

Relationship between Instructional Activities and Students Distraction

Daniel Bang

Ph.D. Student, Department of Multidisciplinary Engineering, Texas A&M University
College Station, TX, USA

Saira Anwar

Assistant Professor, Department of Multidisciplinary Engineering, Texas A&M University
College Station, TX, USA

Syeda Fizza Ali

Ph.D. Student, Department of Multidisciplinary Engineering, Texas A&M University
College Station, TX, USA

Alejandra Magana

W.C. Furnas Professor in Enterprise Excellence, Computer and Information Technology and
Professor, Engineering Education, Purdue University
West Lafayette, IN, USA

Abstract

The Interactive, Constructive, Active, and Passive (ICAP) Framework describes levels of students' engagement based on the in-class activities with more positive experiences leading to more engagement and learning. The ICAP framework hypothesizes that students involved in interactive activities are more likely to be better engaged than students who do constructive activities. Similarly, constructive activities lead to better engagement than active activities, which helps students to stay engaged better than passive activities. Although ICAP describes increased engagement levels, students' behaviors often depend on how instructors approach these activities. Existing research studies highlight the importance and need for student-centered learning activities for students' engagement; there are reported cases where instructors noticed less engaged behaviors besides being introduced to active learning instructional activities. Considering the mixed reported results in the literature, especially in technology and computer science courses, in this paper, we aim to explore the relationship between instructional activities in a technology course and student distraction. To collect the data on instructional activities and distraction, we used a validated instrument, Student Response to Instructional Practices (StRIP). Based on the ICAP framework, the items capture students' responses to classroom instruction on four types of instructional activities (interactive = 6 items; constructive = 6 items; active = 6 items; passive = 3 items). Also, the instrument allows us to capture students' perspectives of their distraction behaviors (3 items) in the classroom. We collected the data from 120 students who voluntarily participated. In this study, we only used the data from students who completed responses to all questions related to instructional activities and distraction. More specifically, this study will answer two research questions: 1) Which aspects of the four instructional activity types (interactive, constructive, active, and passive) are related to students' distraction? 2) Which unique aspects of instruction

distract the students the most? To analyze and answer the research questions, we used XGBoost, a type of gradient-boosted library, to build a model that can measure the importance of each instructional activity type when related to distraction. For the first research question, we used the items within each instructional type and associated them with distraction. For the second research question, we considered all 21 items and identified the top items associated with students' distraction. Results indicate two out of the top three attributes that cause distraction are from Passive engagement. Thus, we can conclude that even during classes designed around student-centered learning activities, certain factors could cause distracted behavior.

Introduction

Students learn most effectively when actively engaged in learning rather than passively listening to class lectures. Studies suggest that to learn "actively" in class, students must be cognitively "engaged" with the content and instructors¹. The components of active learning contrast with passive modes of learning, where students take in class materials without "analyzing, synthesizing, and evaluating" them². Although many existing studies suggest that active learning works³, and instructors are aware of the importance of active learning, there has been a debate on using modes that may engage or disengage students. For example, Chi and Wylie⁴ highlighted that developing teaching methods to promote active learning had three issues. Firstly, having open-ended suggestions for teaching methods, such as promoting engagement with students and having them think about the subject, does not help teachers develop an active classroom learning setting. Second, teachers have limited resources when creating an active learning setting. Third, teachers do not have guides that can help them turn their teaching materials from passive to active. To address the issues, the authors proposed ICAP – Interactive, Constructive, Active, and Passive framework to describe students' modes of engagement⁴.

The ICAP Framework comprises four modes defined by learning activities and their consequential student engagement level. Each of these modes represents a different level of student learning and engagement. The framework hypothesizes that these "different levels of learning" will cause different learning behaviors in students. Interactive learning will get students to learn more than constructive learning, which will get students to learn more than active learning, which will get students to learn more than passive learning⁴. This framework helps instructors see the factors that can help students be more engaged in their learning process.

