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ACADEMIC SUCCESS PREDICTORSFOR ARCHITECTURESTUDENTS AT KANO UNIVERSITY OF SCIENCE AND TECHNOLOGY, WUDIL, KANO STATE, NIGERIA

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ABSTRACT
Academic success, linked to socioeconomic advancement and key positive indicators in life has largely been investigated along STEM courses especially in Nigeria. In this study, academic success was predicted at two levels: second class lower (2.2) and second class upper (2.1) degreesusing 244 questionnaires from architecture undergraduates at Kano University of Science and Technology (KUST) Wudilto test the hypothesis that other factors apart from motivation predict high academic success. Results from Binary Logistic Regression models indicate that achieving a 2.1 degree largely depends on personal attributes, notably how efficiently a student manages time/schedules, some degree of independence as well as conducive learning environments (classrooms, accommodation, external lighting, power supply, worship places and general cleanliness)and not necessarily motivation. This lends credence to Walberg's Theory of Educational Productivity. Overall, mode of entry was the only significant predictor for academic success for both 2.2 (p=0.007,Exp(β)=1.990) and 2.1 (p=0.016, Exp(β)=1.361) class of degree models. This implies that candidates admitted through avenuesother than UTME/JAMB such as Direct Entry have higher chances of graduating with a 2.1 class of degree. Prospective candidates are encouraged to pursue advanced level qualifications prior to admission into architecture as this substantially increases the probability of graduating with a high class of degree.
Keywords: Academic success, Architecture undergraduates, Binary Logistic Regression, Nigeria, Predictors

INTRODUCTION

Academic success, often interchangeably employed in literature with academic achievement or performance generally refers to attainment of set learning objectives, satisfaction with completing academic activities, acquisition of desired skills and competencies as well as overall post college performance, usually measured along the Cumulative Grade Point Average, CGPA (Mainaand Ibrahim, 2019). The preponderance in recent times of studies on academic success is attributed to several interrelated issues. These includelinks to socioeconomic aspects of life such as better employment and income, self-discipline and higher decision-making skills (Dixson*et al.,*2017); high enrolment and high failure rates especially for large classes (Alzen *et al.,*2018) as well ashuge public investment in Higher Education Institutions (HEIs) globally and improvement in education policy interventions locally. Although a comprehensive discussion of factors influencing academic success is beyond the scope of this study,a review of recent literature revealsthat a sizeable number of studies on academic successfocus on Mathematics, Science and Computer related courses as they usually serviceother coursesin HEIs(Table 1).Digressing from this general trend especially in Nigeria, our study focuses on architecture as studies predicting academic success of architecture students are uncommon in literature.

Table 1: Factors and predictors of academic success from recent literature

Factors and Predictors	*Source(s)*
Pre-Entry qualifications: quality of previous schools, entry grades/qualifications	^Aluko et al. (2018), Abdulazeez & Abdulwahab(2018), *Bahadir (2016),
Socio-economic/cultural factors: Parents' income, occupation, education, ethnicity, place of residence	^Opoko et al. (2016), *Zewude & Ashine(2016)
Demographics: Age, Gender, Level	*Asampana et al.(2017), *Adejumo & Adetunji (2013), ^Musa & Saliu (2016), ^Maina & Ojobo (2020)
Personal attributes: Motivation, self-discipline, passion, peer/social relationships, time/personal management	*Alzen et al. (2018), ^Mtan (2017), Fernando (2017), Mabula(2015), *Sule &Saporu(2015), Tanis (2014)
Educational environment/teaching: Lecturer competencies, relationship with staff, information about the course, regulations/environment, counselling services	*Mustapha et al. (2016), ^Opoko et al.(2016), ^Olatunji et al.(2016), ^Oluwatayo et al. (2015)
Quality of University facilities: Classrooms, IEQ, libraries, labs, accommodation, internet, cafeterias, landscaping etc	Ayoola & Balogun (2018), ^Maina et al. (2018)
Utilities: Security, Water, Power supply, sanitation, cleanliness etc	^Maina et al. (2018), Akhihiero(2011)

