Asian Journal of Science and Applied Technology
ISSN: 2249-0698 (P)
Vol.13 No.1, 2024, pp.5-18

www.crijournals.org
DOI: https://doi.org/10.70112/ajsat-2024.13.1.4098

Exploring Attentional Dynamics in Animated Programming Environments: Trajectories, Variability, and Predictors

Abdullahi Yusuf[1], Norah Md Noor[2] and Lateef Adeyemi Yusuf[3]
[1&3]Department of Science Education, Sokoto State University, Nigeria
[2]Department of Social Sciences and Humanities, Universiti Teknologi Malaysia, Malaysia
E-mail: abdullahi.yusuf@ssu.edu.ng, norah@utm.my, lateef.yusuf@ssu.edu.ng
(Received 17 February 2024; Revised 27 February 2024, Accepted 7 March 2024; Available online 19 March 2024)

Abstract - **Researchers have proposed that the ability to pay attention to teachers' instruction is a prerequisite for learning. However, meaningful learning is often challenged by the presence of rule-breaking behaviors. In this study, we argue that although students exhibit different attention-related behaviors in all instructional settings, some behaviors are unique to a typical classroom. It is still unclear what factors uniquely determine students' attention-related behaviors in animated programming environments because of the paucity of research evidence in this area. This study investigates students' attention-related behaviors during animated programming instruction, including attentional growth trajectory, the nature of differences in attention-related behaviors, and predictors of these behaviors. Our analysis involved 8 classroom videos that collected the programming activities of 30 university students in our previous study. The video files were annotated on a one-dimensional, continuous scale, yielding 1,920 timestamped data points. The data on attentional trajectories and differences in attention-related behaviors were analyzed using latent and multi-level growth modeling, respectively, while data focusing on the predictors of attentional processes were analyzed using the Random Forest machine learning algorithm. We found that students' attentional growth trajectory is linear and accelerates toward on-task events. However, these behaviors vary within and between students, leading to differences in attention-related behaviors. The results also revealed that individual and instructional characteristics predict the differences in attention-related behaviors. The findings highlight the importance of structured topics, safe classroom environments, quality instructional support, and interactive multimedia objects that activate students' memory, eliminate task difficulty, and reduce the amount of mental resources required for meaningful learning.**
Keywords: **Attention-Related Behaviors, Within-and Between-Person Variability, Students, Animation, Programming**

I. INTRODUCTION

A. Preamble

Why do students exhibit different attention-related behaviors during instruction? This question was raised in a recent study that found that "a substantial degree of the differences between students in their attention-related behavior can be explained by class membership" [1]. The authors further argue that lesson contents cannot be decisive in predicting students' attention-related behavior based on the assumption that all classroom videos in their study presented introductory lessons to new topics. While we uphold this position, we equally acknowledge the position of previous studies which argued that factors that are unique to individual classrooms overly determine differences in students' attention-related behaviors [2].

More compelling evidence indicates that intense and interactive lessons activate mental structures that permit students to allocate attentional resources toward the learning experience [3]. As many interactive teaching tools continue to emerge due to advancements in technology, lesson contents laden with visuals and simulations have become important drivers of students' attention in the classroom [3, 4]. Notwithstanding these arguments, Goldberg's [1] study remained the sole motivating factor in our quest for further investigations across a broad spectrum of classroom attention and engagement.

During the course of our investigation, we [5] first conducted a study that classified student attention-related behaviors using machine learning algorithms that disclosed important learning profiles. We were able to find three representative sequences that explain students' profiles when they were exposed to block-based programming activities as a supplement to their formal programming teaching. Specifically, we found three clusters of students; the active students (73% of the participants who frequently watch the animation, take notes, sit upright, and do not engage in classroom disruptions), the passive students (81% of the participants who watch the animation, sit forward, but did not take notes), and the "to-passive" learners (a small proportion of students who were unconnected with the lesson but frequently transition to the passive state).

Our second study [6] investigates students' interaction patterns during block-based programming activities. Our findings indicate the presence of four classroom interactions, including a large proportion of students who engage in learner-learner (36.95%) and learner-content interaction (34.54%), and a small proportion who engage in learner-distractor (16.87%) and learner-teacher interaction (11.65%). Across the two studies, we acknowledged the potential of instructional quality to capture and sustain students' attention but were concerned about the presence of passive listeners and reluctant learners who remained unconnected with the learning experience despite the visually appealing nature of the animation and block-based programming environments. In the course of searching for ultimate reasons that explain these differences, we bumped into a prior study that emphasized the certainty of different attention-related behaviors among students regardless of internal and external factors [7]. However, we remained adamant that actions attract reactions.

Although students exhibit different attention-related behaviors in all instructional settings, we argued that some behaviors are unique to a typical classroom due to differences in instructional settings. Therefore, it is important to investigate classroom dynamics in a specific classroom setting and uncover classroom-specific behaviors along with their predictors. For example, while animations have been reported to capture and sustain students' attention across a wide range of disciplines, their attentional effects are not always consistent [3]. To the best of our knowledge, it is still not quite clear what factors uniquely determine students' attention-related behaviors in animated programming environments because of the paucity of research evidence in this area. While we generally acknowledge the importance of class membership in determining attention-related behaviors as proposed by Goldberg and colleagues [1], we strongly oppose their proposal concerning the insignificant importance of individual characteristics and lesson contents. We, therefore, seek to contribute to the ongoing refinement of the attention and engagement literature, while providing more evidence of multiple factors that could predict differences in attention-related behavior, using animated programming classroom as a reference point.

B. Theoretical Explanation of Classroom Attention

Across the literature, students' attention is explained from the lens of three theoretical models that form the basis of research examining students' attention and engagement. The cognitive psychology model proposed that attention is a filtering mechanism that establishes the relationship between an individual's interest and memory activation [8, 9]. This theory further explains that attention facilitates the amount of information that goes into the working memory and helps learners to decide on the right activity they feel is suitable for their learning. Ultimately, the fundamental assumption of the cognitive psychology model is that attention is a positive learning behavior that determines knowledge construction and information processing.

From the lens of the engagement model [10], attention is crucial to learners' investment in learning because it signals certain learning-related processes that should be salient to students' learning. Consistent with this perspective, Goldberg *et al.,* [11] proposed that attention serves as a selection criterion for all instructional activities because it determines the suitable instructional activity to engage in, and the pieces of information to process. The instructional quality model [12, 13] postulates that attention provides information about the quality of instruction and signals to the teacher the need to provide additional instructional support. From the foregoing perspectives, we define attention as a cognitive and behavioral event that influences memory activation, determines the right activity to engage in, and provides information about the quality of an instructional strategy.

C. Student Attention-Related Behaviors during Classroom Instruction

Researchers have proposed that the ability to pay attention to teachers' instruction is a prerequisite to learning [14, 15]. Plenty of research has also proven that attention exhibits the potential for information processing and memory activation [16, 17]. Because learning behaviors are often elusive and difficult to measure, observable attentional cues have been introduced into many research studies, including those conducted in computer vision, contemporary video coding, and self-reports. A typical classroom consists of different attention-related behaviors that characterize teaching quality and the nature of instructional intervention [18]. More often, these behaviors are contrary to the ideal behavioral events expected to occur in the classroom because students divert their attention from classroom activities [19].

Attention-related behaviors occur along two opposite spectrums, ranging from positive (on-task) to negative (off-task). On the positive end, behaviors such as sharing ideas with peers and the whole class, asking questions, raising hands, taking notes, and fixating eyes on the teacher or content are prevalent. Studies have proposed that these behaviors improve students' learning as evidenced by high grades [18]. Conversely, the negative pole consists of rule-breaking episodes including off-point discussions with peers, yelling out, impulsivity, unauthorized random walking, playing with objects, and sleeping. Although some of these behaviors do not distract the class (e.g., sleeping), they are generally classified are non-compliant events in response to teachers' requests [20]. In their earlier study, Floress *et al.,* [21] maintained that these events often result in different externalizing and rule-breaking episodes that disrupt the harmonious flow of classroom interaction.

Concerns have shifted from the importance of positive classroom behaviors to the negative effects of rule-breaking episodes because the latter often force students to exhibit different attention-related behaviors that result in a less elaborate and more superficial understanding [1, 21]. These rule-breaking episodes are often associated with a number of health- and academic-related outcomes, including teachers' burnout [22], greater stress levels [23], and perceived job dissatisfaction [24]. On the side of the students, such episodes are associated with reduced academic performance as evidenced by low grades and graduation rates [25]. Notwithstanding the associated negative effects, different rule-breaking episodes continued to be exhibited by.