Although many studies have emphasized the importance of actively engaging students in their learning, there are reported cases where instructors found it time-consuming⁵. Also, studies have reported evidence of students' overt and covert behaviors, indicating the mixed results of introducing strategies that actively engage students^{6, 7}. For example, some studies reported that interactive activities resulted in more engaged students' behaviors; others have reported declining student engagement and lower satisfaction with using student-centered activities in classes⁸. Also, prior studies suggested that distraction does not completely dissipate as the learning activities move from passive to interactive⁹. Students still experience some level of distraction at any level of learning. This behavior was especially true in the classes related to technology and computer science⁹.

Because of these results, in this study, we focus on behaviors that students could show when engaged in active learning activities. More specifically, this paper focused on understanding the relationship between instructional activities in a computer and information technology course and

students' less engaged behavior: Distraction. Studies suggest that distraction is detrimental to the learning experience^{10, 11}. We hypothesize that the ICAP framework will help understand the factors that disengage students and their distracting behavior in the course lectures.

Using the ICAP framework can inform students' behaviors to engage students, and analyzing what factors contribute to it will help instructors find methods to combat it.

Research Questions

Using the ICAP Framework, we will focus on what generally causes students to become distracted in classes. Knowing this will help instructors understand the general factors in their teaching methods that can cause students to become distracted. More specifically, in this study, we focus on two research questions

RQ1: Which aspects of the four instructional activity types (interactive, constructive, active, and passive) are related to students' distraction?

RQ2: Which unique aspects of instruction distract the students the most?

Literature Review

ICAP and student learning

The ICAP framework uses students' overt behaviors to determine their cognitive engagement level during instructional activities in class. It proposes that instructional activities can be categorized into four modes, resulting in differing engagement levels: Interactive, Constructive, Active, and Passive. The built-in hypothesis of ICAP suggests that the learning outcomes increase as students' engagement level increases from passive to active to constructive to interactive activities⁴. The ICAP framework has been monumental in explaining learning outcomes based on instructional activities. Prior literature has used ICAP in the classroom as well as in the lab settings. Educational researchers have used ICAP as a lens to explain and measure the effectiveness of various instructional activity types. However, literature studies provide mixed results on the effectiveness of instructional activities on students' overt behaviors. Some studies indicated that the ICAP hypothesis holds in the case of different educational settings. For instance, Henderson¹² implemented peer instruction in four different high school physics classes (N=250) but changed how students in each class spent time in between using clickers based on the four modes defined in the ICAP framework. The students either spent time writing alone, discussing concepts with others, or doing both. Regression results were consistent with the ICAP hypothesis. Students in interactive interventions showed learning gains significantly higher than students in other interventions.

Similarly, in another study, university students in introductory biology courses were exposed to either interactive or constructive learning activities¹³. Students engaged more in discussions in interactive activities compared to constructive activities. Moreover, students in the interactive activities showed significant improvement on an eight-item content quiz conducted in a pre and post-format.

Contingent to mixed results, several researchers noted the exceptions to the ICAP hypothesis, where the instructional activities showed a differing overt cognitive engagement than described in the hypothesis. For instance, researchers used ICAP to determine university students' expected

and observed behaviors in a chemistry sequence in small-group learning activities¹⁴. A qualitative thematic analysis showed that students varied in showing their overt behaviors from engagement to disengagement with various parts of an activity. In some instances, higher engagement indicated different learning outcomes.

Furthermore, there have also been more novel uses of ICAP in literature¹⁵. For instance, Morris and Chil5 conducted professional development modules based on the ICAP framework for two middle school science teachers to improve in-class questioning. Using the coding scheme to judge teachers' questioning, the teachers asked questions after the professional development workshop, which generated a higher cognitive engagement. The study reports that teachers asked more questions requiring students to analyze and make inferences about the content than before. Also, on the learning outcome, the student's learning improved when teachers asked more constructive questions during the lesson.

