

MULTILEVEL REGRESSION ANALYSIS OF LEARNING DISTRACTIONS AMONG HIGHER EDUCATION STUDENTS

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Abstract. *Learning distractions, both internal and external, disrupt students' focus and academic performance. Understanding these distractions is crucial for developing effective strategies to mitigate their effects and enhance learning outcomes for university students. Little literature is available on assessing students' learning distractions in Ethiopian universities. The current study aims to identify learning distractions of university students and their correlates using a multilevel regression analysis. A cross-sectional survey with a self-administered questionnaire, quantitative approach grounded in postpositivist and connectivism philosophies, is used to collect data from a sample of 1,380 students at the Addis Ababa Science and Technology University. The data are analyzed using SPSS version 27.0, Winsteps version 5.7.1.0, and R version 4.3.2. The multilevel model with random intercept and random-fixed slopes is used to analyze the learning distraction score of the students. The results show that the average learning distractions score is 33.70 out of 100, indicating moderate learning distraction levels among the students. Most (79.20%) students are in a good state, and 5.07% are academically resilient. About 15.44% of the students need help facing academic problems, and 0.29% require urgent university assistance due to early burnout. A significant portion (51.86%) of the variation in distraction score is due to differences between students' years of stay at the university. Factors affecting learning distraction score include gender, age, income, time spent on social media, and academic resilience. Female students experience lower learning distraction as compared to males. Learning distraction score decreases with an increase in age. An increase in monthly income increases their learning distraction. Student learning distraction increases as the time spent on social media daily increases. Higher academic resilience reduces their distraction score. Interventions based on behavioral, cognitive, and social cognitive learning theories and self-regulated strategies are crucial for managing learning*

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distractions at the university. The intervention may include well-planned training and awareness creation programs for the university students.

Keywords: *Academic Resilience; Learning Distractions; Learning Outcomes; Multilevel Models, University Students*

1. INTRODUCTION

Various scholars define learning outcomes as descriptions of the specific knowledge, skills, attitudes, and abilities students attain through higher education experiences (Allan, 1996; Hussey and Smith, 2008; Prøitz, 2010). The learning outcomes in literature include: learning distraction, academic resilience, plan for self-regulated strategies for future learning, learning motivation, learning satisfaction, research experience, and application of Bloom's taxonomy of knowledge during learning (Bloom et al., 1956; Bloom et al., 1964; Zimmerman, 1986; Zimmerman, 1989; Lopatto, 2004; Martin and Marsh, 2006; Tuan et al., 2005; Schunk et al., 2008; Panadero and Alonso-Tapia, 2014; Stanley, 2015; Ali et al., 2016; Russell et al., 2020; Schmidt, 2020; Kanwar and Sanjeeva, 2022).

Learning distractions are any internal or external factors that interrupt, delay, or hinder a student's focus, concentration, or cognitive engagement during the learning process (Junco and Cotton, 2012; Rosen et al., 2013; Aligolbandi et al., 2015; Schmidt, 2020). Learning distractions can occur from side-talk among students during lectures/group work/studying, smartphone use for social media/messaging/gaming during class, multitasking with laptops such as switching between lecture notes and unrelated websites noise pollution from outside the class room (e.g. construction) or uncomfortable classroom setting, lack of access to learning materials (e.g., textbooks, internet, devices), stress from financial insecurity, anxiety and depression and low self-esteem or fear of failure (Rosen et al., 2013; Aligolbandi et al., 2015; Soyemi and Soyemi, 2020; Koessmeier and Büttner, 2021; Kolhar et al., 2021; Aivaz and Teodorescu, 2022; Kostić and Randelović, 2022; Uyanga et al., 2023). These distractions can arise from digital devices, social media, non-academic tasks, environmental sources, psychological factors, or personal habits. They result in cognitive overload, reduced academic productivity, and decreased ability to retain and process information effectively (Junco and Cotton, 2012; Rosen et al., 2013; Schmidt, 2020; Baumgartner and Wiradhany, 2021; Kostić and Randelović, 2022; Wang, 2022).

According to Soyemi and Soyemi (2020), smartphone usage is one of the most significant sources of distraction, along with mobile calls to teachers, lack of interest in the course, and attraction to the opposite sex. Digital distractions caused by multitasking are highlighted as a significant source of learning disruption (Rosen et al., 2013; Wang, 2022; Aivaz and Teodorescu, 2022). Moreover, academic resilience (Janatolmakan et al., 2021; Nasution and Daulay, 2022; Van-Wky et al., 2022; Wang et al., 2022b; Choi et al., 2023) and social media use (Kross et al., 2013; Woods and Scott, 2016; Demirbilek and Talan, 2017; Dontre, 2021; Koessmeier and Büttner, 2021; Kolhar et al., 2021) are factors for learning distractions.

Excessive social media usage reduces attention and cognitive control, increasing susceptibility to distractions during learning activities (Kross et al., 2013; Demirbilek and Talan, 2017). A systematic review by Woods and Scott (2016) links excessive social media

use to decreased academic performance due to increased distractions and reduced study time. Koessmeier and Büttner (2021) found that excessive social media usage reduces task performance and well-being, recommending interventions to reduce these distractions. Dontre (2021) noted that social media use in the classroom is largely disruptive and increases academic distractions. Kolhar et al. (2021) reported that non-academic social media distracts students from learning. Additionally, studies show that financial stress affects students' well-being (Moore et al., 2021; Nasr et al., 2024).

Embracing academic resilience helps students develop foundational skills that promote brain-body optimization, reducing distractions and enhancing academic success (Van-Wyk et al., 2022). Resilience alleviates the harmful effects of academic stress on school adjustment (Choi et al., 2023) and significantly mediates the relationship between academic burnout and life satisfaction (Wang et al., 2022b). Increasing students' resilience decreases academic burnout (Janatolmakan et al., 2021) and reduces learning distractions (Nasution and Daulay, 2022). Additionally, digital distractions can be effectively managed through self-regulated learning strategies (Wang et al., 2022a).

