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Learning Content and Difficulty Level as Predictors of Student Engagement

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ABSTRACT

The work under consideration explores the predictive value of the learning content type and level of difficulty in student engagement through a data-driven method. The importance of student engagement in academic success is well-established, but few studies have investigated the interactive impact of instructional design and task difficulty through objective behavioral measures. In order to fill this gap, quantitative, cross-sectional design was adopted using a reduced secondary data set of 131 observations. The data were categorical in terms of learning content type, difficulty level, and engagement level, and behavioral measures of pupil dilation and fixation duration. Excel was used to analyze relationships between variables by use of descriptive statistics, cross-tabulation, and multiple regression analysis. Results showed that there were comparatively equal levels of engagement between the types of content and levels of difficulty with slight differences. The mean engagement was slightly higher with interactive content and with lower difficulty levels, but the differences were not statistically significant. The results of the regression showed that the type of learning content and the level of difficulty did not significantly predict student engagement, and the model had a trivial percentage of variance (R2 = 0.0026). The research concludes that instructional variables alone do not have a strong effect on student engagement and that it is likely to be affected by a wider range of cognitive, behavioral and contextual factors. These results underscore the need to take a multidimensional and data-driven perspective in interpreting engagement. Future studies are needed to use more variables and real-life data to reflect the complexity of student engagement within the modern learning contexts.

Keywords – Learning Content Type, Difficulty Level, Instructional Design, Learning Analytics, Behavioral Indicators

1. Introduction

The issue of student engagement has become a key construct in educational research because it is closely linked with the learning outcomes, academic performance and general student success. Recent research emphasizes the concept of engagement as a multidimensional construct that includes a behavioral, emotional, and cognitive aspect that interrelates to create a unified effect on the interaction between students and learning environments (Liem, Fredricks, and Wong 2025; Wong and Liem 2022). Decades of research also affirm that greater engagement is always associated with better academic performance and perseverance in learning settings (Loyola-Carrillo et al. 2025; Martins et al. 2022). In this respect, engagement is both a process and an outcome that is influenced by instructional and environmental elements in educational systems (Kahu and Nelson 2018).

Instruction design especially the nature of learning content provided contributes a lot towards student engagement. Improvements in educational technology have brought various content types like textual, video-based, and interactive learning material with different affordances to interact with the learners (Bond et al. 2020). The studies indicate that interactive and technology-enhanced learning spaces can be more engaging as they can stimulate active participation and cognitive engagement (Amerstorfer and Freiin von Münster-Kistner 2021; Redmond 2018). Likewise, the introduction of artificial intelligence and digital competencies in education has further altered the teaching methods, focusing on the significance of adaptive and interactive content delivery (Ng et al. 2023; Selwyn 2019).

Besides the type of content, another important element that has an impact on student engagement is task difficulty. The intensity of learning materials may influence the motivation, attention and persistence of students. Research shows that the optimal levels of difficulty can arouse engagement by ensuring a balance between difficulty and skill, but overly simple or too challenging tasks can result in disengagement (Barak and Assal 2018; Park and Kim 2022). Moreover, task difficulty interacts with individual differences, including, but not limited to, prior knowledge and self-efficacy to influence the results of engagement (LaGrone 2025). These results indicate the need to match the design of instruction with the cognitive abilities of learners.

The increased use of data-driven learning environments has enabled researchers be able to objectively measure engagement through behavioral and physiological indicators. Innovations in

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learning analytics and learning technologies enable the gathering of real-time data about the interactions between the students and offer more insight into engagement patterns (Coates et al. 2022). These advances have broadened the area of engagement research beyond self-reported measures, and include observable indicators that better reflect the cognitive and behavioral condition of students. Although a lot of research has been conducted on the topic of student engagement, there are still a number of limitations. Although previous researchers have done research on instructional design and task difficulty separately, there is scant empirical evidence on their interaction in influencing engagement. The majority of the studies are inclined to either investigate the effect of the type of content in the technology-mediated learning setting or the effect of the difficulty on motivation and performance (Crompton and Burke 2023; Park and Kim 2022).