Student distraction

Studies suggest that students can have different overt behaviors due to instructional activities. In many cases, these overt behaviors could be different phases, including point of engagement (initial engagement), period of engagement, disengagement, and re-engagement¹⁶. During the phase of disengagement and re-engagement, one notable overt behavior could be a distraction. Gazzalay and Rosen¹⁷ define distraction as stimuli that can disrupt a person. These distraction behaviors could result from something with the instructional activities, teaching style, content discussed in class, or students not valuing the class activity. Also, the distraction could be because of external stimuli, including peers' distracting behavior or the use of technology applications or tools. Most prior literature on distraction focuses on external stimuli such as technology. For example, a literature review on the impact of technology on distraction in students defines academic distraction as the potential of stimuli (external or internal) to interrupt a student while studying¹⁰. The study categorized the reviewed works by the type of technology used by students. The authors reported that using smartphones and social media during lectures has a detrimental impact on student distraction, whereas the impact of laptop usage was found to be less harmful. Similarly, in another study, data gathered from eight introductory science courses through observations, surveys, and interviews showed a statistically significant negative correlation between cell phone usage and students' exam performance¹⁸. Moreover, discrepancies in survey responses and in-class observations suggested that students underreported their usage. Another dimension of distraction explored by Taneja and Fischer¹⁹ describes cyber-slacking as using technology during class time for tasks unrelated to the class. The study conducted partial least squares on survey data from 267 undergraduate students to examine the factors that influenced students' intentions to cyber-slack and found significant influences to be consumerism, escapism, cyber-slacking anxiety, and others' cyberslacking behavior.

Although studies have used the ICAP framework in classroom and lab settings and indicated mixed results on students' engagement and overt behaviors, limited literature explores the impact of instructional activities on these differing overt behaviors. The literature is scarce on students' negative overt behaviors, particularly the ones related to students' disengagement. Also, most studies focused on students' distraction with students' use of technology tools and did not identify the role of instructional activity types in distracting students. This study considers distraction in a broader context to overcome the research gap. We conceptualize it as students' overt behavior, not limited to the use of technology in the classroom, and how it is associated with instructional

activity types used for students' cognitive engagement based on the ICAP framework.

Research Design

We designed a correlational study, where data were collected using quantitative approaches and analyzed using machine learning algorithms.

Participants

The data were collected from 120 sophomore students taking a System Analysis and Design Course at a large R1 University in a computer and information technology department. Students voluntarily participated in the study. The required course introduces students to tools and techniques of systems development. The topics of the course revolved around the introduction to information systems, software development life cycles, methodologies, systems planning, design, implementation, and support. In this study, the data were included from students who participated and gave their consent to include their data in the research as per institutional review and ethical principles. The students participated in an end-of-semester survey and described their perceptions of instructional activities (interactive, constructive, active, and passive) and distracted behaviors. Table 1. summarizes the demographics of the participants.

Table 1. Demographic Information

Race/Gender	Male	Female	Total
White	38	20	58
Asian	13	4	17
Hispanic/Latino	4	1	5
African-American	3	5	8
Total Students	58	30	88

Instrument

To collect the data, we used the validated instrument created by DeMonbrun and colleagues named The Student Response to Instructional Practices (StRIP)²⁰. The StRIP is based on the ICAP framework to analyze the effects of different instructional activities instructors use in their classes²⁰. The instrument captures the students' responses to classroom instruction. Based on the ICAP framework, there are four types of instructional activities. The survey includes the items to capture students' responses to classroom instruction using 21 items (6 for Interactives activities, 6 for constructive activities, 6 for passive activities, and 3 for passive activities). Also, the instrument captures students' perspectives on learning experiences and distraction using three items. The students' perceptions were recorded using a 5-point Likert scale for how often the students observed a particular activity or showed distracted behavior. On the Likert scale, 1 indicated "Never", and 5 indicated "very often". Table 2 provides the sample items from the survey. The distraction category includes three actions: distracting other students during activities, talking about irrelevant topics during said activity, and doing other activities such as surfing the internet and visiting social media.

Table 2 Sample items of the survey

Instructional Activities

(How often did you do each thing in this course?)	
Interactive	Do hands-on group activities during class.
Constructive	Solve problems that have more than one correct answer.
Active	Ask the instructor questions during class.
Passive	Watch the instructor demonstrate how to solve problems.
Students Behavior	
(How often did you react in the following ways?)	
Distraction	I surfed the internet, checked social media, or did something else instead of doing the activity.

