WIP: Do you concentrate? A new computational tool for measuring students' concentration

Wenjia Tan
Tsinghua Laboratory of Brain and Intelligence
Tsinghua University
Beijing, China
tanwenjiaplus@gmail.com

Junhao Zhang
Tsinghua Laboratory of Brain and Intelligence
Tsinghua University
Beijing, China
zhang_jh17@163.com

Yang Gao
Tsinghua Laboratory of Brain and Intelligence
Tsinghua University
Beijing, China
gaoy20@mails.tsinghua.edu.cn

Chingwei Lee
Tsinghua Laboratory of Brain and Intelligence
Tsinghua University
Beijing, China
lcwei@stu.pku.edu.cn

Hui Lin
NetEase Youdao
Beijing, China
linhui@rd.netease.com

Lei Shen
NetEase Youdao
Beijing, China
shenlei@rd.netease.com

Yitao Duan
NetEase Youdao
Beijing, China
duan@rd.netease.com

Stella Christie
Tsinghua Laboratory of Brain and Intelligence
Department of Psychological and Cognitive Sciences
Tsinghua Unviersity
Beijing, China
christie@tsinghua.edu.cn

***Abstract*—This research-to-practice paper explores a new computational tool for measuring students' concentration as indexed by how much a student fidgets. While parents and educators commonly take fidgeting as a sign that students are not concentrating, the evidence supporting this assumption is surprisingly mixed, perhaps due to difficulties to accurately measure fidgeting. To address this, we developed a new algorithm (hereafter Youdao algorithm-YD) to detect fidgeting-concentration. In Study 1, we asked whether YD's rating of concentration—calculated from body fidgeting—actually predicts students' learning performance. We found that YD predicts 7-9-year-olds performance on a paper-based math test, though not their Executive Function (EF). In Study 2, we compared YD to human adults, asking adults to rate fidgeting-concentration of the same students who were rated by YD in Study 1. Surprisingly, while adults have consensus about whether a student is fidgeting and concentrating, their ratings did not predict students' actual math scores. That is, humans and YD differ in their calculation of fidgeting-concentration, and YD's fidgeting calculation more accurately predicts students' learning outcome. Since adults' judgement of concentration may be context-dependent, in Study 3 we asked a new group of adults to evaluate the same students viewed in Studies 1 and 2, but against altered backgrounds of a classroom and a cafe. Despite context variation, adults' ratings of fidgeting- concentration remain consistent, and again as in Study 2, do not predict actual math scores. Overall, our studies showed that humans have a consensus of what counts as fidgeting and concentration, but this perception does not accurately predict academic performance. Since teachers' perception impacts students' outcome, non-human algorithm that more accurately captures fidgeting/concentration can be an immensely useful tool for educators.**

***Keywords*—Concentration, Computational tool, Fidget, Executive Function, Attention, Academic performance**

I. Introduction

Concentration, often assessed by observable behaviors such as fidgeting, mind wandering, or off-task behavior, serves as a key index for educators and parents to gauge children's learning success [1]. Fidgeting, in particular, is commonly perceived as a sign of inattention or spontaneous mind wandering [2]. Teachers and parents frequently instruct students to remain still and attentive, assuming that stillness correlates with engagement and academic performance [3]. However, is this common assumption supported by empirical evidence? Prior research actually suggests a mixed relationship between fidgeting and learning outcomes [4]. Some studies indeed found that fidgeting negatively affect students' academic performance. For example, Merrell and Tymms [5] discovered that excessive fidgeting among 4-6-year-old children correlate with poorer performance in reading and mathematics tasks. Similarly, Hulac [6] observed decreased performance in math tasks among college students exhibiting fidgeting behavior. Yet other studies found that fidgeting can in fact improve academic performance. For example, students with ADHD have improved classroom behavior—better attention—when using fidget spinners [7]. Though yet another study did not find that fidget tools improved(nor worsened) math learning among 3rd graders [8]. In executive function tasks such as working memory tasks, fidgeting has been linked to facilitation of word

This work was funded by NetEase Youdao, Tsinghua University Grant 20222000227

retrieval, particularly in "tip of the tongue" situations where children search for optimal word answers [3]. Another study, Sarver found a positive association between fidgeting and working memory in children [9]. Moreover, some studies suggest that fidgeting behavior increases cerebral activity, thereby enhancing sustained attention and memory [10]. Doodling, a form of fidgeting, has been found to improve memory among college students [11]. However, Soares and Storm found that fidgeting during educational videowatching impaired memory among undergraduate students [12], consistent with findings by Farley, Risko, and Kingstone [13]. At the same time, fidgeting is found to be negatively correlated with other mental tasks. Hartanto discovered that increased fidgeting improved children's performance in cognitive control tasks [14], while Graziano, Garcia, and Landis observed a negative relationship between fidgeting and Executive Function (EF) tasks among kindergarten children [15].

