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| RESEARCH ARTICLE

Developing Students' Mathematical Communication Skill in Junior High School with Various Level of Mathematics Achievement through Generative Learning Model

Evi Hulukati[1] ✉ Sarson W. Dj. Pomalato[2], Wenny Hulukati[3] and Siti Zakiyah[4]
[124]Universitas Negeri Gorontalo Department of Mathematics, Gorontalo, Indonesia
[3]Universitas Negeri Gorontalo Department of Guidance and Counseling, Gorontalo, Indonesia
Corresponding Author: Evi Hulukati, **E-mail**: evihulukati.ung@gmail.com

| ABSTRACT

Mathematical communication skill was the missing piece of the mathematics education failure puzzle for centuries despite its central role in learning activities. Built on top of other process skills, the skill was the tool to construct a more comprehensive conceptual understanding by learning math from different perspectives, sharpening other cognitive skills, and providing important feedback about students' understanding. This study observed how the students' mathematical communication skill was correlated with the application of the generative learning model and how this correlation was influenced by various level of the school's academic achievement in mathematics. It employed a fractional 2x2-factorial design, careful non-probability sampling combined with simple random sampling to pick 171 students, and a validated and reliable scoring system to measure communication skills. Based on the results, the students' mathematical communication skill significantly correlates with the application of the generative learning model. The use of factorial design revealed that this correlation was more determined by applying the generative learning model, not by the level of schools' or students' mathematics achievement. Teachers should be more optimistic about using generative learning models to improve mathematical communication skills, even in classes with lower mathematics achievement levels.

| KEYWORDS

Mathematical Communication, Generative Learning, Factorial Experiment, Learning Activities, Students' Mathematics Achievement.

| ARTICLE INFORMATION

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1. Introduction

Generative learning theory explains the brain processes comprising the production of meaning or individual knowledge. Generative learning theory suggests that learning occurs when learners are actively and cognitively (mentally) organizing and integrating new information into their knowledge structures in meaningful ways. Therefore, learning is defined by learner-generated relationships. Learning is a sense-making process in which one tries to understand what is presented by actively selecting relevant pieces of presented information, mentally organizing them, and integrating them with other knowledge, we already have (Wilhelm-chapin & Koszalka, 2016; Fiorella & Mayer, 2015).

Mathematics education continues to shift from procedure-focused to this more conceptual-understanding learning. Students are being facilitated to recall prior knowledge and connect it with new knowledge, so they will realize what's new to them and organize this new concept into their memory. This way, students will think further and more profoundly than the previous lesson – lengthen and strengthen their chains of knowledge. This generative learning involves five process skills that amplify each other: reasoning and proof, connections, representations, problem-solving, and communication. The last two skills were built on top of other skills and reflected a more comprehensive ability to incorporate the new concept being learned.

Mathematical communication was an intricate yet simplest way to compass meaningful mathematics learning. As illustrated by Wittrock, the father of generative learning theory, "although a student may not understand sentences spoken to him by his teacher, it is highly likely that a student understands sentences that he generates himself" (Wittrock, 1974). By communicating and sharing their ideas, students will learn to be clear, convincing, and precise in their use of mathematical language. By listening to others' explanations, students gain opportunities to develop their understanding from different perspectives. These multiple perspectives help students to sharpen their thinking and make connections. To ensure such perspectives' effectiveness, teachers must manage this communication process to prevent students from performing meaningless discussions. Students shall be directed to explain their arguments and rationales, not just the procedures or summaries. To do this, the teacher will depend on students' mathematical communication skills to clarify students' understanding, detect misconceptions or ambiguities, conduct refinement or amendment, or give some friendly response to engage students more profoundly in the discussion. Mathematical communication provides a valuable feedback mechanism for teachers to navigate the generative learning process.

Conversely, applying generative learning models proved students' mathematical communication skill was corrigible (Cahyaningrum, Syaifuddin, & Effendi, 2017; Hutapea, 2018; Yulianto, 2018). Despite the increasing trend of research, the underlying mechanism of this particular interaction is yet to be clear. As described previously, mathematical communication is an indispensable part of generative learning. In many instruction designs, it builds the whole process of generative learning. Practicing mathematical communication during a generative learning session significantly sharpens students' communication skills, understanding, and proficiency in the subsequent learning sessions. Assuming this mutual effect, perhaps the main concern is not the underlying mechanism behind such a process but which factors may inhibit or compound the effect.

