Asian Journal of Distance Education

Influence of Socio-Demographic Profile on the Motivational Characteristics and Academic Performances of Distance Learners

Yasmin

Abstract: The paper explores and assesses, through quantitative research and data analytics models, as to how socio-demographic profile, work, and family responsibilities may be associated with motivational level and educational attainment or course completion rate of learners enrolled in the undergraduate courses of Indira Gandhi National Open University (IGNOU), the largest distance education University in India. The models, generated using classification tree methods, show that employed and married learners perform better in distance education. Assessing underlying reasons, an empirical study using the Keller's ARCS (Attention, Relevance, Confidence, Satisfaction) framework reveals that course relevance and level of satisfaction while pursuing the study are the two most important factors in keeping distance learners motivated and achieving better academic performance. The quantitative survey also shows that the employed learners have significantly higher levels of motivation, while the others may have difficulty in maintaining their self-motivation during distance learning. The findings are important for Open and Distance Learning (ODL) institutions to understand students' varied expectations of the distance learning experience and the consequences on their motivation levels and academic performances when these expectations are not met.

Keywords: Academic Performance, ARCS Model, Classification Tree, Data Analytics, Educational Data Mining, Motivation, Learners' satisfaction, Open and Distance Learning, Socio-demographic Profile, Generative research

Highlights

What is already known about this topic:

- The underlying reasons for better academic performance in distance education are related to learners' motivation.
- Low motivation levels are also contributing factor to low retention rates in distance education.
- Learners' satisfaction plays a pivotal role in improving motivation for distance learners.

What this paper contributes:

- This study employs a hybrid research methodology deploying the undergraduate student database of IGNOU learners as a data source for the generative research using classification tree models for formulating hypotheses.
- These hypotheses are then validated through evaluative research by analysing the empirical data obtained through a structured questionnaire sample.
- This paper identifies key demographic variables that potentially influence motivation level of distance learners.

Implications for theory, practice and/or policy:

- The findings of this paper provide valuable insights in understanding students' varied expectations from the distance learning experience and the consequences on their motivation and drop out levels when these expectations are not met adequately.
- The findings can be utilised for initiating appropriate policy and programmatic interventions for enhancing motivational level of distance learners and thus reducing their dropout rate.
- The paper demonstrates the potential of data analytics as a generative research tool in the domain of Distance Education.

Published by Asian Society for Open and Distance Education (ASODE), Japan
ISSN 1347-9008 http://www.asianjde.com/

Introduction

In the Open and Distance Learning (ODL) system, the learners' active involvement, enduring commitment and academic success depends upon their motivation level. The ODL learners have greater responsibility for their own learning as they study in isolation with limited support from teachers or peer groups (Schamber, 1994). In such a challenging situation, motivation plays a crucial role in ensuring that learners take an active role in their studies, set achievable goals, and work consistently towards achieving them.

ODL learners are generally of a higher age group, having greater work and family responsibilities than students enrolled in on-campus courses (Harris & Gibson, 2006; Ortagus, 2017). Multiple roles of ODL learners are often attributed to having a significant impact on their learning experiences and academic performance (Waterhouse et al., 2022). Therefore, motivation becomes indispensable for ODL learners to confront challenges in their educational journey. Motivated learners are also more likely to seek assistance when needed and are better at managing their time and prioritizing their studies, leading to successful course completion.

Learners' satisfaction contributes to an effective learning environment and improves students' motivation, which is considered imperative, especially among distance education students for better academic performance (Bolliger, 2004). In this context, the ODL providers must play a key role to formulate strategic approaches for enhancing and sustaining learners' satisfaction and motivation level. This can be achieved through appropriate measures such as designing courses that are relevant as well as engaging, providing timely feedback, creating opportunities for interaction and collaboration, offering support and resources etc., that are tailored to meet learners' distinct requirements.

It is often perceived that instructional design is the key-component of the distance learning process for enhancing and sustaining motivational level and ensuring continued involvement of ODL learners. However, it is observed that even though uniform instructional facilities are made available to all students, different category of students' feel varied satisfaction and motivational level while pursuing their courses, thereby affecting retention rate and academic performances.

Literature

The correlation between learners' satisfaction and academic performance is generally explained by students' interaction with instructional design, learning materials, and their own abilities in navigating learning environments (Kuo et al., 2013; Wei & Chou, 2020; Eom & Ashill, 2016). Zeytinli et al. (2023) argued that satisfaction level of the ODL learners is one of the most important indicators in assessing the effectiveness of the distance education. Researchers have also explored the role of other factors such as employment and family as a source of motivation or challenges for learners. Buck (2016) explored the role of family as a source of motivation to study, namely to improve the family's future financial prospects or to be a role model for children or younger siblings. Park and Choi (2009) argued that other variable components that change over the course, such as satisfaction and relevance of the course, family and organisational support, etc., also influence learners' decision to pursue the course or not.

