Sex-Related Behavioral Differences in Online Math Classes: An Epistemic Network Analysis

Yufei Gu
New York University Abu Dhabi
yg1262@nyu.edu

Kun Xu
Spark EdTech
xukun04@huohua.cn

ABSTRACT

The aim of the present study was to examine the rarely studied existence of sex-related behavior difference in online mathematics classes in China. Epistemic Network Analysis (ENA) was utilized in this study to explore the connection of students' classroom behaviors, and the differences in connection patterns for boys and girls. The class monitoring videos of a sample of 64 students (32 male, 32 female) was coded for microscopic categories of in-class behaviors, and all the codes were organized in the format of adjacent matrix. ENA model showed significant results that girls were more likely to engage in social activities in class, while boys exhibited more disruptive behaviors. There was also a relatively stronger connection between disruptive behaviors and call-out behaviors, and a slightly stronger connection between off-task behaviors and disruptive behaviors, and between disruptive behaviors and direct-no volunteer interactions for boys, compared with girls. This study provided an insight into the connection of different categories of classroom behaviors varied by gender, implying a future direction to examine the relationship between different behavioral connection patterns and students' math achievement in online math classes.

Keywords

sex-related behavioral difference, math achievement, teacher-student interaction, Epistemic Network Analysis (ENA), online math class

1. INTRODUCTION

1.1 Background

Previous studies examining sex-related differences in mathematics performance have reached inconsistent conclusions: while some reported a male advantage in math achievement, other studies only found sex-related differences in certain age groups and certain areas of mathematics ability, or even a female advantage in math exams [5][9][25][15][33].

On the other hand, although various research has been conducted to identify the specific contexts and factors that correlated with the difference in mathematics achievement of female and male students [7][11][14][21], the specific classroom behaviors and level of engagement, which have been linked by previous research to varying levels of mathematics achievement, have rarely been studied [10][26][17][22]. In a study conducted by Hart [13], boys were found to be more involved in public interactions in class with their teachers than girls, and the study indicated significant main effects of gender of students on two sub-categories of public teacher-student interaction: open volunteer interactions, and call-out interactions

1.2 Online Math Classes in China

During the past few years, China has witnessed an explosion of different online education platforms, which provides students with easy access to high-quality learning materials regardless of their geographical location. The bloom of online education also provides researchers with opportunities to conduct observational studies on teacher-student interactions without having to set up a camera or be physically present in the classroom. In this case, online learning platform provides a great opportunity for researchers to examine the behaviors of students of different sex in the online classes without influencing or interrupting how teachers and students behave and interact in class. Thus, the present study utilized the classroom monitoring videos from Spark EdTech, a Chinese K-12 online education platform that aims to cultivate mathematics thinking among mandarin-speaking children, to examine whether sex-related behavioral differences exist in online settings adopting the coding rules used in Hart's framework [13][19][8].

1.3 Epistemic Network Analysis

Epistemic Network Analysis (ENA) is a quantitative ethnographic technique designed to address questions in learning analytics and model the structure of connections in the dataset. Major assumption of ENA includes: 1) a set of meaningful features, which is defined as *codes*, can be identified systematically in the data; 2) the data has local structures, which are referred to as *conversations*; and 3) the way in which *codes* are connected to each other within the *conversations* is an important feature of the data [27][28][29].

ENA models the connections between *codes* by quantifying the co-occurrence of *codes* within *conversations*, generating a weighted network of co-occurrences and visualizations for each unit of analysis in the data accordingly. Since all the networks of units are analyzed simultaneously, ENA could ideally produce a set of networks that can be compared visually and statistically alike. Such a method has been used to not only analyze learning data, but also in other context where structure of connections in the data is meaningful, such as communications among health care team and gaze coordination during collaborative work [31][1]. Having recognized the unique power of ENA in analyzing connections within the data, this study adopted ENA for exploring the connections of students' behaviors in mathematics classes, and the differences between connection patterns for students of different sex.