**Studies on Mathematics/Science subjects, ^Architecturerelated studies*

Several theories have been profferedto explain academic success.Examples include Expectancy Theory, Needs theory (Geiger & Cooper, 1995) and Walberg's Theory of Educational Productivity(Walberg et al., 1986). Expectancy and Needs theories are bothindividualistic in nature and focus on motivation (Geiger & Cooper, 1995). Expectancy theory, developed by Vroom in 1964 posits that the motivation to act "is a combination of the perceived attractiveness of future outcomes and the likelihood one's actions will lead to these outcomes" (Geiger & Cooper 1995:251). This implies a conscious decision made by the student. Needs theory is based on intrinsic subconscious motivation and posits that motivated behaviour is driven by intrinsic needs such as achievement, affiliation, autonomy etecera (Geiger & Cooper, 1995). Walberg's Theory on the other hand hypothesises that psychological individual attributes as well as proximate environments influence cognitive, attitudinal and behavioural outcomes of education (Reynolds & Walberg, 1992). Walberg et al. (1986) list nine factors which at optimal levels, increase student achievement. These are prior achievement/ability, age, motivation/perseverance on learning tasks, quantity and quality of educational experience, home environment, class/school environment, peer group environment and mass media, TVto be specific (Walberg et al., 1986; Reynolds& Walberg, 1992). Walberg's theory provides a parsimonious modelof academic success as it recognises not only individualistic factors but the complexity of human learning by converging on the least number of factors that consistently predict student outcomes (Reynolds & Walberg, 1992; Rugutt& Chemosit, 2005). Consequently, the current study hypotheises that other factors apart from motivation predict academic success for architecture students in line with Walberg's theory. This hypothesis is tested by comparing factors that predict academic success for students with a 2.2 class of degree (considered the lower limit for securing admission to pursue a Masters degree which is a pre-requisite for professional examinations in Architecture) and a 2.1 class of degree, generally considered to be a measure of high academic success in Nigerian universities.Results are expected to inform and guide university authorities, especially registration officers as well as level coordinators who counsel architecture students regarding management of academic performanace from admission to graduation.

MATERIALS AND METHODS

To address our hypothesis, we employed Binary Logistic Regression (BLR) to predict success at two levels.

These are second-class lower degree, 2.2 (CGPA $\geq$2.40, coded successful, 1; else 0) and second-class upper degree,2.1 (CGPA $\geq$3.50, coded successful, 1; else 0). BLR is a category of general linear models employed to predict categorical or binary dependent variables from independent variables which may be categorical or discrete (Bahadir, 2016). Although studies establish other Educational Data Mining (EDM) techniques such as Support Vector Machine (SVM)and Artificial Neural Networks (UNN) capable of high predictive capabilities (Aluko et al., 2018; Bahadir, 2016), we employ BLR principally for two reasons. First, "the methodology for EDM is not yet clearly defined and there are no clear standards about which data mining methods or algorithms are preferable" (Abdulazeez & Abdulwahab, 2018:143). BLR presents clear standards and statistics to check model fitness. Secondly, examples of studies utilising EDM to predict academic success within our study context test only data on previous academic records notably ordinary level results to predict undergraduate academic performance (Aluko et al., 2018; Abdulazeez & Abdulwahab, 2018). These are limitedin terms of school, socio-economic, personal, psychological and other factors influencing academic successin literature. Consequently, data was collected on the aforementioned factors in the 2018/2019 academic session at KUST using a survey questionnaire adapted from Maina et al. (2018).Specific steps for the analyses conducted in SPSS v21 are explained hereunder.

a. Demographic and socio-economic data were analysed descriptively for the entire sample. These relate to gender, age, level, mode of entry, father and mother's educational qualification, place of residency, whether student received counselling or not, motivation to study architecture, major source of funding as well as CGPA, our dependent variable. Results from this section are presented as frequencies (N) and percentages (%) in Table 2. Other variables related to personal, school and psychological factors measured on 5-point likert scales are presented in terms of frequency (N), means (M) and standard deviations (SD). Mean values equal to or above 3 were considered important influences on academic performance. SDs below 1 denote a clustering of likert ratings around the mean (Field, 2013), underscoring agreement of responses for that item. These are presented in Table 3.