Astin (1991) emphasised that full-time learners are more likely to leave the course prematurely because they may find lesser time to complete the course requirements. This is corroborated by another study which shows that learners, who are married, employed, remotely located or in an older age group are most likely to drop out of the course (Yasmin, 2013). Waterhouse et al. (2022), who surveyed a sample of 318 distance learners in the UK, concluded that students' work and family lives affect their satisfaction, but this influence is correlated to their prior educational attainment. However, the study pointed out the limitation that it was conducted on a homogeneous sample of women (87.74%) with a higher age group (30 years and older, which constituted 74.5% of the sample). In another study, Simons et al. (2020) found that a combination of family, tutors and employers provided the support that enabled them to complete their studies in distance education. Personal and social factors of leaners often impact the availability of time and access to the technological tools and resources necessary for distance learning, thus affecting their satisfaction level in the course of study (Karadağ et al., 2021; Ahmed et al., 2020). In contrast, in a Brazilian distance education context, Nasu (2020) concluded that employed students perform better than their unemployed peers and that married students perform better than their single peers. Generalising the scenario, Singh et al. (2012) concluded that there is lack of extrinsic motivation in ODL system, which results in higher dropout rates.

Underlying the reasons, researchers argue that student motivation and self-regulation are of great importance in distance education, especially in the context of the competing demands of family and work (Clarence, 2019; D'Errico et al., 2016; Pekrun et al., 2011). Conducting a causal explanatory-based study, using multiple regression analysis in the context of an Indonesian University, Setiawan et al. (2020) concluded that academic achievement is determined by the intrinsic motivation of its students. In general learning context, Schunk (1995) opined that motivation influences what, how and when students choose to learn. Studies also linked motivation to individuals' cognitive and affective processes such as goals and beliefs, and emphasised the importance of the interaction between learners and the learning environment (Brophy, 2010). Motivation is also related to learner satisfaction (Artino, 2007), perceptions of learning (Kickul & Kickul, 2006) and academic achievement (Yi & Hwang, 2003). Motivation as a predominant factor in interpreting successful learning and achievement is also advanced by some studies (Schunk et al., 2008; Radovan, 2011; Wentzel, 2013).

ODL learners have diverse motivations to join distance courses and thus they cannot be considered as a homogenous group (Yasmin, 2019). Learners may be motivated to enrol in distance learning to advance their careers or improve their job performance (Cannon et. al., 2001). However, once enrolled, the reason for sustaining the learning depends on incentive motivation, where individuals strive to achieve a pre-determined or perceived goal or target (Gagné & Driscoll, 1988). It is therefore important to foster learner motivation throughout the course in order to reduce dropout rates in distance learning programmes. The definite relationship between motivational factors and dropout is complemented by research which shows that low motivation levels are a contributing factor to low retention rates in distance education (Artino, 2007; Keller, 2008; Gorky, 2014; Herbert, 2006; Joo et al., 2011; Lee & Choi, 2013).

Among several conceptual frameworks for understanding the motivational aspects of learning, the ARCS model (Keller, 1983) is a well-known and widely used model of instructional design. The ARCS model is based on four categories, namely Attention (A), Relevance (R), Confidence (C) and Satisfaction (S), which provide a basis for analysing the characteristics of learner motivation. The framework is also used to identify deficiencies in specific areas of learner motivation so that remedial strategies can be developed. Although it was not originally developed for distance education, the ARCS model has become popular to diagnose learner motivation in distance education courses and subsequently improve it through appropriate instructional design (Keller, 2008; Keller & Deimann, 2012; ChanLin, 2009; Hodges & Kim, 2013).

The literature review shows that motivation is an important factor in distance education. It plays a key role in influencing the academic achievements and retention rates of the distance learners especially in the context of the work and family pressure.

The Context

Headquartered at New Delhi, Indira Gandhi National Open University (IGNOU) is the largest ODL Institution in India. IGNOU has a countrywide network of 69 Regional Centres and over 2000 learners support centres. Every year around 0.6-0.7 million students from diverse social and demographic profile, are freshly enrolled in various academic courses of IGNOU. On an average, IGNOU has a cumulative strength of about 3-4 million students. During 2022-23 academic year (July-June), around 720,700 students took admission in over 300 programmes comprising of certificate, diploma, undergraduate, postgraduate, and doctoral courses. Out of these students, about 50.3% are female, 23.6% married and 20.3% are employed. While IGNOU follows a uniform instructional approach such as printed study materials, grading and assignments, student support services etc. to students irrespective of their locations and socio-demographic profiles, it is observed that the completion rate vary widely among different category of students namely married versus unmarried, employed versus unemployed and male versus female.

Research Objective

In the above context, this study seeks to explore through quantitative research and data analytics how the socio-demographic profile, work, and family responsibilities may be associated with the motivational level of ODL learners. It will also examine the impact of learners' motivation on their academic achievements and course completion rates.

The study further proposes to identify the specific categories of students who are likely to excel in the academic persuasion, leading to successful completion of the courses. It will also find out the underlying reasons contributing to the varying academic achievements of ODL learners.

Methodology

In recent times, Educational Data Mining (EDM) and Generative Artificial Intelligence (AI) are increasingly recognized as potent tools in educational research, especially within online learning environments (Davies et. all, 2021; Su and Lai, 2021; Bozkurt & Sharma, 2023a). These technologies are acknowledged for their capacity to provide personalised and adaptive online learning experiences (Bozkurt & Sharma, 2023b). Among different EDM models, ‘prediction models’, ‘structure discovery’, ‘relationship mining’ and ‘discovery with models’ are the most common (Baker & Inventado, 2014). Analysing learners' demographic data is considered a favoured method for predicting their academic achievements and assessing the effectiveness of learning materials (Khare, 2017).

