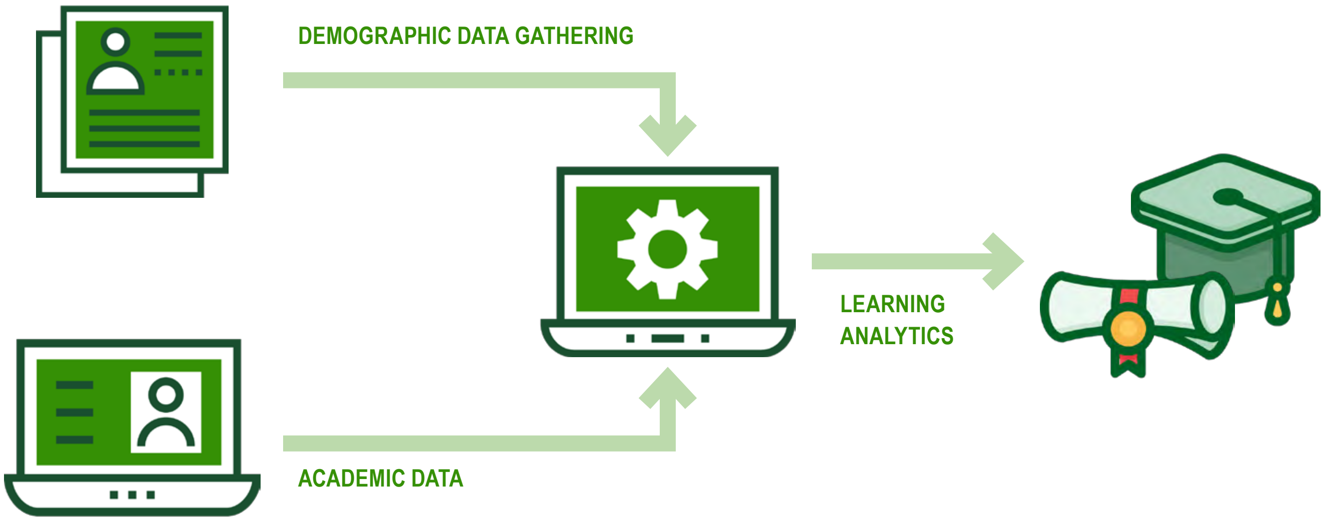

Figure 3. The learning analytics process employed in this study

VI. KEY RESEARCH RESULTS AND FINDINGS

6.1 Rate of Learners' Completion of the AA Program

Analysis of admission and graduation data revealed that from the 1st semester of AY1998–1999 to the 2nd trimester of AY2015–2016, a total of 311 students (14.9 % of 2,140 admitted students) graduated from the AA program. Figure 4 shows the comparison of the number of admitted students and the number of graduated students.

The apparent improvement in program completion can be attributed primarily to the change in the number of units required in the program.

In an ideal circumstance where learners are able to enroll 12 credit units per term, the AA program consisting of 60 academic units can be completed in five academic terms. In the analysis of the graduation data, the rate at which successful learners completed the AA program was measured by determining the average number of terms to graduate from the AA program. As shown in Figure 5, the most number of students who graduated (51) completed the AA program in six terms or about three (3) years. However, on average, the students completed the AA program in eight terms or approximately four years.[1]

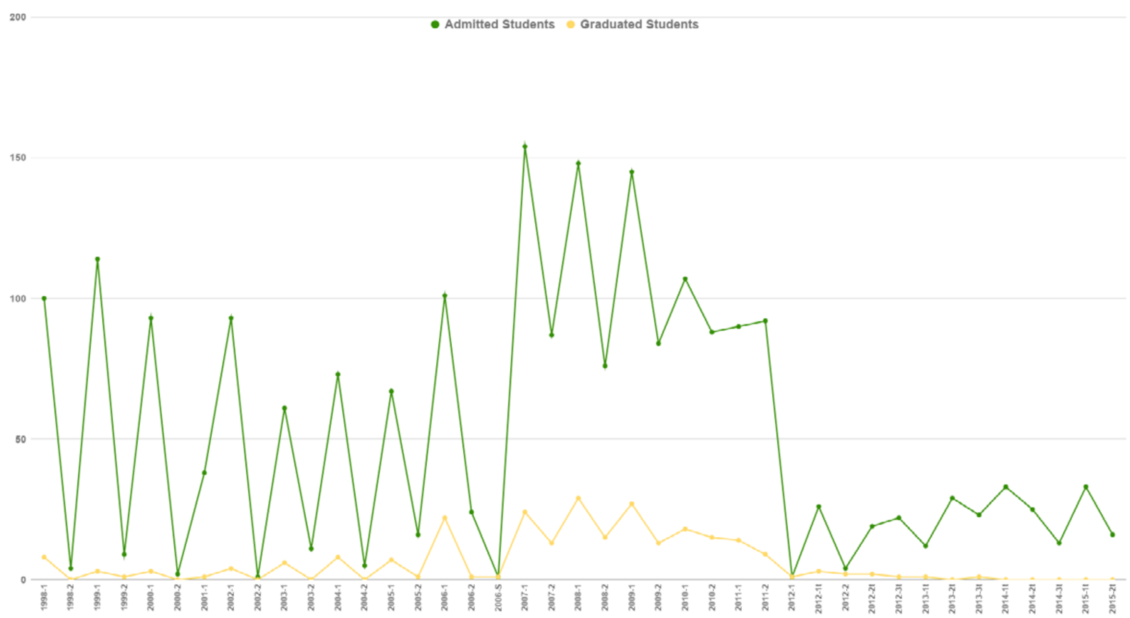

Figure 4. Number of admitted and graduated students in the Associate in Arts program from AY1998-1999 to present

[1] From AY1998–1999 to AY2011–2012, one term is equal to one semester. Since AY2012–2013, one term is equal to one trimester.