Data Analysis

We initially calculated the average of students' perceptions for each instructional activity type based on the number of items. We took the average of all six items for interactive activities for each student. Further, we used these average scores to measure students' level of distraction against each instructional activity. To analyze all the factors' contributions to distraction, we used XGBoost, a gradient-boosted decision tree. XGBoost uses parallel tree boosting to analyze many different types of data problems accurately. We used XGBoost to build a model that can measure the feature importance values of all 21 items related to instructional activities.

To answer the first research question, we measured the feature importance values by grouping items by their corresponding instructional activity and tested it against the average distraction score. For example, when measuring the feature importance for Passive, we made a data frame with four fields (3 fields were based on the three items, and the output field was the average distraction score). We fit an XGBoost model with this data frame and found the three features' importance values to distraction. This process was done for all activity types.

To answer the second research question, we measured the importance value of all items against the average distraction score in one XGBoost model. For this analysis, we included all 21 items of the four activity types along with the student's gender and ethnicity in the data frame. We one-hot encoded the gender and ethnicity variables before data analysis. One hot encoding is transforming categorical variables into a form easily predicted by machine learning algorithms. Also, we normalized all the data before analysis. After setting up this data frame, we fit it into an XGBoost mode to search for the top items that affect the level of distraction students experience during class activities. With this method, we found the important items that contribute to distraction.

Results

RQ1: Which aspects of the four instructional activity types (interactive, constructive, active, and passive) are related to students' distraction?

To answer the first question, we used XGBoost's feature importance values and found the important items in each instructional type related to distraction. We can find the percentage value to analyze which features are important and which are not. After retrieving their score through XGBoost, we divided it by the total possible score. The features with high percentages relative to other features would be considered important.

For Passive instructional activities, we found that all three items (or aspects) contribute heavily to distraction. The maximum possible score here is 2257. Although "Get most of the information

needed to solve the homework directly from the instructor" resulted in a score of 1317 out of 2257, indicating the item as the most contributing factor, the other two items, "Watch the instructor demonstrate how to solve problems" and "Watch the instructor demonstrate how to solve problems," resulted in a score of 1011 and 950.

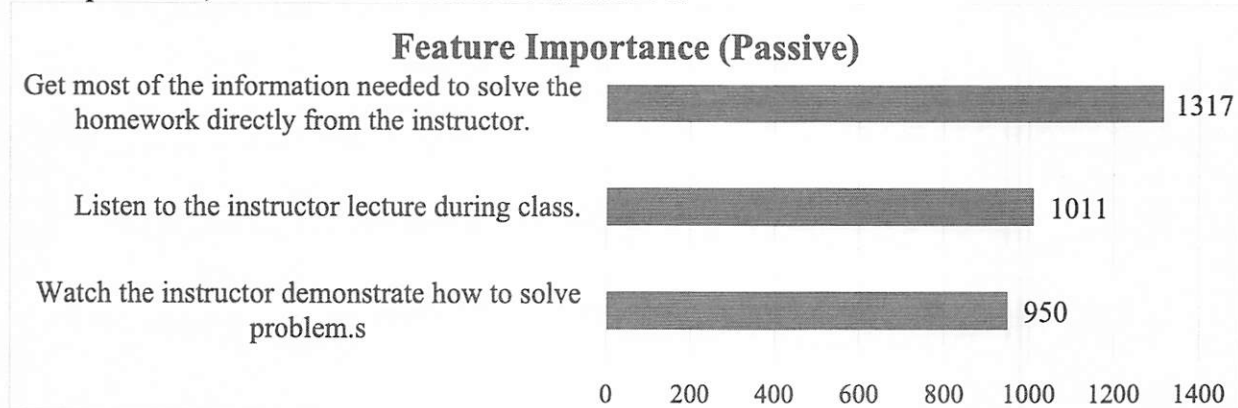


Figure 1, Passive instructional activity and relationship to distraction

For Active instructional activities, the results varied much more and ranged from 250 to 755 between items. The maximum possible score in this category is 3401. The "Ask the instructor questions during class" had a feature importance score of 755 out of 3401, finding the items as contributing, which indicates a high relationship. The four items "Be graded on my class participation", "Solve problems individually during class", "Answer questions posed by the instructor during class", and "Preview concepts before class by reading, watching videos, etc." had a score in a similar range of moderate relationship. However, the "Make individual presentations to the class" scored 250, only finding it contributing, indicating a lower relationship.