1.4 Goals

The present study aims to: 1) examine the existence of sex-related behavioral differences in online math classes in China; 2) explore the connections of students' in-class behaviors and engagement in classroom activities; 3) compare both visually and statistically the structure of connections of mathematics classroom behaviors for students of different sex.

2. METHODS

2.1 Participants

In order to control for the influence of class content and teaching style on students' classroom behavior and engagement, 12 math classes taught by 2 teachers (1 male, 1 female) of the same topic were randomly drawn from all Level 6 mathematical thinking classes of Spark EdTech. Each class consisted of 5 or 6 students of different sex, making up a sample of 64 students (32 male, 32 female). Teachers from both sexes were selected in order to control for the potential interaction effect of students' sex and teacher's sex on students' behavior. The average class duration for Teacher 1 was 49.13 (SD = 2.49) minutes, and the average class duration for Teacher 2 was 45.43 (SD = 0.84) minutes. Since students went through placement exams that determined their math ability before being assigned to different levels of classes, it can be assumed that students of the same level have similar level of mathematics ability. Level 6 class was primarily designed for third-grade students around eight years old. In this sample, students have the average age of 7.46 (SD = 1.63) years old.

2.2 Procedure

Class monitoring videos were viewed and coded by an experienced coder based on the definition of different types of classroom behaviors proposed in Hart's study (1989). Each students' classroom behavior and interactions with teacher was viewed and coded individually, following an event sampling or episodic approach, which has been widely used in the field of developmental psychology [16][18]. Microscopic categories of behaviors were coded in order to demonstrate the initiations and responses of the students and the teacher. When a behavior lasted for more than 20 seconds, such a behavior was coded again in order to indicate the continuity of that behavior. All the codes were organized in the format of adjacent matrix (see Table. 1 for an example) required by Epistemic Network Analysis (ENA), a sample of which can be found below. Then ENA will be applied to the data using the ENA Web Tool (Version 1.7.0) [20].

Student ID	Sex	Teacher ID	social activity	call out	open volunteer	off task	disruptive behavior
001	1	teacher 0	0	1	0	0	0
001	1	teacher 0	0	0	0	1	1
002	0	teacher 1	1	0	0	0	0
002	0	teacher 1	0	0	1	0	0

Table 1. Illustration of Coding Sheet

2.3 Measures

Several subcategories of students' public interaction with teachers were identified in Hart's study [13]. Two sub-categories of public teacher-student interaction which were found to be significantly correlated with students' sex were: *open volunteer interaction*, and *call-out* interaction. Meanwhile, since another category of public teacher-child interaction, direct-no volunteer interaction, is pretty common in online classes, we decided to also include it as a type of behavior to be examined in our study.

An *open volunteer* interaction was coded when the student indicated in some way other than by calling out a desire to respond to a teacher question or to initiate a public interaction with the teacher. A *call-out* interaction was coded when a target student called out the answer to a teacher question before the teacher gave permission for that student to respond. A *direct-no volunteer* interaction was coded when the teacher asked a question and requested that a target student answer who had not indicated in some way a desire to answer the question. The students usually indicated a desire to respond by raising a hand or calling out.

In addition, we combined two types of behaviors that indicated a lack of engagement in mathematics activities in class which were found to be differently correlated with mathematics achievements for boys and girls in a study conducted by Peterson and Fennema [24]. *Off-task behaviors* were defined in this study as behaviors that are irrelevant to class activities. *Social activities* were defined in this study as the engagement in an activity in which the content of the activity involved a social topic, socializing or discussion of personal information or problems. Another category of behaviors – *disruptive behaviors*, which boys and girls differ drastically in the classroom settings was also included in our measure [4][6]. *Disruptive behaviors* were coded in this study when a student was engaged in behaviors that were likely to substantially or repeatedly interfere with the conduct and discipline of the class.