b. To improve parsimony of model parameters, we ran initial BLR for all variables using the two levels of academic success (2.2 and 2.1) with a relaxed *p*/significance value of 0.25 as suggested by Sperandei (2014). Variables that met this criteria, based on Omnibus Tests of Model Coefficients, were then entered into final models to predict success at 2.2 and 2.1 levels. Results from these procedures are presented in Tables 4 and 5 respectively.

c. Model parameters were tested in terms of strength of relationship, goodness of fit, effect sizes, classification tables, beta (β) values, Wald statistic (z^2), odds ratio (Exp(β)) as well as checks to residuals as a final verification of model fitness(Field, 2013).We employed*Hosmer-Lemeshow goodness-of-fit* statistic to assess model fitness, with non-significant results denoting satisfactory model fitness (Asampana et al., 2017). *Cox* and *Snell'smeasure* as well as *Nagelkerke's adjusted value* provide pseudo effect sizes (Field, 2013). These are often employed to gauge variance explained by a logistic regression model (Zewude & Ashine, 2016). Classification tables display predictive capabilities of the model in percentage, the perfect fit being 100%. Beta values (β) are parameters assigned each independent variable measuring the magnitude of contribution made by the variable to the model. We employ Exp(β) values as measures of the odds ratio (Field, 2013). Standardised z scores and residuals reveal discrepancies in the data as well as possible outliers which may influence model fitness (Field, 2013).

RESULTS AND DISCUSSION

Survey questionnaires targeted all students in 200-400 level, totalling 357 candidates in 2018/2019 academic session at KUST. Out of this number, 274 filled questionnaires (77%) were retrieved. We screened out 30questionnairesas CGPA, our dependent variable, was unreported for these cases. All analyses were conducted on 244questionnaires (68%) in SPSS. 100 level students were excluded in the survey for two reasons. First, records for this cohort of students were available for a single semester, thus computation for CGPA was not possible. Secondly, unlike their older and more experienced counterparts at higher levels, 100 level students havelimited campusexperiences necessary to provide objective feedback on school related variables.

Results from the demographic section reveal that frequencies for age were highest between

18-25 years. The most common avenue of securing admission was SSCE/JAMB. Gender distribution was skewedheavily in favour of males (88%) against 7% recorded for females as depicted in Table 2.

These data fit demographic profiles of architecture undergraduates reported in similar studies (Mtan, 2017).Fathers of architecture students were on average more educated than mothers as 63% of fathers have first-degree qualifications compared to 29.4% of mothers.The major source of funding from our dataset came from fathers (61%). While57% of our sample did not receive counselling prior to admission, 57% were self-motivated to study architecture. Respondents residing in Kano account for 47% of the sample, with 21% living in neighbouring States. This presents a localised admission nucleus around Kano and its immediate environment. For academic success in our study, 18% of the sample are classified under the 2.1 category, while 82% fall below this class of degree. Interestingly, these statistics are directly oppositefor the 2.2 class of degree as 18% fall below CGPA of 2.40 while the remaining 82% fall above CGPA of 2.40.

Table 2: Demographic profile of respondents

Level	**N**	**%**	**Academic success**	**N**	**%**		**N**	**%**
200L	70	29%	**2nd CLASS UPPER (2.1)**			**2nd CLASS LOWER (2.2)**		
300L	68	28%	No (0)	199	82%	No (0)	43	18%
400L	106	43%	Yes (1)	45	18%	Yes (1)	201	82%
Age on admission			**Mode of entry**			**Major source of funding**		
Below 18	28	12%	SSCE/JAMB	160	66%	Self	44	18%
18-25	157	64%	DE	72	29%	Father	151	61%
26-35	35	14%	Others	6	2.5%	Mother	26	11%
36-45	2	1%	Missing	6	2.5%	Others	14	6%
Missing	22	9%				Missing	9	4%
Fathers' education			**Mothers' education**			**Residency**		
Primary School	14	6%	Primary School	29	12%	Kano	115	47%
Secondary School	28	12%	Secondary School	67	27%	Zaria	18	7%
Diploma	32	13%	Diploma	50	21%	Kaduna	21	9%
HND/BSc	87	36%	HND/BSc	64	26%	Jigawa	13	5%
MSc	44	18%	MSc	12	5%	Other state capitals	38	16%
PhD	23	9%	PhD	1	0.4%	Non-urban areas	36	15%
Missing	16	6%	Missing	21	8.6%	Missing	3	1%
Received counselling?			**Motivation**			**Gender**		
No (0)	128	57%	Self	140	57%	Male	215	88%
Yes (1)	86	35%	Others	96	40%	Female	18	7%
Missing	20	8%	Missing	8	3%	Missing	11	5%