The study employs a sequential hybrid research method that involves a two-part quantitative data analysis of both primary and secondary data sources. In the first part, a generative research methodology is used for identifying the problem areas. The student admission database of IGNOU serves as the secondary data source for targeted knowledge discovery employing Educational Data Mining (EDM) methodologies. Predictive modelling using classification tree model, among others, is preferred for this purpose as it offers the best approach for predictions when it comes to demographic data such as student information, which is predominantly categorical in nature. The primary objective of this phase is to construct models that can predict which categories of IGNOU students perform better academically than their peer group. Subsequently, research hypotheses are formulated based on these models. The second part involves the application of an evaluative research approach using statistical analysis to investigate the underlying reasons for the problem areas. The research hypotheses, developed in the preceding section, are validated using primary data sources obtained through a structured questionnaire survey using statistical methods. Responses are obtained from randomly selected students enrolled at IGNOU, encompassing both in-person interactions and online surveys.

Data Collection and Analysis

The admission and pass out data of 10, 64,315 students enrolled in IGNOU's undergraduate or bachelor degree programmes between 2011 and 2015 is used as the baseline database. Since majority of students (85-90%) complete the undergraduate programme within four years of admission, a gap of at least four years between the date of admission and the date of graduation is ensured for the longitudinal analysis.

The target or response variable (RV) chosen in this study is the student's degree completion status of the student. The status can be either 'Completed or Passed and graduated' or 'Not completed or dropped out'. Based on the results of the literature review, socio-demographic variables of the students such as gender, marital status and employment status, age group, social status and region are used as independent or explanatory variables for predicting the response variable (RV).

The data set is analysed using SPSS (version-23). The descriptive statistics of the admission data shows that (Table-1) the student population is a heterogeneous mix with a strong bias towards males (61.27%), single (61.60%), unemployed (72.6%) and lower age group (< 25 years) (55.9%). The overall pass out or completion rate is 36.40%.

Table 1. Descriptive statistics of students’ data of bachelor degree programme

Category	Sub Category	Number	Percent	Category	Sub Category	Number	Percent
Gender	Male	652146	61.27	Age Group (in Years)	<25	595572	55.9
	Female	411833	38.7		26-35	325362	30.6
	Others	336	0.03		36-45	118184	11.1
					>45	25197	2.4
Category	Sub Category	Number	Percent	Category	Sub Category	Number	Percent
Marital Status	Married	408896	38.4	Employment Status	Employed	291212	27.4
	Single	655419	61.6		Unemployed	773103	72.6
Course Completion Status	Not Completed	676980	63.6				
	Completed	387335	36.4				

To gain deeper insight, the classification tree method is applied to the entire data set, with half of the data (50%) used for training and the rest for testing or prediction. In applying this method, care is taken to achieve a higher prediction accuracy of the response variable (RV='Completed') than the overall prediction, which includes learners who are unlikely to complete the course (RV= "Not Completed"). This is necessary to minimise the possibility of misclassification of the response variable. The result is tabulated in Table-2. The model is able to predict about 40.2% of the target class of learners (RV='Completed') in the test data set, for an overall prediction rate of about 72.4%.

Table 2. Classification tree model

Sample	Observed	Predicted		
		Not Completed	Completed	Percent Correct
Training (50%)	Not Completed	308155	31036	90.80%
	Completed	116596	76955	39.80%
	Overall Percentage	79.70%	20.30%	72.30%
Test (50%)	Not Completed	306913	30876	90.90%
	Completed	115926	77858	40.20%
	Overall Percentage	79.50%	20.50%	72.40%
Growing Method: CHAID, Dependent Variable: Pass Code, Independent Variables- Gender, Marital Status, Employment Status.				

Since the overall prediction is more than 70%, decision rules are developed to gain insights into the classification tree model. The decision rules show that employed learners are more likely to complete the course (64.2%) than unemployed learners (25.9%). In addition, married learners are more likely to complete the course (46%) than their single counterparts (30.3%). Overall, female learners have a higher completion rate (44%) than their male counterparts (31.6%)

Thus, it can be seen that the completion rate is more for working, married and especially female learners who have to balance multiple areas of life, such as work and family, while pursuing a distance learning programme. The literature review shows that the motivation of distance learners plays a key role, especially in the context of the work and family demands (D'Errico et al., 2016; Pekrun et al., 2011). Therefore, motivation levels should also have a positive correlation with retention and completion rates of distance learners.

Accordingly, the following hypotheses are formulated:
Hypothesis-1(H1): The employed learners are more motivated than unemployed learners.
Hypothesis-2(H2): The married learners are more motivated than unmarried learners.

