Journal of Contemporary Human Insights
Vol. 01, Issue 01 (2026)

Digital Inequality and Learning Gains: Evidence from Digital Literacy Training Environments

Olivia Smith[1*]

[1*]Newcastle University, Newcastle upon Tyne, United Kingdom.
Email: newcastle.olivia@gmail.com

ABSTRACT

This study examines the relationship between digital inequality and learning gains within digital literacy training environments, with a focus on understanding whether socioeconomic and engagement factors influence skill improvement. A quantitative, explanatory research design was adopted using a secondary dataset obtained from Kaggle (Digital Literacy Education Dataset). The final sample consisted of 788 observations after data preprocessing. Learning gain was measured as the difference between post-training and pre-training digital literacy scores. Statistical analyses were conducted using Python, including descriptive statistics, paired-samples t-test, ANOVA, and multiple linear regression. The results indicate significant improvements in digital literacy following training, with a large increase in post-training scores. However, no statistically significant differences in learning gains were observed across household income groups. Regression analysis revealed that most demographic, socioeconomic, and engagement variables were not significant predictors, and the model demonstrated low explanatory power. The study contributes to the literature by focusing on learning gains within digital literacy training environments rather than traditional academic outcomes, providing evidence that structured interventions can mitigate the effects of digital inequality in short-term skill development.

Keywords: Digital inequality; Learning gains; Digital literacy; Training environments; Socioeconomic factors; Educational technology; Learning analytics

1. INTRODUCTION

The accelerated growth of digital technologies has radically reshaped educational systems in different parts of the world, resulting in the creation of technology-mediated learning environments that no longer have the classroom as a physical boundary. Online training systems, online learning platforms, and blended learning are now the focus of education, especially in the post-pandemic period. Nevertheless, even with these developments, there are still great differences in access to digital resources, skills, and opportunities, which is also known as the digital divide. Digital divide ceases to refer to physical access to devices and internet connectivity but to growing disparities in digital skills, usage patterns, and translation of digital engagement into meaningful learning outcomes (Boeskens & Echazarra, 2025; Sirin, 2005).

Digital disparity has become a determining factor in school attendance and success. Disadvantaged socioeconomic backgrounds can be the obstacles to the participation of learners in digital learning settings, including a lack of access to reliable internet, the absence of digital infrastructure, and poor digital literacy (Christanti et al., 2024; Naz & Ali, 2025; Warschauer, 2004). Such inequalities are especially significant in rural and underserved areas, where access and outcomes inequalities in education are further increased by infrastructural inequalities and affordability. Consequently, digital inequality has been a major issue of concern to policymakers and educators who aim to ensure equitable and inclusive education systems.

Over the last several years, the conventional definition of the first-level digital divide, which claims that people have varied access to technology, has yielded to the so-called second-level digital divide, which is characterized by the disparities in digital capabilities and the proficient use of technology as a learning resource (James, 2020; van Deursen & van Dijk, 2019). This change is indicative of an increasing understanding of access as not being sufficient to guarantee meaningful educational outcomes. Rather, the capacity to effectively use digital tools, to build digital competencies, and to actively participate in digital learning environments is a key factor in determining the success of learning. Empirical research has shown that the outcomes of learning are positively related to digital literacy and are often mediated by self-efficacy, engagement, and the learning environment (Yuan et al., 2025).

Meanwhile, the growing adoption of educational technology (EdTech) has brought forth new avenues of solutions to digital inequality as well as new challenges. On the one hand, digital platforms can contribute to flexibility, accessibility, and personalized learning; on the other hand, they can widen existing inequities if learners do not have the resources or abilities to engage effectively (Helsper, 2021; Mhlongo et al., 2023). This two-sidedness of digital technologies is what makes the issue of the impact of digital inequality on learning outcomes in the new learning setting, especially in a non-traditional setting like a digital literacy training program, more elaborate.