D. Factors Predicting Students' Attention-Related Behaviors

Factors predicting students' attention-related behaviors are numerous. Notable among these factors include students' cognitive characteristics [26], classroom management strategies [19], instructional quality [27], class membership [1], and instructional environment [28]. These factors are not exclusive because they tend to differ from one classroom to another. The factors are also not exhaustive due to the continuous emergence of classroom culture. Factors affecting attention-related behaviors are better explained by attribution theory which postulates that the occurrence of behavior is attributed to dispositional and situational variables [29]. In situational attribution, causality is attributed to external factors that are beyond the control of an individual. This may include the nature of the instructional environment, the type of content presented, the materials and strategies used in the presentation, and the overall classroom culture. In dispositional attribution, causality is attributed to internal factors that can be controlled by one's behavioral predisposition. Typical examples include cognitive factors such as intelligence, affective factors such as attitude and self-efficacy, and psychomotor variables such as motor skills in performing a task.

The assumptions of the attribution theory can be applied in all classroom settings, including multimedia environments that involve animations, games, simulations, augmented and virtual realities, and robotics. Although research in these areas is still emerging, peculiar factors include students' cognitive load, spatial ability, and proficiency levels. For example, in their review, Yusuf and Noor [3] emphasized the importance of cognitive load and spatial ability in determining learners' attention and engagement when learning with animations.

Within the domain of cognitive load, research has shown that some students struggle to comprehend information presented in multimedia environments because several visual objects often load their memory [30]. The resultant effect is their demonstration of different attention-related behavior during instruction. The cognitive load effect can be understood from the positions of cognitive load theory [31] which suggests that several visual components of multimedia environments may impose extraneous cognitive load due to the temporal limits of the working memory, and such effect is detrimental to students' attention and overall learning.

Researchers have proposed spatial ability as an alternate cognitive competence to reduce the cognitive load effect and, therefore, encouraged multimedia educators to improve students' spatial ability through various interventions. However, this comes with a cost as differences in spatial abilities could also cause students to exhibit different attention-related behaviors. This position has been extensively explained by the ability-as-compensator hypothesis [32, 33] and the enhancer hypothesis [32, 34]. The fundamental principle of the ability-as-compensator hypothesis is that multimedia environments are more beneficial to students with low spatial ability because interactive visual objects reduce the mental efforts required to work with dynamic illustrations [33]. Conversely, multimedia environments are not beneficial to high spatial-ability learners because they are already equipped with high cognitive functions required to generate a substantial amount of cognitive representations [35]. The enhancer hypothesis opposed this view by claiming that multimedia representations are beneficial to high spatial ability learners. A recent study has confirmed the validity of the enhancer hypothesis by indicating that 3D multimedia environments enhance the visual attention of high-spatial ability learners [35].

Besides cognitive load and spatial ability, learners' prior knowledge and knowledge proficiency level (collectively conceived as experience in some research) have been added to individual characteristics influencing different attention-related behaviors. In the context of multimedia environments, the effect of prior knowledge and knowledge proficiency is explained by the 'expertise reversal' effect [36]. This effect occurs when the changes in learners' expertise are reversed by the relative pedagogical effectiveness of instructional conditions. It should be noted in this research that the term 'expertise' is conceived as a narrow, task-specific proficiency rather than genuine high-level professional expertise. The basic assumption of the expertise reversal effect is that instructional environment developed as additional support to novice learners could be counterproductive to expert or more experienced learners because of their familiarity with the specific contents presented in the environment. On this basis, differences in expertise could also cause different attention-related behaviors among students.

E. Indicators of Students' Attention

Measuring students' attention during classroom instruction has been a rigorous practice even with the advancement of computer vision. Studies have employed several indicators to measure students' attention. In previous years, these indicators were collected using self-reports and observer ratings, but with the advancement of technology, more sophisticated tracking tools have been developed. Although recent tracking tools and deep learning algorithms have proved to be effective, observer ratings are still used in recent research due to the diverging nature of attention indicators that were beyond the power of computing. Several studies have measured students' attention using eye-gaze patterns as a useful indicator [37, 38]. The motivation for using eye-gaze indicators was precipitated from the assumption that they provide accurate information about learners' ability to suppress or engage in visual and auditory distractions. To support this assumption, Hachad *et al.,* [16] maintained that an individual's eye gaze is significantly associated with the "amount of neural processing power they are devoting to a particular task" (p.7361).

The use of eye-gaze data has been marred by many limitations. Eye-gaze estimation is only useful when the eyes can be detected. However, several factors have been found to prevent eye-gaze estimation, including the presence of occlusive, low-resolution, and blurred images [39]. Other factors include the high brightness of images due to lightning. Against these limitations, researchers have combined eye-gaze and head pose data in the assessment of attention-related behaviors. An important assumption is that attention-related behaviors are accurately observed using head direction because people tend to align their heads in the direction of visual stimuli after running their gaze [37]. Compelling evidence shows that head orientations account for about 68.9% of the overall gaze direction and achieved 88.7% accuracy in identifying participants' visual attention.

Although eye gaze and head pose have been recognized as important indicators of attention, they are not sufficient for measuring different attention-related behaviors due to the presence of diversity in the classroom. Boheim *et al.,* [4, 18] argued that engaging in hand-raising can also be regarded as an additional indicator of students' attention regardless of whether they are given the opportunity to speak. Their study indicates that hand-raising is significantly correlated with cognitive engagement during classroom instruction. A summary of the attention indicators extracted from the literature can be found in the Supporting Information (Table I).

F. The Present Study

Existing studies have employed statistical models to explain students' attention-related behaviors, including within- and between-student variability in attentional processes [1, 4, 18]. However, these studies failed to sufficiently explain the influence of each predictor variable but relied on regression estimates that only show probabilities of the causal relationships. In this study, we employed interpretable machine learning algorithms to explain how different attention-related behaviors among students change with regard to different values of the predictor variables. We employed continuous rating of video data as opposed to categorical coding used in previous studies [40]. Goldberg *et al.,* [1] argued that categorical coding "do not account for the entire behavioral spectrum that students can exhibit during instruction (p. 2).

Our data were collected from 8 video files, each lasting an average of 20 minutes of instructional time. The video files were collected during our prior research with programming students in the summer of 2022. The video files had already been edited to exclude classroom preparatory procedures and stored in a departmental repository. While we acknowledge the power of technology to automatically detect and rate visual attention through computer vision and annotation software, we employed a manual rating approach to adequately detect different attention-related behaviors regardless of its time-consuming nature. In this case, we created screenshots of each video file on an interval of 5 seconds and then annotate the screenshots using a continuous rating scale. Using the collected data, we first addressed the participants' growth trajectories in their attentional processes and uncovered their within- and between-person variability across different time points. Secondly, we predicted the occurrence of different attention-related behaviors using variables related to individual and instructional characteristics. The following research questions, therefore, were addressed:

1. What is the growth trajectory of students' attention-related behaviors across different time?
2. What is the students' within- and between-person variability in their attention-related behaviors across different time?
3. Do individual (gender, cognitive load, spatial ability, programming proficiency, programming proficiency, programming attitude) and instructional characteristics (perceived instructional quality, teaching topic, classroom activities) predict students' attention-related behavior?

II. METHODS

A. Participants and Procedure

This study is an extension of our previous research that exposed students to animation and block-based programming activities at a research university. Therefore, the present study was based on the video data that was collected during the studies. In the previous studies, we collected videos of thirty-five- and second-year level students' programming activities (Mean age: 19.8. Male = 23, Female = 12). The participants were observed across eight weeks with a total of eight video files. During the programming instruction, all participants watched a 20-minute animated video (Fig.1) and participated in some programming tasks that supplement their learning. All classroom instruction was recorded using a high-resolution and wide-angle camera to enhance video quality. Informed consent was obtained from the students concerning the use of their video data in this research. The study was approved by the institutional review board.

In addition to the video data, some participants' individual (gender, cognitive load, spatial ability, prior knowledge, programming proficiency, programming attitude) and instructional characteristics (perceived instructional quality) were collected in our previous study, providing an ideal base for the conduct of this research. Inventories used for collecting data on individual and instructional characteristics include cognitive load test [41, 42], paper folding test [43], revised programming attitude scale [44], departmental programming proficiency test, perceived instructional quality scale [13], and a baseline demographic survey that collects the participants' prior knowledge of programming along with their gender category. It should be noted that data on teaching topics and classroom activities were generated from post-analysis of the video files.