Empirical Survey

In order to test the above hypotheses, a structured questionnaire survey is conducted to collect responses from students enrolled at IGNOU. The questionnaire consists of two sections. While section A captures the demographic data of the learners e.g. age group, gender, marital status, employment status etc., section B contains 24 (twenty four) survey items classified into four broad categories namely Attention (A), Relevance (R), Confidence (C) and Satisfaction (S) as per the ARCS model to ascertain the motivation level of the different categories of students. The survey items are selected based on literature review and consultation with domain experts. The response options in section B are based on a 5-point based Likert scale [Strongly Agree (5); Agree (4); Neither agree nor disagree (3), Disagree (2) and Strongly Disagree (1)] to enable meaningful statistical analysis. Of these 24 questions, 6 are rephrased in reverse to ensure that respondents give consistent answers. In addition, respondents are asked to write down a few lines on various aspects of their learning experience and perceived level of motivation while participating in the courses. A test questionnaire is first administered to a small sample to ensure that the final version contains only those relevant questions that can actually elicit the intended responses.

Participants

The population for the study consists of all enrolled and former students of IGNOU. Survey data are collected from 141 IGNOU undergraduate students, 119 females and 22 males, during the months of October and November 2022, through face-to-face interviews and an online survey platform

(SurveyMonkey). The survey response sheets collected from the participants are compiled and organised into one dataset.

The Scale

To estimate the internal consistency or scale reliability of the survey items, 24 survey items are analysed to calculate Cronbach's Alpha, which gives a value of 0.757. In exploratory research, Cronbach's alpha should generally be 0.7 or more. Therefore, the items considered in this study are suitable for further analysis.

Findings

To get a feel for the whole data set, descriptive analysis is conducted using the commercially available statistical software SPSS (version-23). The descriptive statistics show that about 40.4% of the respondents are married and 51.8% are employed. This confirms that working and married learners are adequately represented in the survey sample.

In order to gain further insights, the survey responses are aggregated in four primary variables of ARCS models, namely A (Attention), R (Relevance), C (Confidence) and S (Satisfaction). The overall responses (O) are calculated from the average of these four variables. The descriptive analysis of these five response variables is shown in Table-3.

Table 3. Descriptive statistics of survey responses

	Number of Samples	Minimum	Maximum	Mean	Std. Deviation
Attention (A)	141	2.33	4.5	3.3842	0.41972
Relevance (R)	141	2.83	5	4.1087	0.3994
Confidence (C)	141	2.67	5	3.6667	0.45338
Satisfaction (S)	141	2.67	5	3.8735	0.41781
Overall (O)	141	3.29	4.88	3.7583	0.31565
Scale: 1 (Not True)- to 5 (Very True)					

Hypothesis 1 states that employed learners are more motivated than unemployed learners. In the context of the present study, this means that the mean scores of the five response variables of employed learners (A, R, C, S and O) should be significantly higher than those of their unemployed counterparts.

To test this hypothesis, two independent data sets are created from the survey response data. Data set or Group-1 includes the employed learners and Group-2 includes the unemployed learners. Since the samples are random, independent and normally distributed, a t-test with a significance level of 95% is conducted to determine whether or not the means of these five response variables (A, R, C, S and O) of the two groups are the same. The group statistics and the result of the t-test are shown in Table 4.

Table 4. Hypothesis-1 group statistics & t -test for equality of means

SN	Variables	Groups	N	Mean	Criterion	Sig. (2-tailed)
1	Attention (A)	Employed	73	3.45	Equal variances assumed	0.028
		Unemployed	68	3.3	Equal variances not assumed	0.027
2	Relevance (R)	Employed	73	4.16	Equal variances assumed	0.063
		Unemployed	68	4.04	Equal variances not assumed	0.062
3	Confidence (C)	Employed	73	3.74	Equal variances assumed	0.03
		Unemployed	68	3.58	Equal variances not assumed	0.03

4	Satisfaction (S)	Employed	73	3.92	Equal variances assumed	0.101
		Unemployed	68	3.81	Equal variances not assumed	0.098
5	Overall (O)	Employed	73	3.82	Equal variances assumed	0.008
		Unemployed	68	3.68	Equal variances not assumed	0.007

From Table-4 it is observed that employed learners have higher mean scores on all five response variables than their unemployed counterparts. The t-test shows that for the three variables (A, C and O) the mean scores of employed learners are significantly (> 95%) higher than those of the unemployed group. For the remaining two variables (R, S), the mean values of the employed learners are significantly higher at a confidence level of 90%. Thus, the result supports hypothesis 1 that employed learners are more motivated than unemployed learners.

Hypothesis 2 states that married learners are more motivated than unmarried learners. This means that the mean scores of the five response variables (A, R, C, S and O) should be significantly higher for married learners than unmarried learners. To test the hypothesis, two independent data sets are created from the survey response data. Group 1 consists of married learners, while Group 2 consists of unmarried learners. To determine whether the means of these five response variables (A, R, C, S and O) of the two groups are the same or not, the t-test is conducted with a significance level of 95%. The group statistics and the result of the t-test are shown in Table 5.