Digital literacy training settings are a valuable setting where these dynamics can be studied since they are purposefully structured to improve the digital skills of individuals and fill the skills gap. These programs are intended to provide learners with fundamental skills to operate in digital platforms, access information, and work in knowledge economies. It is also indicated that digital literacy programs could be very effective in enhancing social inclusion, better employability, and human development (Singh, 2025). Nevertheless, it is still unclear to what degree these programs reduce or replicate existing inequalities.

Even though the literature on digital inequality and education is expanding, there are some gaps. To begin with, most of the available literature is on formal learning environments like schools and universities, and little has been done on informal or training-based learning environments. Second, the existing body of work tends to focus on technology or overall academic achievement, but does not investigate learning gains as a direct indicator of skill development. Third, the role of engagement and participation in digital learning has been recognized, although not enough empirical data are available on how interaction between these factors and socioeconomic conditions affects the outcome of learning in digital literacy programs. Moreover, most of the studies are qualitative or mixed-method, and thus there is a gap in quantitative analyses that can give strong, data-driven insights on these relationships (Constancio, 2025).

Against these gaps, the current research aims to investigate the association between digital inequality and learning outcomes in the context of digital literacy training through a quantitative and data-intensive design. This study is also helpful because it does not rely on the conventional outcome measures but reports more immediate learning outcomes in the form of digital skills improvement. Moreover, engagement-related variables are included in the study to investigate their impact on the development of learning outcomes and, thus, provide a more detailed insight into how digital inequality functions. The objectives of the study include the following:

1. To examine the effect of digital inequality on learning gains in digital literacy training environments.
2. To analyze the role of engagement and participation in influencing learning outcomes.
3. To assess differences in learning gains across socioeconomic and geographic groups.
4. To identify the key predictors of learning gains using multivariate statistical analysis.

2. METHODOLOGY

2.1 Research Design

The research design of this study is quantitative and explanatory since it will focus on the relationship between digital inequality and learning gains in the context of digital literacy training. It uses a data-driven method to provide statistical techniques to determine patterns, relationships, and predictors of learning outcomes. It is a cross-sectional study that examines differences in learning gains as determined by socioeconomic and engagement-related factors.

2.2 Data Source

Analysis is performed using a secondary dataset, which is called the "Digital Literacy Education" Dataset, and is acquired through Kaggle (an open-source platform) (Ziya, 2025). Data in the dataset is organized in structured data about the people in digital literacy training programs, such as demographic measures, socioeconomic measures, engagement measures, and pre- and post-training skill measures.

The data fit the study because it includes the major dimensions of digital inequality, including household income, type of location, and level of education, as well as indicators of learner interaction and digital skills acquisition in a technology-mediated classroom setting.

2.3 Variables and Measurement

Learning gain is the dependent variable in this research, which is operationalized as the difference between the scores of digital literacy at the post-training and pre-training stages. These scores reflect the enhancement of such competencies as basic computer knowledge, internet use, and mobile literacy.

The level of household income, the type of location, and the level of education are the key indicators of the digital inequality considered as independent variables. The variables are proxies of the socioeconomic status and access to the digital resources.

Engagement-related variables are used as the explanatory variables, and they are the number of sessions, the number of modules completed, the average time spent in a module, and the degree of engagement. These variables will indicate the level of interaction that the learners have been exposed to in the digital training environment.

The control variables such as age and gender are incorporated to account the potential demographic variables of learning outcomes.

2.4 Data Processing and Preparation

The preprocessing of the data allowed achieving data quality and analytical consistency. Missing values were dealt with by listwise deletion, which left 788 records out of the 1,000 records. The omitted values were mostly clustered in the education level variable.
Among the changes was the learning gain, which involved the pre-training scores and post-training scores per participant. In addition, the composite measures of pre-training and post-training performance were calculated by averaging through a number of dimensions of literacy.

Categorical variables such as the income of the household, type of location, level of engagement or level of education were coded into appropriate formats that were to be processed statistically. The data was also checked on whether it had outliers and inconsistencies and there were no significant anomalies that could have affected the findings.