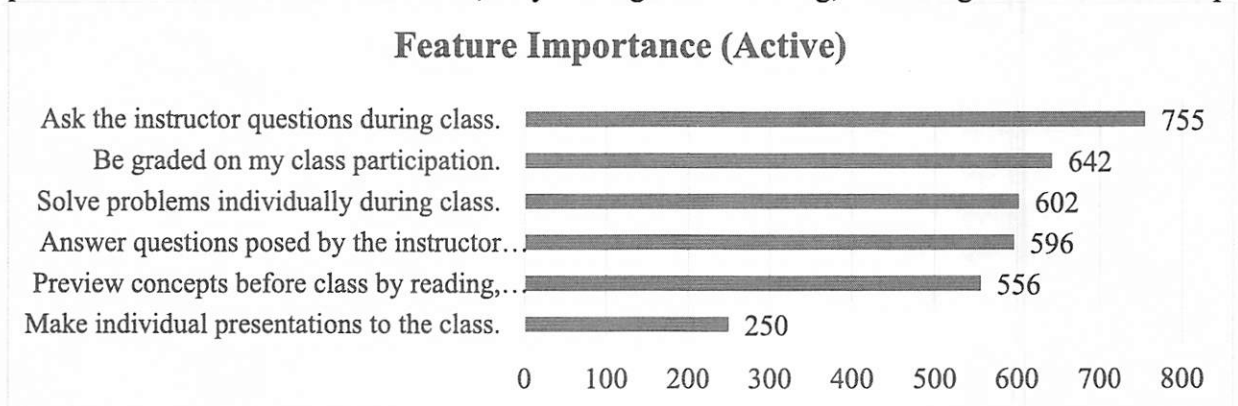


Figure 2. Active instructional activity and relationship to distraction

For Constructive, similar to active instructional activities, the results had a more comprehensive range. The maximum possible score in this category is 3447. Three items, which are: "Make and justify assumptions when not enough information is provided", "Take initiative for identifying what we need to know", and "Find additional information not provided by the instructor to complete assignments," showed a higher relationship with distraction with features scores of 707, 671 and 604 respectively. However, the other three items showed a moderate relationship range of 489 - 487.

Feature Importance (Constructive)

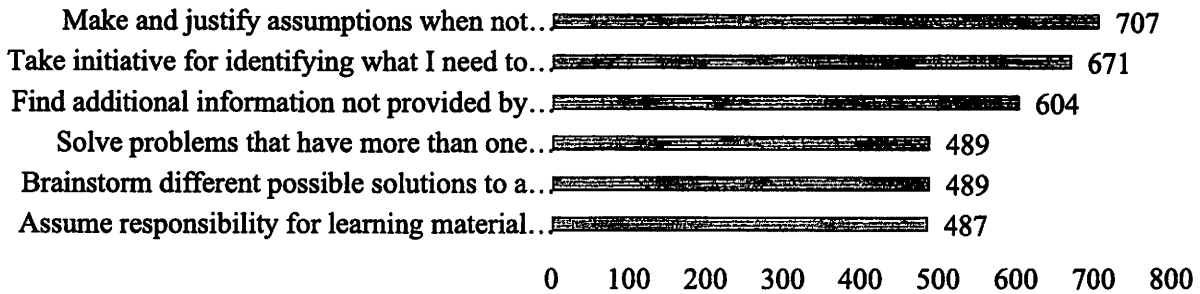


Figure 3. Constructive instructional activity and relationship to distraction

For Interactive instructional activities, we found a more important feature than the rest. The maximum possible score in this category is 3471. "Study course content with classmates outside of class" had an importance score of 781 out of 3471. Other items showed a moderate relationship, where "Work in assigned groups to complete homework or other projects" scored 583, "Be graded based on the performance of my group" had a score of 557, "Solve problems in a group during class" had a score of 548, "Do hands-on group activities during class" scored 512, and "Discuss concepts with classmates during class" had a score of 490.