Schmidt (2020) reports that learning distractions cause tasks to take longer to complete, increase cognitive costs when alternating between tasks, impair long-term memory retention, and alter how the brain processes and stores information (Paul, 2013). Learning distractions often impair a student's ability to absorb, process, and retain information, reducing academic performance, engagement, cognitive development, and overall well-being (Rosen et al., 2013; Baumgartner and Wiradhany, 2021; Kostić and Randelović, 2022). Multitasking-related distractions negatively impact students' concentration during lectures and study sessions (Rosen et al., 2013; Aivaz and Teodorescu, 2022). Addressing learning distractions requires a multi-faceted approach that includes both individual and systemic interventions.

Understanding learning distractions is crucial for developing effective strategies to mitigate their effects and enhance learning outcomes for university students (Junco and Cotton, 2012; Rosen et al., 2013; Schmidt, 2020; Baumgartner and Wiradhany, 2021; Wang, 2022; Koessmeier and Büttner, 2021; Nasution and Daulay, 2022). However, little literature assesses students' learning distraction in Ethiopian universities. The current study aims to fill this gap by investigating learning distractions among university students. The study addresses the following research questions:

1. What are the learning distractions of university students?
2. How do socio-demographic factors, time spent on social media, and academic resilience affect the learning distractions of university students?

This study aims to measure learning distraction levels and identify correlated variables such as socio-demographic factors, time spent on social media, and academic resilience.

2. METHODS

2.1. Research Design

This educational research is conducted using postpositivist philosophical thoughts. Postpositivism represents a shift away from the absolute objectivity and determinism of the classical positivist worldview. It is a philosophical worldview associated with quantitative research (Creswell, 2014). However, unlike the rigid empiricism of positivism, postpositivism holds a more critical and reflective stance toward knowledge generation. It assumes that reality exists but can only be known imperfectly and probabilistically due to the inherent limitations in human observation and reasoning. The research approach is a quantitative method that uses a survey based on students' self-reports in a cross-sectional setting to obtain education-related data from undergraduate university students. In addition, the connectivism view is used to explore students' knowledge from social media and online learning.

We want to conceptualize relationships of variables as follows. The conceptual model consists of: social media (SM), learning satisfaction (Satis), student's learning distraction (LD), academic resilience (Resil), student's learning outcomes (SLO2): self-regulate learning, learning motivation, Bloom's taxonomy, research experience, academic performance of student and other learning outcomes, and factors that may affect outcomes. Social media (SM), learning distraction (LD), learning satisfaction (Satis), and students' academic resilience (Resil) may affect each other in any direction, assuming some dynamicity. The factors such as age, gender, income, and year of stay (batch) at university correlate with these learning outcomes.

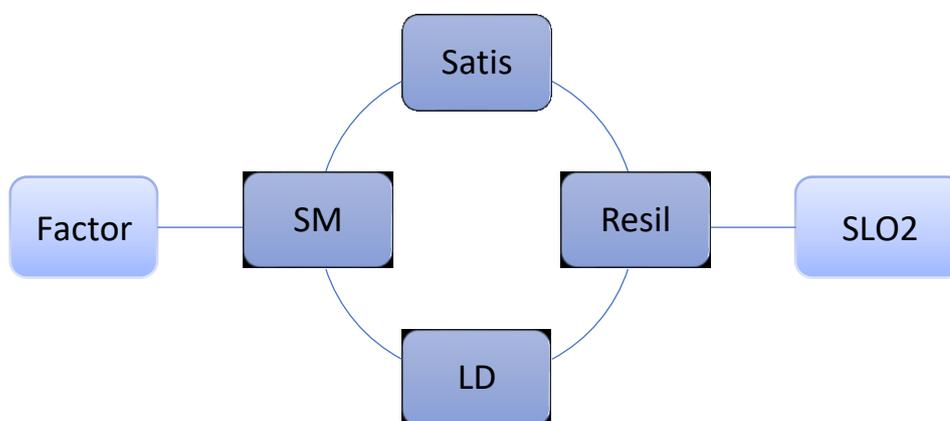


Figure 1. Conceptual model of the study.

Hypotheses:

1. Factors: gender, age, income, and year of stay at university significantly affect students' learning distraction.
2. Social media usage, learning satisfaction, academic resilience, research experience, and Bloom's taxonomy usage significantly affect student learning distraction.

2.2. Study Population

The study was conducted on undergraduate students of Addis Ababa Science and Technology University (AASTU). The colleges at the University are: Applied Sciences, Architecture and Civil Engineering, Biological and Chemical, and Electrical and Mechanical Engineering. The University has first-year students under the College of Engineering Stream, Applied and Natural Sciences. The study population is a set of all regular undergraduate students of the University in the 2022/23 GC academic year. A sample is taken from the total population of 6593 regular students.

2.3. Sampling Design and Techniques

A stratified random sampling technique is used to select n participants from five batches in proportion to size. The stratification is done by considering student colleges, departments, and the year of stay at the university. The sample size determination for this study is done using (Verma and Verma, 2020) by considering two groups: the first year as group 1 for first-year students, and the second year or higher as group 2 for senior students.

The sample is computed as $n = 2 * n_1$, where $n_1 = \frac{p*(1-p)*Z_{\alpha/2}^2}{d^2}$, p is the proportion of the students who are distracted from their learning which is 0.26 as estimated from the pilot study, d is margin of error taken to be 0.03353, and $\alpha = 0.05$ is level of significance; thus, $n_1 = \frac{p*(1-p)*Z_{\alpha/2}^2}{d^2} = \frac{0.26*(1-0.26)*1.96^2}{0.03353^2} = \frac{0.73912384}{0.023^2} = 657.431 \approx 658$. By adding 5% non-response rate, n_1 is 690. This implies that $n = 2 * 690 = 1380$. Thus, a sample of 1380 students was taken from 6593 undergraduate students of AASTU.