Fig. 1 Screenshot of the animated instruction

Each participant was assigned a unique identification, which was used in their reidentification during data entry. We excluded the data of two students beforehand because their demographic data was incomplete. We further excluded the data of three students because they did not return their consent forms. Overall, we analyzed eight video files consisting of 30 participants. The measurement indicators can be found in the Supporting Information (Table II).

B. Annotation of Attention-Related Behaviors

We took screenshots of the video files at an interval of 5 seconds and then manually annotated the screenshots on a one-dimensional, continuous rating scale. We modified the continuous rating scale proposed by Goldberg *et al.,* [1] to suit the purpose of the study. In our previous studies, we proposed time interval ratings of 5 minutes as a sufficient approach in synchronizing the concurrent recording of separate streams of behaviors. The annotation took into consideration the broad spectrum of different attention-related behaviors of the students within the ICAP framework [45]. The screenshots were annotated on a symmetric scale ranging from 1, indicating extremely off-task, to 10, indicating extremely on-task (see Fig.2). Values closer to 5 are rather passive behaviors in which the participants lean their heads on their hands, sit backward or sideways while watching the animation (on-task) or shift their gaze away from the animated instruction (off-task). In total, we annotated 1920 screenshots (12 per minute x 20 minutes x 8 videos, see sample in Fig.3).

C. Analysis of Teaching Topics and Classroom Activities

From the video files, we did not provide information on teaching topics and classroom activities in our previous studies because they are time-variant variables. For example, we narrated a wide variety of sub-topics via the animation throughout each instructional period. In addition, we engaged the students in different classroom activities during each instruction to reinforce their learning. Before the analysis of teaching topics and classroom activities, we first transcribed the audio content of the video files into text with Google Cloud, an automatic speech recognition engine. The transcribed data appeared as a sequential text stream with relevant timestamps. We then sent the transcribed data and the video files to two computer science educators. From the transcribed data, the teaching topics were generated and categorized into main themes (see Table II in Supporting Information). The classroom activities on the other hand were annotated from the raw video files on a three-point continuous scale, ranging from 1 = expository to 3 = hands-on. Values closer to 2 are more or less interactive activities where students were engaged in question-and-answer sessions or other collaborative activities. Data concerning teaching topics and classroom activities were generated and entered in steps of five seconds to match the annotation of the attention indicators.

III. ANALYSIS

We estimated the participants' growth trajectories of attentional processes (RQ1) using latent growth modeling (LGM) with lavaan R package and examined their within- and between-person variability (RQ2) using multilevel growth model (MGM) with nlme R package. The LGM is a continued version of Structural Equation Modeling (SEM) applied in the analysis of growth trajectory that occurred over time [46]. Like SEM, it applies the same criteria for determining how well the model fits the data. The MGM is also a growth curve modeling technique but permits the estimation of inter-individual differences and intra-individual change over time by modeling their variances.

For the LGM, two major models have been proposed, including linear and quadratic models. Fig.4 represents the linear model while Fig.5 represents the quadratic model. Among the two models, a factor loading of 1 was assigned to the intercept (i.e., ICEPT). This represents the hypothesized attention-related behaviors when the growth curve begins. The factor loadings for the slope (0, 1, 2, 3, 4, 5, 6, and 7) assumed that the growth pattern is linear and that variations in attention-related behaviors have a proportional effect that either accelerates or decelerates. On the other hand, factor loadings for the quadratic latent factor (0, 1, 4, 9, 16, 25, 36, and 49) assumed that attention-related behaviors occur in a U shape. In order to choose a robust model between the linear and quadratic model, four indicators were employed as baseline comparisons to test for the model fit: Akaike information criterion (AIC), Bayesian information criterion (BIC), chi-square test; Tucker-Lewis Index (TLI); Comparative Fit Index (CFI); and root-mean-squared error of approximation (RMSEA). As a rule of thumb, a model is considered to be fit if: AIC and BIC values are lower; chi-square (p-value) > 0.05; TLI > 0.85; CFI > 0.9; RMSEA < 0.05).For the MGM, two models have also been proposed, including the fixed and random effect models. The fixed effect assumed that the variation in attention-related behaviors across time is constant within- and between-persons while the random effects assumed that such variations occur at random.

To analyze the predictors of attention-related behaviors (RQ3), we fitted our data in five supervised machine learning (ML). These include linear regression, random forest, elastic net regularized regression, support vector machine, and Naïve Bayes. Among the ML models, random forest (RF) fared better, based on several performance metrics (see Table I), and was then used as the robust algorithm. To avoid overfitting and improve the efficiency of the RF model, we split the data into 10 folds and then performed a 10-fold cross-validation using 9-folds as the training set, and the remaining subset (k-1) as the test set. This method improved the accuracy of the RF model by 3.2%, yielding 97.3% accuracy.

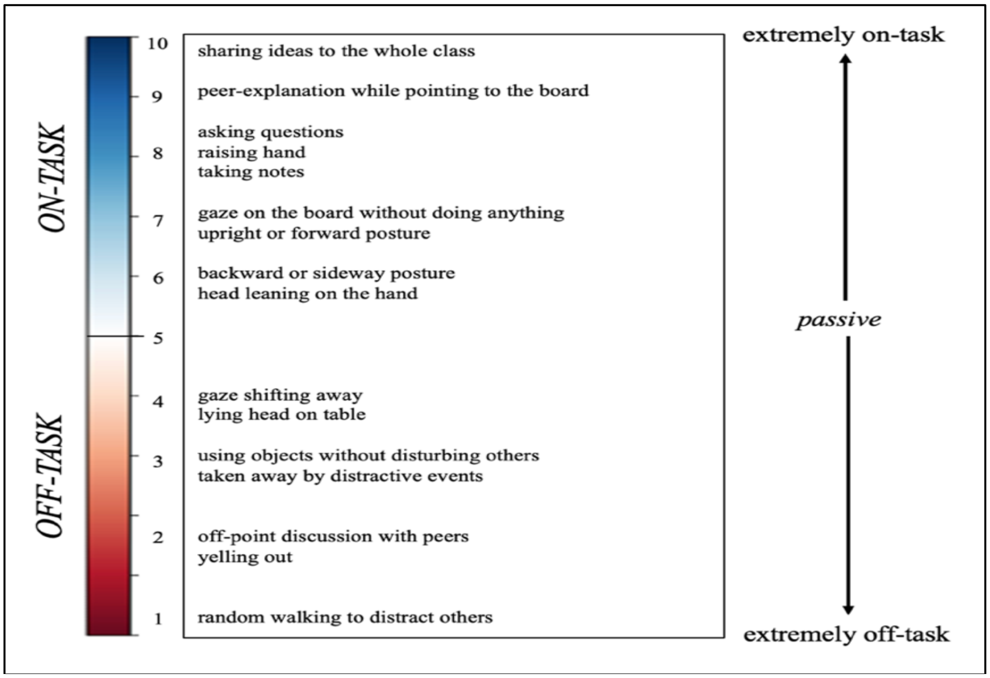

Fig. 2 Template for behavioral annotation, Adapted from Goldberg *et al.,* [1]