Further, much of the available evidence is based on self-reported information, which can be biased and does not necessarily reflect the true extent of student engagement. Studies that employ behavioral and cognitive measures, including physiological reactions and measures of attention, to evaluate engagement more objectively are lacking (Steenberghs, Lavrijsen, and Verschueren 2023). The gap in the literature is that there is a lack of multiple instructional factors that are integrated as predictors of student engagement. Although both content type and task difficulty are considered to be important determinants, they are seldom considered as one analytical entity. Past research has mainly investigated these variables separately, which does not allow viewing their impact on each other and their overall effect on engagement outcomes (Liem et al. 2025).

Also, objective engagement indicators based on behavioral data, including eye-tracking and physiological indicators are minimally used. Most engagement research remains based on subjective evaluations and there is a gap in the evidence based on observable patterns of engagement. This gap has to be filled to move forward with data-driven educational research and enhance the accuracy of engagement measurement. The current research paper seeks to fill these gaps by looking at how instructional variables predict student engagement. Particularly, the research aims to examine the impact of the type of learning content on engagement, assess the effect of the complexity of the learning level, and identify the predictive power of these two

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factors. The study hypothesizes the following based on the theoretical and empirical literature. To begin with, the type of learning content is likely to have a strong impact on student engagement, with various types of instructional content offering different degrees of cognitive stimulation and interactivity. Second, the level of difficulty is expected to influence the engagement, and the best levels of difficulty should encourage greater involvement.

2. Methodology

2.1 Research Design

The study design is a quantitative, cross-sectional study that aims at examining the relationship between the variables of instruction and student engagement. The study is exploratory and predictive and will seek to determine the effects of differences in the type of learning content and the level of difficulty on the degree of student engagement. The cross-sectional type of design would be suitable since the data is the observation taken at one point in time and it is possible to identify patterns and associations without control. The quantitative method allows objective measurement and statistical analysis of the outcomes of engagement by observable indicators.

2.2 Dataset Description

The research utilizes a secondary dataset, namely Student Engagement Dataset that has been preprocessed and narrowed down to the analytical goals of the research. The final data has about 131 observations. A stratified balanced sampling method was used to make sure that the various types of learning content, level of difficulty, and level of engagement were well represented. This will improve the representativeness of the data and minimize the chances of sampling bias. The data set consists of categorical and numerical variables of student engagement based on behavioral and cognitive measures of interaction with instructional material of learners (Ziya 2025).

2.3 Variables

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The analysis focuses on the independent and dependent variables in line with the research objectives. The independent variables are the learning content type and level of difficulty. Learning content type is a categorical variable that describes the format or mode of instructional content that is delivered to learners, e.g., text based, video based or interactive content. Difficulty level is also a categorical variable, which denotes the complexity of the learning material, and is usually broken down into easy, medium, and hard.

Student engagement is the dependent variable and is operationalized by the variable engagement label and is categorized into low, medium and high levels. Besides these variables, the dataset has supportive variables like pupil dilation, blink rate, and fixation period. These variables give additional information on cognitive and behavioral engagement but are not taken as the main predictors in the regression analysis.

2.4 Data Processing

The dataset has gone through a set of preprocessing steps before analysis to ensure data quality and consistency. The data were also kept intact by eliminating duplicate entries if they existed. The reduced dataset already had a balanced stratified sampling process, and the key categories were represented proportionally. Categorical variables such as the type of learning content, level of difficulty, and engagement label were coded numerically where it is essential to enable the use of Excel to perform statistical analysis. The completeness of the dataset was also checked and no major missing or inconsistent values were detected that could influence the analysis.

2.5 Data Analysis Techniques

The statistical analysis was done in Microsoft Excel on a systematic basis. First, descriptive statistics were calculated to characterize the distribution of variables, frequencies and percentages of categorical data. This gave a rough picture of the data and assisted in determining the overall trends. The connection between the type of learning content and student engagement, or the level of difficulty and engagement, was then analyzed using cross-tabulation. The trends and differences in engagement across categories could be identified with the help of this analysis.

Correlation analysis was done to further examine the relationship among variables, after the coding of categorical variables into numbers. Calculation of Pearson correlation coefficients was

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done to determine the strength and direction of linear relationships between the variables. Lastly, a multiple regression analysis was conducted to determine the predictive value of the type and level of learning content on student engagement. The dependent variable of this model was engagement label, whereas learning content type and difficulty level were independent variables. The regression analysis helped determine the contribution of the individual and combined contribution of the predictors, and the overall explanatory power of the model using the coefficient of determination.