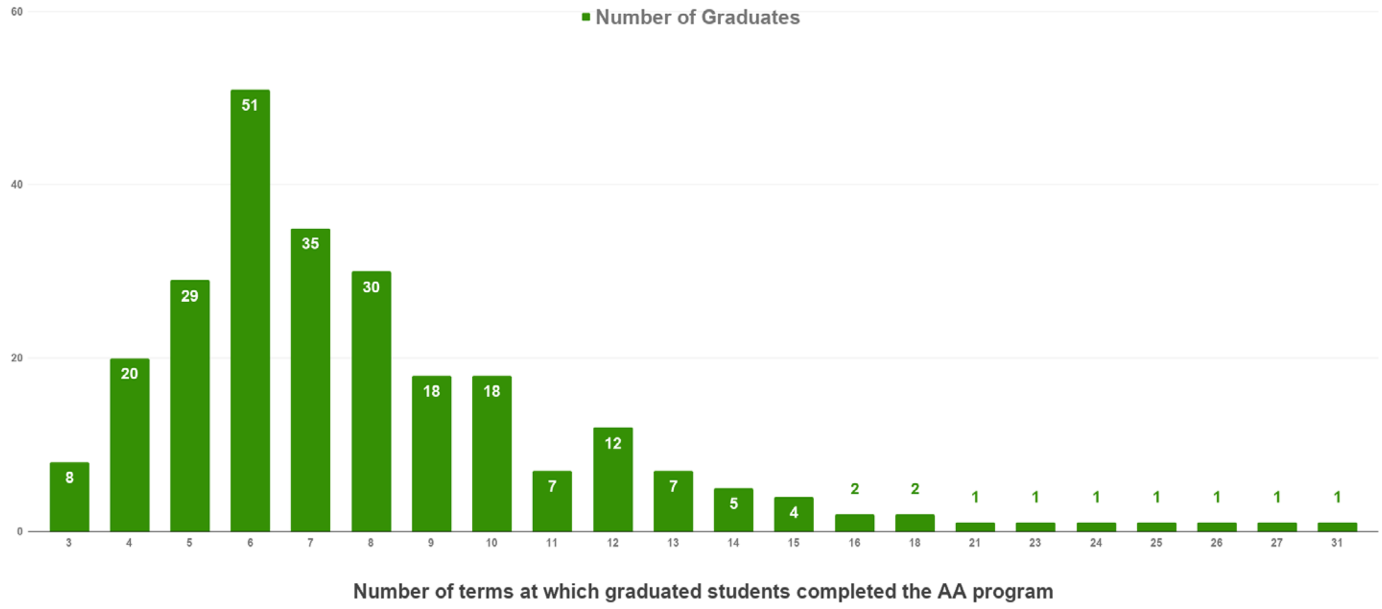

Figure 5. The rate at which students completed the AA program (number of terms)

Further analysis of the rate of completion (or the number of terms for a student to complete the program) showed that there is a significant increase in the rate of completion among students admitted from AY2005–2006 to the present compared to students who were admitted from AY1998–1999 to AY2004–2005. Graduates who were admitted from AY1998–1999 to AY2004–2005 completed the AA program on average, in 13 terms (6.5 years), while graduates who were admitted from AY2005–2006 to AY2013–2014 completed the AA program in approximately 8 terms (4 years).

In addition, the percentage of students who graduated since AY2005–2006 is three times the percentage of students who graduated prior to this point (Figure 6). From AY1998–1999 to AY2004–2005 a total of 39 students (6.46%) among 604 admitted students completed the program, while from AY2005–2006 to AY2014–2015, a total of 272 students (18.26%) among 1489 admitted students completed the program.

The apparent improvement in program completion can be attributed primarily to the change in the number of units required in the program. In AY2005–2006, a revised curriculum with a reduced number of required academic units — i.e., from the original curriculum of 72 units to 60 units — was implemented. While there may be other factors that contributed to the increase in the rate of completion, the reduction in the number of units required by the new curriculum has a significant effect ($\alpha = 0.01$) that favors the students' faster completion of the AA program.

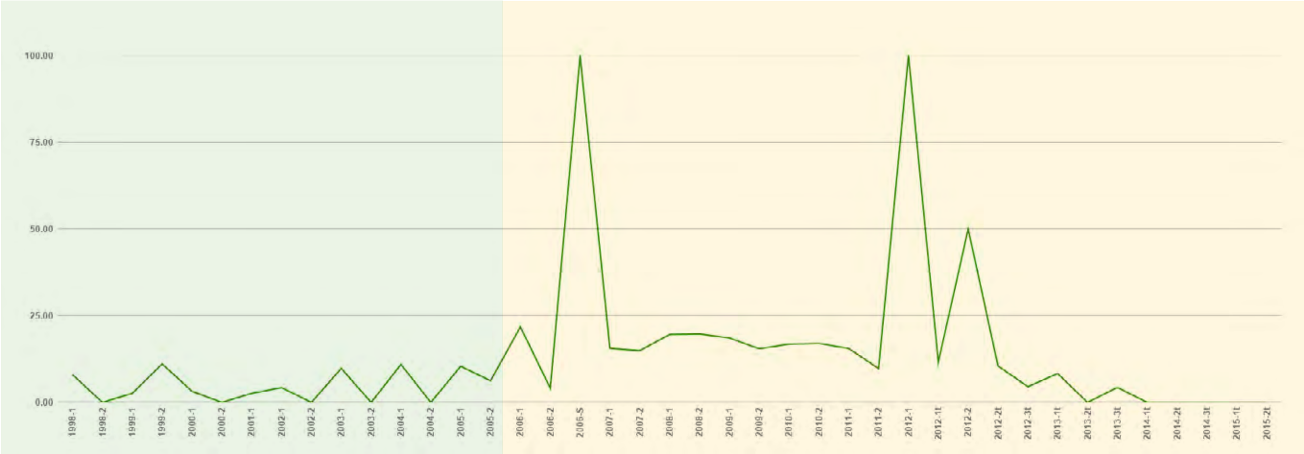

Figure 6. Percentage of students who graduated from the Associate in Arts program

6.2 Student Characteristics and Attributes Contributing to Program Completion

Gender. Since it opened in the 1st semester of AY1998–1999, the AA program has admitted a total of 2,410 students. Of this number, there are an almost equal number of male (1,339) and female (1,071) students (Figure 7). However, a significantly greater number of female students have graduated from the program (Figure 8). As of the 3rd trimester AY2013–2014, 61.8% of the graduates are female.