Fig. 3 Sample of annotations of video screenshots

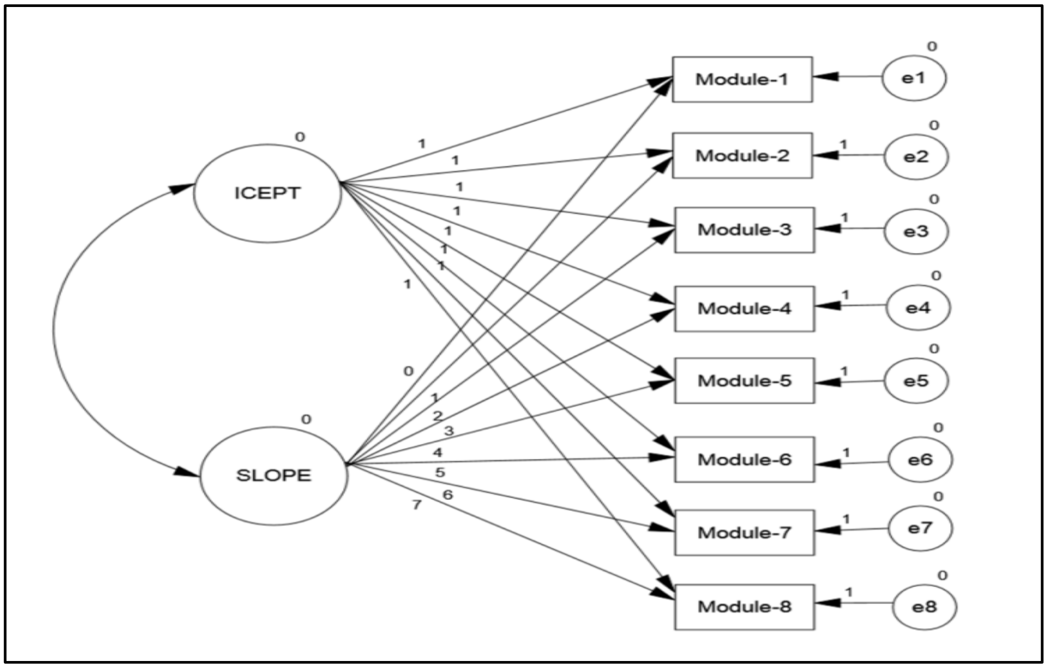

Fig. 4 Linear growth model

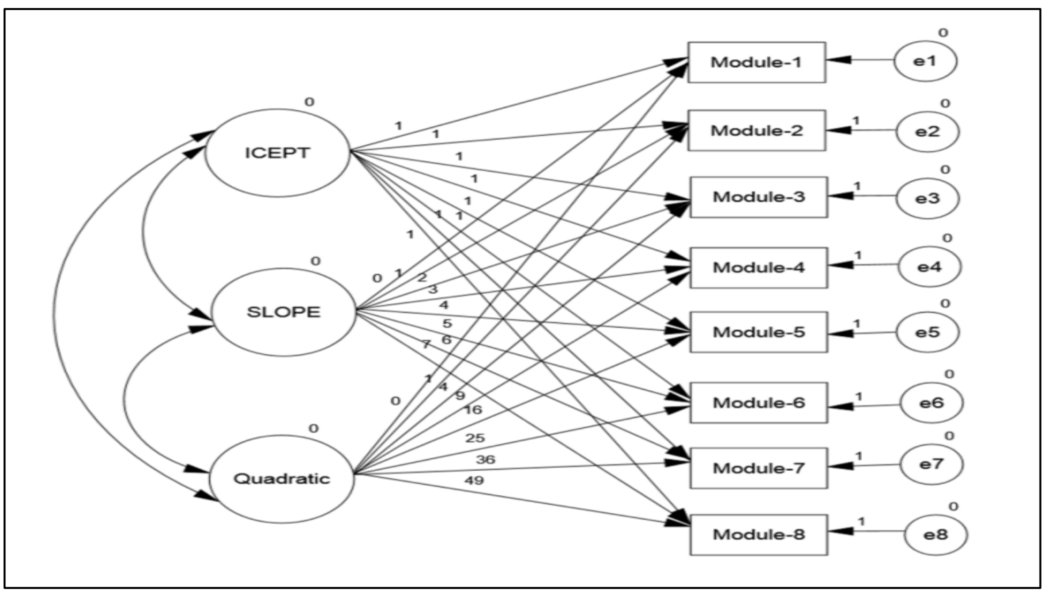

Fig. 5 Quadratic growth model

To further improve the predictive performance of the RF model, we implemented hyperparameter tuning and pre-processing in a nested resampling approach [47]. This method allowed us to test for optimal model settings while keeping the train and test datasets strictly separated. We computed the permutation variable importance using the PIMP algorithm [48] to measure the impact of the predictors in the RF models.

The PIMP algorithm outputs the important predictors by measuring a decrease in the model's prediction performance after permuting the response variable [49]. We used the accumulated local effects (ALE) [50] plot to visualize how the predictors influence attention-related behaviors. All analyses addressing the research questions were done in R version 4.2.2.

TABLE I PREDICTIVE MODEL ACCURACY

Method	Accuracy	RMSE	R-square
Multiple linear regression	76.4%	2.82	0.35
Elastic Net	67.3%	3.57	0.29
Random forest	94.1%	1.28	0.54
Naïve Bayes	79.1%	2.01	0.37
Support Vector Machine	91.2%	1.33	0.51
Random forest + 10-fold cross validation	97.3%	1.07	0.55

IV. RESULTS OF THE STUDY

1. RQ1 Participants' Growth Trajectory of Attention-Related Behaviors over Time: After estimating the two growth models, the linear growth curve was a better model (see Table II). The model has an improved model fit (lower AIC and BIC; Chi-square = 157.67; df = 38; p-value < 0.00; TLI = 0.96; CFI = 0.96; RMSEA = 0.02) compared to the quadratic model which has a mediocre model fit. This suggests that the participants' attention-related behaviors over time occur in a linear pattern and can progress in upward or downward trend.

TABLE II BASELINE COMPARISONS

Baselines	Linear growth model	Quadratic growth model
AIC	3254.22	3974.58
BIC	3142.203	3833.76
Chi-Square	117.67	68.91
Degree of freedom	233	26
p-value	0.000	0.000
TLI	0.963	0.553
CFI	0.972	0.461
RMSEA (p-value)	0.021	0.237

The major importance of LGM is to model the mean variance and slope of growth progression across different time. From Table III, participants' initial average attention-related behavior was 5.76 with a mean variation of 13.2%. This indicates that, on average, the participants demonstrated a number of on-task behaviors. The average rate of progression of the participants' attention related-behaviors is 1.32, with a mean variation of 18.4%.Considering the linearity of our model, the mean slope value indicates that the participants' attentional processes increase or decrease by 1.3 units, with a significant variation across the students. The significance value of the covariance demonstrates the importance of the intercept and slope in determining the participants' growth trajectories in their attentional processes. The negative correlation between intercept and slope also indicates that the participants' attention-related behaviors seemed to converge to a moderate degree.

TABLE III PARAMETER ESTIMATES FOR LGM

	Estimate	S. E	p-value
Mean intercept	5.763	0.032	0.000
Mean slope	1.321	0.031	0.025
Intercept variance	0.263	0.046	0.011
Slope variance	0.184	0.026	0.031
Covariance	0.487	0.033	0.000
Correlation (r) = -0.346, p-value = 0.021			

2. RQ2 Within- And Between-Person Variability in Attention-Related Behaviors over Time: Before estimating the within- and between-person variability, we conducted a data visualization to explore individual participants' variation in their attention across the eight weeks intervention duration using the lattice R package. This visualization provided us with some insight into how they vary within and between themselves. From the visualization (see Fig. S1 in Supporting Information), there isa large proportion of the participants who exhibit an increase in attention from off-task to on-task; there are several others who exhibit relatively stable off-task or on-task; and there are few others who show a decrease in attention from on-task to off-task. Based on these variations, it is apparent that the participants exhibit different attention-related behaviors. Our multilevel growth model shows that the random effect is a better model compared to the fixed effect and baseline models (AIC = 981.27, BIC = 993.55, LogLik = -483.63). This indicates that students' attention-related behaviors vary over the eight weeks of intervention.

Table IV shows the unconditional multilevel growth model. There is a significant variation between the participants in their attention-related behaviors (estimate = 5.341, p-value = 0.00). There is also a significant variation within individual participants in their attention-related behaviors (estimate = 2.185, p-value = 0.021). To provide more insight into the within- and between-person variability, we calculated the inter-class coefficient (ICC) using the expression below:

$$\rho = \sigma_0 / (\sigma_0 + \sigma_\varepsilon) = 5.341 / (5.341 + 2.185) = 0.71$$

Where:
σ_0 is the between-person variation, and
σ_ε is the within-person variation

TABLE IV UNCONDITIONAL MULTILEVEL GROWTH MODEL

Variance	Estimate	S. E	p-value
Between-person	5.341	0.322	0.000
Within-person	2.185	0.046	0.021
Proportion of total variance of between-persons:			0.71
Proportion of total variance of within-persons:			0.29

The inter-class coefficient of 0.71 shows that about 71% variations of the participants' attention-related behaviors are accounted for by between-persons while the remaining 29% of the variation is accounted for by within-persons. The significant variations of within- and between-persons are indications that differences in students' attention-related behaviors come from the differences that exist within each student and the ones that exist between the students. However, the differences that exist between the students are a more important indicator of students' attention-related behaviors. Compelling evidence can be seen in Figure S1 in Supplementary Information where most of the participants have different intercepts (between-persons) but with a relative growth rate (within-persons) over time.