2.6 Ethical Considerations

The research is founded on the secondary data, which includes no personally identifiable data. In this regard, there are a few ethical issues related to the use of data. The data was utilized solely for academic and research purposes and all the analyses were done in accordance with the normal ethical requirements in secondary data research.

3. Results

3.1 Descriptive Statistics

The minimized dataset comprised 131 observations and had the essential variables necessary to conduct the analysis. There was a fair balance in the distribution of cases based on the type of learning content, the level of difficulty and the level of engagement. Table 1 shows that Interactive and Text content types had 44 observations (33.59%), and Video content had 43 observations (32.82%). On the same note, the distribution of levels of difficulty was almost equal with 42 cases (32.06) being Easy, 45 cases (34.35) Medium and 44 cases (33.59) Hard. The level of engagement was also similar, with Low (32.06%), Medium (34.35%), and High (33.59) categories being almost equal. This equal dispersion helps in the credibility of comparative studies carried out in later parts.

Table 1. Descriptive Distribution of Key Variables

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Category	Frequency	Percentage
Content: Interactive	44	33.59
Content: Text	44	33.59
Content: Video	43	32.82
Difficulty: Easy	42	32.06
Difficulty: Medium	45	34.35
Difficulty: Hard	44	33.59
Engagement: Low	42	32.06
Engagement: Medium	45	34.35
Engagement: High	44	33.59

3.2 Engagement by Content Type

The relationship between learning content type and student engagement is presented in Table 2. The results show that Interactive and Text content types gave the same distributions of the level of engagement where 31.82% of students were in the low category, 34.09% in the medium category, and 34.09% in the high category. The same trend was observed with video content with low engagement (32.56), medium engagement (34.88), and high engagement (32.56).

Table 2. Engagement Level by Learning Content Type

Learning_Content_Type	Low	Medium	High	Low_%	Medium_%	High_%	Mean_Engagement	SD	N
Interactive	14	15	15	31.82	34.09	34.09	1.023	0.821	44
Text	14	15	15	31.82	34.09	34.09	1.023	0.821	44
Video	14	15	14	32.56	34.88	32.56	1.000	0.816	43

The average scores of engagement also prove the low difference in content types. The mean engagement score with Interactive and Text content was 1.023, and with Video content, it was a little lower, 1.000, as shown in Figure 1. The mean engagement of Interactive Content was the highest, but the differences between the content types were insignificant, which means that the type of learning content alone did not have a significant impact on the level of engagement in this data set.

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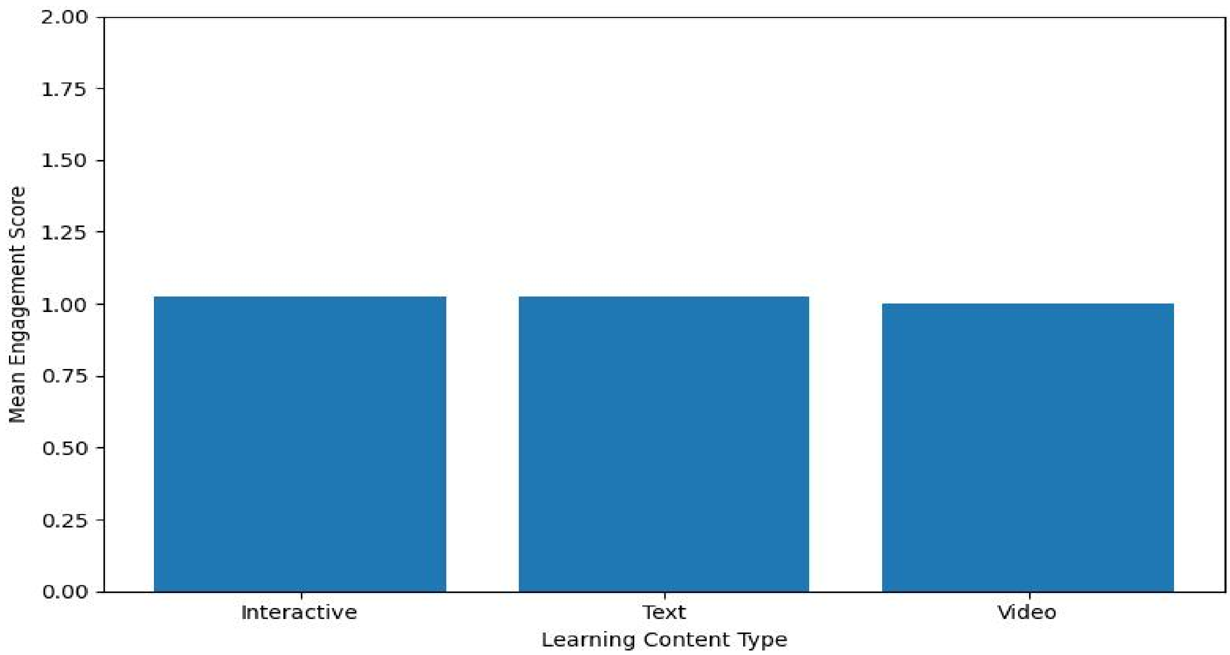