2.4. Data Collection Tools

A questionnaire focusing on learning outcomes including learning distractions is developed by adopting the standard scales of Brief Resilience Scale (BRS) (Smith et al., 2008), Indicators of Academic Resilience (Herrman et al., 2011; Al Omari et al., 2023), Psychological Wellbeing (WHO, 1998), Learning Distractions of Students (Aligolbandi et al., 2015; Soyemi and Soyemi, 2020; Dontre, 2021; Aivaz and Teodorescu, 2022; Wang, 2022; Wang et al., 2022a), Self-regulated learning (Zimmerman, 1986; Zimmerman, 1989; Panadero and Alonso-Tapia, 2014; Russell et al., 2020), Usage of Bloom Taxonomy in learning (Bloom et al., 1956; Bloom et al., 1964), Academic Motivation (Tuan et al., 2005; Conradty and Bogner, 2022), Academic Satisfaction (Kanwar and Sanjeeva, 2022), Research Experience (Lopatto, 2004), Physical Health Status and Rosenberg self-esteem scale (RSES) (Rosenberg, 1965). Moreover, questions about the socio-demographic information of students and social media usage are included. The sampled students self-administered the questionnaire independently from the beginning of July to the end of August 2023. The researchers supervise the data collection. To check the consistency and validity of the questionnaire, a pilot study was conducted on 30 randomly selected students. The pilot study helped identify the questionnaire's coherence and obtain relevant data.

2.5. Data Collection Procedure

Primary data are collected from sampled students by trained enumerators. The researchers monitored the process, and AASTU grants permission. The questionnaire includes a consent statement informing students about the study's purpose, procedures, voluntary participation, confidentiality, and their right to withdraw at any time.

The response variable considered in this study is the learning distraction score of a student. Twenty-seven Likert-scale questions with five levels (never, rarely, sometimes, often, always) are used to collect self-report data from the selected students. The learning distractions of a student are computed as an aggregated score scaled to 100%.

The predictors are: gender (male, female), age (in years), year of stay at university (1st, 2nd, 3rd, 4th, 5th year), monthly income of student (local currency), time spent on social media per day (in hours) and academic resilience (score aggregated and scaled to 100%).

2.6. Statistical Models and Analysis

The collected data are cleaned, coded, and recoded until they are ready for statistical inference. The Cronbach alpha test (Taber, 2017) and Rasch analysis (Rachman and Napitupulu, 2017) are used to test the validity of the constructs developed for the study. They are analyzed using descriptive statistics and a multilevel regression model.

2.7. Multilevel Linear Regression Model

A multilevel multiple linear regression model is a statistical model that is used to analyze the relationship between one dependent (continuous) variable and independent variables (continuous or categorical) when there is a correlation between observations (Hox, 2002; Gelman and Hill, 2006). In this study, we consider the two-level model where the 1st level refers to students and 2nd level refers to the year of stay/batch having J number of academic levels.

The two-level model for random intercept and some random slopes and others fixed slopes with model assumptions is given in Gelman and Hill (2006). The observation model for the i^{th} learning distraction score of a student in j^{th} group Y_{ij} is defined:

$$Y_{ij} = \beta_{0j[i]} + \beta_{1j[i]} X_{1ij} + \dots + \beta_{mj[i]} X_{mij} + \beta_{(m+1)} X_{(m+1)ij} + \dots + \beta_p X_{pij} + \epsilon_{ij}$$

$$\beta_{0j[i]} = \beta_0 + U_{0j[i]}$$

$$\beta_{mj[i]} = \beta_m + U_{mj[i]} \tag{1}$$

where $i = 1, 2, 3, \dots, n$ and n represents the sample size, $j = 1, 2, 3, \dots, J$ with J number of groups, which can be 5 or 2; $k = 1, 2, 3, \dots, m, m + 1, \dots, p$ with p number of predictors. $\beta_{0j[i]}$'s is random intercept with β_0 representing the average values of the response, $\beta_{kj[i]}$ random effects for $k = 1, 2, 3, \dots, m$, β_k 's are fixed effects coefficients for $k = m + 1, m + 2, \dots, p$, X_{kij} 's are covariates from the two levels, ϵ_{ij} 's are random error of the model, and $U_{0j[i]}$, $U_{kj[i]}$ represent random effects due to individual difference with/between year of stay at university.

Intra-class correlation (ICC) is a crucial statistical measure in multilevel models that quantifies the proportion of the total variance in the outcome variable attributable to differences between groups or clusters. ICC is computed by $\frac{\sigma_u^2}{\sigma_\epsilon^2 + \sigma_u^2}$ (Hox, 2002; Gelman and Hill, 2006).

The restricted maximum likelihood is used to estimate the parameter in a multilevel model, and the likelihood ratio test is used to test whether applying the model to the data is appropriate. AIC and BIC are used to select fitted models (Gelman and Hill, 2006). The computations and illustrations are made in the software: SPSS version 27.0 (George and Mallery, 2021), Ministep Rasch version Winsteps 5.7.1.0 (Bond et al, 2020), and R version 4.3.2 (Davies, 2016).

2.8. Ethical Consideration

This study adhered to strict ethical guidelines to protect participants' rights and well-being. Before data collection, ethical permission was obtained from AASTU, and all procedures were conducted following these guidelines. Participants were informed about the study's purpose, procedures, potential risks, and benefits, and oral informed consent was provided before participation. Confidentiality and anonymity were maintained by assigning unique identification codes instead of personal identifiers. Data were stored securely, accessible only to authorized researchers, and used exclusively for academic purposes. Participants were allowed to withdraw at any stage without any repercussions. Moreover, efforts were made to minimize potential biases and ensure that the assessment tools were culturally appropriate and non-discriminatory. By implementing these ethical safeguards, the study ensured the integrity and credibility of the research while prioritizing the rights and dignity of the participants.