Descriptive data, presented in Table 3 reveal that five variables achievedmean values above 3.0. These include attending lectures, relationship with other students, collaboration with colleagues, quality of lecturers' experience as well as cost of materials for assignment. These variablesalso occupy the same positions from results of a similar study at Kaduna State University (Maina & Ojobo, 2020), implying uniformity in perception of these factors on academic performance of architecture students in northwest Nigeria. On average, attending lectures was the most influential variable influencing academic performance for architecture students at KUST.Closely related to quality of lecturer's experience ranked fourth in Table 3, attending lectures underscores the influence lectures and lecturers have on academic performance of architecture students.In second place,relationship and collaboration with other studentssupport findings by Oluwatayo et al.(2015) that academic performance of architecture students is influenced by their peers especially at lower levels.Cost of materials, ranked fifth supports the assertion that students of architecture in public universities are affected more by economic factors compared to their counterparts in private universitiesbecause materials employed in design studio often require substansive monetary investment. Architecture is generally regarded as an expensive course (Maina & Ojobo, 2020). Considering the architecture curriculum revolves around design studio, the observation that quality of studios, ranked in 27^{th}place supports reports thatthe role studio culture plays in architecture education is on the decline(Opoko et al., 2016).

Table 3: Ranking of school, socio-economic and personal factors based on mean values

Variable	N	Mean	SD	Rank	Variable	N	Mean	SD	Rank
Attending lectures	243	3.76	1.045	1	Security	236	2.17	.999	18
Relationship with other students	244	3.68	1.045	2	Availability of worship facilities	240	2.15	1.168	19
Collaboration with colleagues	234	3.42	1.038	3	Campus environment	232	2.13	.978	20
Quality of lecturers' experience	234	3.14	.893	4	Overall quality of classrooms	235	2.08	.980	21
Cost of materials for assignments	234	3.04	1.275	5	Availability/quality of shopping facilities	240	1.97	.970	22
Quality natural light in classrooms	244	2.97	1.084	6	Power supply	243	1.93	1.034	23
Interactive sessions in class	232	2.87	1.045	7	Relationship with non-academic staff	235	1.87	1.084	24
Quality of natural light in studios	233	2.74	1.154	8	Water supply	239	1.82	1.008	25
Quality of library facilities	239	2.56	1.031	9	Availability/quality of cafeterias	240	1.75	.920	26
Personal time management	236	2.54	1.016	10	Overall quality of studios	242	1.74	.897	27
General state of cleanliness	240	2.46	1.058	11	Quality of hostels/accommodation	241	1.73	.860	28
Information at registration	238	2.43	.942	12	Quality of furniture	242	1.71	.859	29
External lighting	239	2.42	1.142	13	Indoorscaping	231	1.71	.739	29
Quality of air in studios	232	2.38	1.030	14	Quality of workshops	237	1.68	.811	31
Acoustic quality in classrooms	233	2.36	1.016	15	Departmental environs/landscaping	237	1.64	.850	32
Quality of air in classrooms	238	2.33	1.033	16	Quality of toilet/sanitary facilities	237	1.61	.935	33
Relationship with academic Staff	241	2.25	.961	17	Internet Connectivity	241	1.61	.898	33

Results from models predicting success at second class lower (2.2) and second class upper degrees (2.1), reveal that mode of entry was the only variable found to be significant in both cases. For success at 2.2 class of degree in Table 4, the odds of succeeding increases 1.990 times the mode of entry (*p=0.007*). With the exception of motivation, a personal factor, all other variables with positive β values relate to the institution. It is interesting to note that personal time management and counselling record negative β values (and Exp(β) values less than 1), meaning a decrease in these two variables increases the probability of achieving a 2.2 class of degree. General level of cleanliness, information about the architecture program at registration, attending lectures as well as lecturers' experience/competence were likewise non-significant but important predictors at KASU, having recorded Exp (β) values greater than 1 (Maina & Ojobo, 2020).