Intentional learning science (especially instructional science) was a model of complexity theory where the unlimited variation in instructional design and its application meets the complicated nature of the human knowledge system, including mathematics. This produces double uncertainties (Ni & Branch, 2017). Aside from being a practical cousin of constructivism, the generative learning theory also provides a complete perspective on learning activity, making it a second cousin to behaviorism. The theory brings together our understanding of learning processes and the design of external stimuli or instruction (Lee, Lim, & Grabowski, 2007). Stimuli, motivation, attention, self-regulation, and other behavioral processes bring more complexity to generative learning, thus doubling the uncertainty of its outcome. However, in particular abstraction, there must be an optimum degree of generality that we can observe, analyze, and conclude.

With infinite factors involved in improving students' mathematical communication skills through the generative learning model, the need to use fractional factorial design trials emerges. A factorial experiment is an experiment whose design consists of two or more factors, each with discrete possible values or "levels", and whose experimental units take on all possible combinations of these levels across all such factors. Such an experiment allows the investigator to study the effect of each factor on the response variable and the effects of interactions between factors on the response variable. In a fractional factorial design, only an adequately chosen fraction of the treatment combinations required for the complete factorial experiment is selected to be run. The subject of interest here is the decision about which run to make and which to leave out.

Wu and Hamada proposed three principles for selecting which fraction of treatment should be run first. For an interaction to be significant, at least one of its parent factors should be significant first heredity-of-effect principle. These parent factors produce lower-order effects that are more important than higher-order effects hierarchy-of-effect principle, and the number of the relatively essential effects is a relatively small sparsity-of-effect principle (Wu & Hamada, 2009). Thus, to study the effect of the generative learning model in improving students' mathematical communication skills, one must ensure the significance of some basic factors and their interactions before studying their sub-factors and interactions. Branch already identified eight elements in instructional design: student, content, media, teacher, peers, time, goal, and context (Branch, 1999). These entities are simplified into two lower-order factors: student and school, while the school factor is the sum of the last seven entities, including curriculum, teachers' professionalism, scheduling, day-to-day class management, facilities, and the class social environment.

The purpose of the current study was to observe the effect of the generative learning model in improving students' mathematical communication skills in interaction with the student factor and school factor previously described. Using a factorial design, especially to study such basic interactions, would undoubtedly result in the aliasing of effects and difficulties in generalization. Therefore, the main idea behind this study was to provide supporting facts required to establish hypotheses and designs for future observations of more detailed sub-factors and interactions in the generative learning model and students' mathematical communication skills.

2. Methodology

2.1 Design

This study was a class experiment using fractional factorial design to observe how the generative learning model could improve the students' mathematical communication skills in interaction with the student-factor and school factor. The student-factor was measured by the students' mathematical achievement (score) in the last end-of-grade exam. At the same time, the school factor was the average of graduated students' *NEM (Nilai Ebtanas Murni or national exit exam score)* for mathematics at the last exit exam. The population of this study was students in all junior high schools in Gorontalo province of Indonesia. This study used pretest and posttest scores to measure the improvement of students' mathematical communication skills after treatment.

2.2 Sampling

To bring forward the effect of the difference in schools' and students' mathematics achievement, a non-probability sampling must be conducted at the first stage of sampling to select two schools by their mathematics average *NEM*. Two schools were selected *SMPN 2* Gorontalo and *SMPN* Kabila; abbreviated as *SMPN2G* and *SMPNK*) for their highest and lowest achievement, respectively, as the source of four 8th-grade classes (four treatment groups) in this 2x2-factorial trial. Before selecting classes, all students' previous (7th) end-of-grade mathematics scores were collected from both schools. The normality and Levene tests showed the equality of variance on the normally distributed score – taken independently for each school. After averaging the scores by class, the mean difference test for each school also showed no significant difference between classes and within classes. The average score for *SMPN2G* and *SMPNK* were 6.9253 and 6.5863, respectively. Based on these results, a simple random sampling was conducted to pick two classes (HG and HC) from the highly-achieving *SMPN2G*. HG was the experimental class taught with a generative learning model, while HC was the control class taught with a non-generative approach. The same technique was also used to select two classes (LG and LC) from the lowly-achieving *SMPNK*. From the total number of 171 students in the four classes, a simple random sampling was used to pick 30 students from each class to be sub-grouped by their mathematics achievement into "high" and "low" levels of mathematics achievement, 15 students each. Despite this sub-grouping, all 171 students still received the treatment.

2.3 Instruments

This study used two main instruments: lesson plans and a scoring system developed to measure mathematical communication skills. Other instruments are students' worksheets, questionnaire sheets, and questionnaire manuals. Two lesson plans developed for this trial were consistent with the mathematics curriculum for 8th-grade students in Indonesia. Both sets have similar content and materials but are different in learning activities. They consisted of four identical subjects: (1) function and relation, (2) Pythagoras theorem, (3) parallelogram, rhombus, kite, trapezoid, and (4) ratio and proportionality. The first set was for the experimental classes. Therefore, it was fully optimized for a generative learning model. The second set for the control classes was developed to minimize the use of generative learning processes.