3. RESULTS

3.1. Reliability and Validity of the Constructs

The reliability and consistency of the instruments used were verified using the Cronbach's alpha test and Rasch analysis. The instrument showed a high reliability with a Cronbach's alpha value of 0.86. The respondents' reliability was also high at 0.84, with a separation index of 2.28, indicating that respondents could be divided into four major groups.

Regarding item statistics, the PTMEA CORR and Item Fit showed that all items (B1-B26) had positive PTMEA CORR values, confirming their validity and ability to distinguish respondents' abilities. Items B3 and B12 were the most difficult, while item B10 was the easiest. Item B19 had higher Infit and Outfit MNSQ values, indicating some confusion. The Van den Wollenberg Q1 Test (Parallel ICCs/IRFs) result is insignificant (van den Wollenberg Q1 Test of Parallel ICCs/IRFs: 466.9880 with 456 degrees of freedom and p-value of 0.3509). This suggests that the items will likely effectively measure a single construct for unidimensionality. The PTMEA CORR results confirmed the items' reliability in measuring students' learning outcomes and applying various learning theories.

3.2. Summary of Participants' Information

Table 1: Description of demographic and economic variables of students.

Variables (Continuous)	Min	Max	Mean	Std. Dev
Age of student (year)	18	27	21	1.7
Monthly income (local currency)	100	2000	607	477
Variables (Categorical)	Categories		Counts (%)	
Gender of Student	Male		804 (58.3)	
	Female		576 (41.7)	
Residence of the Student	Rural		774 (56.1)	
	Urban		606 (43.9)	
Year of stay at the University	First year		690 (50.0)	
	Second year		265 (19.2)	
	Third year		180 (13.0)	
	Fourth year		114 (8.3)	
	Fifth year		131 (9.5)	

Table 1 describes the demographic and economic variables of students. About 58.3% of the students are males, while 41.7% are females. Students' ages range from 18 to 27 years, with an average of 21 and a standard deviation of 1.7 years. More than half (56.1%) come from rural areas, while 43.9% are from urban areas. The percentage of respondents from the first year to the fifth year is 50.0%, 19.2%, 13.0%, 8.3%, and 9.5%. According to the students' self-reports on income, their average monthly income is 607 with a standard deviation of 477 and a range of 100 to 2000 in local currency.

3.3. Descriptive Analysis of Indicators of the Learning Distractions

The indicators of learning distractions of the students consist of 27 questions. Table 2 provides a summary of the learning distractions of university students. Self-report survey on academic learning distractions revealed that 56.6% of students sometimes use social media during class, with only 2.7% always and 3.3% often using it, suggesting a minimal to severe impact. Senior students reported higher social media usage (65.9%) than freshmen (59.5%). Additionally, 36.2% of students send text messages during class.

The self-report indicates that students use social media in the classroom to refer to lecture topics at varying levels: 31.3% sometimes, 19.2% often, and 13.3% always. While regulated social media use can be beneficial, it can also lead to distractions. Theories of self-regulated learning emphasize managing focus and resources. Additionally, large proportions of students never eat food (85.1%), chew gum (69.3%), or use perfume (66.2%) in class, aligning with behaviorism theory, which stresses managing student behavior and setting clear expectations. Reported learning distractions include conversations with friends during studying (64.10%) and class (60.60%), late arrivals, personal mobile calls, attraction to the opposite sex, and corridor noise, all of which can interfere with cognitive processes. Furthermore, 36.3% of students never felt sick in class, while 43.9% rarely did, indicating a need for better university health care services. This underscores the importance of managing distractions and promoting health to enhance academic performance.

Table 2: Summary of indicators of learning distractions of University students.

Statement	Never	Rarely	Sometimes	Often	Always
1. I use social media in the classroom	260 (18.8)	254 (18.4)	784 (56.8)	45 (3.3)	37 (2.7)
2. I remain online with social media while attending the lecture	694 (50.3)	341 (24.7)	258 (18.7)	47 (3.4)	40 (2.9)
3. I play games during the class lecture	860 (62.3)	259 (18.8)	259 (18.8)	2 (0.1)	0 (0)
4. I send a text message during class	412 (29.9)	316 (22.9)	499 (36.2)	153 (11.1)	0 (0)
5. I use many social media while studying in class	159 (11.5)	307 (22.2)	523 (37.9)	207 (15.0)	184 (13.3)
6. I use social media in the classroom to refer to the topic being lectured on	163 (11.8)	337 (24.4)	432 (31.3)	265 (19.2)	183 (13.3)
7. I remain online with open social media while doing homework	169 (12.2)	326 (23.6)	574 (41.6)	216 (15.7)	95 (6.9)
8. I play games during class/studying	1025 (74.3)	124 (9.0)	226 (16.4)	5 (0.4)	0 (0)
9. I send text messages while studying	431 (31.2)	470 (34.1)	290 (21)	167 (12.1)	22 (1.6)
10. I use social media while studying out of class in order to refer to the lecture topics	98 (7.1)	198 (14.3)	536 (38.8)	319 (23.1)	229 (16.6)
11. Eating food in class	1174 (85.1)	53 (3.8)	98 (7.1)	34 (2.5)	21 (1.5)
12. Chewing gum in class	956 (69.3)	236 (17.1)	140 (10.1)	45 (3.3)	3 (0.2)
13. Use of perfume in class	914 (66.2)	188 (13.6)	124 (9.0)	94 (6.8)	60 (4.3)
14. Noise due to movement in the corridor	455 (33.0)	296 (21.4)	348 (25.2)	233 (16.9)	48 (3.5)
15. Noise due to a late-coming student to class	271 (19.6)	323 (23.4)	581 (42.1)	147 (10.7)	58 (4.2)
16. Teacher's lateness to class	201 (14.6)	336 (24.3)	633 (45.9)	117 (8.5)	93 (6.7)
17. Attraction to the opposite sex	362 (26.2)	322 (23.3)	432 (31.3)	212 (15.4)	52 (3.8)
18. My feeling of sickness in class	501 (36.3)	606 (43.9)	101 (7.3)	102 (7.4)	70 (5.1)
19. Noise from other classes	391 (28.3)	601 (43.6)	194 (14.1)	9 (0.7)	185 (13.4)
20. Noise from vehicles, construction, etc.	447 (32.4)	114 (8.3)	500 (36.2)	266 (19.3)	53 (3.8)
21. Telephone or mobile calls to the Lecturer	383 (27.8)	360 (26.1)	465 (33.7)	169 (12.2)	3 (0.2)
22. Mobile calls to the students near me	233 (16.9)	355 (25.7)	576 (41.7)	91 (6.6)	125 (9.1)
23. Mobile calls to my mobile	352 (25.5)	269 (19.5)	599 (43.4)	95 (6.9)	65 (4.7)
24. My friend talking to me during class	149 (10.8)	395 (28.6)	626 (45.4)	188 (13.6)	22 (1.6)
25. I talk to my friend during class	229 (16.6)	361 (26.2)	600 (43.5)	125 (9.1)	65 (4.7)
26. My friend talks to me while I am studying	138 (10.0)	357 (25.9)	723 (52.4)	43 (3.1)	119 (8.6)
27. I talk to my friend while studying	188 (13.6)	367 (26.6)	581 (42.1)	139 (10.1)	105 (7.6)