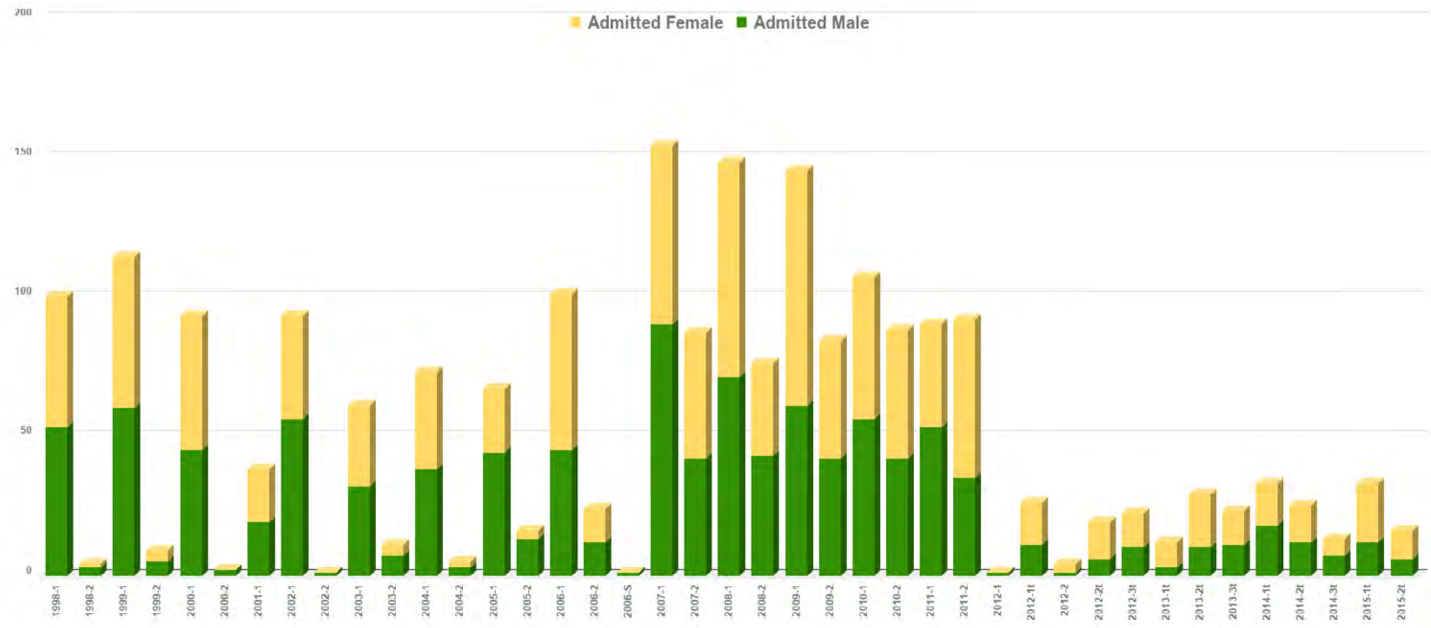

Figure 7. Gender distribution of students admitted to the AA program

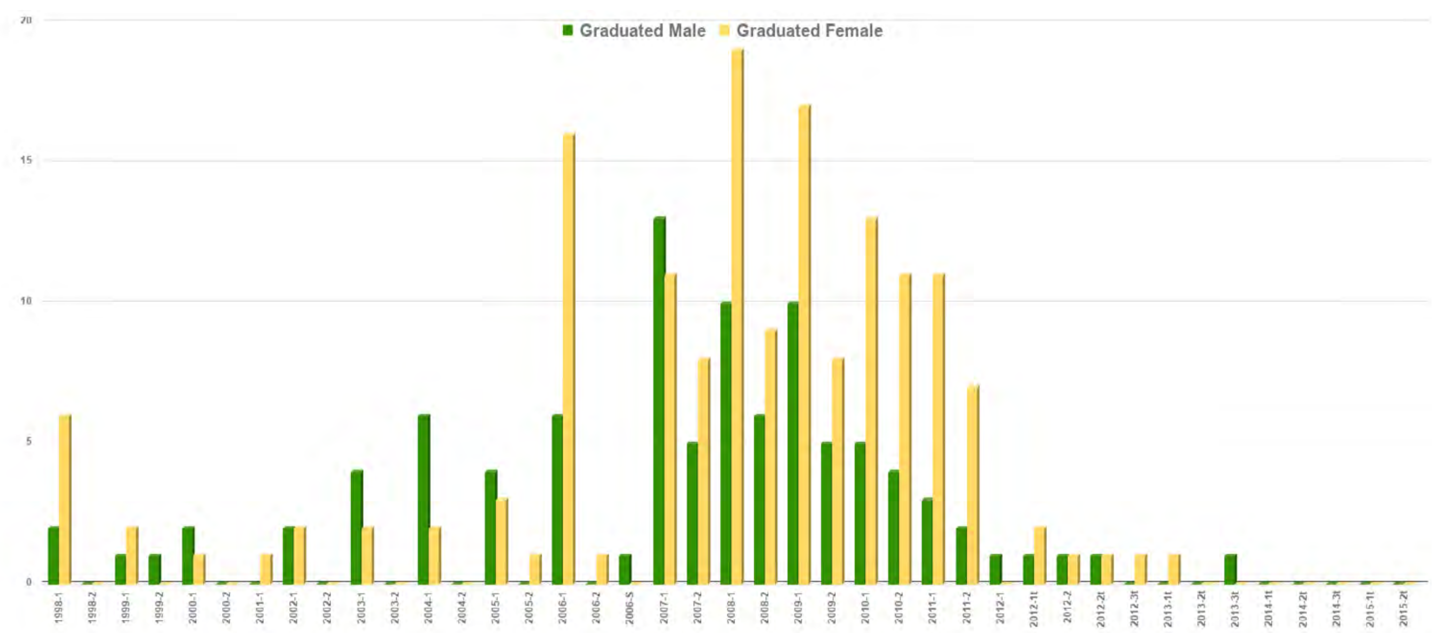

Figure 8. Gender distribution AA program graduates

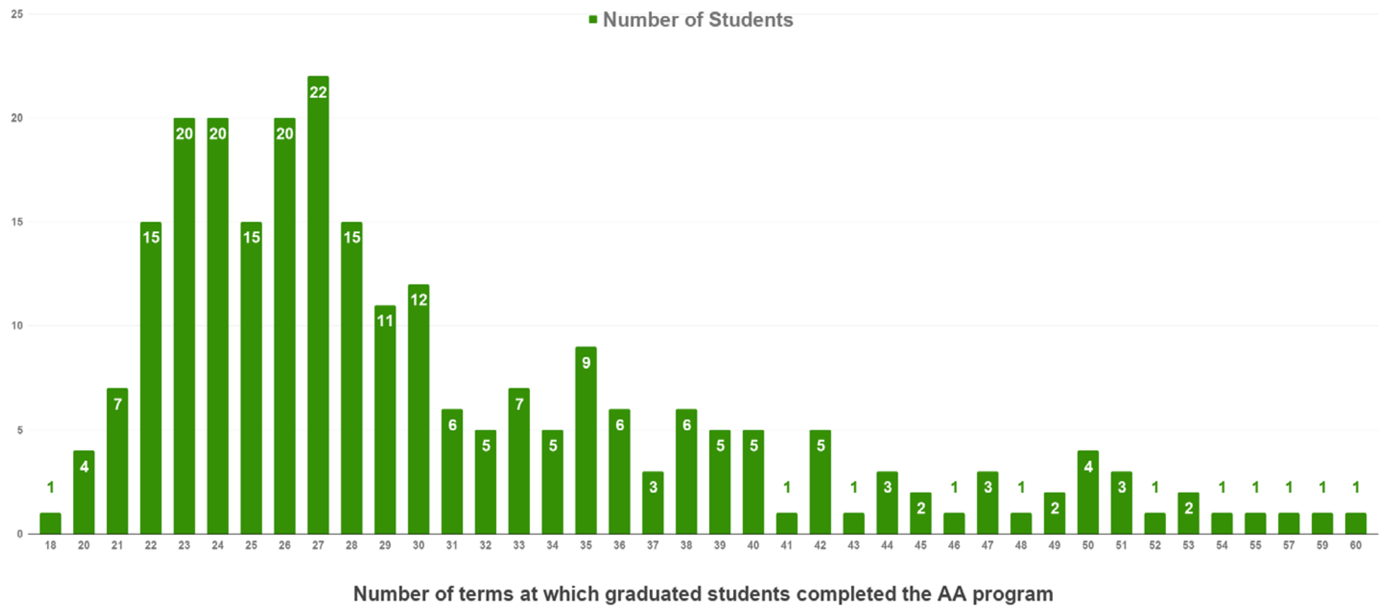

Figure 9. Age distribution of AA program graduates

Age. Analysis of available demographic data shows that students who completed the AA program are 18 to 67 years old. A majority (64%) of them are between 20 and 30 years old (Figure 9). This suggests a higher probability for younger learners to be more successful in completing the program which, in turn, may be due to the greater capability of younger learners to adapt to the online mode of learning.