2.5 Analytical Approach

Python was used to carry out the analysis by use of libraries like Pandas, NumPy to manipulate data, Seaborn and Matplotlib to visualize the data, and finally Statsmodels to model the data.

The first statistical tool was descriptive statistics, which were used to summarize the data and give an overview of the important variables. This was then accompanied by inferential analysis to analyze the differences and relationships between variables.

The paired-samples t-test was used to determine the statistical significance of the difference between pre- and post-training scores in order to determine the effectiveness of the training program.

A one-way analysis of variance (ANOVA) was conducted to test the differences in the gains of learning (between the socioeconomic groups) based on the categories of household income.

The effects of demographic, socioeconomic, and engagement variables on learning gains were estimated by way of multiple linear regression analysis. This method allowed the determination of important predictors, as well as the estimation of the relative importance of each variable, and the influence of other variables was eliminated.

2.6 Ethical Considerations

The research is fully founded on the secondary data collected in a publicly available Kaggle dataset. The data is anonymized and will not include any personally identifiable information. In this sense, the research will not conduct any direct human involvement or institutional ethical approval. All analyses were carried out in compliance with the ethical principles of using secondary data, and the source of data has also been mentioned.

3. RESULTS

3.1 Sample Profile and Data Quality

The data had 1,000 observations and 23 variables in the first place. On post-processing, 788 cases were left to be analyzed. The decrease in the sample size was explained by the fact that the variable Education_Level had missing values (212 missing values), whereas all other variables were complete. It means that the main cause of loss of data was one demographic field, not systematic failure to measure several constructs, thus less likely to have a wide measurement bias within the sample that was retained. The resulting analytic sample is thus a reflection of 78.8 percent of the original and offers a large enough base on which to do inference.Data quality controls revealed that there were no duplicates in the cleaned data and that all variables used in the construction of outcomes and modeling were accessible to the final sample. The feature engineering was done to form three main variables: Pre_Training_Avg, Post_Training_Avg, and Learning_Gain (a post-training average- pre-training average). The initial five records showed a significant positive change among the participants, which corroborated the fact that the transformation was effectively applied and that the training intervention was effective in bringing about some measurable change at the individual level.

3.2 Descriptive Statistics of Key Variables

The table below (Table 1) provides the descriptive statistics of the key variables used in the research. The mean age of the respondents was 41.15 years (SD = 13.44), and the range of age was 18 to 64 years of age, which means that the training setting targeted a diverse adult group, rather than a student group with a specific definition. The pre-training performance was 25.20 (SD = 8.90), and the post-training performance was 60.33 (SD = 10.46), which indicated that a significant change in digital literacy skills occurred upon taking part in the training program (see Table 1).

The average learning gain was 35.13 points (SD = 5.15) with a minimum learning gain of 21.00 and a maximum learning gain of 49.67 points. Relatively low variance about a high mean value means that the improvement was both good and uniform across the sample. Indicators of engagement reflected moderate to high engagement rates, with participants finishing an average of 10.01 modules and having an average of 19.99 sessions. The mean performance of the quiz was 80.34, and the mean score of Overall_Literacy_Score was 60.31. The aggregate of these values indicates that the cohort was highly active and had gained meaningful skills in the digital training environment (see Table 1).