Figure 1. Mean student engagement by learning content type

Figure 1. Mean student engagement by learning content type

3.3 Engagement by Difficulty Level

The involvement of students in the various levels of difficulty is shown in Figure 2. The findings indicate that the mean engagement score was the highest at the Easy difficulty (1.071), then Medium and Hard (with slightly lower scores). This trend is typical of a slight decrease in involvement as it becomes. The variations in the levels of difficulty, however, were not very large, which means that difficulty level did not impact engagement to a significant degree. Although Easy content seems to be slightly more appealing, the general tendency does not provide a high or steady impact across classes.

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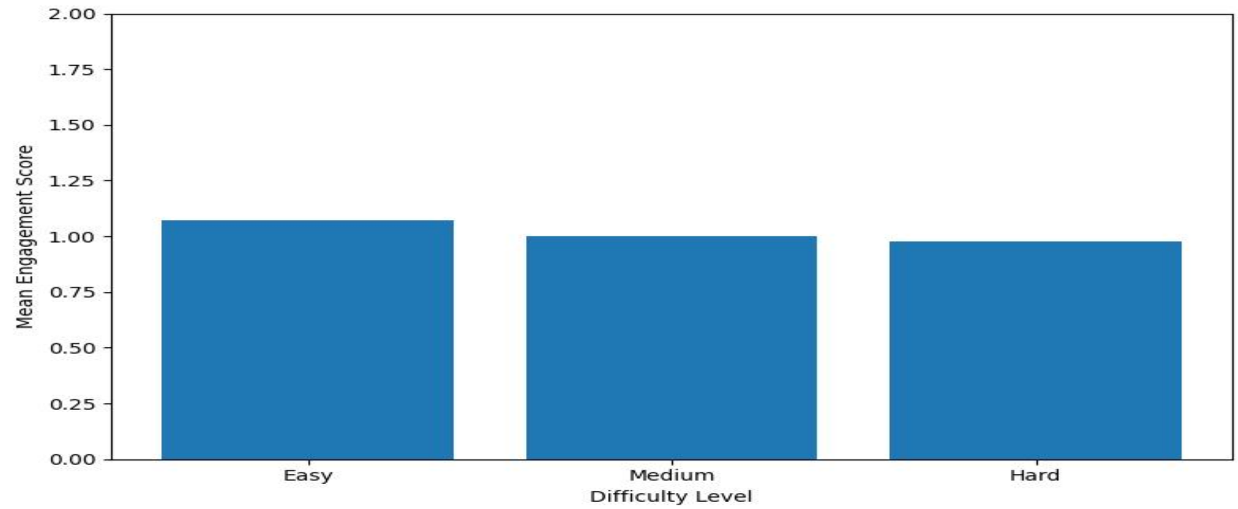

Figure 2. Mean student engagement by difficulty level

3.4 Regression Analysis

The results of the multiple regression analysis are presented in Table 3. The model analyzed the predictive impact of the type of learning content and level of difficulty on student engagement. The regression coefficients with Interactive content and Easy difficulty as reference categories did not show any statistically significant effects of any predictor.

Table 3. Multiple Regression Results

Variable	Coefficient	Std_Error	t_value	p_value	CI_Lower	CI_Upper
Intercept	1.0793	0.1630	6.6232	0.0000	0.7568	1.4018
C(Learning_Content_Type)[T.Text]	-0.0000	0.1759	-0.0000	1.0000	-0.3481	0.3481
C(Learning_Content_Type)[T.Video]	-0.0236	0.1769	-0.1335	0.8940	-0.3737	0.3265
C(Difficulty_Level)[T.Medium]	-0.0714	0.1770	-0.4036	0.6872	-0.4217	0.2788
C(Difficulty_Level)[T.Hard]	-0.0945	0.1780	-0.5310	0.5963	-0.4467	0.2577

In particular, the coefficient of Text content was 0.0000 ($p = 1.0000$), which means that there was no difference in relation to the reference category. There was a small negative coefficient (-

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0.0236, $p = 0.8940$) in video content, and non-significant negative impacts were also noted in Medium difficulty (-0.0714, $p = 0.6872$) and Hard difficulty (-0.0945, $p = 0.5963$).