3. DATA ANALYSIS AND RESULTS

3.1 Definition of ENA Elements

In the present study, the *units of Analysis* were defined as all lines of data relative to a single value of student' sex subsetted by student ID. For instance, one unit included all the lines that represented the occurrence of each category of behaviors for one single student.

In our ENA model, the following codes, which corresponded to the aforementioned five categories of classroom behaviors, were included: social_activity, direct_no_volunteer, off_task_behavior, open_volunteer and disruptive_behavior.

Conversations were defined as all lines of data related to a single value of Teacher Name. For instance, one *conversation* consisted of all the lines associated with one of the two teachers.

3.2 Procedure of ENA

The ENA algorithm adopts a moving stanza window to generate a network model for each line in the data, showing how *Codes* in the current line are connected to codes that appear within the recent temporal context [30], defined as 4 lines (each line plus the 3 previous lines) within a given conversation. The corresponding networks are aggregated for all lines for each *unit of analysis* in the model. In this model, we aggregated the resulting networks using a binary summation where the networks for a given line reflect the presence or absence of the co-occurrence of each pair of *codes*.

The networks for all *units of analysis* in the present model were normalized before being subjected to a dimensional reduction, in order to account for the different amounts of coded lines of different *units of analysis* in the data. In terms of dimensional reduction, a singular value decomposition was utilized, which produces orthogonal dimensions that maximize the variance explained by each dimension [2][28][31].

3.3 ENA Model

Networks were visualized using network graphs where nodes correspond to the *codes*, and edges reflect the relative frequency of co-occurrence, or strength of connection, between two *codes.* The result is two coordinated representations for each unit of analysis: 1) a plotted point graph, which represents the location of that unit's network in the low-dimensional projected space, and 2) a weighted network graph. The positions of the nodes in the network graph are fixed and determined by an optimization routine minimizing the difference between the plotted points and their corresponding network centroids. Because of this co-registration of network graphs and projected space, the positions of the network graph nodes—and the connections they define—can be used to interpret the dimensions of the projected space and explain the positions of plotted points in the space. Our model had co-registration correlations of 0.92 (Pearson) and 0.92 (Spearman) for the first dimension and co-registration correlations of 0.97 (Pearson) and 0.97 (Spearman) for the second. These measures indicate that there is a strong goodness of fit between the visualization and the original model according to the rule-of-thumb by Shaffer, Collier & Ruis [28].

Mean networks for boys' and girls' behaviors in online math classes were constructed by averaging the connection weights across individual networks, and were compared using network difference graphs. These graphs are calculated by subtracting the weight of each connection in one network from the corresponding connections in another (See Figure 3 for a comparison ENA Model for student behaviors in online math classes by sex).

According to Figure 3, the network centroids for boys and for girls differ along the x-axis. There is a relatively stronger connection between disruptive behavior and call out behaviors in online math classes for boys compared with girls. In addition, there is a slightly stronger connection between off-task behaviors and disruptive behaviors, and between disruptive behaviors and direct-no volunteer interactions for boys, compared with girls.

4. CONCLUSIONS AND IMPLICATIONS

The present study examined the differences in the structure of connections of classroom behaviors for boys and girls in online mathematics classes in China using Epistemic Network Analysis (ENA). The results indicated a significant difference along the x-axis of the model, suggesting that in our sample, girls were more engaged in social activities and open volunteer interactions with the teacher, while boys exhibited more disruptive behaviors during the class. The difference in off task behavior and call out interaction for boys and girls were not significant. Such a finding is largely consistent with the study conducted by Hart [13], except for we did not find a significant effect of sex on call out interactions. Such an inconsistency might be due to the unique characteristics of online classroom settings, where girls tend to experience higher influence of social presence on their satisfactory level in class, and thus are equally, or even more active in online discussion than boys [32][23].