Table 3: Summary of aggregated scores of learning distractions, resilience, and daily social media usage.

Variables	Min	Max	Mean	Std. Dev
Time spent on social media per day (in hours)	1	9	3.31	1.62047
Learning distraction (score 100)	7.41	76.85	33.7	9.52987
Academic resilience (score 100)	29.17	100.00	63.89	14.34100

Table 3 provides a detailed summary of the aggregated scores for learning distraction, resilience, and daily social media usage. Students spend an average of 3.31 hours per day on social media, with usage ranging from 1 to 9 hours and a standard deviation of 1.62, indicating varied usage patterns. Learning distraction scores average 33.7, ranging from 7.41 to 76.85, with a standard deviation of 9.53, suggesting moderate distraction levels with significant differences among students. Academic resilience scores

average 63.89, ranging from 29.17 to 100, and have a standard deviation of 14.34, showing high resilience among students but with notable individual differences.

3.4. Analysis of Learning Outcomes Vs Year of Stay at University and Gender

Table 4: ANOVA results for learning distractions by year of stay at university.

		Sum of Squares	Degree of Freedom	Mean Square	F	p-value
Learning distractions * Year of stay at university	Between Groups	185.920	4	46.480	3.305	0.0105
	Within Groups	19338.000	1375	14.064		
	Total	19523.902	1379			

Table 4 compares the means of learning distractions concerning the students' year of stay at the university. The ANOVA results indicate that learning distraction scores significantly differ among the different years of stay ($p = 0.0105$). In educational contexts, the variations in learning distraction score across different years can be attributed to developmental changes, varying cognitive loads, and adjustments in academic demands.

3.5. Categorizing the Students by their Satisfaction-Resilience Status

Categorizing the respondents by scores (low when $< 50/100$, high when $\geq 50/100$) by learning distraction and satisfaction measures. There are four states: good state if high satisfaction $\geq 50/100$ and if low learning distraction $< 50/100$; resilient if high satisfaction $\geq 50/100$ and if high learning distraction $\geq 50/100$; early burnout if low satisfaction $< 50/100$ and if high learning distraction $\geq 50/100$; academic problem if low satisfaction $< 50/100$ and if low learning distraction $< 50/100$.

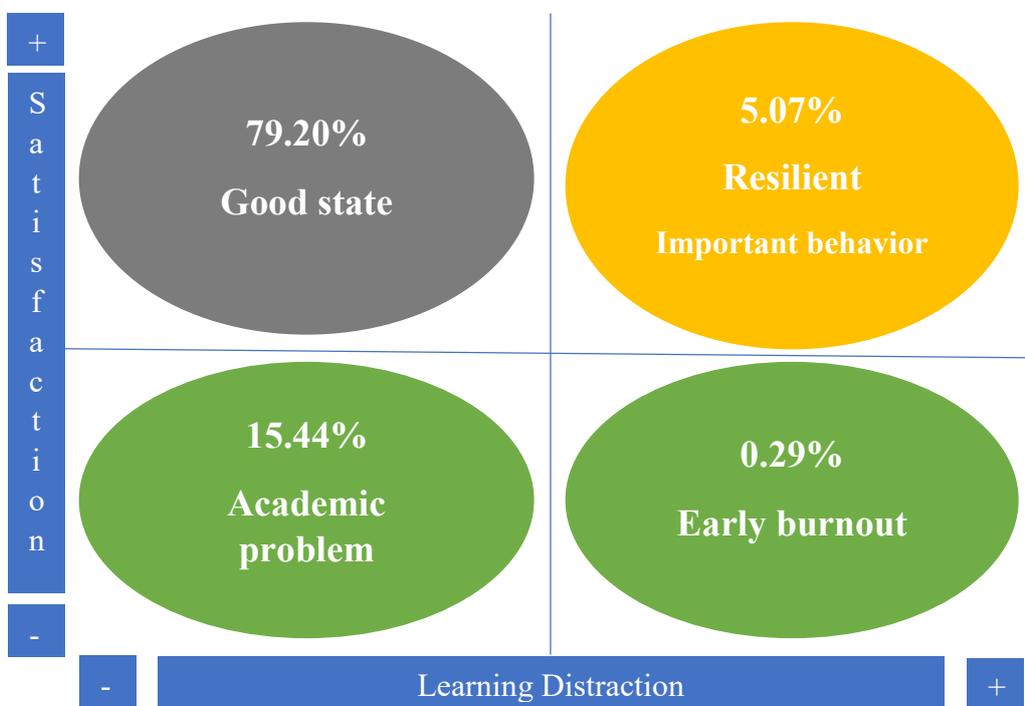


Figure 2: Academic results model for the students.