The overall model was very weak, with an R2 of 0.0026, which means that the predictors accounted for only 0.26% of the variation in student engagement. The adjusted R^2 value was negative (-0.0291), and the model was not statistically significant ($F = 0.0818$, $p = 0.9879$). These findings are also graphically represented in Figure 3, which represents the pattern of interaction between the type of learning content and the level of difficulty, with very little difference in the interactions.

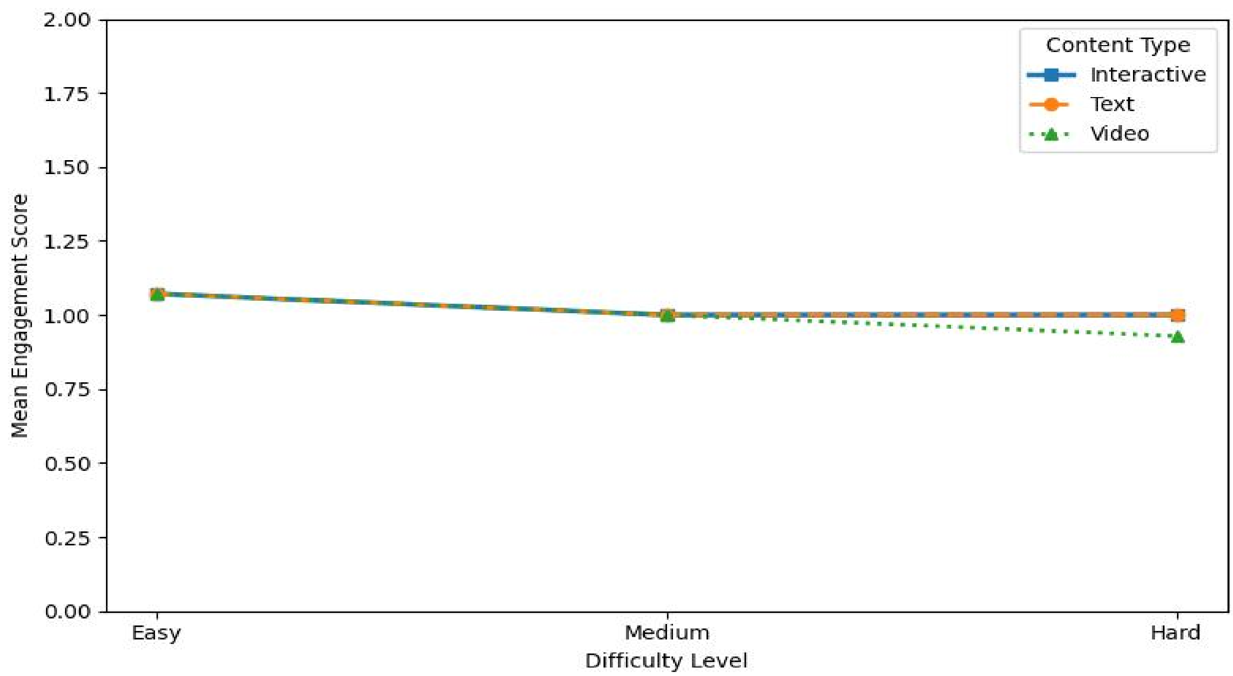

Figure 3. Interaction of learning content type and difficulty level on student engagement

3.5 Key Findings

The overall results of the descriptive, comparative, and regression analysis suggest that the type of learning content and the level of difficulty did not have a significant impact on student engagement in the current dataset. There was a slight difference in the mean engagement levels in Interactive Content and Easy difficulty, but these were not significant. None of the predictors was statistically significant, and the overall explanatory power of the model was very low as indicated in Table 3. Hard difficulty had the largest coefficient of the predictors in absolute terms,

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but this was a weak and statistically nonsignificant effect. The pattern of interaction, as depicted in Figure 3, also supports the fact that the interaction between the content type and the difficulty level does not substantially differ in the engagement outcomes.