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Civil status. Majority of the students admitted to the AA program are single or unmarried (89.1%) and only a few are married (10.5%). The rest of the admitted students are either divorced or legally separated. Of the 311 graduates admitted to the AA program, 280 are single (90.03%), while 30 are married (9.64%).

Occupation. More than half of the students admitted to the AA program were full-time students and unemployed (53.8%) while others were employed (44.3%) in various professions. Of the 927 students with full-time employment, 146 (15.7%) have graduated from the AA program. In contrast, only 3.6% of students without employment have been able to complete the program. These results indicate the important role of a source of income or employment in the success of students in the AA program.

Location. The graduates of the AA program were located in 65 areas in the Philippines and five areas outside the country (offshore). The most number of graduates were located in Metro Manila (120 graduates, or 38.6% of the total number

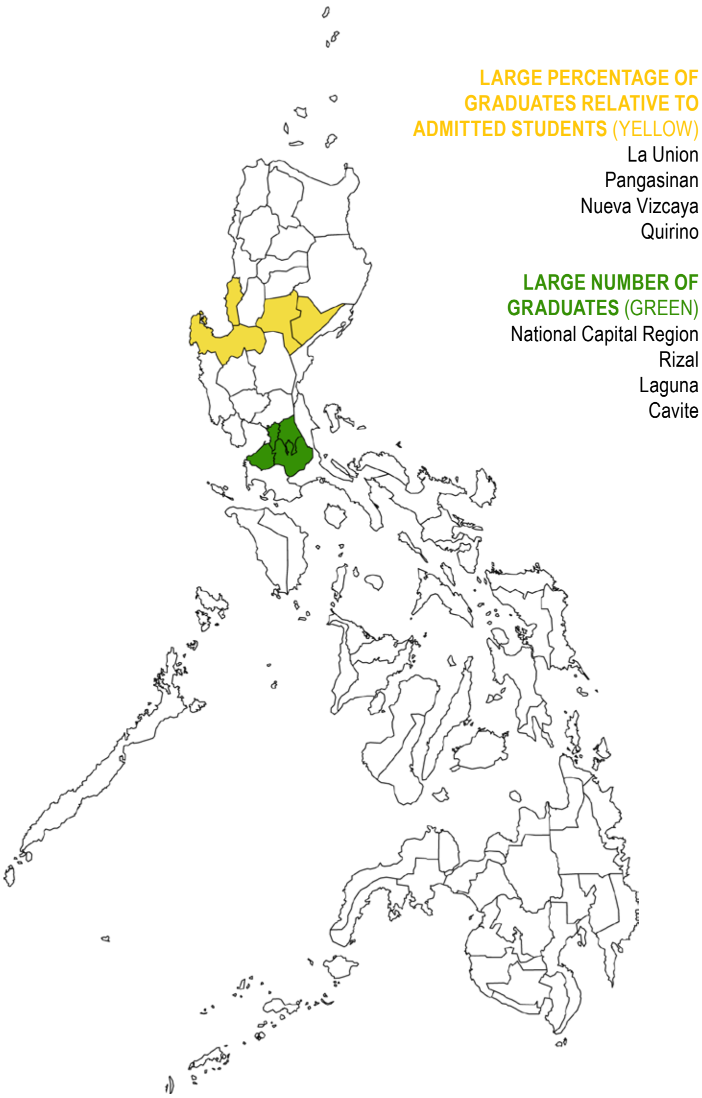

Figure 10. Map of the Philippines showing the areas where (i) a large number of graduates (green) and (ii) a large percentage of graduates relative to admitted students (yellow) are coming from

The high number of graduates from these areas can be attributed to the fact that many AA students reside in Metro Manila (1,132) and the Southern Tagalog provinces.

of graduates). A substantial number of graduates were also located in the provinces of the Southern Tagalog region, namely, Laguna (11.3%), Rizal (5.1%), and Cavite (4.5%). The high number of graduates from these areas can be attributed to the fact that many AA students reside in Metro Manila (1,132) and the Southern Tagalog provinces.

Looking at the number of students who graduated relative to the number of admitted students from a particular area, a relatively higher completion rate can be observed in the Northern Luzon regions, namely, La Union and Nueva Vizcaya (50%), Pangasinan (48%), and Isabela (40%). Figure 10 shows a map of the Philippines indicating the areas where a large number of AA graduates come from.

6.3 Previous Academic Experiences and Success in the AA Program

One of the factors that contribute to persistence in higher education is the learner's previous academic experiences (Tinto, 1975). In the AA program, applicants to the program who are returning to school from a period of being out-of-school is common. Moreover, the extent of their prior experience of post-secondary or tertiary level education varies.

Earned credit units and completion rate. Current data indicate that almost 70% of students admitted to the AA program have previously earned college/university credit units ranging from 1 unit to 98 units. Further analysis of previous enrolment data suggests that 49% of learners who earned more than 36 credit units[2] from their college enrolment prior to UPOU successfully completed the AA program (Figure 11). On the other hand, all learners (100%) who did not enroll in any college or university prior to their enrolment in UPOU have not yet completed the program.

General weighted average from previous enrolment and completion rate. Results shown in Figure 12 indicate that almost 50% of the students with a passing general weighted average (GWA 1.00 to 2.99) from their previous enrollment have already graduated from the AA program. In contrast, the majority (98.8%) of the students who had not earned credits or had failing GWA (i.e., less than 3.0) from their previous enrollment (prior to the AA program) have not yet completed the AA program. These results suggest that their previous academic experiences contributed positively to their AA program completion.graduates come from.

[2] Most universities and colleges in the Philippines offer programs with 36 credit units of courses per year.

One of the factors that contribute to persistence in higher education is the learner's previous academic experiences (Tinto 1975).