Table 4: Model parameters for success with Second Class Lower Degree (2.2)

Variable	β	SE	Wald	df	Sig	Exp(β)	95% CI for Exp (β) Lower	Upper
Mode of Entry	**.688**	**.256**	**7.206**	**1**	**.007**	**1.990**	**1.204**	**3.289**
Motivation	.523	.455	1.323	1	.250	1.687	.692	4.112
Interactive sessions in class	.337	.251	1.812	1	.178	1.401	.857	2.290
General level of Cleanliness	.245	.258	.901	1	.342	1.278	.770	2.118
Information about Architecture at registration	.213	.265	.646	1	.422	1.237	.736	2.080
Attending lectures	.191	.215	.786	1	.375	1.210	.794	1.846
Campus environment	.142	.284	.250	1	.617	1.153	.661	2.011
Lecturer experience/competence	.013	.306	.002	1	.966	1.013	.556	1.846
Personal time management	-.032	.251	.016	1	.899	.969	.592	1.584
Counselling	-.356	.495	.516	1	.473	.701	.265	1.850
Constant	-2.070	1.554	1.774	1	.183	.126		

In direct contrast to findings on the relationship of personal time management and success at 2.2, success at 2.1 class of degree highly depends on this personal attribute as it records the highest odds ratio in Table 5. Although personal time management fails to achieve significance in the model (*p=0.123*), this result reveals that the odds of achieving a 2.1 class of degree increases 1.412 timeswith this variable, supporting findings by Mtan (2017) in the same institution with responses from final year undergraduate students.Mode of entry (*p*=0.016) was found to be the only significant predictor of academic success at 2.1 class of degree, similar to success at 2.2 class of degree in Table 4. Considering this variable is ordinal, this result implies that the higher the entrance level, the higher the probability that a candidate will achieve a minimum 2.2 and high 2.1 class of degree. This observation does not come as a surprise, considering the 2.1 cohort is subsumed within the larger 2.2 sample. Notwithstanding, Adejumo and Adetunji (2013) also established that students admitted at DE level had the highest odds of achieving a first class degree at the University of Ilorin. Likewise, findings from Musa and Saliu (2016) support this trend, as DE male architecture undergraduates at Ahmadu Bello University consistently record high grades in core courses namely Architectural Design, Building Construction and Structures.

The other seven variables with positive β values are school factors related to comfort of students and offer differences between students with a 2.1 CGPA and those with 2.2 class of degree. For instance, campus environment and motivation, which record positive β values for success for the 2.2 modelare the opposite in the 2.1 model. The latter is very revealing, suggesting that motivation alone is unlikely to aid a candidate achieve 2.1 class of degree as motivation records the highest negative β value in Table 5, in sharp contrast to its high position in Table 4. These findings support our earlier hypothesis, that motivation alone is unlikely to predict academic success in architecture undergraduates, in line with Walberg's theory of Educational Productivity.

Table 5: Model parameters for success with Second Class Upper Degree (2.1)

							95% CI for Exp (β)	
Variable	β	SE	Wald	df	Sig	Exp(β)	Lower	Upper
Personal time management	.345	.224	2.378	1	.123	1.412	.911	2.188
Mode of Entry	**.308**	**.128**	**5.838**	**1**	**.016**	**1.361**	**1.060**	**1.747**
Overall quality of classrooms	.291	.262	1.231	1	.267	1.337	.800	2.235
Availability and quality of hostels/accommodation	.234	.282	.691	1	.406	1.264	.728	2.196
Attending lectures	.224	.222	1.010	1	.315	1.250	.809	1.934
External lighting	.222	.195	1.305	1	.253	1.249	.853	1.829
Availability of worship facilities	.139	.180	.597	1	.440	1.149	.808	1.635
Power supply	.024	.248	.009	1	.924	1.024	.630	1.665
General state of cleanliness	.020	.231	.008	1	.930	1.021	.649	1.604
Campus environment	-.001	.243	.000	1	.996	.999	.620	1.608
Quality of air in classrooms	-.039	.248	.025	1	.876	.962	.591	1.565
Water supply	-.082	.249	.107	1	.744	.922	.565	1.503
Quality of toilet/sanitary facilities	-.134	.295	.207	1	.649	.874	.490	1.560
Motivation	-.516	.394	1.716	1	.190	.597	.276	1.291
Constant	-5.153	1.173	19.288	1	.000	.006		