In general, the findings indicate that the type of learning content and the level of difficulty do not have a significant influence on the engagement of students in the dataset, and that other variables might have a more pronounced role in defining the difference in the engagement.

4. Discussion

The results of this research show that the type of learning content and the level of difficulty had a slight impact on the engagement of students in the dataset under analysis. Descriptive results, though, indicated that interactive content was slightly more engaged and lower difficulty levels were achieved, but these were not statistically significant. This implies that isolated instructional variables might not be as strong determinants of engagement, but rather more complicated interactions between learner characteristics and contextual elements. The earlier studies also highlight the dynamism of engagement and its fluctuation in different situations, and the variability of engagement depends on both personal and environmental factors (Järvinen et al. 2022).

The slightly increased involvement in less challenging content can be attributed to the effect of cognitive load in learning. In cases where work is too challenging, learners can become overloaded with the cognitive load, which decreases their capacity to stay active. On the other hand, tasks of medium difficulty are frequently linked to improved motivation and longer attention (Martínez et al. 2019). Findings of this study indicate that there is weak evidence to support the assumption that instructional variables can be a significant predictor of engagement. Although the previous research has also suggested the significance of content design and task difficulty, it is also important to note that engagement is influenced by larger psychological and contextual issues (Ulmanen, Tikkanen, and Pyhältö 2024). As an illustration, studies regarding the engagement theory indicate that meaningful engagement, emotional connection, and the social context are essential elements of long-term engagement (Lange and Stewart 2023).

Unlike previous research that has shown significant impacts of technology-enhanced learning conditions on engagement, the present results suggest that merely changing the content format might not be enough to elicit substantial differences (Tamim et al. 2021). In a similar vein, the studies of immersive and interactive technology indicate that engagement advantages are not only dependent on the type of content but also on the ability of these tools to be incorporated into an instructional design (Mulders, Buchner, and Kerres 2020).

In a general sense, the results are in line with the recent debates on the shortcomings of entirely technological methods of engagement. Technology in education does not necessarily ensure greater learning results unless it is complemented with the relevant pedagogical approaches (Castañeda and Selwyn 2020). Besides, digital competence framework also emphasizes that instructional practices should be oriented to the needs and competencies of learners instead of focusing on the variation of content only (Caena and Redecker 2019).

This research has significant implications for educators and institutions. To teachers, the findings imply that to create effective learning environments, it is not enough to pick certain types of content or change the level of difficulty. Although interactive content and suitably challenging tasks can also play a role in engagement, they will have a marginal effect without taking into account the overall pedagogical strategies. Instructors must aim at designing quality learning experiences that incorporate interaction, feedback, and support for the learners (Pischetola 2021).

In the case of educational institutions, the results indicate that teaching and learning should be approached based on data. Even though the present study has used behavioral measures of engagement, the low predictive strength of the instructional variables indicates that institutions need to include a broader spectrum of data sources, such as psychological and contextual factors, to gain a better understanding of the engagement patterns. The combination of analytics and pedagogical design will help make decisions more efficient and enhance learning outcomes (Sharma et al. 2023).

The research paper adds to the literature by analyzing the predictive value of type of learning content and level of difficulty through a data-driven methodology. Even though the results did not indicate significant effects, they offer evidence that instructional variables alone do not determine engagement, thus validating multidimensional models of engagement. The findings

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support the premise that engagement is a result of a complex of cognitive, emotional, and contextual factors and not of single design factors (Järvinen et al. 2022).

Although the study has contributed, there are various limitations that must be recognized. To begin with, the sample size used was relatively small, about 131 observations, which might not be representative of the rest of the population. Second, the dataset did not include demographic and contextual data, including age, gender, and cultural background, which may have an impact on engagement patterns. Third, the secondary and simulated data can limit the extent to which the results can be applicable to the actual classroom situation. These shortcomings emphasize the importance of being cautious when interpreting the results.

These limitations should be overcome in future research by using larger and more varied datasets gathered in actual educational contexts. The inclusion of demographic and multicultural variables would help to have a more holistic picture of the way various groups of learners interact with instructional material (Bakth 2022). Longitudinal studies might also provide information about the progression of engagement over time and in relation to evolving instructional situations. Further, in future research, the authors need to examine other elements that determine engagement, including motivation, self-efficacy, and social interaction. The combination of these variables and teaching design variables may offer a more comprehensive model of engagement.