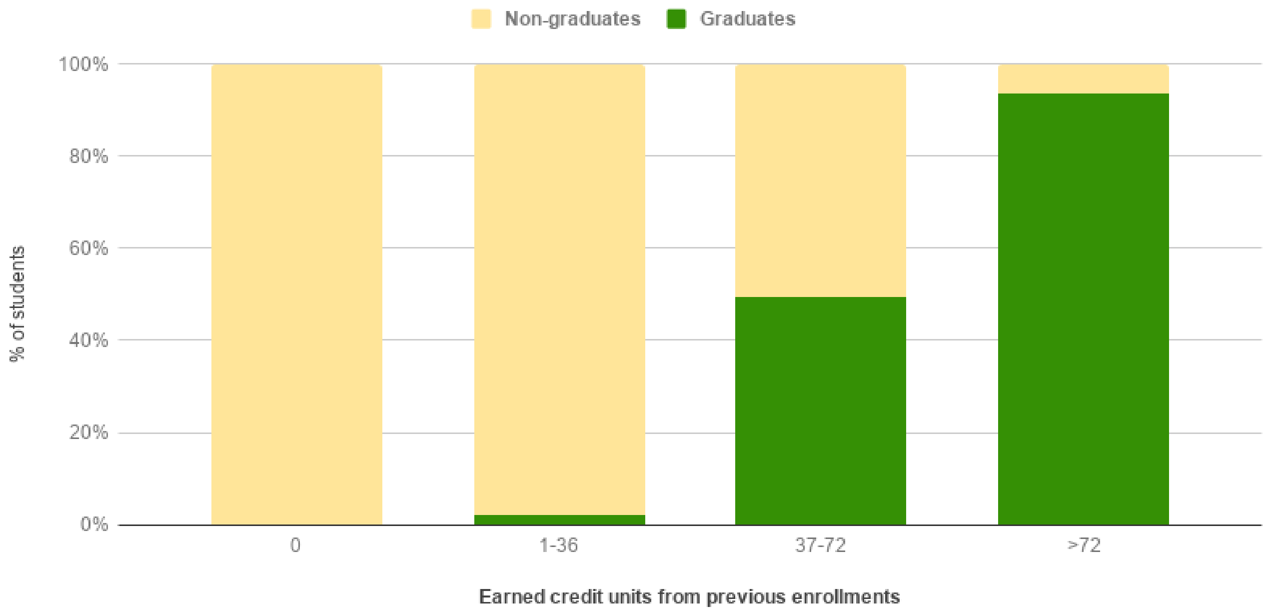

Figure 11. Completion rate of learners with previous college enrolment prior to their enrolment in the AA program

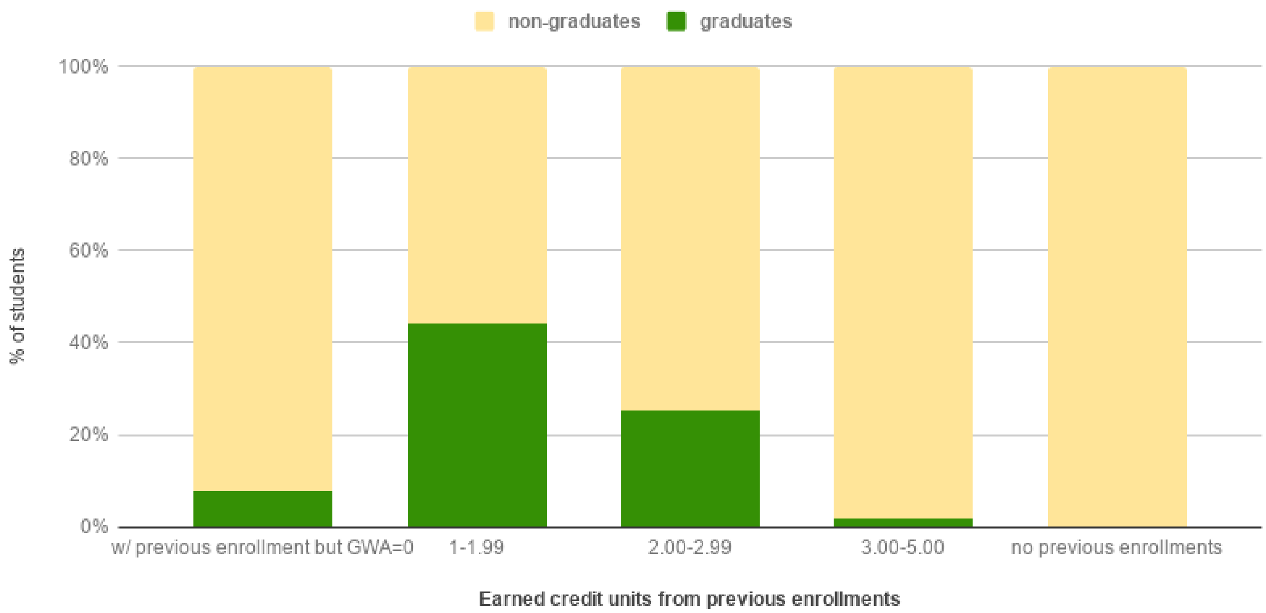

Figure 12. Previous GWA of learners and their completion rate in the AA program

6.4 Distance Education (DE) Readiness and AA Program Completion

The DE Readiness Module, which is composed of three topics, was first administered to applicants for admission to the AA program in 2013. Since then, the completion of the DE Readiness Module has become one of the requirements for admission to the AA program. This module is designed to provide applicants with a preview of what it is like to be an online DE student at UPOU. It allows assessment of the applicant's readiness to study at UPOU.

Results of analysis of data on the relationship between completion of the DE Readiness Module and completion of the AA programs indicate a positive correlation in terms of two dimensions, as discussed below.

Greater success in completing the program. The DE Readiness Module was offered to applicants at beginning 2013, which means that all students who were admitted to the AA program from 1998 to 2012 did not go through the module. Of the 1,956 admitted students during the 15-year period prior to 2013, only 14.2 % (278 students) completed the AA program. Upon introduction of the DE Readiness Module in 2013, the success rate has been observed to increase to 20.3%. The preparation of applicants to undertake a program in an online and DE environment that the DE Readiness Module affords is a factor in this increase in the completion rate.

This supports the previous finding that completion of the DE Readiness Module may promote program completion as it prepares the learners for the DE mode of learning.

Further analysis of the contribution of learners' completion of the DE Readiness Module to program completion shows that almost all (99%) of the non-completers from AY1998–1999 to AY2012–2013 had not taken the DE Readiness module. This supports the previous finding that completion of the DE Readiness Module may promote program completion as it prepares the learners for the DE mode of learning.

Shorter period of completion of the AA program. Further analysis of the results also indicated an apparent shortening of the period required to complete the program among those who completed the DE Readiness Module. The 20.3% of 133 students admitted beginning 2013 who completed the program did so in an average of 5.29 terms or simply 6 trimesters. Graduates who did not go through the DE Readiness Module completed the AA program at an average of 8 trimesters.

6.5 Learners' Course Enrollment Behavior

One of the determinants of academic behavior and learner attributes is the choice of courses that learners enroll in while they are in the AA program. The revised curriculum of AA implemented beginning AY2011–2012 is composed of 45 units of General Education (GE) courses, of which a total of 18 units are prescribed and 27 units are elective courses. The remaining 15 academic units are required courses. The AA program also includes 8 units of Physical Education (PE) and 6 units of courses mandated by the National Service Training Program (NSTP). This curriculum is summarized in Table 1.

Enrollment in required courses. Since COMM 1, COMM 2, MATH 11, COMP ED 1 and COMP ED 2 as well as PI 100 are required courses, enrolment in these courses is expected to be high at all times (Figure 13). Comparing the enrollment of graduated and unsuccessful students in these courses, it is observed that the enrollment in COMM 1, COMP ED 1, MATH 1 and MATH 11 by students who have not yet completed the program, are approximately four to six times higher than the enrollment of graduated students. Furthermore, across the 11 required courses, it can also be observed that enrollment of unsuccessful students in these four courses is almost doubled compared to the other courses. These findings suggest that the frequency of repeated enrollment in these courses is high for unsuccessful students. This result may further imply that these courses may play an important role in the delay of a student's completion of the AA program. Further analysis of students' performance in each of these courses is necessary to fully understand the cause of their failure in these courses. Likewise, academic support such as bridge courses and an enhanced tutoring system may be essential to improve their performance in these courses.