Figure 2 illustrates the academic outcomes and psychological status of students. Based on the analysis, 79.20% (1093 out of 1380) of the students are in a good state, indicating that most students have experienced high satisfaction and low learning distraction. This is a very important behavior that can be achieved by increasing satisfaction levels while reducing distractions. About 5.07% (70) of the students are resilient concerning their satisfaction and learning distraction scores. This suggests that a small portion of students have managed to maintain high satisfaction despite experiencing high distractions. This state is considered an important behavior, and higher institutions can teach students how to achieve such a state. Approximately 0.29% (4) of students are in an early burnout state, as measured by low satisfaction and high distraction scores. Student burnout is a significant issue that often leads to physical, emotional, and mental exhaustion. It may manifest as fatigue, decreased motivation, and helplessness. These 0.29% of students need urgent help and counseling. The fourth state is when students are in academic trouble, characterized by low satisfaction and low distraction scores. Fortunately, only about 15.44% (213) of students are found to be in this state. This situation requires attention from the university to address the problems effectively.

The four states of a student (good state, resilient state, early burnout state, and academic problem state) are dynamic in the sense that they may change over time. It can be modeled by a stochastic process with four states.

3.6. Multilevel Models

The multilevel model is fitted to investigate the extent to which the variation in students' learning distraction is explained by their year of stay at university as a grouping variable. Based on this model, we identify and assess the variability between and within these groups. First, a null model is fitted to determine whether a multilevel model is appropriate. If deemed appropriate, we proceed by fitting three different models: a random intercept model with a fixed slope, a fixed intercept model with a random slope, and a random intercept model with a random slope. These models are then compared, and the most suitable model is selected and fitted as the final model.

3.6.1. Fitting the Null Model

The null model is fitted by considering a random intercept model to see whether fitting a multilevel model is appropriate. Estimates of model parameters are conducted using the method of restricted maximum likelihood. The results are displayed in Table 5.

Table 5: Estimates of model parameters.

Fixe Effects				
Predictor	Estimate	Std. Error	95% CI for Estimate	P-value
Intercept	16.6570	0.20382	(16.2405, 17.12120)	< 0.0001
Random Effects				
Group	Variance	SD	95% CI for Estimate	
Intercept	0.13804	0.37154	(0.0000, 0.8499)	
Residual	14.06399	3.75020	(3.6143, 3.8949)	
Intra-class Correlation Coefficient (ICC) = 0.0097 (0.97%).				

Table 5 provides detailed estimates for the parameters of the multilevel model, including both fixed and random effects. The ICC of the null model is 0.0097 (0.97%), indicating that only about 0.97% of the total variability in learning distractions is explained by differences between groups (year of stay at the university). In comparison, the majority of the variability (99.03%) is due to within-group differences. The estimated average value of learning distractions is 16.657, indicating that the average score of learning distractions is 16.657 whenever the students are male and there is no effect of income, time spent on social media, or academic resilience.

Variance of the intercept across years of stay at the university is 0.13804, with a standard deviation of 0.37154. The 95% confidence interval for this variance ranges from 0.0000 to 0.8499. This suggests some variability in the intercept across years of stay at university, but the confidence interval includes zero, indicating that this variability might not be statistically significant. However, descriptive data analysis shows that learning distractions differ across years of stay at the university, which is supported by the ANOVA test.

The fitted null model with no predictors is:

$$\begin{aligned} \hat{Y}_{ij} &= \hat{\beta}_{0j[i]} + \hat{\varepsilon}_{ij} \\ \hat{\beta}_{0j[i]} &= \hat{\beta}_0 + \hat{U}_{0j[i]} \\ \widehat{LD}_{ij} &= 16.6570 + \hat{U}_{0j[i]} + \hat{\varepsilon}_{ij} \end{aligned} \tag{2}$$

where $i = 1, 2, \dots, n$ and $j = 1, 2, 3, 4, 5$.

Testing whether fitting a multilevel model is appropriate is done using the likelihood ratio test. The result is given in Table 6.

Table 6: Likelihood ratio test of null model.

Model: Learning Distraction ~ (1 Year of stay at University)					
	Npar	LogLik	LRT	Df	p-value
(1 Year of stay at University)	2	-3787.70	4.67	1	0.0307

Table 6 demonstrates that the likelihood ratio test of the null model, at a 5% significance level, supports the appropriateness of fitting a multilevel model to the data. This model includes random effects for the “year of stay at university”, accounting for variability in learning distractions due to differences in students’ years at the university. The significant p-value (0.0307) indicates that incorporating these random effects significantly improves the model fit, suggesting that learning distraction scores are better explained by considering the different years of stay at university. Ignoring this factor could lead to less accurate conclusions about the factors that affect the learning distractions score.

3.6.2. Fitting the Final Two-level Model

After comparing various models, the final model is selected to consist of: gender, income, and academic resilience at the first level as fixed predictors; age and time spent on social media at the second level as both fixed and random predictors. The results are displayed in Table 7.

Table 7: Restricted maximum likelihood estimates of model parameters.

Fixed Effects				
Predictors	Estimate	Std. Error	95% CI	p-value
Intercept	21.9378	1.96324	(16.3519 , 27.4247)	0.0033
Gender (ref: Male): Female	-0.4959	0.19152	(-0.8734 , -0.1216)	0.0097
Age	-0.3149	0.09969	(-0.5892 , -0.0406)	0.0425
Income (Birr)	0.0011	0.00015	(0.0008 , 0.0014)	< 0.0001
Time on SM (hours)	0.2428	0.06049	(0.1048 , 0.3785)	0.0038
Academic resilience score	-1.3684	0.09451	(-1.5517 , -1.1802)	< 0.0001
Random Effects				
Group	Name	Variance	SD	95% CI
Year of stay at University	Intercept	11.51842	3.39388	(1.0194, 10.6407)
	Age	0.03279	0.18107	(-1.0063 , -0.9633)
	Time on SM	0.00187	0.04320	(0.0714 , 0.5398)
Residual		10.69293	3.27000	(3.1436 , 3.3878)
ICC = 0.5186 (51.86%).				