5. Conclusion

This research study investigated how the type of learning content and the level of difficulty can predict student engagement through a data-driven method. The results show that although some differences in the engagement levels were noted between the content types and the levels of difficulty, the differences were insignificant and statistically non-significant. The interactive content and reduced difficulty levels had a slightly higher engagement; though the general outcomes indicated that the instructional variables do not have a strong predictive power on student engagement. The regression analysis also supported the fact that the type of learning content and level of difficulty did not significantly predict engagement and the model only explained a trivial level of variance. These results demonstrate that student engagement is a complex phenomenon, which is a multidimensional construct that is affected by a variety of cognitive, behavioral, and contextual factors in addition to the simple elements of instructional design. Although predictive effects were not very high, the research study is relevant to the existing body of knowledge that has highlighted the significance of data-driven research in comprehending engagement. Behavioral indicators offer a more objective viewpoint than the conventional self-reported indicators. Finally, although instructional design is significant, to improve student engagement, a more holistic approach that combines the pedagogical strategies, learner characteristics, and contextual factors is needed. Further studies are needed to elaborate on these results, including the use of various variables and real-life data to gain a deeper insight into the processes underlying student engagement.

6. References

1. Amerstorfer, Carmen M., and Clara Freiin von Münster-Kistner. 2021. "Student Perceptions of Academic Engagement and Student-Teacher Relationships in Problem-Based Learning." *Frontiers in Psychology* 12:713057.

2. Bakth, Faizun N. 2022. *Understanding the Longitudinal Association Between Chronic Peer Victimization and Academic Efficacy: Testing the Mediating and Moderating Role of Sleep*. Wayne State University.

3. Barak, Moshe, and Muhammad Assal. 2018. "Robotics and STEM Learning: Students' Achievements in Assignments According to the P3 Task Taxonomy—Practice, Problem Solving, and Projects." *International Journal of Technology and Design Education* 28(1):121–44. doi:10.1007/s10798-016-9385-9.

4. Bond, Melissa, Katja Buntins, Svenja Bedenlier, Olaf Zawacki-Richter, and Michael Kerres. 2020. "Mapping Research in Student Engagement and Educational Technology in Higher Education: A Systematic Evidence Map." *International Journal of Educational Technology in Higher Education* 17(1):2. doi:10.1186/s41239-019-0176-8.

5. Caena, Francesca, and Christine Redecker. 2019. "Aligning Teacher Competence Frameworks to 21st Century Challenges: The Case for the European Digital Competence

Framework for Educators (*DIGCOMPEDU)* .” *European Journal of Education* 54(3):356–69. doi:10.1111/ejed.12345.

6. Castañeda, Linda, and Neil Selwyn. 2020. *Reiniciando La Universidad: Buscando Un Modelo de Universidad En Tiempos Digitales*. Editorial uoc.

7. Coates, Hamish, Xi Gao, Fei Guo, and Jinghuan Shi. 2022. *Global Student Engagement: Policy Insights and International Research Perspectives*. Routledge.

8. Crompton, Helen, and Diane Burke. 2023. “Artificial Intelligence in Higher Education: The State of the Field.” *International Journal of Educational Technology in Higher Education* 20(1):22. doi:10.1186/s41239-023-00392-8.

9. Järvinen, Jussi, Elina E. Ketonen, Lauri Hietajärvi, and Katariina Salmela-Aro. 2022. “From High Peaks to Deep Valleys: Using a Situation-and Person-Oriented Approach to Assess within-and between-Student Variation in Momentary Engagement and Disengagement.” *Learning and Instruction* 82:101685.

10. Kahu, Ella R., and Karen Nelson. 2018. “Student Engagement in the Educational Interface: Understanding the Mechanisms of Student Success.” *Higher Education Research & Development* 37(1):58–71. doi:10.1080/07294360.2017.1344197.

11. LaGrone, Nikki. 2025. “The Relationships Between Learner Socio-Demographic Factors, Self-Efficacy, Culture, and Student Engagement in the Online Learning Environment.” PhD Thesis, Northern Illinois University.

12. Lange, Alex C., and D. L. Stewart. 2023. “High-Impact Practices.” Pp. 221–36 in *Rethinking college student development theory using critical frameworks*. Routledge.