3. RQ3 Predictors of Students' Attention-Related Behaviors: Results from the random forest-based PIMP algorithm (Fig.6) indicate six important predictors of attention-related behaviors, including attitude, perceived instructional quality, spatial ability, cognitive load, teaching topics, and programming proficiency levels. Explanations of the influence of these predictors can be found in ALE plots presented in Fig.7. From the plots, it can be observed that gender, prior knowledge, and classroom activities do not have significant influence as evidenced by their stationary trend. On the other hand, there is an upward trend of attention-related behavior in relation to an increase in attitude toward programming from negative to positive. This suggests that participants with positive attitudes toward programming are more likely to engage in on-task events compared to those with negative attitudes. Perceived instructional quality had a positive effect on attention-related behavior as indicated by an upward trend. By implication, students who had positive perceptions about instructional activities are more likely to have attentional behaviors that are related to on-task compared to those with negative perceptions.

The results also show that spatial ability successfully predicts students' attention-related behaviors. The upward trend indicates that an increase in attention-related behaviors from off-task to on-task is significantly associated with increased spatial ability. Thus, students with high spatial ability are more likely to engage in quality on-task events while those with low spatial ability are more likely to engage in off-task events, suggesting the validity of the enhancer hypothesis. Another important predictor is the cognitive load. The results show a decrease in attention-related behaviors from on-task to off-task events. This downward trend demonstrates that students with low cognitive load engaged more in on-task events while those with high cognitive load engaged in off-task events.

Differences in teaching topics also show a significant effect on attention-related behavior. The moderate downward trend suggests that students were more engaged in on-task events when exposed to simple topics such as fundamentals of Java, variables, methods, and conditionals. However, students' attention moved slightly to off-task as more complex and difficult topics are presented, including loops, strings, and arrays.

Lastly, students' attention-related behaviors are predicted by programming proficiency level. From the results, novice and intermediate programmers (mean scores: 1 to 11) had relatively stable attention that relates to on-task events. Conversely, expert programmers (mean scores: 12 to 15) frequently engaged in off-task behaviors. It should be noted that a high level of expertise does not lead to extreme off-task behaviors and low-level expertise does not lead to extreme on-task behaviors. This suggests the less importance of programming proficiency in predicting attention-related behaviors. Nevertheless, there is evidence of expertise reversal effect concerning attention-related behaviors. Overall, students' attention-related behaviors are influenced by individual and instructional characteristics.

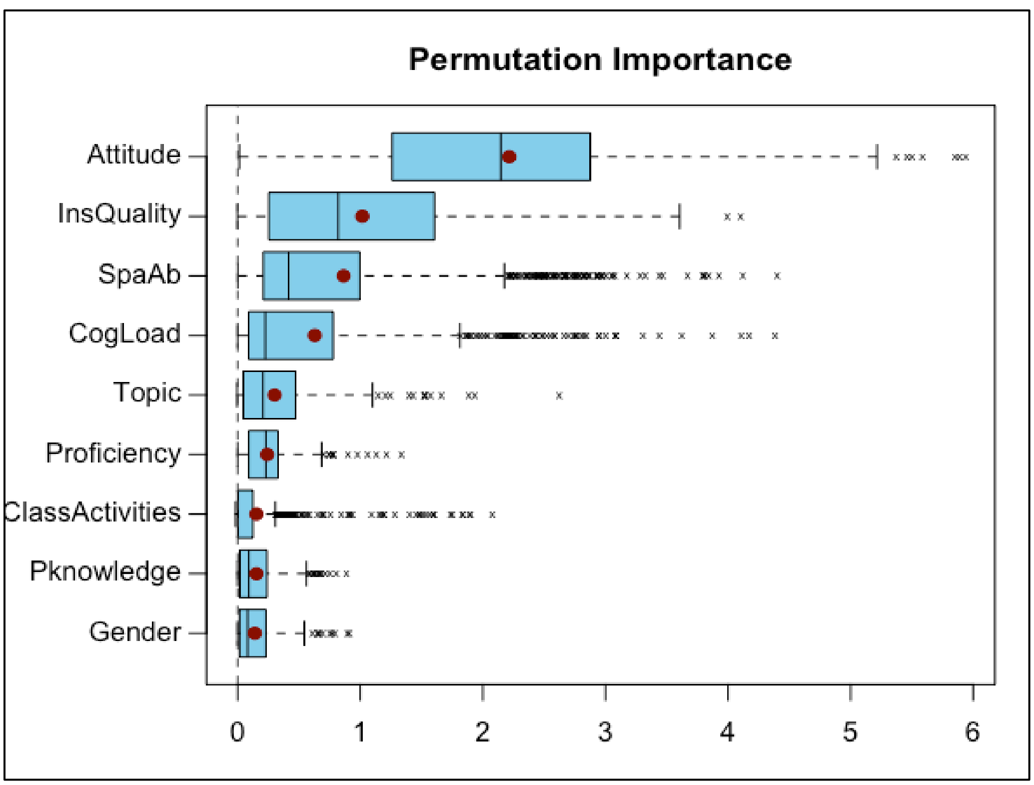

Fig. 6 Variable Importance estimated from PIMP algorithm

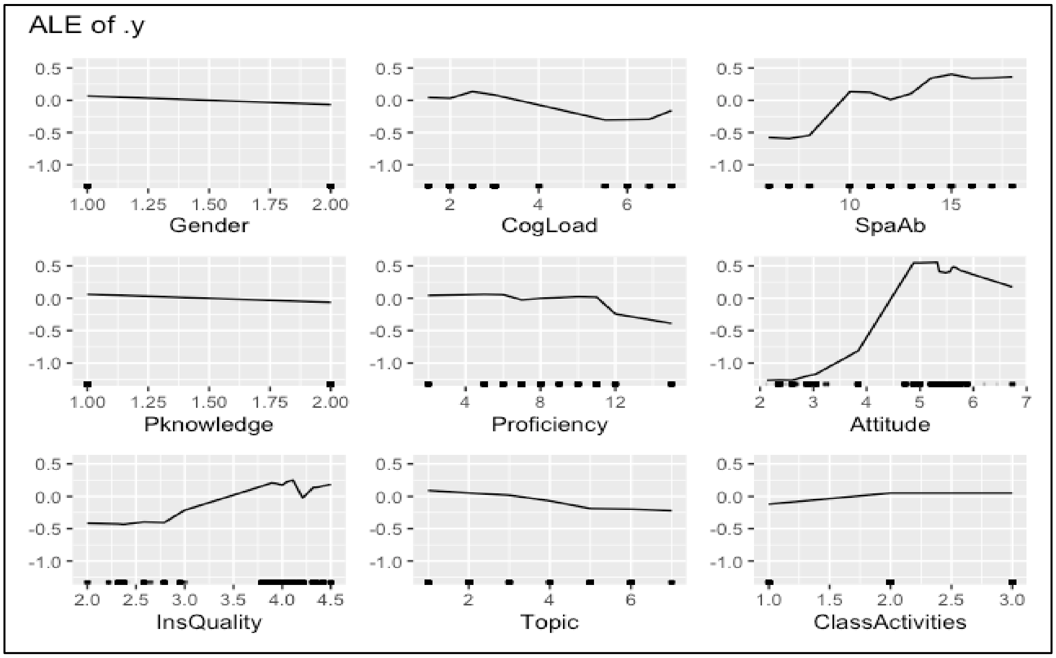

Fig. 7 Accumulated local effect plots

V. DISCUSSION OF THE STUDY

This study investigates whether individual and instructional characteristics influence students' attention-related behaviors in the context of animated programming instructions. We adopted a continuous coding system by Goldberg *et al.,* [1] to collect students' attention-related behaviors in eight programming lessons that utilized an animated instructional package. We analyzed the resulting time-series data with statistical approaches that permitted us to model students' growth trajectory, within- and between-person variability, and the predictors of their attention-related behaviors.

First, we found that the trajectory of overall students' attention-related behaviors is linear rather than quadratic. On average, the students demonstrate significant on-task events at the initial stage of the instructions but also show a significant improvement in their attentional processes as the lessons proceed. However, these behaviors tend to be idiosyncratic as a considerable number of participants remained stable or decelerated in their attention-related behaviors while others exhibited increasing quality attention. Therefore, we further our analysis to model differences within and between participants using a robust multilevel growth model. An inspection of the variability shows that the participants vary within and between themselves, confirming significant differences in their attentional processes. Previous studies have supported our findings by confirming that students exhibit different attention-related behaviors during classroom instruction [1, 45]. However, we propose that these behavioral differences are unique to individual students and are important characteristics of a typical classroom setting. We also propose that the differences in attentional processes are largely accounted for by the variations that exist between the students as opposed to the variations that exist within the students. Although we found that the students' attention-related behaviors converge to a certain degree, the high between-person variability calls for urgent interventions to narrow students' attentional processes in a typical animated programming classroom.