Table 7 shows the results of a two-level multilevel model with random intercepts and fixed slopes. The fitted model, which takes into account the effect of the year of stay at the university, is appropriate at the 5% level of significance. The variance for the learning distraction score at the residual level is estimated to be 10.69293. The estimated variance for the learning distraction score due to differences between groups (years of stay at the university) is 11.51842. The variance due to age and time spent on social media across batches is estimated to be 0.03279 and 0.18107, respectively. The 95% confidence intervals for the variance of the random effects (intercept, time spent on social media, and age) suggest that including these random effects in the model is important. The ICC value of this model is 0.5186, indicating that approximately 51.86% of the total variability in the learning distraction score is attributed to differences between groups (years of stay at the university), which is very high.

Gender, age, income, time spent on social media, and academic resilience significantly affect the learning distraction score of students at the 5% significance level. The intercept for the learning distraction score is 21.938, indicating that the average learning distraction score for students is 21.938 when the students' gender, income, time spent on social media, and academic resilience are set to zero. Female students experience fewer learning distractions than male students. As students become older, their learning distraction score declines. A one Birr increase in monthly income increases the learning distraction score by 0.001, suggesting that higher income has a minimal effect on increasing distraction. A one-hour increase in time spent on social media increases the learning distraction score by 0.243, indicating that more time on social media significantly increases distraction. Conversely, a unit increase in academic resilience is associated with a 1.368 decrease in the learning distraction score, implying that higher resilience significantly reduces learning distraction.

The model assumptions were checked and fulfilled, indicating that the model is appropriate for the data sets. The fitted model for the response variable Y_{ij} is:

$$\hat{Y}_{ij} = \hat{\beta}_{0j[i]} + \hat{\beta}_{1j[i]} Age_{ij} + \hat{\beta}_{2j[i]} TimeSM_{ij} + \hat{\beta}_3 Gender_{ij} + \hat{\beta}_4 Income_{ij} + \hat{\beta}_5 Resilience_{ij} + \varepsilon_{ij}$$

$$\hat{\beta}_{0j[i]} = \hat{\beta}_0 + \hat{U}_{0j[i]}$$

$$\hat{\beta}_{1j[i]} = \hat{\beta}_1 + \hat{U}_{1j[i]}Age_{ij}$$

$$\hat{\beta}_{2j[i]} = \hat{\beta}_2 + \hat{U}_{2j[i]}TimeSM_{ij}$$

$$\begin{aligned} \widehat{LD}_{ij} = & 21.9378 - 0.3149 Age_{ij} + 0.2428 TimeSM_{ij} - 0.4959 Gender_{ij} + 0.0011 Income_{ij} - \\ & 1.3684 Resilience_{ij} + \hat{U}_{0j[i]} + \hat{U}_{1j[i]}Age_{ij} + \hat{U}_{2j[i]}TimeSM_{ij} + \hat{\epsilon}_{ij} \end{aligned} \quad (3)$$

where number of random effect is $m = 2$, $i = 1, 2, \dots, n$ and $j = 1, 2, 3, 4, 5$.

The actual prediction model for learning distraction score of the student is in Equation (3). This approach allows predicting students' learning distraction score given values of individual- and group-level predictors.

4. DISCUSSION

Learning distractions from physical surroundings or external factors, such as late students entering the classroom, teacher lateness, noise from other classrooms, vehicles, construction, and mobile phone calls, are observed in this study. Our study is consistent with the findings of Aligolbandi et al. (2015). These distractions are linked to behavioral and cognitive learning theories (Schunk, 2012) and can create cognitive load, hindering the overall learning experience if not addressed. On the other hand, learning distractions caused by personal habits or multitasking arise from behaviors that divide attention and reduce focus on learning tasks (Junco and Cotton, 2012; Kostić and Randelović, 2022). Our study shows that conversations with friends during class or while studying are reported. Theoretically, these distractions can be managed if students practice self-regulated learning strategies (Wang, 2022), which align with behaviorism, cognitive, and social learning theories (Bandura, 1977; Schunk, 2012).

In this study, attraction to the opposite sex is observed as a learning distraction, consistent with Soyemi and Soyemi's (2020) findings. Such distractions can divert attention and create emotional preoccupations that interfere with classroom engagement (Wang, 2022). Feelings of sickness during class are also observed as learning distractions in the current study. These can be related to cognitive and social learning theories (Bandura, 1977; Schunk, 2012). Social media usage, including using multiple social media sites while studying, using social media in the classroom to refer to lecture topics, and using social media while studying, are also learning distractions observed in the current study. This aligns with Aivaz and Teodorescu (2022). Such distractions negatively impact students' ability to concentrate during lectures and study sessions (Rosen et al., 2013), creating cognitive overload, preventing sustained attention, and disrupting the learning flow. It is suggested to use self-regulated learning to reduce these distractions, as stated in the literature (Wang et al., 2022a), with the help of cognitive learning theory (Schunk, 2012).

The learning distractions reported by students in the current study arise from environmental factors, personal habits and multitasking, psychological factors, and digital or social media usage. These distractions can be effectively managed and mitigated through applying behavioral, cognitive, and social cognitive learning theories (Bandura, 1977;

Schunk, 2012). Learning theories provide a structured framework for addressing and reducing learning distractions among students (Wang, 2022). Also, the implementation of self-regulated learning strategies is needed to manage and minimize learning distractions, enabling students to maintain focus and improve their academic performance (Wang et al., 2022a).

The study shows that most students (79.20%) are in a good state, with high satisfaction and low distraction scores. Small portions (5.07%) are resilient, maintaining high satisfaction despite high learning distractions. A very few (0.29%) are in early burnout and need urgent help. Lastly, 15.44% are in academic trouble, requiring university intervention.