Enrollment in elective courses. Enrolment data in Figure 14 show that both graduated and non-graduated students enrolled in almost the same set of elective courses: ENG 157, COMM 3 and HUM 1 in the Arts and Humanities domain; SOC SCI 2, SOC SCI 1, and PHILO 1 in the Social Sciences and Philosophy domain; and NAT SCI 1 and NAT SCI 2 in the Mathematics, Science and Technology domain. This finding suggests that a student's choice of elective courses does not necessarily affect their completion of the program.

Table 1. The curriculum of the Associate in Arts program

Academic courses required in the AA program		Credits units
General Education courses		
Arts and Humanities (AH) domain	Prescribed: COMM 1, COMM 2	6
	Electives: ENG 157, COMM 3, HUM 1, HUM 2	9 *(choose 3 courses only)*
Social Sciences and Philosophy (SSP) domain	Prescribed: HIST 1, HIST 2	6
	Electives: PHILO 1, SOC SCI 1, SOC SCI 2, SOC SCI 13	9 *(choose 3 courses only)*
Math, Science and Technology (MST) domain	Prescribed: MATH 1, STS	6
	Electives: MATH 2, NAT SCI 1, NAT SCI 2, MS 1	9 *(choose 3 courses only)*
Other required courses		
Required courses	MATH 11, PHILO 173, COMP ED 1, COMP ED 2	12
Mandated course	PI 100	3

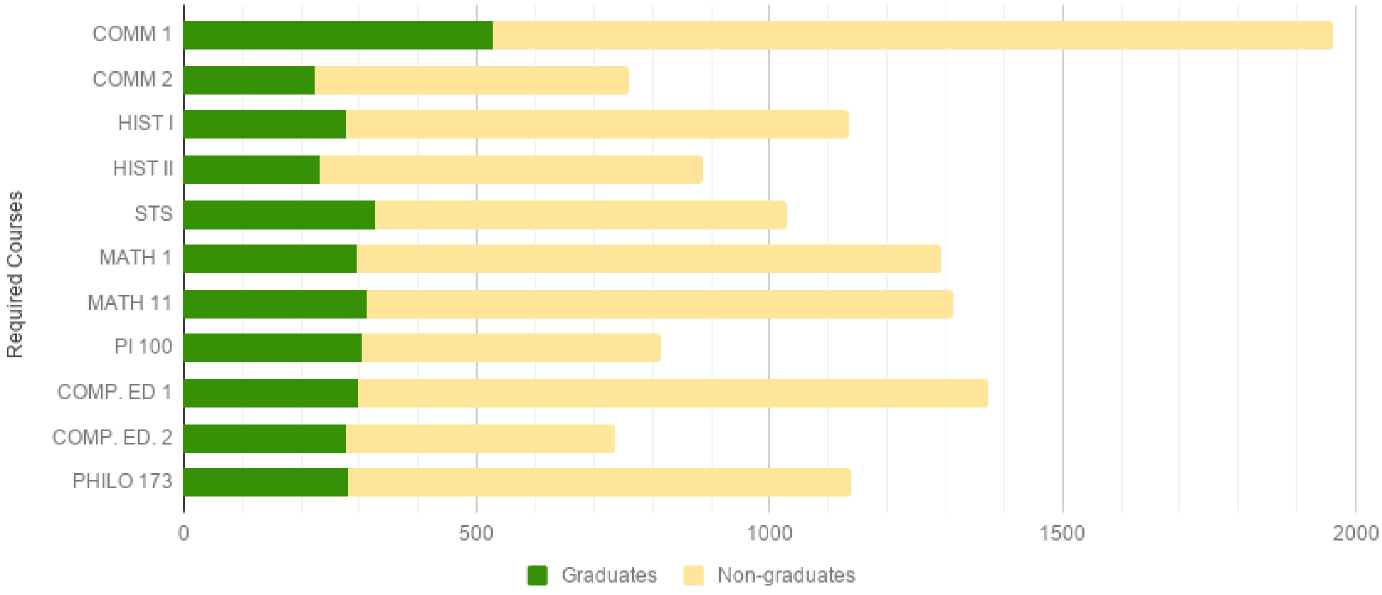

Figure 13. Enrolment in required courses in the AA program

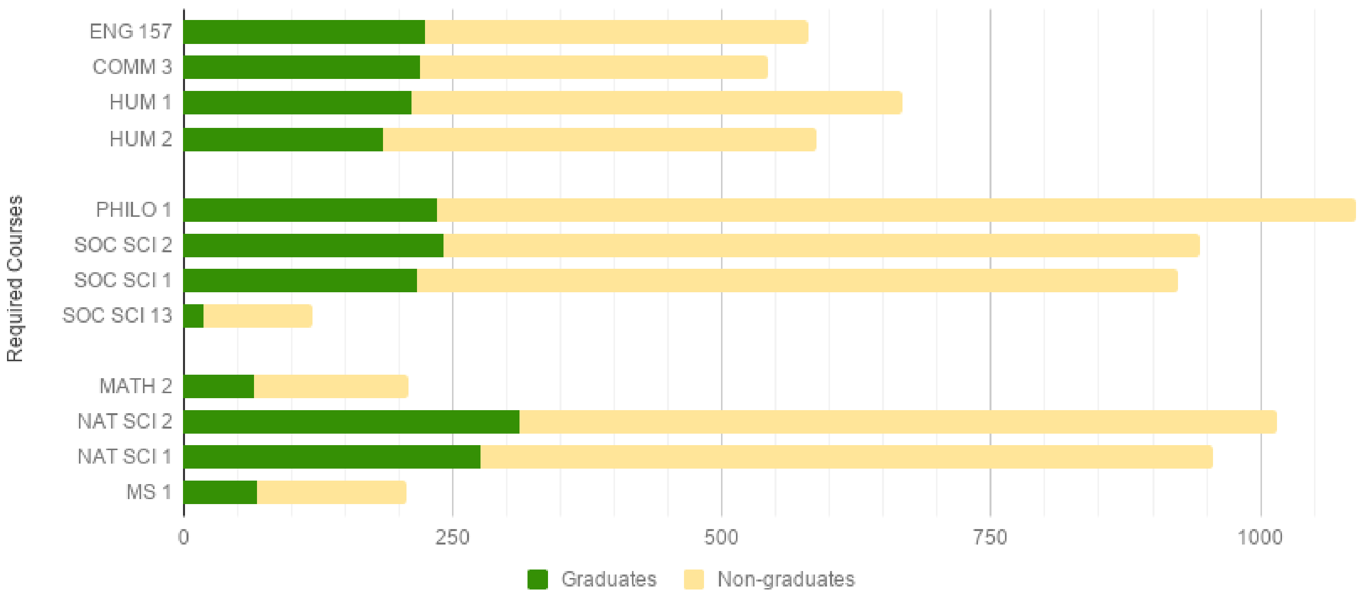

Figure 14. Enrolment in elective GE courses

6.6 Learner's Academic Behavior in the LMS

MyPortal, the UPOU LMS, is a Moodle-based platform where all course material and course activities are located. Since almost all course-level transactions occur in MyPortal, the academic behavior of AA students can be extracted from this platform. During data gathering, however,[3] the extraction of relevant information from this platform posed significant challenges to the researchers due to the following reasons:

1. The use of MyPortal began in mid-2002 when UPOU started online course delivery. Because of this, the population of AA students that have been included in this aspect of the study is limited to those who used the system — i.e., those admitted from the 2nd semester of AY2002–2003 onwards. A total of 1640 students were included in the analysis.