Why do different tasks yield different relationships between fidgeting and learning outcomes? One potential explanation is that many previous works employed artificial fidgeting behavior rather than using naturally occurring ones. Most studies manipulated the presence and absence of fidgeting by providing fidget tools rather than observing students' natural fidgeting that take place in everyday learning contexts [16], [17]. Since natural fidgeting is indicative of various states of the mind—ranging from inattention [18], boredom [2] to arousal regulation [19], naturally occurring fidgeting behavior may serve different functions. For example, one child might fidget because they are bored, while another might fidget in order to relieve stress [4]. When studies artificially manipulated fidgeting, it is possible that the variation of these artificially imposed fidgeting can serve differential cognitive functions, such making students inattentive in one, while helping them to reduce stress and be more attentive in another. Understandably, fidgeting studies have mostly focused on manipulated rather than naturally occurring fidgeting behaviors because it is a lot more challenging to quantify and measure natural fidgeting. For one, measuring fidget behavior can be labor intensive; for example studies may ask human coders to watch children's fidgeting in classrooms [20]. Secondly, natural fidget behavior is difficult to quantify because it is unclear which parameter is the most indicative and/or important for gauging concentration. For example, while eye gaze has been commonly used as an attention index [21], it does not always accurately reflect concentration, as children may maintain gaze interaction with teachers while mind wander [20]. Measures such as subjective questionnaires are limited in predicting fidgeting behavior [18], while objective measures such as fMRI may be susceptible to artifacts caused by head movement during spontaneous fidgeting [22]. In sum, measuring natural fidgeting is challenging, and we need a new tool to accurately measure naturally occurring fidgeting.

In the current study, we fill this gap by developing a new computational tool for measuring fidgeting behavior. Developed by Netease Youdao, the YD algorithm uses several parameters—such as head movements and body postures to calculate how much a student fidgets. As discussed, people commonly take fidgeting as a sign of not concentrating, resulting in worse learning. Therefore, one important goal for this research is to test whether the YD algorithm for measuring fidgeting actually predicts whether a student learns well or not. We first describe in details the algorithm, and then the logic of benchmarking the algorithm against students' actual learning performance.

The YD algorithm was trained on a dataset of thousands of labeled videos and recordings of children engaged in natural learning activities, enabling it to recognize nine distinct behaviors: studying paper materials, computer interaction (including screen viewing and keyboard/mouse operations), phone interaction, tablet use, resting on the desk, leaving the seat, playing with toys, looking around, and eating or drinking. The algorithm used duration (t_i) and weighted behavior (W_i) to output the general behavior flow (called FocusAvg in the algorithm). Additionally, it took the stability of learning flow into account, so that it took the longest continuous study duration (K) and any other study sessions lasting over 10 minutes (K_n), and calculated into another variable called YD-StableCoef. The YD then calculates a concentration score using the following function:

$$\text{YD-Concentration} = f(\text{FocusAvg}, \text{YD-StableCoef}) \quad (1)$$

$$f(\text{FocusAvg}) = \alpha \sum_{t_i} W_i \quad (2)$$

$$f(\text{YD-StableCoef}) = K + 0.1K_n + \beta \quad (3)$$

In this model, α and β are constants that adjust the influence of FocusAvg and YD-StableCoef on the overall YD-Concentration score, respectively.

To benchmark whether YD's fidgeting calculation actually correlates with learning performance in Study 1, we asked students to do a math test and an EF task, and ask YD to give students' concentration (fidgeting) scores. The question is whether YD's scores predict actual performance. In Studies 2 and 3, we compared this benchmarking with that of humans' perception of fidgeting and concentration. That is, we wanted to know whether human adults accurately predict learning outcomes based on students' fidgeting-concentration, and how does this judgment compares to YD's judgments.