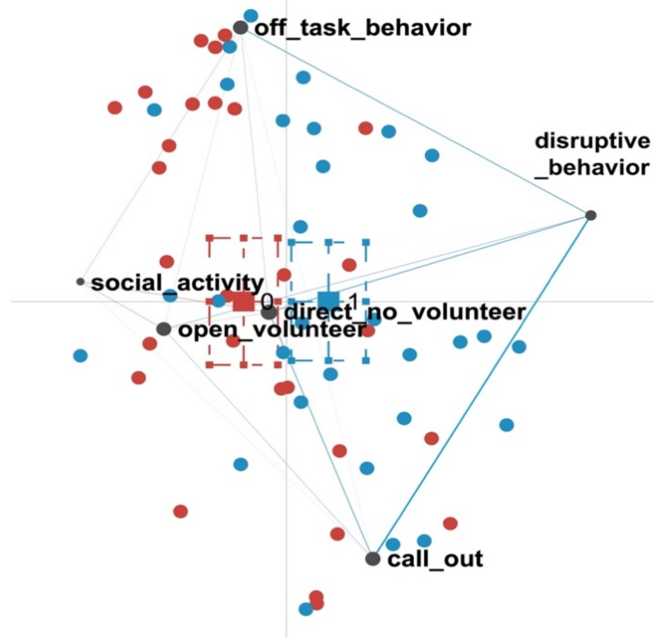

Figure 3. Comparison ENA Model for Student Behavior in Online Math Classes by Sex

*Note: Blue represent boys, red represents girls

Thus, in order to elevate their level of satisfaction in online math classes, girls might be more motivated to engage in interactions with their teachers by calling out their answers to teachers' questions than they would normally do in traditional classrooms. Another possible explanation to this phenomenon is the reward system designed by Spark EdTech, a leading online education technology company in China, for its online mathematical thinking classes, where students could receive "little stars" from their teachers by answering questions and participating in classes. Such a reward system could encourage students to participate in classes, and to become the first to respond to the questions by calling out the answers.

Another conclusion we could reach according to the comparison graph is that there is a relatively stronger connection between disruptive behavior and call-out behavior for boys compared with girls. Such a connection indicates that while boys call out their answers to teachers' questions more often, they are more likely to also become disruptive in class by interrupting teacher's lecture or interaction between other students and teacher. It could be implied that boys are more expressive and active in classes, yet such behaviors could become disruptive if they could not regulate their level of activeness in class or if they disregard class disciplines.

In addition, there is a slightly stronger connection between off-task behavior and disruptive behaviors, and between disruptive behaviors and direct-no volunteer interactions. Such connections indicate that boys are more likely to violate discipline in class and be disengaged in class activities at the same time, and teachers are more likely to call on disruptive boys to answer questions, compared with girls. Such findings were consistent with the findings of research conducted in face-to-face classroom settings, that teacher tended to attend more to boys because they were more likely to exhibit disruptive behaviors in class [8][6]. All the findings mentioned above implied the necessity to recognize the difference in boys' and girls' behavioral patterns in online math classes, and to call for the development of a more gender-sensitive guidance for online teaching, which had been pointed out recently by several researchers [3].

One major limitation of this study is the relatively small sample size. However, since each student's behaviors during a full-length class were coded, we still obtained statistically significant results. At the meantime, due to the time constraint, all the videos were coded by only one coder, which might lead to biased data. The fact that the coder had more than 1000 hours experience of video coding and maintaining an inter-rater reliability of more than 0.9 might, to some extent be able to account for such a limitation. Another limitation of the study arises from the nature of class monitoring videos, which might not always be able to fully capture students' behaviors in class. Scarcely, when students wrote on a notebook or scratch paper, coder was unable to distinguish whether they were taking notes or engaging in off-task behaviors such as sketching. These ambiguous behaviors were not coded, and thus might lead to a slight underrepresentation of students' off-task behaviors.