2. Since its first use in 2002, three versions of MyPortal have been used by UPOU. There is a discrepancy in the kind of data that are kept or archived in each version. In the cleaning of the archived data, it was apparent that a complete data set was only available beginning 2012. Before 2012, there was no readily available "log-in" data. Unless a massive interpolation of the available data would be performed, no relevant log-in data could be used before 2012. [The importance of the "log-in" data will be explained further in the section below.] Because of this, the research focused only on the academic behavior of students who used MyPortal from 2012 onwards.

3. Massive cleaning of data from MyPortal was required during data gathering and organization. A number of "serial conversions" was necessary for the information to be usable for analytics. This requires a large amount of time for data deduction and reduction. As a result, only partially analyzed "log-in" data were obtained.

Based on the available archived data from MyPortal from 2012 and onwards, the following information can be gathered: 1) log-in data of the student; 2) student's submission of assignments; 3) quizzes/exams accomplished by the student; and 4) discussion forums participated in by the student. But due to the difficulty of cleaning the data, the research team was able to analyze the log-in data only.

[3] Other academic transactions such as pen-and-paper examinations, students' consultations with the FIC, presentations and discussions through video-conferencing, etc. are done outside the course site or outside the LMS.

Learners' average log-in frequency in MyPortal. A student's log-in/log-out in MyPortal may serve as an online tracker of student course activity during the term. It captures information on the frequency of a student's access to the course site (within a day or within a week), how much time is spent by the student on the course site, at what time a student most frequently visits the course site, the assignments that have been submitted, the quizzes and exams that have been taken, etc.

From the available log-in data sourced from all available courses in MyPortal, the frequency of student access to course sites was determined by measuring the number of days (in an academic term of 12 weeks) that the students accessed their course sites. This information was used instead of the actual log-in count due to the probability of a student being logged out unintentionally, which would require the student to log in again.

The results of this analysis indicate that students who completed or graduated from the program accessed their course sites at an average of 23.51 days per term or 73.5% of equivalent daily sessions.[4] On the other hand, unsuccessful students accessed their course sites 13.71 days per term (42.8%) on average. The significantly higher frequency of accessing the course site among students who completed the program ($\alpha = 0.05$) suggests that this behavior contributes to program completion. Students who accessed their course sites less frequently were more likely not to complete a course, which further results in poor performance in the program. Consequently, they were more likely to be unsuccessful in completing the program.

Log-in frequency and enrolled units. To determine whether the frequency of accessing the course sites depends on the student's academic load (or the number of units enrolled by the student), the correlation between the frequency of log-in and the enrolled units was measured. The graph in Figure 15 shows a weak correlation ($r = 0.295$) between the frequency of log-in and the units enrolled by the students. Students who enrolled 3 units (1 course), 6 units (2 courses), and 9 units (3 courses) accessed

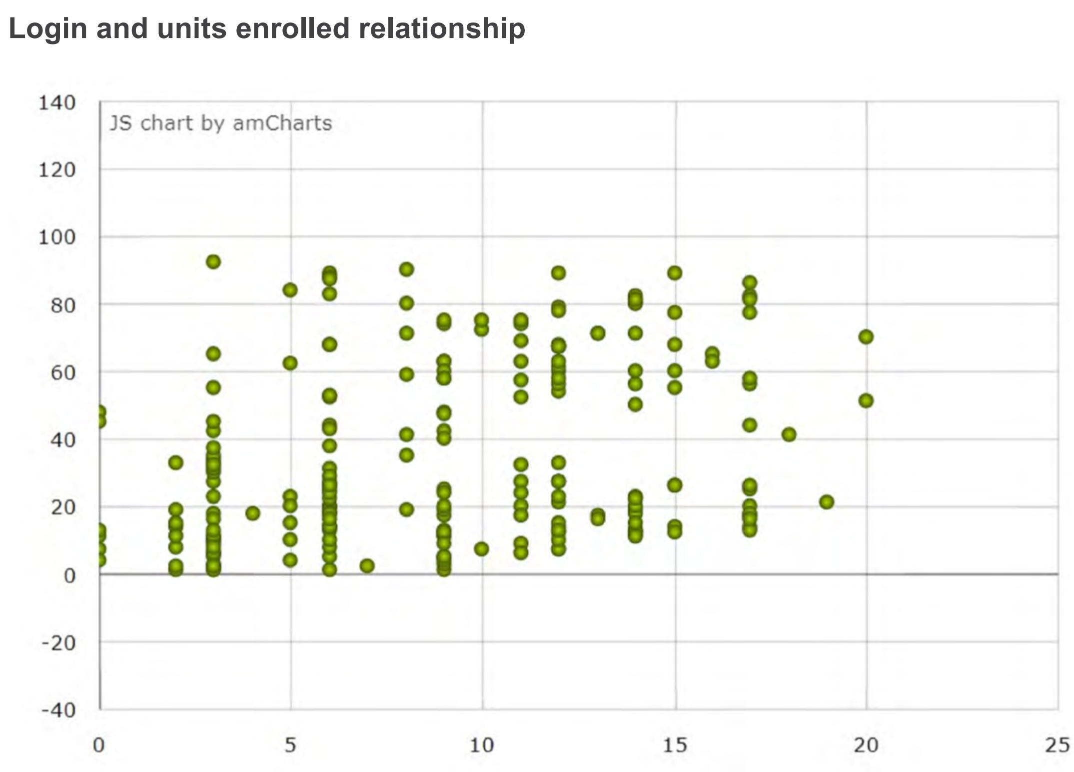

Figure 15. Correlation between log-in frequency (days per term) and number of units enrolled per term

[4] In a conventional class setting in the Philippines, a three-unit course requires 48 hours of class sessions. If each session is 1.5 hours per day, it will require 32 days of meetings for the whole academic term. In this study, the "32 days per term" is used as equivalent to one term in UPOU.