Table 1. Descriptive Statistics of Study Variables (N = 788)

Variable	Mean	SD	Min	Max
Age	41.15	13.44	18.00	64.00
Pre-Training Average Score	25.20	8.90	1.00	46.33
Post-Training Average Score	60.33	10.46	32.33	89.33
Learning Gain	35.13	5.15	21.00	49.67
Modules Completed	10.01	3.17	5.00	15.00
Average Time per Module	20.10	5.88	10.07	30.00
Quiz Performance	80.34	11.92	60.00	100.00
Session Count	19.99	6.01	10.00	30.00
Adaptability Score	74.78	14.32	50.00	100.00
Feedback Rating	2.98	1.41	1.00	5.00
Skill Application	75.48	14.98	50.00	100.00
Overall Literacy Score	60.31	10.50	32.40	89.90

3.3 Learning Gains Before and After Training

The comparison of the results between pre- and post-training reveals a significant and statistically significant improvement in the digital literacy performance. Based on Figure 1, it can be seen that the mean score increased to 60.33 after training, as compared to the mean score before training, which was 25.20, and the average increase in score was 35.13 points. The numerical trend of Figure 1 attests to the fact that the performance of the learners has increased significantly after completing the digital literacy program.

A paired-samples t-test was carried out to determine whether this improvement was statistically significant using the averages of pre-training and post-training. The findings indicated that the t-statistic (t = 191.3325) was extremely large with a p-value less than 0.001, which means that the change in scores was very significant and could hardly have been due to chance. These results support with great empirical evidence the efficacy of a digital literacy training environment to produce quantifiable learning outcomes (see Figure 1).

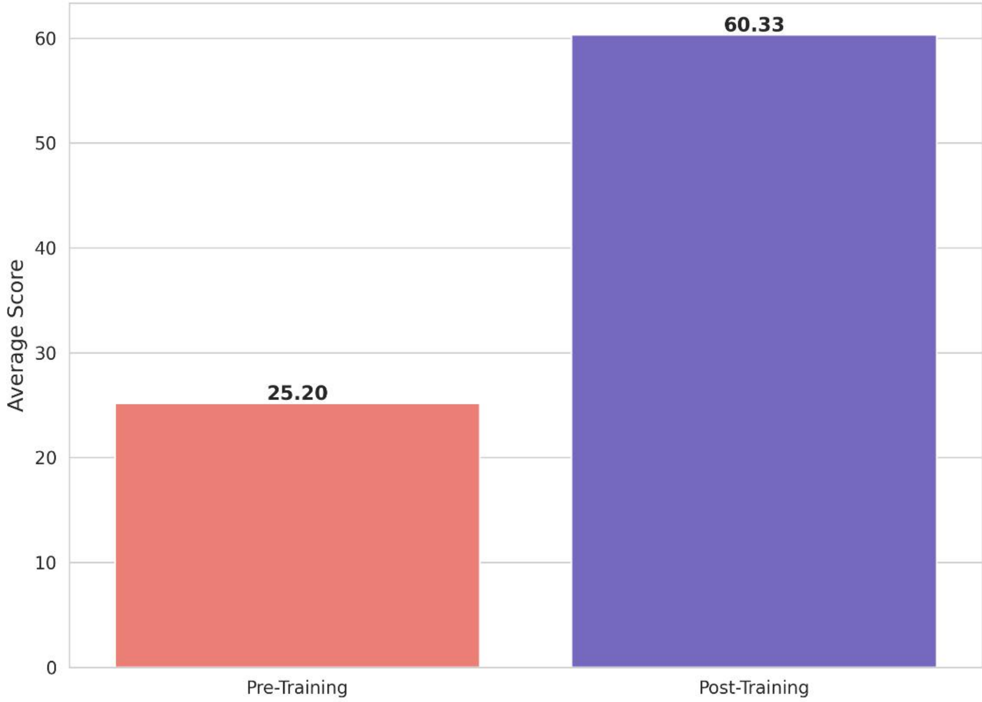

Figure 1. Average Pre-Training and Post-Training Scores

3.4 Group-wise Differences in Learning Gains by Digital Inequality Indicators

Table 2 shows the learning gains distribution by household income and type of location. The average learning scores were high in all the groups, with a range of 34.72 to 36.34 points. The greatest increase was found in the high-income semi-rural population (36.34), whereas the smallest increase was found in the low-income rural population (34.72). Nevertheless, these differences were not big, which means that the training environment produced widely similar gains in terms of socioeconomic/geographic categories (see Table 2).