II. Study 1

A. Design, Participant, and Procedure

To test YD's efficiency and accuracy in measuring fidget behavior, we asked YD to calculate concentration scores of 7-13-year-olds ($N = 35$, $M = 9.05$ years, $SD = 2.13$ years) as they are doing a math test and an Attention Network Test, ANT [23]. We chose a math test because math performance is commonly correlated with overall academic performance [24]. The math test is test tailored to children's grade level and ability [25]. The ANT test is chosen because this is widely-used test to measure Executive Function (EF), attention and concentration [26]. Prior literature suggests that when a child exhibits higher attention, they can better exclude distractions and focus on the task at hand, resulting in better academic performance [27]. Each child took 30 minutes of the paper-based math test and 15 minutes of ANT computer-based test. Each session was recorded by a lamp-hardware that is embedded with the YD algorithm. The lamp is always positioned on the left-hand side of the desk (from the perspective of the student), and it was designed to look like a common desk-lamp, so students can study as usual. The YD algorithm generated a YD-Concentration score after assessing the entire 45 minutes of the test-taking session.

B. Results

We first scored children's accuracy on the math test (Child-ActualMath) and ANT test (Child-ActualEF). Following this, we analyzed whether YD-Concentration scores correlate with math and ANT performance. The results revealed a significant positive correlation between YD-concentration and Child-ActualMath ($r = 0.451$, $p = 0.009$). That is, higher YD-Concentration scores were correlated with higher Child-ActualMath scores. Analyzing each component of YD algorithm in details, we found that this positive correlation was particularly driven by one parameter, the YD-StableCoef (YD-StableCoef and Child-ActualMath $r = 0.509$, $p = 0.005$). This suggests that the algorithm's calculation of fidgeting concentration can predict children's actual math test relatively well. However, there is no significant correlation between YD-Concentration and children's performance on the ANT task. Neither was there a correlation between YD-StableCoef and Child-ActualEF. Since prior research suggests a strong link between EF(assessed using ANT) and math performance, we wanted to know whether this is also the case among our participants. Indeed, aligned with prior works, we found that Child-ActualEF accuracy is positively correlated with math scores ($r = 0.386$, $p = 0.048$). However, Child-ActualEFReactionTime(ActualEF-RT) is negatively correlated with ChildActualMath ($r = -0.556$, $p = 0.003$). That is, there is a speed-accuracy tradeoff in ANT task [28], and this may be one reason why it is more difficult for the YD algorithm to capture the essence of EF performance.

III. Study 2

Study 1 shows that YD's judgment of fidget-concentration can predict students' math performance relatively well. In Study 2, we wanted to know whether humans, like YD, can also accurately predict whether a student is doing well or not in a test, based on their fidget behavior. Our motivations are twofolds: first, no prior works have empirically asked whether human's judgement about (others') concentration accurately predict learning outcomes; second, we wanted to compare YD's accuracy with that of humans.

A. Method

To accomplish this, we extracted 30-second video clips from the full 45 minutes recordings of each child evaluated by YD in Study 1 ($N = 35$). It's difficult for human raters to watch 45 minutes $\times$ 35 children, so our rationale is to give a representative 'slice'—hence the 30-second videos were cut from the middle of each video. We then asked adults ($N = 593$, aged $24 - 35$ years, $M = 33.97$ years, $SD = 3.94$ years) to rate each child's concentration, posture, fidgeting, and predicted math performance on a scale of 1-5.

B. Results

Even from a mere 30-second video clips, adults gave consistent judgements about whether a child is concentrating or not (Cronbach's $\alpha = 0.957 - 0.963$). As expected, adults judged children who fidgeted a lot to be not concentrating, HumanRated-Concentration is negatively correlated with HumanRated-Fidget ($r = -0.905$, $p < 0.001$). Likewise, adults think that children who concentrated (fidgeted less) should do well in a math test (HumanRated-Concentration is positively correlated with HumanRated-Performance, $r = 0.974$, $p < 0.001$). Interestingly however, this correlation does *not* hold when measured against children's actual scores, either in math or ANT. That is, HumanRated-Concentration and HumanRated-Fidget do not correlate with ChildActualMath (Table I). YD-Concentration scores predict children's actual math performance (Study 1), whereas adults' ratings of concentration do not predict children's actual math scores (Study 2). This data suggests that humans differ from YD in how they perceive fidgeting-concentration. Using the benchmark of math performance, YD has better accuracy than humans in predicting whether a child's fidgeting affects their learning outcomes.

IV. Study 3

We found it somewhat surprising that YD is more accurate than humans, and we wanted to know whether human judgment of fidget-concentration would change in different contexts [29]. For example, perhaps humans would be more accurate if they were evaluating students doing tests in classrooms. To test this hypothesis, in Study 3 we asked a new group of adults to rate the same 35 videos as in Studies 1 and 2, but with a modified backround of either a classroom or a café.