Table 5. Hypothesis-2 group statistics & t -test for equality of means

SN	Variables	Groups	N	Mean	Criterion	Sig. (2-tailed)
1	Attention (A)	Married	57	3.45	Equal variances assumed	0.124
		Single	84	3.33	Equal variances not assumed	0.121
2	Relevance (R)	Married	57	4.1	Equal variances assumed	0.932
		Single	84	4.11	Equal variances not assumed	0.929
3	Confidence (C)	Married	57	3.63	Equal variances assumed	0.451
		Single	84	3.69	Equal variances not assumed	0.436
4	Satisfaction (S)	Married	57	3.95	Equal variances assumed	0.072
		Single	84	3.82	Equal variances not assumed	0.061
5	Overall (O)	Married	57	3.78	Equal variances assumed	0.421
		Single	84	3.74	Equal variances not assumed	0.402

It is observed from Table-5 that for three (A, S, O) out of the five response variables, the mean score for married learners is slightly higher than that for unmarried learners. While single or unmarried learners have a higher mean score for Confidence (C), the mean score for relevance (R) is almost the same in both groups. However, the t-test did not establish any significant (> 95%) inequality in means for any of the five response variables, except that married learners are more satisfied when attending the courses (confidence level-93%). Thus, the analysis does not support hypothesis 2 that married learners are more motivated than unmarried learners.

Discussions and Conclusion

For identifying the category of students who are likely to successfully complete the course, a classification tree method is applied to the undergraduate student database of IGNOU for developing predictive models. These models show that employed and married students perform better than unemployed and unmarried peers respectively. This reaffirms the research findings of Nasu (2020) that employed and married students perform better than their unemployed and single counterparts.

The literature review reveals that the underlying reasons for better academic performance are related to learners' motivation (Schunk et al., 2008; Radovan, 2011; Wentzel, 2013). For analysing the characteristics of learner motivation and linking it with academic performance and socio-demographic profile of learners, an empirical survey based on ARCS model (Keller, 2008; Keller & Deimann, 2012; ChanLin, 2009; Hodges & Kim, 2013) is conducted. The empirical survey data is deployed to test the hypotheses formulated on the basis of predictive models.

Out of four components of the ARCS model, in the current study, Relevance(R) is found to be the most important factor (mean=4.10) in enhancing and sustaining the motivation of distance learners. IGNOU learners are found to have a better understanding that the courses are relevant for achieving their personal and professional goals. Satisfaction (S) comes second with a mean of 3.87, meaning that IGNOU learners are generally satisfied with what they have achieved during the learning process. This is supported by the findings of Zeytinli et al (2023) that while developing a course, particular attention should be given to identify how student satisfaction is impacted by specific course elements.

Confidence (C) is defined as the belief in oneself that one will be able to achieve the goals. The study shows a positive bias (mean=3.66) of this component in the overall ARCS model. Among the four response variables, Attention (A), which refers to catching learners' concentration and anchoring the curiosity factor in them to learn, has the lowest value (Mean=3.38). The results indicate that instructional design and study materials need to be further improved to keep learners' attention. This is similar to the result obtained in the studies conducted by Zeytinli et al (2023) that learning process affect satisfaction level of ODL learners and help them build self-confidence in academic life.

Among the 24 survey items, the top five factors that contribute to learner motivation are (i) To accomplish my goal, it is important that I do well in this course, (ii) If I work hard, I can perform well in the course, (iii) The things I am learning in this course will be useful to me, (iv) As I started studying, I feel confident that I could complete the course, (v) I feel good that I get praise from family and friends when I perform well in the course. Thus, IGNOU learners appreciate better that they benefit from the course and receive recognition when they perform well in their studies.

The qualitative comments or feedback from the learners who participated in the face-to-face survey confirm the findings of the data analysis that relevance, confidence and satisfaction are the most important motivating factors in distance education. Some of these comments are 'the course was important for promotion', 'I got promoted after becoming graduate', 'I am working in a Petrol Pump, so at least I should be a graduate', 'I am working in a hotel so I am doing the Bachelor of Hotel Management course', 'I feel good after studying this course', 'I got recognition for studying the course', 'If I do assignment myself, passing examination is easy', 'I have got honours in economics by studying myself', etc. One female divorcee student mentioned that she is currently doing casual jobs and that her job prospects will improve after graduation and she will be able to earn more and can send her child to a big school. Another female student commented that after completing her graduation she will have a better marriage prospect. The other female student shared that her husband is doing odd jobs and after graduation she can also financially support the family.

The survey responses further indicate that employed learners can understand the course materials better (mean: 3.48) and perceive that they will benefit much from the course (mean: 3.92) than unemployed counterparts (mean: 2.87 & 3.65). Unemployed learners also face more difficulty in pursuing the course (mean: 3.48) than employed learners (mean: 3.26).

The preceding analysis is consistent with the findings of the literature studies that learners are motivated to take up and complete distance learning in order to enhance their career or improve their performance at work (Cannon et. al., 2001, Nasu, 2020). The analysis also confirms that learners' intrinsic motivation levels, individuals' cognitive and affective processes, such as goals and beliefs, and self-regulation in the distance learning process, especially in the context of competing job demands, are important factors in academic performance (Pekrun et al., 2011, D'Errico et al., 2016). For employed learners, distance learning offers the opportunity to develop time management skills that help them balance work and home life and provide them with the chance to excel in academic courses (Clarence, 2019; Simons et al., 2020).