As we consider the whole spectrum of attention and engagement, it is quite surprising that the students exhibit different attention-related behaviors that range from off-task to on-task engagement even when they are taught in a dynamic multimedia environment that has visual and sensory appeal. We expected that there should be a high degree of convergence in their attention-related behaviors toward on-task engagement due to the sensory-appealing nature of multimedia environments. Previous studies have acknowledged the potential of animated instructional packages to substantially capture and sustain quality attention [2, 51]. However, Kelly [7] earlier warned that students would often show different attention-related behaviors in the same classroom setting regardless of the quality of instructional strategies used. We, therefore, believed that there must unique factors that are likely to account for such behaviors.

We implemented a machine learning algorithm to examine factors predicting differences in students' attention-related behaviors. Our algorithm revealed the importance of some individual and instructional characteristics in predicting attention-related behaviors. With regard to individual characteristics, we found that attitude, cognitive load, spatial ability, and programming proficiency are important predictors. Regarding attitude effects, we found that a positive attitude causes an increase in quality attention and vice versa. We propose that having a positive attitude toward a subject can help students pay better attention during instruction. When students are optimistic and believe they can succeed, they are more likely to engage with the material being presented. Conversely, a negative attitude can lead to disinterest or even hostility toward the instruction, making it difficult for students to focus. In support of our position, a previous study has shown a substantial relationship between attitude and learning outcome, indicating that attitudinal effects are important predictors of attention [52].

We also found the presence of a cognitive load effect on attention-related behaviors. Students with high cognitive load were more likely to engage in off-task events while those with low cognitive load engaged more in on-task events. The importance of the cognitive load effect in the context of multimedia environments has been extensively explained by cognitive load theory [31]. This theory proposed that the transitory nature of multimedia elements has the potential to overload students' memory. To counterbalance this transition, the students would then engage in quality off-task behaviors as a sign of memory saturation and weak cognitive processing challenges [30]. Such processing challenges may be severe if the presented instruction is complex and unfamiliar to the students. In their recent study, Yusuf and Noor [3] reported that high processing demands as a result of cognitive load will force students to be very selective in what they deem necessary and important during instruction. One prior study has provided more explanation and argued that the cognitive load effect depends on the duration of the entire animated lessons [53]. Thus, students are more likely to experience a high cognitive load under long-section animation, leading to high off-task engagement. Overall, the cognitive load effect calls for the design and integration of simple and interactive multimedia environments into teaching for improving students' quality attention.

We found some evidence of the enhancer hypothesis [32] as participants with high spatial ability engaged more in on-task classroom events. Prior studies that supported our study have confirmed the validity of the enhancer hypothesis by indicating that 3D multimedia environments enhance the visual attention of high-spatial ability learners [35]. The present study also found some evidence of the expertise reversal effect because novice and intermediate programmers engaged more in on-task behaviors while the expert programmers engaged more in off-task behaviors. We propose in our previous study that animated instructional environments are sometimes not inclusive because they are largely beneficial to novice and intermediate programmers but become counterproductive to expert programmers.

Explanations have been offered for the reason of the expertise reversal effect in most animated environments. According to Kalyuga [54], this effect occurs when learners are presented with already familiar information. In such cases, learners may process the information too quickly and ignore its content, as they are more focused on anticipating higher-level mental objects. Previous studies have also found that incorporating dynamic animation as additional instructional guidance can be more beneficial for novice learners, but counterproductive for experts who do not require such guidance [55]. This is because; experts need to reconcile the additional guidance with existing information in their schema, which further increases their cognitive load.

Within the domain of individual characteristics, we were not able to replicate prior findings that indicate significant effects of gender and prior knowledge on students' attention-related behaviors [56, 57]. We, therefore, propose that everyone is capable of developing different attention-related behaviors regardless of their gender category and level of exposure to animated instruction. As science educators, we always understand and appreciate the need for gender inclusivity. For this reason, expanding programming tools to meet the expectations of all gender categories has been our top priority. We, therefore, question the intervention fidelity and overall validity of prior studies that reported gender effect on attentional processes. We strongly believe that this effect could be weakened when all gender categories are carried along during instruction. This effort is within the capacity of teachers as opposed to other individual student characteristics.

In addition to individual student characteristics, we also found important predictors of attention-related behaviors in relation to instructional characteristics. Important predictors include perceived instructional quality and teaching topics. Specifically, we found that students who perceived our instruction as having high quality were more attentive during instruction as evidenced by their on-task behaviors. The effect of perceived instructional quality on attentional processes can be explained from the lens of learning style. Every classroom is made up of students with unique differences in terms of learning style. Research has shown that students perceive classroom instruction as having quality when it meets their learning preferences [13]. Specifically, three components of instructional quality have been proposed to positively impact students' attention, including a safe and orderly classroom, cognitive activation, and teacher support. Fauth *et al.,* [58] supported this finding by demonstrating that teacher support, cognitive activation, and classroom management were significantly related to the development of subject-specific interest, leading to positive attention-related behaviors. In their study, Goldberg *et al.,* [1] reported a significant effect of cognitive activation and classroom management on students' attention-related behaviors. From these compelling pieces of literature evidence, it is evident that perceived instructional quality plays a critical role in shaping students' attention-related behaviors.

As the requirements for classroom dynamics become necessary for every classroom setting, we included information about teaching topics and classroom activities in our analysis. Our results demonstrate that teaching topics predict attention-related behaviors. Specifically, we found that simple topics attracted students to exhibit quality on-task engagement as opposed to difficult topics. This finding opposed the results of a prior study which revealed that lesson contents cannot be decisive in predicting students' attention-related behavior [1]. While teaching topics was an important predictor of attention-related behaviors, we could not find a significant effect of classroom activities. However, we did not rule out the significant effect of this predictor as prior research has reported such an effect with convincing evidence [1].

Based on these findings, we proposed that students' attention-related behaviors can be explained by individual (attitude, cognitive load, spatial ability, proficiency level) and instructional characteristics (teaching topics). To this end, our study has successfully added additional factors to the determinants of attention and engagement behaviors, thereby contributing to the ongoing refinement of instructional models. However, we still feel that these factors are not exhaustive. Therefore, other studies are needed to come up with more convincing factors. In the meantime, future research exploring instructional effectiveness should pay closer attention to classroom dynamics [1]. Researchers examining the effectiveness of an instructional strategy should also know that such strategies might be prone to error due to the unavoidable occurrence of attention-related behaviors in every classroom setting. The within- and between-person variability of students' attentional processes should be controlled to a higher degree.

VI. LIMITATIONS OF THE STUDY

The major limitation of this study is the use of continuous rating that involves annotations of video data in steps of 5-second interval. We have some concerns about this because some behaviors occur in milliseconds and using the 5-second interval might leave out important behavioral occurrences [1]. However, while time interval coding could lack the accuracy of recording onset and offset events, several authors accept it as a subtle approach to synchronize the concurrent recording of separate streams of behaviors [40, 59]. In our recent study, we proposed that 5-second intervals are more sufficient to capture useful information about students' behavior as well as track an adequate number of discrete data points for statistical analysis. Therefore, employing a 5-second interval rating could have substantial validity.

VII. CONCLUSION

Our study has demonstrated the potential of utilizing rich video data to investigate growth trajectories in attention-related behaviors and to examine the determinants of such behaviors. By employing statistical models, we have found that the overall participants' growth trajectory in attentional processes is linear and accelerates relatively over time. However, the level of this growth trajectory is idiosyncratic to individual students, thereby creating unique variations between and within them. The results of the study highlight the important role of individual and instructional characteristics in shaping students' attention. Firstly, the extent to which students attach meaningful feelings, beliefs, and actions toward a subject can influence their behavior in the classroom. Furthermore, their cognitive abilities, including levels of invested mental effort, task difficulty, spatial abilities, and expertise, strongly influence their behavior. On the other hand, instructional characteristics that are unique to individual classrooms also predict students' attention. These include cognitive activation, teacher support, classroom management, and teaching topics. The study underscores the importance of structured topics, safe classroom environments, quality instructional support, and interactive multimedia objects to activate students' memory, alleviate task difficulty, and reduce the mental resources required for meaningful learning. While these can be highly effective, encouraging students to demonstrate positive behaviors during instructions can help teachers cultivate an engaging classroom culture. Teachers can reassure students that they will achieve meaningful learning if they maintain positive behaviors. To this end, we recommend that further research be conducted to uncover additional determinants of attention-related behaviors.