The same pattern of income is also found in Figure 2, where the distribution of learning gains among the low-, medium-, and high-income groups overlaps significantly. The interquartile ranges are very similar, and the high-income group seems to have a slightly higher median gain, though there is a significant overlap between the two, indicating that there is not much practical separation between the income categories. This graphic finding justifies the qualitative finding that household income was not a powerful discriminator of learning gains in this sample (see Figure 2 and Table 2).

Table 2. Group-wise Distribution of Learning Gains by Household Income and Location Type

Household Income	Location Type	N	Mean Pre-Training	Mean Post-Training	Mean Learning Gain	Mean Quiz Performance	Mean Session Count

Low	Rural	334	25.46	60.18	34.72	80.45	20.03
Low	Semi-Rural	134	24.79	60.13	35.34	79.46	19.65
Medium	Rural	152	25.65	61.05	35.41	79.26	19.82
Medium	Semi-Rural	69	24.40	59.45	35.05	82.38	20.91
High	Rural	70	24.66	60.33	35.68	81.61	20.39
High	Semi-Rural	29	24.89	61.23	36.34	80.79	18.83

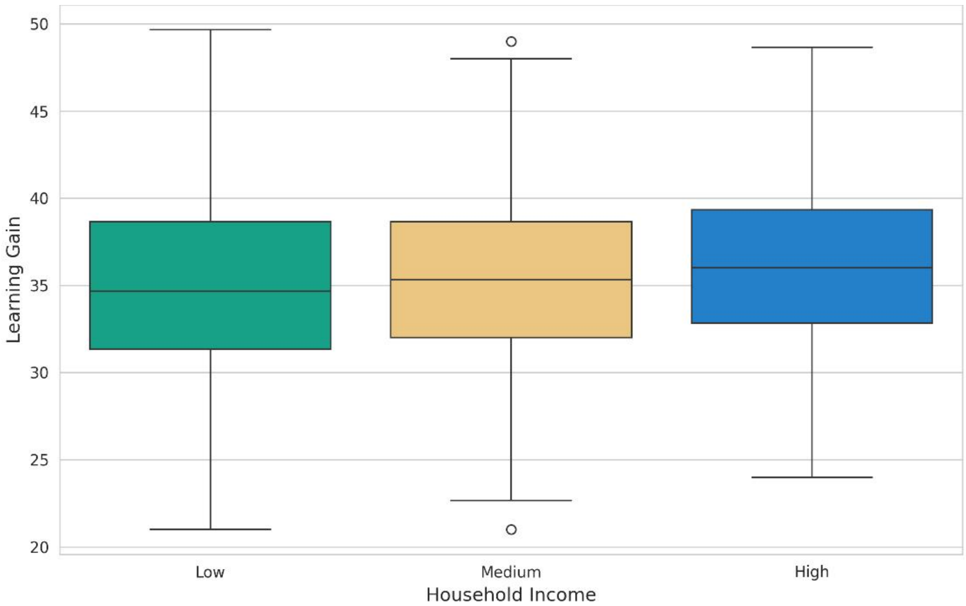

Figure 2. Learning Gain Across Household Income Groups

Figure 3 also analyzes the learning gains by the level of engagement and location type. The bar plot shows that there is a slight deviation between low, medium, and high engagement categories, and the variations between the rural and semi-rural learners are also small. The general trend indicates that the gains, both in engagement and location subgroups, were fairly balanced, which supports the conclusion that the training intervention yielded consistent returns under either of these background conditions (see Figure 3 and Table 2).