This study used a custom scoring system developed by the author to measure mathematical communication skills. The score was calculated using a questionnaire of 10 items reflecting the degree of quality correctness and quantity comprehensiveness of students' communication about their mathematical ideas. Furthermore, the scoring system only evaluated the content, not the psychosocial aspects of communication skills. As each item has a score ranging from 0 to 5, the maximum total score was 50. The proposed version of this questionnaire consisted of 15 items but had been truncated after being validated using Pearson product-moment correlation test. The reliability value was 0.71 or classified as "high" according to the Guildford coefficient of reliability (Kline, 2008). The validation and reliability tests were conducted using Anates® v4.09 (software developed by Karno To and Yudi Wibisono). Earlier, the questionnaire was also reviewed and accepted by a team of validators involving mathematics experts and teachers. The teacher who led the class filled out the questionnaire, and the researcher calculated the score. The test was conducted twice as a pretest and posttest.

2.4 Experiment procedure

Earlier before treatment, a pilot study was conducted in one of the 8th-grade classes in *SMPN* 1 Gorontalo to: (1) test and refine the content and tool to be used in a real experiment, (2) train and select the eligible teachers and observers, (3) study the teachers' problems while delivering the lesson and adjust the class procedure if necessary, and (4) study the students' cognitive and social response including how the mathematical communication skill could be improved, then make some adjustment on the lesson plan or other aspects of the research.

Before starting the treatment, a pretest of mathematical communication skills was carried out on the last mathematics session at each class, just before the next mathematics session involving the treatment agenda. The real treatment consisted of 16 lesson sessions. Four sessions for each class were conducted on different days. The generative learning model in the experimental classes (HG and LG) was conducted with five steps of activities through full discussion: (1) orientation, (2) idea mining and presentation, (3) challenge and reconstruction, (4) application, and (5) recheck and refine. The teachers were responsible for guiding the problem-solving process by recalling and applying the previously acquired mathematical concepts. In the closing phase, the students were asked to recognize the new concepts they had already learned and to share their ideas about how to deal with other similar problems. Meanwhile, the learning model for the control classes (HC and LC) consisted of a slide presentation by the teacher followed by questioning and a discussion phase. The role of the teacher here was to deliver the concept and ensure that the students understood by asking them and answering any questions. Any generative learning processes in the control classes occurred naturally without being forced intentionally through scaffolding, as done in the experimental classes.

The mathematical communication skill measurement was conducted in each class during the last session. A cross-observation between teachers and students was also conducted via additional questionnaires to provide complementary data about teachers' and students' performance, problems, and suggestions during the treatment sessions.

2.5 Data analyses

This study was to observe the effect of an independent variable (the application of the generative learning model as a categorical variable) and two other independent variables (the school's mathematics achievement and the student's mathematics achievement – both are simplified as categorical variables) on a single dependent variable (the improvement in mathematical communication skill as continuous numeric or interval variable). The sample was divided into four analysis groups: highly-achieving students in highly-achieving schools (StHScH), lowly-achieving students in highly-achieving schools (StLScH), highly-achieving students in lowly-achieving schools (StHScL), and lowly-achieving students in lowly-achieving schools (StLScL). Such is to evaluate the effect within the context of its interaction with various combinations of schools' and students' mathematics achievement as the dependent variable was later proved to be normally distributed ($\alpha = 0.05$), the most suitable parametric analysis to test the inter-correlation was the factorial ANOVA. Four ANOVA tests were also done to evaluate the effect on the four analysis groups. All calculation was done using SPSS for Windows version 11.5.

3. **Results**

3.1 Gain scores of the mathematical communication skill

Table 1 provides information regarding the pretest and posttest mean scores of students' mathematical communication skills for each group and the improvements after treatment. Groups with a generative learning model got the most improvement in their mathematical communication skill after the treatment, especially in groups with higher mathematics achievement. The generative learning model improves the mathematical communication skill of the highly-achieving students in highly-achieving schools (StHScH group) up to 18.73 (±1.73) pts (or 152.65% of their pretest score) compared with the lowly-achieving student in lowly-achieving school (StLScL group), which only increased 5.66 (±2.19) pts (or 48.5% of the pretest score).

Table 1. Pretest mean score, posttest mean score and the mean gain percentage of students' mathematical communication ability by groups.