A. Method

A new group of parents ($N = 657$) and teachers ($N = 109$) gave the same ratings as in Study 2, except that the background of the video was changed to either classrooms or cafés. Lately, cafés are considered as a place of after-school studying [30], so we used café background as a comparison group. Each participant rated a total of six 30-second videos, 3 cafés and 3 classrooms.

B. Results

Teachers and parents do not differ in their judgment of concentration and fidgeting, and these judgments are consistent across the café and classroom contexts. As in Study 2, these judgments do not accurately predict actual math scores (café: parents $t = 1.029$, $p = 0.312$, teachers $t = 0.461$,

TABLE I
CORRELATION BETWEEN YD-CONCENTRATION AND OTHER VARIABLES

	YD		**HumanRated**			**Child**		
	Concentration	**StableCoef**	**Concentration**	**Fidget**	**Performance**	**ActualMath**	**ActualEF-accuracy**	**ActualEF-RT**
YD-Concentration	1							
YD-StableCoef	0.970**	1						
HumanRated-Concentration	-0.08	-0.15	1					
HumanRated-Fidget	0	0.1	-0.905**	1				
HumanRated-Performance	-0.081	-0.143	0.974**	-0.890**	1			
Child-ActualMath	0.451*	0.509**	-0.029	0.1	-0.068	1		
Child-ActualEF-accuracy	0.296	0.305	0.099	0.019	0.127	0.386*	1	
Child-ActualEF-RT	-0.151	-0.16	0.038	-0.106	0.046	-0.556**	-0.101	1

* $p < 0.05$, ** $p < 0.01$

$p = 0.648$; classroom: parents $t = -1.424$, $p = 0.165$, teachers $t = -1.490$, $p = 0.146$)

V. GENERAL DISCUSSION

Motivated by the need to quantitatively and accurately measure fidgeting, we developed a new algorithm to measure students' concentration. Using the benchmark of students' performance in a math test, we found that the YD algorithm is promising, as its concentration-score significantly correlates with students' actual math scores. Interestingly, when we compared YD with humans (Studies 2 & 3), humans were not as accurate as YD in predicting students' performance based on their concentration and fidgeting. That is, when adults think that a student is fidgeting and therefore not concentrating, this does not necessarily translate into low math performance. This mismatch between adults' perception of a student's concentration and their actual performance is significant. Research shows that educators' perception about a student— whether one is an attentive student or not—could influence teachers' attitudes and behaviors toward that student [31]. For instance, a classroom study found a negative correlation between student fidgeting and academic performance [7]. However, caution is warranted as this correlation relies on teachers' subjective reports. It's possible that teachers, perceiving a student as fidgety, may further judge their attention and performance as poor, resulting in expectations of under performance from the "poor student," thus perpetuating the Pygmalion effect [32]. Such biases towards fidgeting inevitably impact children's educational processes and outcomes.

Our new results suggest that human-perceived fidgeting is not a reliable index for predicting children's concentration and subsequent learning outcomes. Surprisingly, the YD algorithm is more accurate than humans, at least in predicting performance in a math test. What underlies the difference between humans and YD? As noted in the results of Study 1, one component of the YD that particularly predicts math performance is the YD-StableCoef. Unlike simply detecting whether a fidget behavior occurs or not (e.g., a change in body posture), this metric focuses on the duration of a student's concentration, considering factors such as the "longest study duration (K)" and "study durations over 10 minutes (K_n)" Notably, additional weighting is applied when the longest study duration exceeds 25 minutes. That is, instead of assessing whether students can control their fidgeting at any given moment during their study period, the YD algorithm looks for sustained periods of focus over the whole duration of study. Recall that our human raters, unlike the YD, only viewed 30 seconds of a student "studying" , before rating about the student's concentration and predicting their performance. It is possible if humans watch the entire 45 minutes session instead, their judgment of fidgeting may be more similar to that of YD. However, we think this is unlikely, since in many cognitive tasks, humans are prone to make judgments about other humans from a mere few seconds of interaction/viewing [33]. Since humans may not always be accurate in judging concentration level, automated algorithm that (more) accurately judges concentration-fidgeting can serve as a useful tool for educators. Such tool can help alleviate teacher's negative bias about students' behavior—not all fidgeting necessarily means inattentiveness. At the same time, tools like the YD algorithm can help improve students' concentration, for example, students can be given a reminder/nudge when their YD-StableCoef (concentration score) is low. Much future work is to be done to continue improving the accuracy of the algorithm. For example, here we only benchmarked the YD against a math test and an EF (ANT) test. Future studies should expand the types of test to understand whether the correlation between YD concentration score and learning performance holds for other kinds of tests, for example for reading comprehension. It would also be interesting to test YD with different population of learners, for example, with younger children or individuals with ADHD. Tweaking and testing the algorithm against different learning tasks and populations not only allow us to develop applicable teaching tools, but also to understand more precisely the complex relationship between bodily movements (fidgeting) and cognitive functions (attention and concentration).