On the other hand, the survey responses reveal several factors related to learners' environment (Brophy, 2010) and perceptions of learning (Kickul & Kickul, 2006), that adversely affect learners' motivation such as (i) It is difficult to remember the content of the course, (ii) I find it hard to keep my attention because the course material is difficult to understand, (iii) I am not able to understand many topics in the course material, (iv) I cannot predict what grade I will get in my assignments and in the exam, (v) I face difficulty in pursuing the course, etc. These statements are corroborated by qualitative comments or feedback from learners who participated in the face-to-face interview, namely 'I need someone to explain the study material on certain difficult topics'; 'I am used to a regular classroom teaching learning environment where the teacher explains a certain topic and then I study the topic'; 'I found that the marks obtained in assignment evaluation are less than expected, perhaps did not practice well how to write the answer to a particular assignment'; 'I am studying in ODL mode for the first time therefore it will take some time for me to adjust to the ODL environment'; 'I am finding difficult to study the entire syllabus using the Self Learning Material (SLM)'.

The different nature of distance education, compared to face-to-face education is likely to pose additional challenges for ODL learners (Waterhouse et al., 2022). Unlike on-campus education, ODL does not provide students with exclusive learning time and space. ODL learners must therefore create and manage their own space and time for learning (Schamber, 1994). In distance learning without a physical teacher, it can be difficult for learners to maintain the pace of learning and managing time pressures already experienced with intensive work and family commitments (Waterhouse et al., 2022) One married female learner shared that she has to take care of the children, teach the children at home, cook, manage the household, attend social events with family members and receive guests at home.

Being physically separated, the institute and the counsellors have less influence on the motivation of the learners. ODL thus creates a sense of isolation and learners may have difficulty maintaining their motivation for the course. This, supplemented by lower self-motivation, can lead to distractions from learning. Literature survey also reveals that low motivation levels contribute to low retention rates in distance education (Joo et al., 2011; Lee & Choi, 2013). This is reaffirmed through qualitative survey of IGNOU learners who often prefer to learn selectively or to learn only with a view to passing the examination and obtaining a degree.

The results of the study affirm that relevance of the course and satisfaction during study are the two most important factors in motivating learners (Park and Choi, 2009). The results also indicate that the employed leaners have significantly higher levels of motivation, while other categories of learners find it difficult to maintain their self-motivation during distance learning. The relatively lower attention of distance learners confirms the need to include the element of curiosity in the design of teaching materials in order to engage learners in a lasting way. The characteristics of students also need to be taken into account when developing online distance education services and courses.

The study has a few limitations. The first part of the study considered the entire student database, the sample of the empirical study consisted mainly of female learners (84.4%). Furthermore, this study is conducted at only one ODL institution and is limited to undergraduate students. Therefore, the results may not be applicable in a broader context. Similar studies at other ODL institutions and correlation of results could help improving overall learner experience and foster further success of ODL in both national and international perspective. The generative research model concluded that married learners perform better academically than unmarried counterparts. However, the ARCS model could not substantiate the model. Future research may therefore be needed to investigate the possible reasons for the apparent superior academic performance of married undergraduate students, taking into account parameters such as age profile, differences in lifestyle and personal goals, etc.

ODL institutions have diverse student profile. This research finding will help these institutions to understand students' varied expectations from the learning experience and the consequences on their motivational level if these expectations are not met.

References

Ahmed, S., Hegazy, N. N., Malak, H. W. A., Kayser, C. W., Elrafie, N. M., Hassanien, M., Al-Hayani, A., Saadany, S. E., Ai-Youbi, A. O., & Shehata, M. H. (2020). Model for utilizing distance learning post COVID-19 using (PACT)™ a cross sectional qualitative study. *BMC Medical Education*, *20(*1*).* https://doi.org/10.1186/s12909-020-02311-1

Artino, A. (2007). Motivational beliefs and perceptions of instructional quality: predicting satisfaction with online training. *Journal of Computer Assisted Learning*, *24*(3), 260–270. https://doi.org/10.1111/j.1365-2729.2007.00258.x

Astin, A. W. (1991). The Changing American College Student: Implications for Educational Policy and Practice. *Higher Education*, *22*(2), 129–143. http://www.jstor.org/stable/3447248

Baker, R.S., Inventado, P.S. (2014). Educational Data Mining and Learning Analytics. In: Larusson, J., White, B. (eds) Learning Analytics. Springer. https://doi.org/10.1007/978-1-4614-3305-7_4

Bolliger, D. U. (2004). Key Factors for Determining Student Satisfaction in Online Courses. *International Journal on E-Learning*, *3*(1), 61–67. https://www.learntechlib.org/p/2226/article_2226.pdf

Bozkurt, A., & Sharma, R. C. (2023a). Generative AI and prompt engineering: The art of whispering to let the genie out of the algorithmic world. *Asian Journal of Distance Education*, *18(*2*),* i-vii. https://doi.org/10.5281/zenodo.8174941

Bozkurt, A., & Sharma, R. C. (2023b). Challenging the status quo and exploring the new boundaries in the age of algorithms: Reimagining the role of generative AI in distance education and online learning. *Asian Journal of Distance Education*, *18(*1*),* i-viii. https://doi.org/10.5281/zenodo.7755273

Brophy, J. E. (2010). Motivating Students to Learn (3rd ed.). Routledge.