Our study reveals that social media use significantly affects students' learning distractions, consistent with Dontre (2021). This can lead to decreased academic performance and increased emotional issues such as depression, anxiety, and mood swings (Woods and Scott, 2016; Kolhar et al., 2021). Kolhar et al. (2021) identified the impact of social media on learning distractions and emotional well-being. Woods and Scott (2016) further demonstrated a clear link between heavy social media use and decreased academic performance, attributing this to increased distractions and reduced study time. Additionally, excessive social media usage impairs attention and cognitive control, exacerbating learning distractions (Kross et al., 2013; Demirbilek and Talan, 2017). Koessmeier and Büttner (2021) also emphasize the adverse effects on task performance and overall well-being, advocating for effective interventions to manage social media distractions. This body of literature underscores the urgent need for strategies to help students balance social media use with academic responsibilities.

The research indicates that students who face and overcome learning difficulties experience fewer learning distractions, aligning with existing literature on resilience and its relationship with learning distractions. Studies by Van-Wyk et al. (2022) and Choi et al. (2023) demonstrate that academic resilience reduces distractions and mitigates the negative effects of academic stress, promoting academic success and better school adjustment. Wang et al. (2022b) found that resilience mediates the relationship between academic burnout and life satisfaction, while Janatolmakan et al. (2021) reported that increased resilience is associated with decreased academic burnout. Nasution and Daulay (2022) also showed that academic resilience reduces learning distractions.

The two-level multilevel model analysis reveals that 51.86% of the variability in learning distraction scores is due to differences between years at the university. This suggests that a significant portion of the variability in the learning distraction score of the student is between years of stay at university rather than within these groups.

5. CONCLUSIONS

This research is grounded in postpositivist and connectivist views, employing a quantitative approach. The cross-sectional survey is conducted to collect data from 1,380 undergraduate students out of a total of 6,593. The instruments are validated for consistency and reliability. The data on learning distraction scores are analyzed using multilevel models.

The study has identified various learning distractions in university academic settings, including social media usage, text messaging, noise, mobile calls, late arrivals, and peer conversations, along with health-related issues. The student has a moderate distraction

level with average score of 33.7 out of 100. On average, students spent 3.31 hours per day on social media. Most (79.20%) of the students are in a good state, and 5.07% are academically resilient. However, 15.44% of the students need help facing academic problems, and 0.29% require urgent assistance from the university as they are in an early burnout state.

Approximately 51.86% of the variability is due to differences in the students' year of stay at the University. The students' learning distraction score is affected by gender, age, income, time spent on social media, and academic resilience. Female and older students experience lower distractions, whereas higher monthly income and time on social media increase the distraction score of students. An increase in academic resilience score significantly reduces the learning distraction score of the students.

Interventions related to behavioral, cognitive, and social cognitive learning theories, combined with self-regulated learning strategies, are vital for addressing learning distractions. Targeted initiatives focusing on reducing social media usage, enhancing academic resilience, and addressing financial concerns can significantly improve students' learning experiences. A broader assessment across Ethiopian universities is recommended to develop context-specific strategies for mitigating learning distractions and fostering an optimal learning environment. Future research may focus on learning distractions of students at many more Universities in the country.

The study is limited to only one University, so the findings cannot be generalized to other Universities. The study uses self-reported responses of students about their learning distractions that may introduce response bias and potentially affect the conclusions.

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Acknowledgments

I would like to express my deepest gratitude to Dr Ayele Taye Goshu, Associate Professor, my research supervisor, for his invaluable guidance, encouragement, and unwavering support throughout the course of my PhD journey. His insightful feedback, patience, and academic wisdom have been instrumental in shaping the direction and quality of this work.

I am especially grateful to the students of AASTU, the dedicated data collectors, the supportive staff, and the administrators of AASTU who generously contributed their time and efforts to facilitate data collection. Their cooperation and openness were vital to the success of this research.

I sincerely thank the Department of Mathematics and Kotebe University of Education for their administrative and academic support, and the University library staff for maintaining a supportive environment throughout my stay while working on this paper.

Lastly, and most importantly, I would like to express my gratitude to the reviewers and the Chief Editor of *Advanced Education*, as well as to the journal, for publishing this paper free of charge.

Funding

The primary author received limited funding for the survey research from Kotebe University of Education.

Availability of Data

The data used in this study are confidential and not provided.

Conflict of Interest

The authors declare that there is no conflict of interest.

БАГАТОРІВНЕВИЙ РЕГРЕСІЙНИЙ АНАЛІЗ ВІДВОЛІКАНЬ ПІД ЧАС НАВЧАННЯ СЕРЕД СТУДЕНТІВ ЗАКЛАДІВ ВИЩОЇ ОСВІТИ

Анотація. Відволікання під час навчання — як внутрішні, так і зовнішні — порушують концентрацію студентів та їхню академічну успішність. Це дослідження присвячене аналізу відволікань під час навчання у закладах вищої освіти Ефіопії, виконане з використанням кількісного підходу та постпозитивістської філософії. У рамках перехресного опитування 1380 студентів Університету науки і технологій Аддис-Абеби виявлено, що 2,97% перебувають на ранній стадії емоційного вигорання і потребують термінової допомоги. Середній показник рівня відволікань становить 33,70 зі 100, що свідчить про помірний рівень відволікань. Попри це, 43,33% студентів повідомляють про високий рівень задоволеності процесом навчання. Значна частка варіації показників відволікань — 51,86% — зумовлена відмінностями між роками перебування в університеті. Чинниками, що впливають на рівень відволікань, є стать, дохід, вік, час, проведений у соціальних мережах, та академічна стійкість. Студентки та старші за віком студенти менше відволікаються, тоді як вищий дохід і більше часу в соцмережах підвищують рівень відволікань. Вища академічна резильєнтність суттєво знижує рівень відволікань. Для їх подолання необхідні інтервенції, що базуються на поведінкових, когнітивних та соціально-когнітивних теоріях навчання, а також стратегіях саморегуляції.

Ключові слова: академічна стійкість, відволікання під час навчання, результати навчання, багаторівневі моделі, студенти університетів.