13. Liem, Gregory Arief D., Jennifer A. Fredricks, and Zi Yang Wong. 2025. “Sociocultural Perspectives On Student Engagement: Recent Advances and New Insights.” https://www.emerald.com/books/edited-volume/20932/chapter/107194143.

14. Loyola-Carrillo, Paola, Alejandro Vega-Muñoz, Guido Salazar-Sepúlveda, Miseldra Gil-Marín, and José Adsuar-Sala. 2025. "Studying Engagement in Educational Settings: A Mapping Review on High-Impact Academic Engagement Research." *Frontiers in Psychology* 16:1519509.

15. Martínez, Isabel M., Carolyn M. Youssef-Morgan, Maria J. Chambel, and Alexandra Marques-Pinto. 2019. "Antecedents of Academic Performance of University Students: Academic Engagement and Psychological Capital Resources." *Educational Psychology* 39(8):1047–67. doi:10.1080/01443410.2019.1623382.

16. Martins, Juliana, Jennifer Cunha, Sílvia Lopes, Tânia Moreira, and Pedro Rosário. 2022. "School Engagement in Elementary School: A Systematic Review of 35 Years of Research." *Educational Psychology Review* 34(2):793–849. doi:10.1007/s10648-021-09642-5.

17. Mulders, Miriam, Josef Buchner, and Michael Kerres. 2020. "A Framework for the Use of Immersive Virtual Reality in Learning Environments." *International Journal of Emerging Technologies in Learning (iJET)* 15(24):208–24.

18. Ng, Davy Tsz Kit, Jac Ka Lok Leung, Jiahong Su, Ross Chi Wui Ng, and Samuel Kai Wah Chu. 2023. "Teachers' AI Digital Competencies and Twenty-First Century Skills in the Post-Pandemic World." *Educational Technology Research and Development* 71(1):137–61. doi:10.1007/s11423-023-10203-6.

19. Park, Sunyoung, and Nam Hui Kim. 2022. "University Students' Self-Regulation, Engagement and Performance in Flipped Learning." *European Journal of Training and Development* 46(1–2):22–40.

20. Pischetola, Magda. 2021. "Teacher Professional Development in Higher Education and the Teknosofikum Project." *Learning Tech–Tidsskrift for Læremidler, Didaktik Og Teknologi* 10(1):46–75.

(ISSN: 2208-2115)
Vol. 12, Iss. 01, 2026
DOI: 10.53555/es.v12i1.2516

21. Redmond, Petrea. 2018. “An Online Engagement Framework for Higher Education.” *Online Learning*. https://www.academia.edu/download/85300879/370.pdf.

22. Selwyn, Neil. 2019. *Should Robots Replace Teachers?: AI and the Future of Education*. John Wiley & Sons.

23. Sharma, Anuj, Alex Koohang, Nripendra P. Rana, Salma S. Abed, and Yogesh K. Dwivedi. 2023. “Journal of Computer Information Systems: Intellectual and Conceptual Structure.” *Journal of Computer Information Systems* 63(1):37–67. doi:10.1080/08874417.2021.2021114.

24. Steenberghs, Nina, Jeroen Lavrijsen, and Karine Verschueren. 2023. “Teacher-Student Relationships and Engagement of High-Ability Students: An Exploration from the Perspective of the Academic Risk Hypothesis.” *High Ability Studies* 34(2):249–73. doi:10.1080/13598139.2023.2189573.

25. Tamim, Rana M., Evgueni Borokhovski, Robert M. Bernard, Richard F. Schmid, Philip C. Abrami, and David I. Pickup. 2021. “A Study of Meta-Analyses Reporting Quality in the Large and Expanding Literature of Educational Technology.” *Australasian Journal of Educational Technology* 37(4):100–115.

26. Ulmanen, Sanna, Lotta Tikkanen, and Kirsi Pyhältö. 2024. “Sense of Relatedness and Study Engagement as Mediators between Students’ Peer Support and Life Satisfaction.” *European Journal of Psychology of Education* 39(3):2603–17. doi:10.1007/s10212-024-00858-x.

27. Wong, Zi Yang, and Gregory Arief D. Liem. 2022. “Student Engagement: Current State of the Construct, Conceptual Refinement, and Future Research Directions.” *Educational Psychology Review* 34(1):107–38. doi:10.1007/s10648-021-09628-3.

28. Ziya. 2025. “Student Engagement Dataset.” https://www.kaggle.com/datasets/ziya07/student-engagement-dataset-using-eeg.