Feature Importance (Interactive)

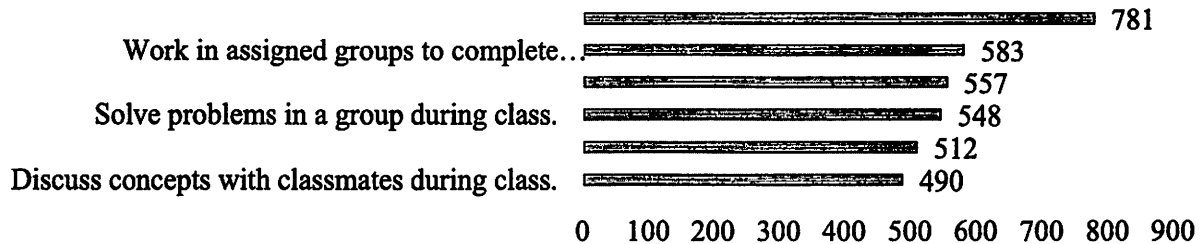


Figure 4. Interactive instructional activity and relationship to distraction

RQ2: Which unique aspects of instruction distract the students the most?

For research question 2, we focused on analyzing all the items and found the important items that contribute to distraction when observing all instructional activities through XGBoost's feature importance values. We then compare it with the maximum possible score to see which features have the highest percentage.

We found the top three items that contribute the most to the overall distraction students experience in class. The maximum possible score is 3020. The first factor is "Get most of the information needed to solve the homework directly from the instructor," with a feature importance score of 263. The second is "Listen to the instructor lecture during class," with a score of 232. The third factor is "Make and justify assumptions when not enough information is provided," with a score of 229. Notably, two of the three items belong in the Passive category while one belongs in the Constructive category. This strongly indicates that, overall, Passive engagement generates the

most distraction.

Feature Importance (Overall)