Comparing both models, we generally find marginal differences between achieving a high class of degree (2.1) over the generic 2.2 class of degree as both reveal mode of entry is the only significant predictor of academic success. However,close examination reveals achieving a 2.1 class of degree largely depends on personal attributes, notably how effectively a student personally manages time, aided by comfortable school facilities and not necessarily motivation (an important variable in the 2.2model). Mtan (2017) notes that three skills related to effective time management influence academic performance. These are self-discipline, organisation and prioritisation of activities. Mtan (2017) concludes that high achieving students exhibit all three skills while self-discipline is a challenge for average students. Our study findings suggest thatself-discipline related to personal time management likely explains why candidates who graduate with a 2.1 class of degree manage to fit into the labour market often seamlessly within a different discipline (such as Banking and Finance) from courses studied in school. Although the 2.2 model includes quality of lecturer experiences/competence in this and previous studies (Maina & Ojobo, 2020), 2.1 candidates display higher levels of independence with variables such as lecturers' experience/competency, relationship and collaboration with colleagues and other students. These do not feature in the 2.1 model depicted in Table 5as they fail to achieve significance even at 0.25 relaxed p value in the initial screening suggested by Sperandei (2014). Attending lectures however does, suggesting that although2.1 students display independence, they still require some level of supervision and guidance in order to succeed, again supporting the general idea of multiple non-individualistic predictors proffered in Walberg's theory. As a limitation however, this study requiresreplication in other schools for findings to be generalisable.

Results from model fitness (Cox and Snell's measure, Nagelkerke's adjusted values) reveal small effect sizes (12.9-21.9% for the 2.2 model and 12.3-19.3% for the 2.1 model). Checks to residuals reveal no alarming misfit of data. Degree of prediction using classification tables revealed that the 2.2 model correctly classified 85.2% while 81.2% was recorded for the 2.1 model. Both models record non-significant Hosmer and Lemeshow test results. Compared to results from Abdulazeez and Abdulwahab (2018) as well as Aluko et al. (2018) however, other EDM models are likely to produce better prediction values. We observe from our analyses that higher prediction values using BLR occur in larger proportioned samples, with lower proportions recording the highest misclassified scores. This is another area future EDM models can improve upon.

CONCLUSION

This study established predictors of academic success at second-class lower degree (2.2) andsecond-class upper degree (2.1) for undergraduate architecture studentsat KUST. BLRanalyses reveal three major findings. First, mode of entry was the only significant predictor of academic success in both models. Secondly,personal time management and independence largely explains the difference between graduating with a 2.2 and 2.1 degree in architecture. These findings lend credence to our hypothesisthat other factors apart from motivation predict academic success for architecture students in line with Walberg's theory.Thirdly, attending lectures as well as school related variables also feature largely in both models, implying that conducive learning environments specifically good classrooms, accommodation, external lighting, power supply, worship places and general cleanliness influence academic success for architecture students. In order to improve on academic success, it is imperative that KUST authorities employ onlycompetent and diligent lecturers to facilitate collaborative relationships between students with their peers and with staff. Adequate maintenance of school facilities notably classrooms, hostels/accommodation, external lighting, power supply, worship places as well as general cleanliness will also enhance probability of students achieving a minimum 2.1 class of degree. Importantly, prospective candidates are encouraged to pursue advanced level qualifications prior to admission into architecture as the probability of graduating with a high class of degree increases. This in turn substantially improves employability potentials for graduates in future.

Authors' contributions

J. J. M. conceptualised, analysed data and supervised writing of the paper. A. T. Z., I. A. A. and R. A. S. organised, collected, collated and prepared data employed in the study.

Conflict of Interest

Authors declare no conflict of interest.

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