Buck, S. (2016). In Their Own Voices: Study Habits of Distance Education Students. *Journal of Library Information Services in Distance Learning*, *10*(3–4), 137–173. https://doi.org/10.1080/1533290x.2016.1206781

Cannon, M., Umble, K., Steckler, A., & Shay, S. (2001). We're living what we're learning: Student perspectives in distance learning degree and certificate programs in public health. *Journal of Public Health Management and Practice*, *7*(1), 49 – 59. https://www.jstor.org/stable/44968095

ChanLin, L. (2009). Applying motivational analysis in a Web-based course. *Innovations in Education and Teaching International*, *46*(1), 91–103. https://doi.org/10.1080/14703290802646123e

Clarence, Ng, (2019). Shifting the focus from motivated learners to motivating distributed environments: a review of 40 years of published motivation research in Distance Education, *Distance Education*, *40*(4), 469-496. https://doi.org/10.1080/01587919.2019.1681892

Davies, R., Allen, G., Albrecht, C., Bakir, N., & Ball, N. (2021). Using Educational Data Mining to Identify and Analyze Student Learning Strategies in an Online Flipped Classroom. Education Sciences, *11*(11), 668. https://doi.org/10.3390/educsci11110668

D'Errico, F., Paciello, M., & Cerniglia, L. (2016). When emotions enhance students' engagement in e-learning processes. *Journal of E-Learning and Knowledge Society*, *12*(4), 9–23. https://doi.org/10.20368/1971-8829/1144

Eom, S. B., & Ashill, N. J. (2016). The Determinants of Students' Perceived Learning Outcomes and Satisfaction in University Online Education: An Update. *Decision Sciences Journal of Innovative Education*, *14*(2), 185–215. https://doi.org/10.1111/dsji.12097

Gagne, R. M., & Driscoll, M. (1988). Essentials of Learning for Instruction (Expanded, Subsequent). Pearson College Div.

Gorky, S. M. (2014). Modeling the determinants of student retention in distance education institutions. *International Journal of Continuing Engineering Education and Life-Long Learning*, *6*(2), 15. https://search.informit.com.au/documentSummary;dn=321689432407430;res=IELHSS

Harris, M. E., & Gibson, S. G. (2006). Distance Education vs Face-to-Face Classes: Individual Differences, Course Preferences and Enrollment. *Psychological Reports*, *98*(3), 756–764. https://doi.org/10.2466/pr0.98.3.756-764

Herbert, M. (2006). Staying the Course: A Study in Online Student Satisfaction and Retention. *Online Journal of Distance Learning Administration*, *9*(4). https://www.westga.edu/~distance/ojdla/winter94/herbert94.pdf

Hodges, C. B., & Kim, C. (2013). Improving college students' attitudes toward mathematics. *TechTrends*, *57*(4), 59–66. https://doi.org/10.1007/s11528-013-0679-4

Joo, Y. H., Lim, K., & Kim, E. K. (2011). Online university students' satisfaction and persistence: Examining perceived level of presence, usefulness and ease of use as predictors in a structural model. *Computers & Education*, *57(2),* 1654–1664. https://doi.org/10.1016/j.compedu.2011.02.008

Karadağ, E., Su, A. and Ergin-Kocaturk, H. (2021). Multi-level analyses of distance education capacity, faculty members' adaptation, and indicators of student satisfaction in higher education during COVID-19 pandemic, *International Journal of Educational Technology in Higher Education*, *18(*1*).* https://doi.org/10.1186/s41239-021-00291-w.

Keller, J. M. (1983). Motivational design of instruction. In C. M. Reigeluth (Ed.), Instructional design theories and models: An overview of their current status. Hillsdale, NJ: Erlbaum.

Keller, J. M. (2008). An Integrative Theory of Motivation, Volition, and Performance. *Technology, Instruction, Cognition & Learning*, *6*(2), 79-104. http://terrikrause.com/Content/documents/Keller2008IntegrativeTheory.pdf

Keller, J. M. & Deimann, M. (2012). Motivation, volition and performance. In R. A. Reiser and J. V. Dempsey (Eds.) *Trends and Issues in Instructional Design and Technology* (3rd ed., pp. 84 - 95). Pearson Education, Inc.

Khare, Pankaj (2012). Learning Analytics of Postgraduate Sociology Students of Indira Gandhi National Open University, India, *Asian Journal of Distance Education*, *12(*1*),* 4-16. http://www.asianjde.com/ojs/index.php/AsianJDE/article/view/235/215

Kickul, G., & Kickul, J. (2006). Closing the Gap: Impact of Student Proactivity and Learning Goal Orientation on E-Learning Outcomes. *International Journal on E-Learning*, *5*(3), 361–372. https://eric.ed.gov/?id=EJ735716

Kuo, Y., Walker, A., Belland, B. R., & Schroder, K. E. E. (2013). A predictive study of student satisfaction in online education programs. *The International Review of Research in Open and Distributed Learning*, *14*(1), 16. https://doi.org/10.19173/irrodl.v14i1.1338

Lee, Y., & Choi, J. (2013). A structural equation model of predictors of online learning retention. *The Internet and Higher Education*, *16*, 36–42. https://doi.org/10.1016/j.iheduc.2012.01.005

Nasu, V. H. (2020). Accounting Students' Performance in Distance Education: A Study Focused on Sociodemographic Factors. *Journal of Information Systems and Technology Management*. https://doi.org/10.4301/s1807-1775202017007