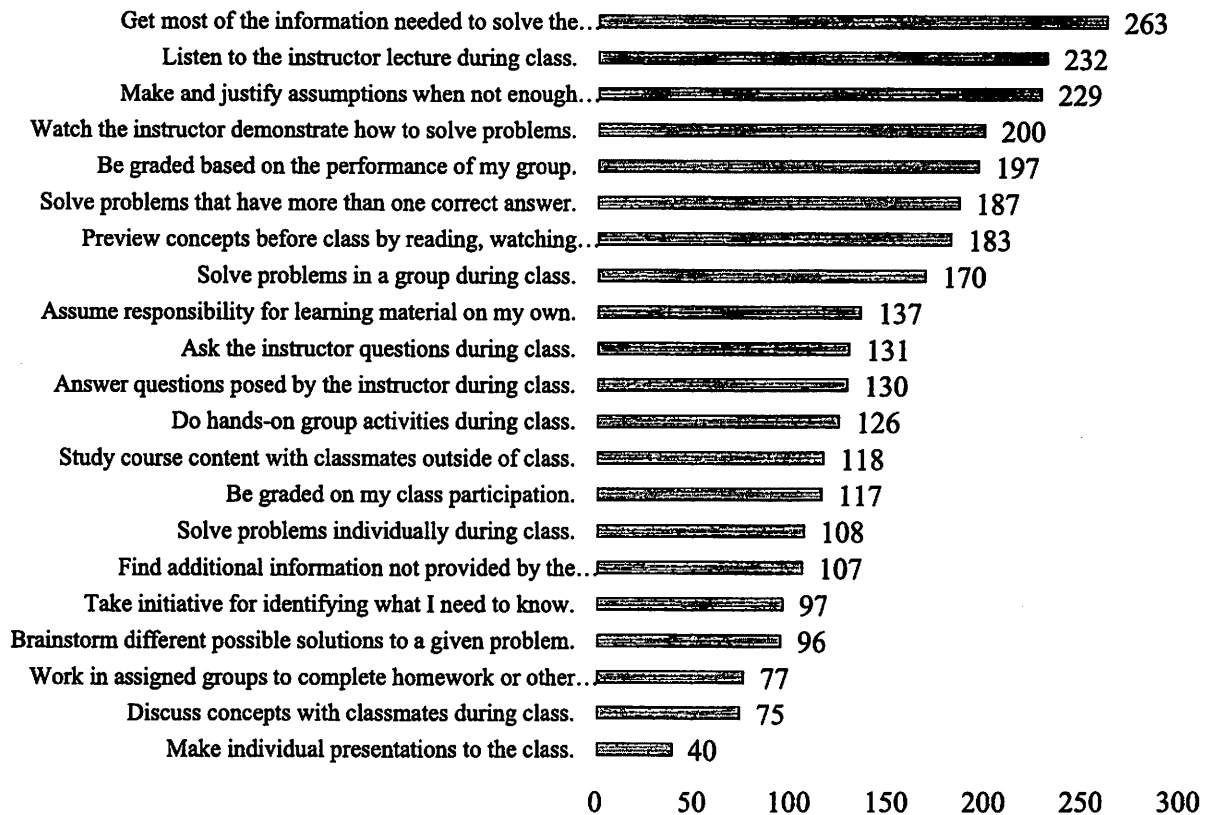


Figure 5. Overall Items and their contribution to students' distracting behavior

Discussion

With the increasing focus on instructional activities in class to engage students, it is equally important to identify the factors contributing to students' varying overt behaviors. With this study, we highlight that distraction is an overt behavior that needs special attention and deserves a spotlight. Consequently, this study identified the in-class instructional activities that may contribute to students' distraction. We used the ICAP (interactive, Constructive, Active, and Passive) framework to classify instructional activities in a student-centered active learning course into four types. Using the items defined in The Student Response to Instructional Practices (StRIP), we identified and analyzed the features contributing to students' class distraction.

The paper's results align with the ICAP hypothesis⁴ and indicate that all three features of Passive engagement have high feature importance values when associated with distraction. Interestingly, instructors giving information on how to solve assignments contribute to students' distraction the most, even when measuring all feature importance values at once. The probable explanation could be rooted in students not finding that information useful or repetitive. From Active instructional activities, asking questions to the instructor causes the most distraction. One probable explanation could be that students feel distracted when other students (peers) ask questions, as they may find

it irrelevant. Or the students could be distracted as they may already know the answer. Also, the other explanation could be associated with students not actively paying attention to certain aspects of the lecture. The non-attentive behavior could lead to asking questions to connect old and new knowledge and retrieve information. While such questions may be relevant to the student who asked the question, it may be of lesser importance to other students. The results of constructive instructional activities showed that students having to make and justify assumptions when insufficient information was provided might cause distraction. This indicates that instructors could make informed choices and align the content, assessment, and pedagogy²¹ for clarity of information for students.

The study results are compelling as they provide information on distracting features in each student-centered learning activity. Looking at the top features of each category may help the instructors design the classroom experience focusing on engagement and distraction for a cohesive learning experience. For example, besides highlighting the top features that distract students, the study also indicates that students were engaged or less distracted during most constructive and all interactive activities. This aligns with findings from prior studies that have shown that students are more engaged during interactive activities¹³. For example, students having to solve problems with more than one answer, brainstorming different possible solutions for given problems, and assuming responsibility for learning the teaching materials on their own will prevent them from becoming distracted. It was also noteworthy that while group work effectively prevents distraction, it conversely causes distraction when a group has to work outside class. Also, assigning students to make individual presentations in class scored very low, indicating that this strongly prevents students from becoming distracted. It may be conducive for instructors to assign presentation assignments to students, if possible, frequently.