Overall, the present study is mostly consistent with existing research on sex difference in students' behaviors in traditional in-person classrooms. The novel findings of an insignificant sex-related differences in call-out behaviors could be attributed to the uniqueness of online class settings and the reward system adopted by Spark EdTech. To our knowledge, this study is the first of its kind to employ Epistemic Network Analysis (ENA) to examine the structure of connections of students' classroom behaviors in online math classes in China and conduct a comparison of such connection patterns between boys and girls. Thus, the findings of this study could serve as the first step to examine the relationship between different behavioral patterns in online math classes and math achievement, and to develop a gender-sensitive guidance for online teaching.

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6. REFERENCES

[1] Andrist, S., Collier, W., Gleicher, M., Mutlu, B., & Shaffer, D. (2015). Look together: Analyzing gaze coordination with epistemic network analysis. *Frontiers in Psychology*, 6(1016).

[2] Arastoopour, G., Swiecki, Z., Chesler, N. C., & Shaffer, D. W. (2015). Epistemic Network Analysis as a tool for engineering design assessment. *Presented at the American Society for Engineering Education*, Seattle, WA.

[3] Asterhan, C. S., Schwarz, B. B., & Gil, J. (2012). Small-group, computer- mediated argumentation in middle-school classrooms: The effects of gender and different types of online teacher guidance. *British Journal of Educational Psychology*, 82(3), 375-397.

[4] Beaman, R., Wheldall, K., & Kemp, C. (2006). Differential teacher attention to boys and girls in the classroom. *Educational review*, 58(3), 339-366.

[5] Benbow, C. P., & Stanley, J. C. (1980). Sex differences in mathematical ability: Fact or artifact?. *Science*, *210*(4475), 1262-1264.

[6] Brophy, J. & Good, T. (1974) *Teacher–student relationships: causes and consequences* (New York, Holt, Rinehart & Winston).

[7] Chipman, S. F., Brush, L. R., & Wilson, D. M. (Eds.). (2014). *Women and mathematics: Balancing the equation.* Psychology Press.

[8] Chiu, M. S., & Whitebread, D. (2011). Taiwanese teachers' implementation of a new 'constructivist mathematics curriculum': How cognitive and affective issues are addressed. *International Journal of Educational Development*, 31(2), 196-206.

[9] Downey, D. B., & Vogt Yuan, A. S. (2005). Sex differences in school performance during high school: Puzzling patterns and possible explanations. *Sociological quarterly*, 46(2), 299-321.

[10] Evertson, C. M., Anderson, C. W., Anderson, L. M., & Brophy, J. E. (1980). Relationships between classroom behaviors and student outcomes in junior high mathematics and English classes. *American educational research journal,* 17(1), 43-60.

[11] Fennema, E. (1984). Girls, women, and mathematics. In E. Fennema & M. J. Ayer (Eds.), *Women and education: Equity or equality?* (pp. 137-164). Berkeley, CA: McCutchan

[12] Grieb, H., & Easley, J. (1984). In Steincamp, M. and ML Maehr (Eds.) *Women in Science*; Volume 2: Advances in Motivation and Achievement," A primary school impediment to mathematical equity; can studies in role-dependent socialization." Greenwich, CT.

[13] Hart, L. E. (1989). Classroom processes, sex of student, and confidence in learning mathematics. *Journal for Research in Mathematics Education*, *20*(3), 242-260.

[14] Hargreaves, M., Homer, M., & Swinnerton, B. (2008). A comparison of performance and attitudes in mathematics amongst the 'gifted'. Are boys better at mathematics or do they just think they are?. *Assessment in Education: Principles, Policy & Practice*, 15(1), 19-38.

[15] Hyde, J. S., Fennema, E., & Lamon, S. J. (1990). Gender differences in mathematics performance: a meta-analysis. *Psychological bulletin*, *107*(2), 139.

[16] Kuczynski, L., & Kochanska, G. (1990). Development of children's noncompliance strategies from toddlerhood to age 5. *Developmental Psychology*, 26(3), 398.