References

[1] F. M. Newmann, *Student Engagement and Achievement in American Secondary Schools*. New York, NY, USA: Teachers College Press, 1992, pp. 1234.

[2] J. S. Carriere, P. Seli, and D. Smilek, "Wandering in both mind and body: individual differences in mind wandering and inattention predict fidgeting," Canadian Journal of Experimental Psychology/Revue canadienne de psychologie expérimentale, vol. 67, no. 1, pp. 19, 2013.

[3] K. J. Pine, H. Bird, and E. Kirk, "The effects of prohibiting gestures on children's lexical retrieval ability," Developmental Science, vol. 10, no. 6, pp. 747-754, 2007.

[4] K. Perrykkad and J. Hohwy, "Fidgeting as self-evidencing: A predictive processing account of non-goal-directed action," New Ideas in Psychology, vol. 56, p. 100750, 2020.

[5] C. Merrell and P. B. Tymms, "Inattention, hyperactivity and impulsiveness: Their impact on academic achievement and progress," British journal of educational psychology, vol. 71, no. 1, pp. 43-56, 2001.

[6] D. M. Hulac, K. Aspiranti, S. Kriescher, A. M. Briesch, and M. Athanasiou, "A multisite study of the effect of fidget spinners on academic performance," Contemporary School Psychology, vol. 25, pp. 582-588, 2021.

[7] K. B. Aspiranti and D. M. Hulac, "Using fidget spinners to improve on-task classroom behavior for students with ADHD," Behavior Analysis in Practice, vol. 15, no. 2, pp. 454-465, 2022.

[8] K. E. Croley, D. D. Drevon, D. M. Decker, M. D. Hixson, and K. C. Radley, "The effect of the fidget cube on classroom behavior among students with perceived attention difficulties," Behavior Analysis in Practice, vol. 16, no. 2, pp. 547-557, 2023.

[9] D. E. Sarver, M. D. Rapport, M. J. Kofler, J. S. Raiker, and L. M. Friedman, "Hyperactivity in attention-deficit/hyperactivity disorder (ADHD): Impairing deficit or compensatory behavior?," Journal of abnormal child psychology, vol. 43, no. 7, pp. 1219-1232, 2015.

[10] S. Rickman, A. Johnson, and C. Miles, "The impact of chewing gum resistance on immediate free recall," British Journal of Psychology, vol. 104, no. 3, pp. 339-346, 2013.

[11] J. Andrade, "What does doodling do?," Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition, vol. 24, no. 1, pp. 100-106, 2010.

[12] J. S. Soares and B. C. Storm, "Putting a negative spin on it: Using a fidget spinner can impair memory for a video lecture," Applied Cognitive Psychology, vol. 34, no. 1, pp. 277-284, 2020.

[13] Farley, E. F. Risko, and A. Kingstone, "Everyday attention and lecture retention: the effects of time, fidgeting, and mind wandering," Frontiers in psychology, vol. 4, p. 619, 2013.

[14] T. A. Hartanto, C. E. Krafft, A. M. Iosif, and J. B. Schweitzer, "A trial-by-trial analysis reveals more intense physical activity is associated with better cognitive control performance in attention-deficit/hyperactivity disorder," Child Neuropsychology, vol. 22, no. 5, pp. 618-626, 2016.

[15] P. A. Graziano, A. M. Garcia, and T. D. Landis, "To fidget or not to fidget, that is the question: A systematic classroom evaluation of fidget spinners among young children with ADHD," Journal of attention disorders, vol. 24, no. 1, pp. 163-171, 2020.

[16] K. Burnet, J. Blackwell, E. Kelsch, E. D. Hanson, K. Stone, S. Fryer, D. Credeur, P. Palta, and L. Stoner, "Cerebrovascular function response to prolonged sitting combined with a high-glycemic index meal: A double-blind, randomized cross-over trial," Psychophysiology, vol. 58, no. 8, e13830, 2021.