The study results must be viewed in light of several limitations and possible future directions. First, the data were collected from one student-centered computer science course. Future studies can use the ICAP framework in more than one course and courses in other disciplines. Second, we collected the data from a relatively small dataset of 120 students. Future studies can be designed to collect data from larger sample sizes to strengthen the statistical power. Third, in this study, we used the data for one overt behavior, i.e., distraction. Future studies can use other overt behaviors and emotions such as frustration, anger, disengagement, etc. Fourth, we only relied on students' self-reported evidence in this study. Prior literature suggests students tend to underreport the frequency of their technology usage¹⁷. Although students' self-reported evidence can be an accurate measure²², other sources of information or process data, including classroom observations²³, verbal records of students' conversations and questions, and teachers' perceptions of students' overt behaviors, could be helpful for future studies. Fifth, in the current study, we designed a correlational study with no comparison group. Future studies can consider a quasi-experimental research design for generalizability. Also, future studies can be designed around other novel approaches, such as multi-modal approaches²⁴, for a holistic understanding of the phenomena.

Conclusion

This study is one of the few in computing and engineering literature highlighting the importance of overt behaviors in students engaged in student-centered learning activities. In literature, we have seen many examples which suggest that student-centered learning works over traditional

mechanisms³. This study focused on the elements in different instructional activities that distract students in the class. The study's results and approach are novel as it validates the ICAP hypothesis indicating that with interactive activities, students are less distracted than with constructive, active, or passive activities; it also informs that what in-class activities may lead to students' distraction the most. The study results are a resource for course designers and instructors to choose the balance of different classroom activities to keep students engaged. The less engagement course activities have with students. The less likely students will pay attention and learn appropriately in class. Also, the study methodology indirectly helps the instructors to evaluate their classes and classify in-class activities using the ICAP framework.

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DANIEL BANG

Daniel (Sung Je) Bang is a Ph.D. student at the department of Multidisciplinary Engineering at Texas A&M University. He earned his M.S. in Computer Engineering from the College of Engineering, Texas A&M University,

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University of North Texas, Denton, TX*

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USA. His research interests include utilizing machine learning to analyze social interactions and evaluating social phenomena in the online space.

SAIRA ANWAR

Dr. Saira Anwar is an Assistant Professor at the Department of Multidisciplinary Engineering, Texas A&M University, College Station. She received her Ph.D. in Engineering Education from the School of Engineering Education, Purdue University, USA. She earned her M.S. in Computer Science from the National University of Computer and Emerging Sciences, Pakistan. Dr. Anwar also holds an M.Sc. in Computer Science from Punjab University College of Information Technology, Pakistan. Her research program is to help develop students' understanding of conceptually hard concepts in STEM courses and includes 1) design of innovative (e.g., technology-mediated, integrated STEM) learning environments. 2) design, implement and measure the effectiveness of emergent and inclusive curriculum units, courses, and programs. and 3) evaluate the effectiveness of instructional strategies. She was awarded the 2020 outstanding researcher award by the School of Engineering Education, Purdue University. Also, she is the recipient of the Apprentice Faculty Grant Award, 2022 by the ERM division.

SYEDA FIZZA ALI

Syeda Fizza Ali is a doctoral student at the Department of Multidisciplinary Engineering at Texas A&M University, focusing on Engineering Education. She also works as a Graduate Research Assistant at the Department of Multidisciplinary Engineering, and has a background in software engineering. Her research interests include promoting equity and inclusivity in engineering, improving student mental health, and the development of educational technology tools to improve learning experiences.

ALEJANDRA MAGANA

Dr. Alejandra Magana is the W.C. Furnas Professor in Enterprise Excellence in the Department of Computer and Information Technology and Professor in the School of Engineering Education at Purdue University. Dr. Magana holds a B.E. in Information Systems and an M.S. in Technology, both from Tec de Monterrey, and an M.S. in Educational Technology and a Ph.D. in Engineering Education, both from Purdue University. Her research program investigates how model-based cognition in Science, Technology, Engineering, and Mathematics (STEM) can be better supported by computational disciplinary practices such as computation, modeling and simulation, data science practices, and artificial intelligence.