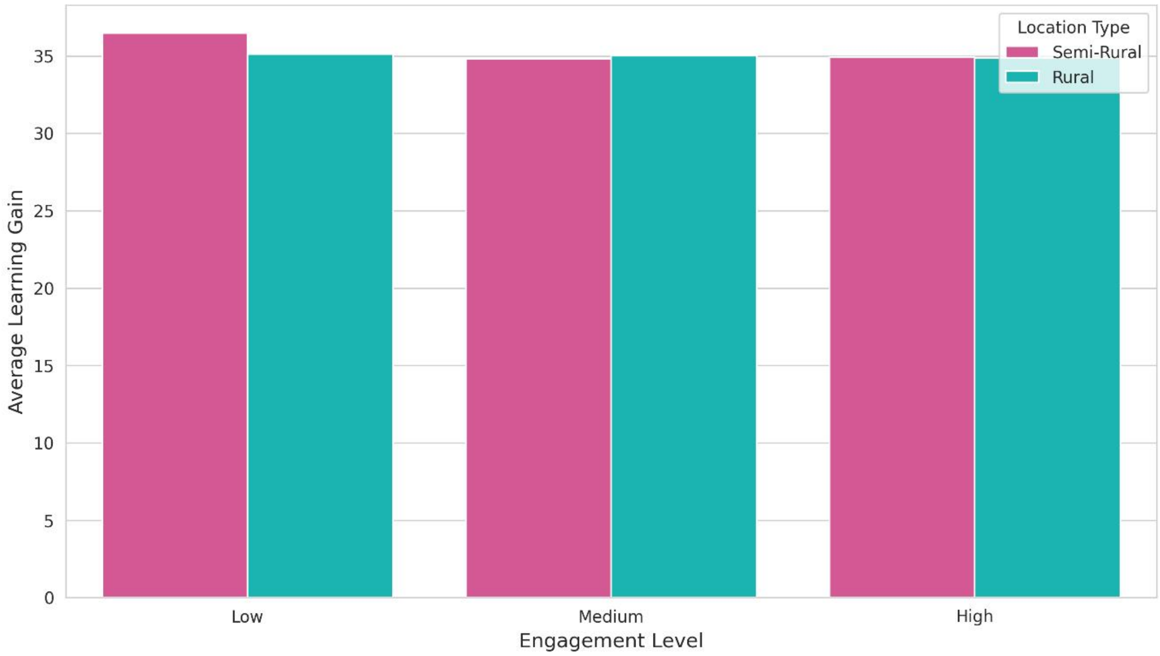

Figure 3. Learning Gain by Engagement Level and Location Type

3.5 Inferential Test of Income-based Differences

A one-way ANOVA was performed to test the difference in learning gains between households with high and low incomes formally. It was determined that there were no significant differences between low, medium, and high-income groups, $F(2, 785) = 1.627$, $p = 0.1972$. This finding supports the conclusion that the minor descriptive variations in Table 2 and Figure 2 are not statistically significant differences in learning gains between income groups.

3.6 Multivariate Predictors of Learning Gain

The combined effects of demographic, socioeconomic, and engagement variables on learning gain were estimated with the help of a multiple linear regression model (see Table 3). The majority of the predictors did not show significant values, such as gender, the level of education, the type of location, the level of engagement, modules studied, average time spent on a module, quiz results, adaptability score, feedback rating, and application of skills.

There were two variables with marginal associations. Learning gain had a positive correlation with household income ($\beta = 0.9765$, $p = 0.0894$), and the number of sessions had a weak positive correlation ($\beta = 0.0588$, $p = 0.0578$). These effects were not significant by conventional standards, but they indicate that the greater the level of participation and higher socioeconomic status, the less significant the gains could be. The coefficients of the non-significant categories of engagement level are consistent with Figure 3, that indicated minor differences between engagement groups (see Table 3 and Figure 3)

Table 3. Multiple Linear Regression Results for Predictors of Learning Gain

Variable	Coefficient	Std. Error	t-value	p-value
Intercept	34.2278	2.2207	15.4133	0.0000
Gender (Male)	-0.2017	0.3901	-0.5170	0.6053
Gender (Other)	-0.4967	0.6704	-0.7409	0.4590