Login and GWA relationship

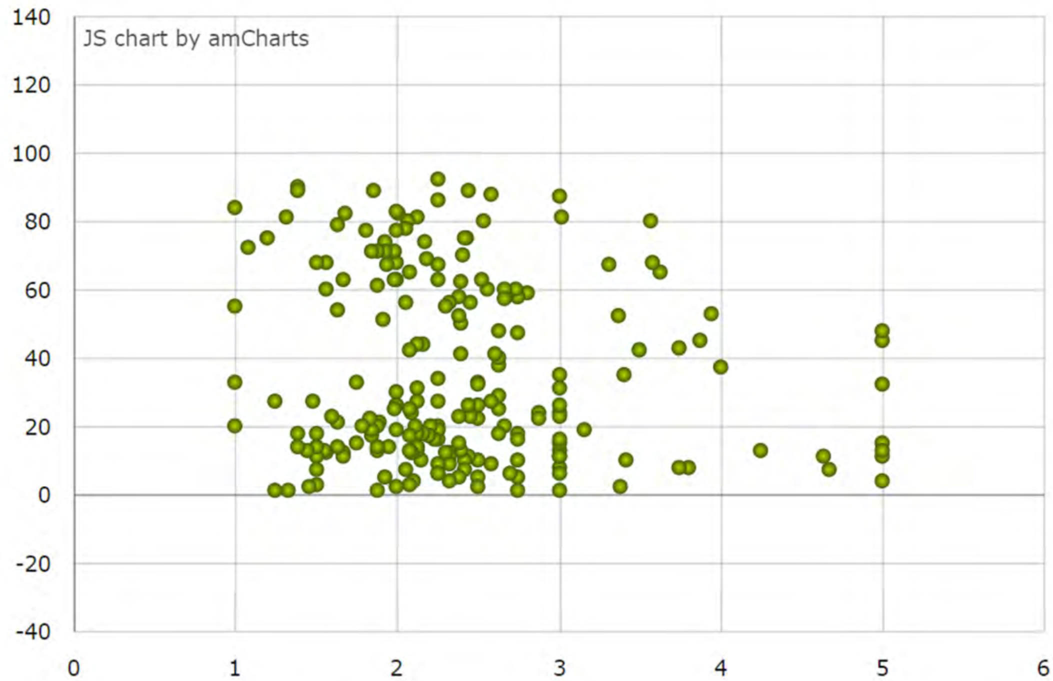

Figure 16. Correlation between log-in frequency (days per term) and general weighted average (GWA) per term

the course site at an almost equal frequency. This may be explained by the fact that as long as the student is enrolled in a given term, they will have to access MyPortal, regardless of the number of units they enrolled.

Log-in frequency and general weighted average. Figure 16 shows the frequency of log-in (counts per month) against the general weighted average (GWA) per term. The highest grade in UP and in UPOU is 1.0 while the failing grade is 5.0. Figure 16 indicates that a majority of students who accessed the course site more than 20 days per term received passing grades ranging from 1.0 to 3.0. On the other hand, students who accessed the course site less than 20 days per term received grades below the passing mark of 3.0.

The frequency of log-in indicates the number of times a student virtually attends class. A log-in frequency of 20 days per term would be similar to physically attending a face-to-face or conventional class at least once a week in a 12-week term. The analysis shows that the frequency of a student's access to the course site has a positive correlation (r = 0.114) to their performance in the class. That is, the higher the frequency of log-in, the greater is the student's interaction with the course material and the more likely the students will pass the course and survive in the AA program. This can further be validated by analyzing the extent of course material views by a student every time they accessed the course site.

6.7 A Preliminary Model to Predict Success in the AA Program

Based on the demographic data and information on the completion of the DE Readiness Module, a preliminary model to predict program completion or program success was obtained by logical regression. The model is described by Equation 1:

Equation 1:

$$P\,(Y+1) = \frac{e^{-2.354067-.58408\text{stgender}-.5986688\text{civilstatus2}-.0001699\text{age\_entry}+.2855489\text{occupation}+.300934\text{length\_terms}}}{1+e^{-2.354067-.58408\text{stgender}-.5986688\text{civilstatus2}-.0001699\text{age\_entry}+.2855489\text{occupation}+.300934\text{length\_terms}}}$$

This model predicts the probability (P) of completing the program (in terms of percentage) based on static variables such as age, gender, civil status, and occupation. It describes the degree of association of variables (i.e., demographic, readiness for distance education, and length of residency in the program) with the outcome (graduated or not graduated). Based on this model, gender, civil status, and age are strong determinants of a learner's success as evidenced by their odd's ratio. Moreover, a learner's readiness to undertake the AA program via online DE mode is also shown to contribute significantly to the completion of the program.

This statistical model can be further improved by incorporating other possible variables such as their academic behavior in MyPortal.

VII. CONCLUSION AND RECOMMENDATIONS

This study was able to identify key characteristics of students who have successfully completed the AA program. Based on the analysis of their demographic information, it is found that students' age, gender, civil status, occupation, and location are major factors that contribute to their completion of the program. Completion of the Distance Education Readiness module before beginning the AA program has also been found to have a positive impact on program completion. Moreover, prior academic experiences gained by the students before entering the AA program has been found to have a positive impact on students' success in the program.

A statistical model that can predict the probability of a student to succeed in the AA program based on their demographic characteristics and their completion of the Distance Education Readiness Module was derived in this study. However, further improvement in the model is necessary to incorporate academic factors that have been found to contribute significantly to student's success. Such factors include the student's enrollments of required and prescribed courses as well as their activities in the LMS

A key aspect of this study is the proposal for the development of a student support system based on the characteristics and attributes of learners as well as their academic behaviors. This student support system will allow the students to improve their progress in the program. For example, it is evident that most learners in the AA program struggle in their Mathematics courses. To address this, the University may design and implement intelligent tutoring systems that will allow provision for assisted Mathematics learning.

VIII. THE INTERVENTION SYSTEM: THE STUDENT SUPPORT SYSTEM

With the aid of learning analytics, some of the characteristics and attributes as well as academic behaviors of the successful learners in the AA program have been determined and understood. These results will allow UPOU to establish a student support system for undergraduate students. Based on the findings, this study proposes the following framework for this student support system as a mechanism to promote learner success and program completion (see Table 2).

Although there are aspects that can be addressed by a student support system, there are learner characteristics and attributes that cannot be addressed by such like gender, civil status, and age.

Table 2. A framework for a student support system for undergraduate students in UPOU

Factors affecting persistence and attrition	Goals of the intervention	Required information or data for learning analytics in support of the goal	Targeted student support system
Pre-admission factors	To equip new students with academic skills that they will need to be prepared for distance education	• Demographic characteristics • Past academic history	• DE Readiness Module • Bridge course for online learning skills • Bridge courses for college-level literacy and numeracy skills
	To provide assistance to new students who are financially challenged and who are part-time students	• Demographic (socio-economic) information	• Established scholarship and financial assistance • Pre-study counseling
After-admission factors	To provide feedback to continuing students about their academic performance and progress	• Academic effort as measured by academic behavior in the LMS • Grades in courses taken in UPOU	• Program advising • Academic consultation • Real-time email messaging system and reminders of academic standing
	To provide continued assistance to students with deficiency on digital literacy	• Demographic (location) information • Academic background • Academic performance	• Bridge course on digital literacy
	To provide at-risk students with academic assistance	• Activities in the LMS	• Tutoring system (i.e. intelligent tutoring system) • Academic clinics

IX. PROJECT INFORMATION AND OUTPUTS

Early findings from this research study were presented at academic conferences, as follows:

Reyes, C. T. (2016, October 26-29). Applying learning analytics in an open and distance learning institution in the Philippines. In the *30th Annual Conference of Asian Association of Open Universities (AAOU)*. Crowne Plaza Galleria Manila, Philippines.

Reyes, C. T. (2016, April 3-6). Exploring the use of learning analytics to enhance the learner support system of the undergraduate students of UPOU. In the *Asian Conference on Education and International Development*. Kobe Art Center, Kobe, Japan.

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