Ortagus, J. C. (2017). From the periphery to prominence: An examination of the changing profile of online students in American higher education. *Internet and Higher Education*, *32*, 47–57. https://doi.org/10.1016/j.iheduc.2016.09.002

Park, J., & Choi, H. J. (2009). Factors Influencing Adult Learners' Decision to Drop Out or Persist in Online Learning. *Educational Technology & Society*, *12*(4), 207–217. https://www.jstor.org/stable/jeductechsoci.12.4.207

Pekrun, R., Goetz, T., Frenzel, A. C., Barchfeld, P., & Perry, R. P. (2011). Measuring emotions in students' learning and performance: The Achievement Emotions Questionnaire (AEQ). *Contemporary Educational Psychology*, *36*(1), 36–48. https://doi.org/10.1016/j.cedpsych.2010.10.002

Radovan, M. (2011). The Relation between Distance Students' Motivation, Their use of Learning Strategies, and Academic Success. *Turkish Online Journal of Educational Technology*, *10*(1), 216–222. http://files.eric.ed.gov/fulltext/EJ926571.pdf

Schamber, Linda. (1994). Relevance and information behaviour, Annual Review of Information Science and Technology (ARIST), *29*, 3-48. https://eric.ed.gov/?id=EJ491620

Schunk, D. H. (1995). Self-efficacy and education and instruction. In J. E. Maddux (Ed.), Self-efficacy, adaptation, and adjustment: Theory, research, and application (pp.281-303). New York, NY: Plenum Press.

Schunk, D. H., Pintrich, P. R., & Meece, J. L. (2008). Motivation in education: theory, research, and applications (3rd ed.). Upper Saddle River, N.J.: Pearson/Merrill Prentice Hall.

Setiawan, R.I., Aprillia, A. and Magdalena, N. (2020). Analysis of antecedent factors in academic achievement and student retention, *Asian Association of Open Universities Journal*, *15(*1*),* 37–47. https://doi.org/10.1108/aaouj-09-2019-0043.

Simons, J., Leverett, S. and Beaumont, K. (2019). Success of distance learning graduates and the role of intrinsic motivation, *Open Learning: The Journal of Open, Distance and e-Learning*, *35 (*3*),* 277-293. https://doi.org/10.1080/02680513.2019.1696183

Singh, S., Singh, A., Singh, K. & Sharma, A. (2012) Academic Motivation in Open versus Traditional Education in India. *Asian Journal of Distance Education*, *10(1),* 45-51. http://www.asianjde.com/ojs/index.php/AsianJDE/article/download/203/186

Su, Y., & Lai, C. F. (2021). Applying educational data mining to explore viewing behaviors and performance with flipped classrooms on the social media platform Facebook. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.653018

Waterhouse, P., Samra, R., & Lucassen, M. (2022). Distance education students' satisfaction: Do work and family roles matter? *Distance Education*, *43(1),* 56–77. https://doi.org/10.1080/01587919.2021.2020622

Wei, H., & Chou, C. (2020). Online learning performance and satisfaction: do perceptions and readiness matter? *Distance Education*, *41*(1), 48–69. https://doi.org/10.1080/01587919.2020.1724768

Wentzel, K.R. (2013). Motivating Students to Learn (4th ed.). Routledge. https://doi.org/10.4324/9780203108017

Yasmin. (2019). A Learning Analytics Approach to Identify Factors Influencing Enrolment in Open and Distance Learning in India, *Asian Journal of Distance Education*, *14(2),*16-25. http://www.asianjde.com/ojs/index.php/AsianJDE/article/view/419/280

Yasmin. (2013). Application of the classification tree model in predicting learner dropout behaviour in open and distance learning. *Distance Education*, *34*(2), 218–231. https://doi.org/10.1080/01587919.2013.793642

Yi, M. Y., & Hwang, Y. (2003). Predicting the use of web-based information systems: self-efficacy, enjoyment, learning goal orientation, and the technology acceptance model. *International Journal of Human-Computer Studies*, *59*(4), 431–449. https://doi.org/10.1016/s1071-5819(03)00114-9

Zeytinli Ünal, M., Ünal, S.,& Çakıroğlu, Ü.(2023). Measuring satisfaction with distance education: A scale development study for secondary and high school students. *Asian Journal of Distance Education*, *18(1),*33-52. https://doi.org/10.5281/zenodo.7553876

About the Author(s)

Yasmin; yasmin@ignou.ac.in; Indira Gandhi National Open University, New Delhi, India; https://orcid.org/0000-0002-5328-599X

Author's Contributions (CRediT)

Yasmin: Conceptualization, methodology, formal analysis, investigation, data curation, writing—original draft preparation, writing—review and editing. The author has read and agreed to the published version of the manuscript.

Acknowledgements

Not applicable.

Funding

Not applicable.

Ethics Statement

An ethics review was not applicable.

Conflict of Interest

The author does not declare any conflict of interest.

Data Availability Statement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Article History

Submitted: March 15, 2024 – Accepted: May 15, 2024.

Suggested citation:

Yasmin. (2024). Influence of Socio-Demographic Profile on the Motivational Characteristics and Academic Performances of Distance Learners. *Asian Journal of Distance Education, 19*(2), 34-48. https://doi.org/10.5281/zenodo.11194377