Education (Primary)	-0.0392	0.4570	-0.0858	0.9316
Education (Secondary)	-0.0307	0.4593	-0.0669	0.9467
Income (Medium)	0.3776	0.4254	0.8877	0.3750
Income (High)	0.9765	0.5742	1.7005	0.0894
Location (Semi-Rural)	0.3251	0.4067	0.7994	0.4243
Engagement (Medium)	-0.5818	0.4238	-1.3729	0.1702
Engagement (High)	-0.6779	0.5234	-1.2951	0.1957
Age	0.0211	0.0138	1.5343	0.1254
Modules Completed	0.0214	0.0589	0.3637	0.7161
Avg. Time per Module	-0.0106	0.0316	-0.3368	0.7364
Quiz Performance	-0.0075	0.0155	-0.4816	0.6302
Session Count	0.0588	0.0309	1.9000	0.0578
Adaptability Score	-0.0047	0.0130	-0.3605	0.7186
Feedback Rating	0.1256	0.1316	0.9543	0.3402
Skill Application	-0.0042	0.0124	-0.3363	0.7367

3.7 Model Fit and Explanatory Power

The explanatory power of the regression model was very low. The model accounted for merely 1.91% of the variance in learning gain ($R2 = 0.0191$), and the adjusted R2 was negative (- 0.0025), which implies that the predictors had no effect on the fit compared to a null model. The overall model F-test was also not significant ($p = 0.5940$), indicating that the combination of the predictors did not have a significant effect on explaining variation in learning gains (see Table 3).

3.8 Synthesis of Main Empirical Findings

The findings indicate that the participants had significant and statistically significant changes in digital literacy after training, as indicated by the high mean difference between the pre-training and post-training scores, and the significant paired t-test (see Figure 1 and Table 1). Meanwhile, the magnitude of these gains was also fairly comparable among income, location, and engagement groups, and there are no statistically significant differences in the magnitude of gains based on income and no significant multivariate predictors of gain magnitude (see Table 2, Figure 2, Figure 3, and Table 3). All in all, the evidence indicates that the digital literacy training climate was generally effective across all groups of participants, but indicators of digital inequality that were measured had weak explanatory power regarding the differences in learning gains.

4. DISCUSSION

The results of the paper give valuable information on the connection between digital inequality and learning outcomes in digital literacy training settings. The findings show that the participants underwent significant and statistically significant changes in digital literacy after training in terms of large post-training scores and the highly significant paired t-test. This result is consistent with the previous studies that indicated that well-structured digital training initiatives can be successful in building digital skills and facilitating the acquisition of various types of skills in diverse learners (Eshet, 2004; Ng, 2012). The fact that the same pattern of learning improvement was observed in this study also confirms the idea that properly structured digital literacy interventions can produce significant results irrespective of the initial level of skills.

Nonetheless, unlike what digitization inequality theory would suggest, the analysis revealed that there were few signs that socioeconomic determinants like household income and place had a strong effect on learning gains. Descriptive and inferential analysis revealed that the differences in outcomes between income groups were not huge, and the results obtained with the help of ANOVA showed that these differences were not statistically significant. This result contrasts with the previous research that has focused on the potent role of socioeconomic status on academic achievements (Reardon, 2014; Wei et al., 2011). It is possible that the training environment was an equalizing mechanism, which gave the learners normal access to resources and structured learning opportunities that minimized the effect of external differences.

On the same note, variables pertaining to engagement that are assumed to be the critical determinants of learning outcomes failed to come out as powerful predictors of the regression model. Despite a positive but insignificant effect on session count, the majority of indicators of engagement were statistically insignificant. This is unlike other studies that emphasize the role of learner interaction in the digital setting, especially in learning online and self-managed (Henrie et al., 2015; Kahu, 2013). The comparatively homogenous learning benefits that have been noted among the degrees of engagement, as shown in Figure 3, may indicate that the training program was adequately designed such that it established baseline levels of engagement and performance, therefore limiting variation of individual differences in engagement.