[17] Li-Grining, Christine P., Carolina Maldonado-Carreno, Elizabeth Votruba-Drzal, and Kelly Haas. 2010. "Children's Early Approaches to Learning and Academic Trajectories through Fifth Grade." *Developmental Psychology* 46 (5): 1062–77.

[18] Liu, M., Chen, X., Rubin, K. H., Zheng, S., Cui, L., Li, D., ... & Wang, L. (2005). Autonomy-vs. connectedness-oriented parenting behaviours in Chinese and Canadian mothers. *International Journal of Behavioral Development*, *29*(6), 489-495.

[19] Ma, X. (1999). Gender differences in growth in mathematical skills during secondary grades: A growth model analysis. *Alberta journal of educational research*, 45(4).

[20] Marquart, C. L., Hinojosa, C., Swiecki, Z., Eagan, B., & Shaffer, D. W. (2018). Epistemic Network Analysis (Version

1.7.0) [Software]. Available from http://app.epistemicnetwork.org

[21] Neuville, E., & Croizet, J. C. (2007). Can salience of gender identity impair math performance among 7–8 years old girls? The moderating role of task difficulty. *European Journal of Psychology of Education*, 22(3), 307-316.

[22] Park, S. Y. (2005). Student engagement and classroom variables in improving mathematics achievement. *Asia Pacific Education Review*, 6(1), 87-97.

[23] Park, C., & Kim, D. G. (2020). Exploring the Roles of Social Presence and Gender Difference in Online Learning. *Decision Sciences Journal of Innovative Education*, *18*(2), 291-312.

[24] Peterson, P. L., & Fennema, E. (1985). Effective teaching, student engagement in classroom activities, and sex-related differences in learning mathematics. *American Educational Research Journal*, 22(3), 309-335.

[25] Reis, S. M., & Park, S. (2001). Gender differences in high-achieving students in math and science. *Journal for the Education of the Gifted*, *25*(1), 52-73.

[26] Robinson, K., & Mueller, A. S. (2014). Behavioral engagement in learning and math achievement over kindergarten: A contextual analysis. *American Journal of Education*, 120(3), 325-349.

[27] Shaffer, D. W. (2017). *Quantitative ethnography*. Madison, WI: Cathcart Press.

[28] Shaffer, D. W., Collier, W., & Ruis, A. R. (2016). A tutorial on epistemic network analysis: Analyzing the structure of connections in cognitive, social, and interaction data. *Journal of Learning Analytics*, 3(3), 9–45.

[29] Shaffer, D. W., & Ruis, A. R. (2017). Epistemic network analysis: A worked example of theory-based learning analytics. In C. Lang, G. Siemens, A. F. Wise, & D. Gasevic (Eds.), *Handbook of learning analytics* (pp. 175–187). Society for Learning Analytics Research.

[30] Siebert-Evenstone, A., Arastoopour Irgens, G., Collier, W., Swiecki, Z., Ruis, A. R., & Williamson Shaffer, D. (2017). In Search of Conversational Grain Size: Modelling Semantic Structure Using Moving Stanza Windows. *Journal of Learning Analytics*, 4(3), 123–139. https://doi.org/10.18608/jla.2017.43.7

[31] Sullivan, S., Warner-Hillard, C., Eagan, B., Thompson, R. J., Ruis, A. R., Haines, K., ... & Jung, H. S. (2018). Using epistemic network analysis to identify targets for educational interventions in trauma team communication. *Surgery*, 163(4), 938-943.

[32] Tsai, M. J., Liang, J. C., Hou, H. T., & Tsai, C. C. (2015). Males are not as active as females in online discussion: Gender differences in face-to-face and online discussion strategies. *Australasian Journal of Educational Technology*, *31*(3).

[33] You, Z. (2010). Gender differences in mathematics learning. *School Science and Mathematics,* 110(3), 115-118.