REFERENCES

[1] P. Goldberg, W. Wanger, T. Seidel, and K. Sturmer, "Why do students exhibit different attention-related behavior during instruction? Investigating effects of individual and context-dependent determinants," *Learning and Instruction*, vol. 83, pp. 1-16, 2023. [Online]. Available: https://doi.org/10.1016/j.learninstruc.2022.101694.

[2] A. Helmke and A. Renkl, "The Munich attention inventory (MAI): An instrument for the systematic behavioral observation of student attention in the classroom," *Diagnostica*, vol. 38, no. 2, pp. 130-141, 1992.

[3] A. Yusuf and N. M. Noor, "Research trends on learning computer programming with program animation. A systematic mapping study," *Computer Applications in Engineering Education*, vol. 31, no. 6, pp. 1552-1582, 2023. [Online]. Available: https://doi.org/10.1002/cae.22659.

[4] R. Boheim, M. Knogler, C. Kosel, and T. Seidel, "Exploring student hand-raising across two school subjects using mixed methods: An investigation of an everyday classroom behavior from a motivational perspective," *Learning and Instructions*, vol. 65, p. 101250, 2020. [Online]. Available: https://doi.org/10.1016/j.learninstruc.2019.101250.

[5] A. Yusuf, and N. M. Noor, "Using multimodal learning analytics to model students' learning behavior in animated programming classroom," *Education and Information Technologies,* 2023. [Online]. Available: https://doi.org/10.1007/s10639-023-12079-8.

[6] A. Yusuf, N. M. Noor, and M. Roman-Gonzalez, "Interaction patterns during block-based programming predict computational thinking: Analysis of the differences in gender, cognitive load, spatial ability and programming proficiency," *AI, Computer Science and Robotics Technology,* 2024. In press.

[7] S. Kelly, "Classroom discourse and the distribution of student engagement," *Social Psychology of Education*, vol. 10, no. 3, pp. 331-352, 2007. [Online]. Available: https://doi.org/10.1007/s11218-007-9024-0.

[8] J. F. Kihlstrom and L. Park, "Cognitive psychology: Overview," *Reference Module in Neuroscience and Biobehavioral Psychology*, 2018. [Online]. Available: https://doi.org/10.1016/B978-0-12-809324-5.21702-1.

[9] C. Wickens, “Attention: Theory, principles, models and applications,” *International Journal of Human-Computer Interaction*, vol. 37, no. 5, pp. 403-417, 2021. [Online]. Available: https://doi.org/10.1080/10 447318.2021.1874741.

[10] J. A. Fredricks, P. C. Blumenfeld, and A. H. Paris, “School engagement: Potential of the concept, state of the evidence,” *Review of Educational Research*, vol. 74, no. 1, pp. 59-109, 2004. [Online]. Available: https://doi.org/10.3102/00346543074001059.

[11] P. Goldberg *et al.,* “Attentive or not? Toward a machine learning approach to assessing students’ visible engagement in classroom instruction,” *Educational Psychology Review*, vol. 33, pp. 27-49, 2021. [Online]. Available: https://doi.org/10.1007/s10648-019-095 14-z.

[12] A.-K. Praetorius, E. Klieme, B. Herbert, and P. Pinger, “Generic dimensions of teaching quality: The German framework of three basic dimensions,” *ZDM Mathematics Education*, vol. 50, no. 3, pp. 407-426, 2018. [Online]. Available: https://doi.org/10.1007/s11858-018-0918-4.

[13] R. Scherer, T. Nilsen, and M. Jansen, “Evaluating individual students’ perceptions of instructional quality: An investigation of their factor structure, measurement invariance, and relations to educational outcomes,” *Frontiers in Psychology*, vol. 7, no. 110, 2016. [Online]. Available: https://doi.org/10.3389/fpsyg.2016.00110

[14] E. R. Campbell, “Can ‘eye’ tell if you are paying attention? The use of mobile eye-trackers to measure academic engagement in the primary-school classroom,” 2014. [Online]. Available: https://eth eses.whiterose.ac.uk/8644/1/2.4.15.pdf.

[15] C.-M. Chen, J.-Y. Wang, and C.-M. Yu, “Assessing the attention levels of students by using a novel attention aware system based on brainwave signals,” *British Journal of Educational Technology*, vol. 48, no. 2, pp. 348-369, 2017. [Online]. Available: https://doi.org/10. 1111/bjet.12359.

[16] T. Hachad *et al.,* “A novel architecture for student’s attention detection in classroom based on facial and body expressions,” *International Journal of Advanced Trends in Computer Science and Engineering*, vol. 9, no. 5, pp. 7357-7366, 2020. [Online]. Available: https://doi.org/10.30534/ijatcse/2020/68952020.

[17] J. Zaletelj and A. Košir, “Predicting students’ attention in the classroom from Kinect facial and body features,” *EURASIP Journal on Image and Video Processing*, vol. 80, 2017. [Online]. Available: https://doi.org/10.1186/s13640-017-0228-8.

[18] R. Boheim, T. Urdan, M. Knogler, and T. Seidel, “Student hand-raising as an indicator of behavioral engagement and its role in classroom learning,” *Contemporary Educational Psychology*, vol. 62, p. 101894, 2020. [Online]. Available: https://doi.org/10.1016/j.ced psych.2020.101894.

[19] E. T. Pas *et al.,* “Profiles of classroom behavior in high schools: Associations with teacher behavior management strategies and classroom composition,” *Journal of School Psychology*, vol. 53, no. 2, pp. 137-148, 2015. [Online]. Available: https://doi.org/10.1016/ j.jsp.2014.12.005.

[20] U. Kessels and A. Heyder, “Not stupid, but lazy? Psychological benefits of disruptive classroom behavior from an attributional perspective,” *Social Psychology of Education*, vol. 23, pp. 583-613, 2020. [Online]. Available: https://doi.org/10.1007/s11218-020-095 50-6.

[21] M. T. Floress et al., “Externalizing behaviors within general, at-risk, and special education preschool classrooms: A preliminary investigation,” *Preventing School Failure: Alternative Education for Children and Youth*, vol. 62, no. 4, pp. 279-288, 2018. [Online]. Available: https://doi.org/10.1080/1045988X.2018.1443424.

[22] E. M. Skaalvik and S. Skaalvik, “Dimensions of teacher burnout: Relations with potential stressors at school,” *Social Psychology of Education*, vol. 20, no. 4, pp. 775-790, 2017. [Online]. Available: https://doi.org/10.1007/s11218-017-9391-0.

[23] R. J. Collie, J. D. Shapka, and N. E. Perry, “School climate and social-emotional learning: Predicting teacher stress, job satisfaction, and teaching efficacy,” *Journal of Educational Psychology*, vol. 104, no. 4, pp. 1189-1204, 2012. [Online]. Available: https://doi.org/10.10 37/a0029356.

[24] D. H. Gebbie *et al.,* “The role of teacher efficacy in strengthening classroom support for preschool children with disabilities who exhibit challenging behaviors,” *Early Childhood Educ Journal*, vol. 40, no. 1, pp. 35-46, 2012. [Online]. Available: https://doi.org/10.1007/s106 43-011-0486-5.

[25] C. Blank and Y. Shavit, “The association between student reports of classmates’ disruptive behavior and student achievement,” *AERA Open*, vol. 2, no. 3, pp. 1-17, 2016. [Online]. Available: https://doi. org/10.1177/2332858416653921.

[26] J. Lee, T. Park, and R. O. Davis, “What affects learner engagement in flipped learning and what predicts its outcomes?” *British Journal of Educational Technology*, vol. 53, no. 2, pp. 211-228, 2018. [Online]. Available: https://doi.org/10.1111/bjet.12717.

[27] C. M. Muller *et al.,* “Peer influence on disruptive classroom behavior depends on teachers’ instructional practice,” *Journal of Applied Developmental Psychology*, vol. 56, pp. 99-108, 2018. [Online]. Available: https://doi.org/10.1016/j.appdev.2018.04.001.

[28] G. Lu, K. Xie, and Q. Liu, “What influences student situational engagement in smart classrooms: Perception of the learning environment and students' motivation,” *British Journal of Educational Technology*, vol. 53, no. 6, pp. 1665-1687, 2022. [Online]. Available: https://doi.org/10.1111/bjet.13204.