This interpretation is further supported by the low explanatory power of the regression model. Having an R2 of 0.0191, the model explains a relatively small percentage of the variance in learning gains and, hence, the variables included in it fail to cover the factors that affect the improvement of the skill comprehensively. This result is in line with the studies that learning outcomes in computer-based settings are influenced by a complex interaction of cognitive, motivational, and contextual variables that are not necessarily represented by the standard demographic or behavioral variables (Richardson et al., 2012). There is thus a possibility that unobserved factors, like intrinsic motivation, learning experience, or instructional quality, may have a greater influence on causing learning gains.

Theoretically, the findings can be applied in the developing conceptualization of digital inequality since they highlight that the effect can be different in a circumstance and the type of outcome assessed. Although it has been demonstrated that digital inequality will affect access and participation, its impact on short-term learning gains in structured training environments may be less significant. It helps to argue that all of the drawbacks of socioeconomic inequalities can be reduced by specific interventions, at least in controlled learning environments (Hargittai, 2010; Selwyn, 2021). Simultaneously, the findings do not mean that digital inequality is insignificant, but they help to realize that it is necessary to differentiate the various aspects of inequality and the impacts on distinct educational outcomes.

The study is limited in a number of ways despite its contributions. To begin with, secondary data limits the study to the variables included in the dataset, which eliminates the possibility of incorporating factors that may be of significance, including motivation, prior digital experience, or quality of instructional design. Second, the data lacks a longitudinal study and does not allow the study to analyze long-term learning outcomes and a causal relationship. Third, the use of listwise deletion as a method of dealing with missing data could have introduced some level of selection bias, especially when the missing values were not randomly distributed. Also, the explanatory power of the regression model is rather low, which can indicate that the determinants of learning gains could not be included, which restricts the interpretability of the predictive analysis. Lastly, the dataset itself is a particular training situation, and it might influence the extent to which the results can be generalized to other educational environments.

The limitations should be overcome in future research by integrating longitudinal designs, which would enable studying the learning patterns over a period and evaluating the ability to develop skills in the long term. The combination of primary data collection techniques, including surveys or experimental designs, would allow including other variables connected with motivation, self-efficacy, and instructional quality. Furthermore, the contribution of contextual variables, including program design and instructional strategies, to learning results in online contexts should be examined as a topic of future research. The comparative study of the learning conditions of different types, including formal education and informal training programs, would also allow a more in-depth understanding of how digital inequality operates in different settings.

Greater depths of digital inequality such as differences in digital practices, learning models and exposure to support networks, could also be further examined in future studies. The existence of intricate relationships which are not reflected in the traditional regression models can be determined using the advanced approaches to analysis, including structural equation modeling or machine learning techniques (Baker et al., 2016). Also, cross-cultural research would be useful in the study of how digital inequality appears in various socioeconomic and geographic settings.

5. CONCLUSION

This study examined how digital inequality is associated with learning outcomes in a digital literacy training setting in a quantitative, data-driven study. The results show that after the training, the participants recorded significant digital literacy skill advancement, which shows that the structured digital-based learning interventions are effective. The significant improvement of the post-training scores proves that these programs may prove to be effective in facilitating the digital competencies among various categories of learners. The study, however, found that there exists some limited evidence to justify the role of digital inequality in determining the level of learning gains. No statistically significant differences were observed between socioeconomic variables (income of household and geographical location) and engagement variables showed only fringe implications. This finding is an indication that the training setting could have been used as an equalizing factor, offering equal learning opportunities to the participants regardless of their backgrounds. Although these results are positive, the low explanatory power of the regression model shows that the learning gains are determined by other factors that are not included in the dataset, including motivation, previous experience, and the quality of instruction. Altogether, the paper illuminates the opportunities of digital literacy training tools to decrease the gap in skills acquisition, but also indicates that more research should be conducted to get a clearer view of the processes that drive the outcomes in digital settings.

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