[17] R. Koiler, A. Schimmel, E. Bakhshipour, P. A. Shewokis, and N. Getchell, "The impact of fidget spinners on fine motor skills in individuals with and without ADHD: An exploratory analysis," Journal of Behavioral and Brain Science, vol. 12, no. 3, pp. 82-101, 2022.

[18] S. Lis, N. Baer, C. Stein-en-Nosse, B. Gallhofer, G. Sammer, and P. Kirsch, "Objective measurement of motor activity during cognitive performance in adults with attention-deficit/hyperactivity disorder," Acta Psychiatrica Scandinavica, vol. 122, no. 4, pp. 285-294, 2010.

[19] E. K. Spencer-Mueller and M. J. Fenske, "Note-taking for the win: Doodling does not reduce boredom or mind-wandering, nor enhance attention or retention of lecture material," Quarterly Journal of Experimental Psychology, vol. 17470218231222402, 2023.

[20] K. E. Godwin, M. V. Almeda, H. Seltman, S. Kai, M. D. Skerbetz, R. S. Baker, and A. V. Fisher, "Off-task behavior in elementary school children," Learning and Instruction, vol. 44, pp. 128-143, 2016.

[21] J. Henderson and F. Ferreira, *The Interface of Language, Vision, and Action: Eye Movements and the Visual World*. New York, NY, USA: Psychology Press, 2013.

[22] L. E. Engelhardt, M. A. Roe, J. Juranek, D. DeMaster, K. P. Harden, E. M. Tucker-Drob, and J. A. Church, "Children's head motion during fMRI tasks is heritable and stable over time," Developmental cognitive neuroscience, vol. 25, pp. 58-68, 2017.

[23] J. Fan, B. D. McCandliss, T. Sommer, A. Raz, and M. I. Posner, "Testing the efficiency and independence of attentional networks," Journal of cognitive neuroscience, vol. 14, no. 3, pp. 340-347, 2002.

[24] M. M. Dubuc, M. Aubertin-Leheudre, and A. D. Karelis, "Relationship between interference control and working memory with academic performance in high school students: The Adolescent Student Academic Performance longitudinal study (ASAP)," Journal of adolescence, vol. 80, pp. 204-213, 2020.

[25] D. H. Clements and J. Sarama, *Learning and Teaching Early Math: The Learning Trajectories Approach*. New York, NY, USA: Routledge, 2020.

[26] T. L. Blankenship, M. A. Slough, S. D. Calkins, K. Deater-Deckard, J. Kim-Spoon, and M. A. Bell, "Attention and executive functioning in infancy: Links to childhood executive function and reading achievement," Developmental Science, vol. 22, no. 6, e12824, 2019.

[27] C. Blair and C. C. Raver, "School readiness and self-regulation: A developmental psychobiological approach," Annual Review of Psychology, vol. 66, pp. 711-731, 2015.

[28] L. Cragg and C. Gilmore, "Skills underlying mathematics: The role of executive function in the development of mathematics proficiency," Trends in Neuroscience and Education, vol. 3, no. 2, pp. 63-68, 2014.

[29] O. Goethe, H. Sørum, and J. Johansen, "The effect or non-effect of virtual versus non-virtual backgrounds in digital learning," in *Human Interaction, Emerging Technologies and Future Systems V: Proceedings of the 5th International Virtual Conference on Human Interaction and Emerging Technologies (IHIET 2021), Aug. 27-29, 2021 and the 6th IHIET: Future Systems (IHIET-FS 2021), Oct. 28-30, 2021, France*, Springer International Publishing, 2022, pp. 274-281.

[30] Y. S. Purwadi and E. M. Manurung, "Cafes: new learning and knowledge production space for millennial students," Journal of Economics and Business, vol. 3, no. 1, 2020.

[31] A. Friedrich, B. Flunger, B. Nagengast, K. Jonkmann, and U. Trautwein, "Pygmalion effects in the classroom: Teacher expectancy effects on students' math achievement," Contemporary Educational Psychology, vol. 41, pp. 1-12, 2015.

[32] J. Chang, "A Case Study of the 'Pygmalion Effect': Teacher Expectations and Student Achievement," International Education Studies, vol. 4, no. 1, pp. 198-201, 2011.

[33] R. Adolphs, D. Tranel, and A. R. Damasio, "The human amygdala in social judgment," Nature, vol. 393, p. 471, 1998.