[29] F. Heider, *The psychology of interpersonal relations*. New York: Wiley, 1958. [Online]. Available: https://doi.org/10.1037/10628-000

[30] R. Ploetzner, S. Berney, and M. Betrancourt, “When learning from animations is more successful than learning from static pictures: Learning the specifics of change,” *Instructional Science*, vol. 49, pp. 497-514, 2021. [Online]. Available: https://doi.org/10.1007/s11251-021-09541-w.

[31] J. Sweller, P. Ayres, and S. Kalyuga, *Cognitive load theory*. New York: Springer, 2011.

[32] T. N. Höffler, “Spatial ability: Its influence on learning with visualizations - A meta-analytic review,” *Educational Psychology Review*, vol. 22, pp. 245-269, 2010. [Online]. Available: https://doi. org/10.1007/s10648-010-9126-7.

[33] T. N. Höffler and D. Leutner, “The role of spatial ability in learning from instructional animations – Evidence for an ability-as-compensator hypothesis,” *Computers in Human Behavior*, vol. 27, no. 1, pp. 209-216, 2011. [Online]. Available: https://doi.org/10.10 16/j.chb.2010.07.042.

[34] T. Huk, “Who benefits from learning with 3D models? The case of spatial ability,” *Journal of Computer Assisted Learning*, vol. 22, no. 6, pp. 392-404, 2006. [Online]. Available: https://doi.org/10.1111/ j.1365-2729.2006.00180.x

[35] A. B. Chikha, A. Khacharem, K. Trabelsi, and N. L. Bragazzi, “The effect of spatial ability in learning from static and dynamic visualizations: A moderation analysis in 6-year-old children,” *Frontiers in Psychology*, vol. 12, 2021. [Online]. Available: https:// doi.org/10.3389/fpsyg.2021.583968.

[36] S. Kalyuga, P. Ayres, P. Chandler, and J. Sweller, “The expertise reversal effect,” *Educational Psychologist*, vol. 38, no. 1, pp. 23-31, 2003. [Online]. Available: https://doi.org/10.1207/S15326985EP 3801_4.

[37] S. Afroze, M. R. Hossain, and M. M. Hoque, “Deep Focus: A visual focus of attention detection framework using deep learning in multi-object scenarios,” *Journal of King Saud University – Computer and Information Sciences*, vol. 34, pp. 10109-10124, 2022. [Online]. Available: https://doi.org/10.1016/j.jksuci.2022.10.009

[38] A. Arslanyilmaz and J. Sullins, “Eye-gaze data to measure students’ attention to and comprehension of computational thinking concepts,” *International Journal of Child-Computer Interaction*, 2021. [Online]. Available: https://doi.org/10.1016/j.ijcci.2021.100414.

[39] B. N. Anh, N. T. Son, P. T. Lam, L. P. Chi, N. H. Tuan, N. C. Dat, *et al.,* “A computer-vision based application for student behavior monitoring in classroom,” *Applied Sciences*, vol. 9, no. 22, p. 4729, 2019. [Online]. Available: https://doi.org/10.3390/app9224729.

[40] A. Andrade, G. Delandshere, and J. A. Danish, “Using multimodal learning analytics to model student behaviour: A systematic analysis of behavioural framing,” *Journal of Learning Analytics*, vol. 3, no. 2, pp. 282-306, 2016. [Online]. Available: http://dx.doi.org/10.186 08/jla.2016.32.14.

[41] S. Kalyuga, P. Chandler, and J. Sweller, “Managing split-attention and redundancy in multimedia instruction,” *Applied Cognitive Psychology*, vol. 13, pp. 351-371, 1999. [Online]. Available: https://doi.org/10.1002/(SICI)1099-0720(199908)13:4<351::AID-ACP589>3.0.CO;2-6.

[42] F. Paas, "Training strategies for attaining transfer of problem-solving skill in statistics: A cognitive load approach," *Journal of Educational Psychology*, vol. 84, pp. 429-434, 1992. [Online]. Available: https://doi.org/10.1037/0022-0663.84.4.429.

[43] R. B. Ekstrom, J. W. French, and H. H. Harmann, *Manual for kit of factor-referenced cognitive tests*. Princeton, NJ: Educational Testing Service, 1976.

[44] A. Yusuf and N. M. Noor, "Revising the computer programming attitude scale in the context of attitude ambivalence," *Journal of Computer Assisted Learning*, vol. 39, no. 6, pp. 1751-1768, 2023. [Online]. Available: https://doi.org/10.1111/jcal.12838.

[45] M. T. H. Chi and R. Wylie, "The ICAP framework: Linking cognitive engagement to active learning outcomes," *Educational Psychologist*, vol. 49, no. 4, pp. 219-243, 2014. [Online]. Available: https://doi.org/10.1080/00461520.2014.965823.

[46] R. P. Corcoran and J. O'Flaherty, "Longitudinal tracking of academic progress during teacher preparation," *British Journal of Educational Psychology*, vol. 87, pp. 664-682, 2017. [Online]. Available: https://doi.org/10.1111/bjep.12171.

[47] C. Stachl, Q. Au, R. Schoedel, S. D. Gosling, G. M. Harari, and D. Buschek *et al.,* "Predicting personality from patterns of behaviour collected with smartphones," *Proceedings of the National Academy of Sciences of the United States of America*, 2020. [Online]. Available: https://doi.org/10.1073/pnas.1920484117.

[48] A. Altmann, L. Tolosi, O. Sander, and T. Lengauer, "Permutation importance: A corrected feature importance measure," *Bioinformatics*, vol. 26, no. 10, pp. 1340-1347, 2010. [Online]. Available: https://doi.org/10.1093/bioinformatics/btq134.

[49] G. Casalicchio, C. Molnar, and B. Bischl, "Visualizing the feature importance for black box models," in *Machine learning and knowledge discovery in databases*, M. Berlingerio *et al.,* (Eds.), Springer International Publishing, 2019, pp. 655-670. [Online]. Available: https://doi.org/10.1007/978-3-030-10925-740.

[50] D. W. Apley and J. Zhu, "Visualizing the effects of predictor variables in black box supervised learning models," *Journal of the Royal Statistical Society Series B: Statistical Methodology*, vol. 82, no. 4, pp. 1059-1086, 2020. [Online]. Available: https://doi.org/10.1111/rssb.12377

[51] G. Ebel and M. Ben-Ari, "Affective effects of program visualization," in *Proceedings of the Second International Workshop on Computing Education Research*, 2006, pp. 1-5. [Online]. Available: https://doi.org/10.1145/1151588.1151590.

[52] R. Gwinn and I. Krajbich, "Attitudes and attention," *Journal of Experimental Social Psychology*, vol. 86, p. 103892, 2020. [Online]. Available: https://doi.org/10.1016/j.jesp.2019.103892.

[53] I. A. Spanjers, P. Wouters, T. van Gog, and J. G. van Merrienboer, "An expertise reversal effect of segmentation in learning from animated worked out examples," *Computers in Human Behavior*, vol. 27, pp. 46-52, 2011. [Online]. Available: https://doi.org/10.1016/j.chb.2010.05.011.

[54] S. Kalyuga, "Relative effectiveness of animated and static diagrams: An effect of learner prior knowledge," *Computers in Human Behavior*, vol. 24, no. 3, pp. 852-861, 2008. [Online]. Available: https://doi.org/10.1016/j.chb.2007.02.018.

[55] B. Aysolmaz and H. A. Reijers, "Animation as a dynamic visualization technique for improving process model comprehension," *Information & Management*, vol. 58, p. 103478, 2021. [Online]. Available: https://doi.org/10.1016/j.im.2021.103478

[56] S. M. Aguillon *et al.,* "Gender differences in student participation in an active-learning classroom," *Life Sciences Education*, vol. 19, no. 2, 2020. [Online]. Available: https://doi.org/10.1187/cbe.19-03-0048.

[57] I. Shubina and A. Kulakli, "Critical thinking, creativity and gender differences for knowledge generation in education," *Reading and Writing Quarterly*, vol. 10, no. 1, pp. 3086-3093, 2019. [Online]. Available: https://doi.org/10.20533/licej.2040.2589.2019.0405.

[58] B. Fauth *et al.,* "Student ratings of teaching quality in primary school: Dimensions and prediction of student outcomes," *Learning & Instruction*, vol. 29, pp. 1-9, 2014. [Online]. Available: https://doi.org/10.1016/j.learninstruc.2013.07.001.

[59] A. Yusuf *et al.,* "COVID-19 guidelines: A multimodal video analysis of student behavioral compliance during senior secondary certificate examination," *International Journal of Innovative Research in Technology, Basic and Applied Sciences*, vol. 6, no. 1, pp. 33-48, 2020.