<table>
<tr><th rowspan="2">Gene-rative learning</th><th rowspan="2">School level</th><th rowspan="2">Student level</th><th rowspan="2">N</th><th rowspan="2">Pre-test mean score</th><th rowspan="2">Post-test mean score</th><th colspan="6">Improvement (gain score) in mathematics communication skill</th></tr>
<tr><th>Mean</th><th>Gain %</th><th>Mean</th><th>Gain %</th><th>Mean</th><th>Gain %</th></tr>
<tr><td rowspan="4">Yes</td><td rowspan="2">High (HG)</td><td>High</td><td>15</td><td>12.27</td><td>31.00</td><td>18.73</td><td>152.65</td><td rowspan="2">15.54</td><td rowspan="2">128.39</td><td rowspan="4">13.97</td><td rowspan="4">115.43</td></tr>
<tr><td>Low</td><td>15</td><td>11.93</td><td>24.27</td><td>12.34</td><td>103.44</td></tr>
<tr><td rowspan="2">Low (LG)</td><td>High</td><td>15</td><td>12.53</td><td>26.20</td><td>13.67</td><td>109.10</td><td rowspan="2">12.40</td><td rowspan="2">102.48</td></tr>
<tr><td>Low</td><td>15</td><td>11.67</td><td>22.80</td><td>11.13</td><td>95.37</td></tr>
<tr><td rowspan="4">No</td><td rowspan="2">High (HC)</td><td>High</td><td>15</td><td>12.13</td><td>23.47</td><td>11.34</td><td>93.49</td><td rowspan="2">8.57</td><td rowspan="2">72.23</td><td rowspan="4">8.47</td><td rowspan="4">71.76</td></tr>
<tr><td>Low</td><td>15</td><td>11.60</td><td>17.40</td><td>5.80</td><td>50.00</td></tr>
<tr><td rowspan="2">Low (LC)</td><td>High</td><td>15</td><td>11.80</td><td>22.87</td><td>11.07</td><td>93.81</td><td rowspan="2">8.37</td><td rowspan="2">71.28</td></tr>
<tr><td>Low</td><td>15</td><td>11.67</td><td>17.33</td><td>5.66</td><td>48.50</td></tr>
</table>

By design, the purpose of this study was to observe the improvement of mathematical communication skills by comparing the posttest and pretest scores or evaluating the gain scores. However, there was a common pitfall in computing the difference between pre- and post-test scores. The gain score controls for individual differences in pretest scores were obtained by measuring the posttest score relative to each student's pretest score. Still, the gain score analysis does not control for the differences in pretest scores between the two groups collectively. As happened in this study, there was an enormity of gain scores in the highly-achieving groups that rose twice beyond expectation, which might reflect students' differences in adapting the pretest and posttest technical aspects (or other interacting factors) that cannot be easily avoided. Therefore, to minimize bias, this study used the posttest mean score instead to observe the mathematical communication skill improvement for the next analyses. The posttest score was reliable enough to reflect the latest students' mathematical communication skills because the difference in the effect of various inputs from the three independent factors is still considered.

3.2 The effect of generative learning model on students' posttest mean score

As the Kolmogorov-Smirnov test yielded normally-distributed posttest mean scores and the Levene test to assess the equality of variance also displayed homogenous results across all analysis groups, four tests of ANOVA were used to analyze the effect on those groups (Table 2). The data showed a significant correlation in all but the last group (StLScL). This result suggests that a generative learning model could improve students' mathematical communication skills at almost all levels of schools' or students' mathematics achievement, except for the lowly-achieving students in lowly-achieving schools.

Table 2. ANOVA test results on four analysis groups

Analysis group		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
St_HSc_H	Between Groups	2,745.633	1	2,745.633	53.586	.000
	Within Groups	1,434.667	28	51.238		
	Total	4180.300	29			
St_LSc_H	Between Groups	681.633	1	681.633	13.068	.001
	Within Groups	1,460.533	28	52.162		
	Total	2,142.167	29			
St_HSc_L	Between Groups	672.133	1	672.133	13.228	.001
	Within Groups	142.667	28	50.810		
	Total	2,094.800	29			
St_LSc_L	Between Groups	145.200	1	145.200	2.801	.105
	Within Groups	1,451.600	28	51.843		
	Total	1,596.800	29			

3.3 The factorial effects and interactions on students' posttest mean score

The factorial ANOVA result displayed a significant correlation among the generative learning model, students' level, and schools' level with the students' posttest mean score ($p = 0.05$) (Table 3). The same result was also found in interaction models involving the application of the generative learning model. However, there was no significant correlation in interaction models involving the school's and student's levels.

Table 3. The factorial ANOVA test result

No.	Source	Sum of Squares	df	Mean Square	F	Sig.
1.	**Independent variables**					
	The application of the generative learning model	5,757.356	1	5,757.356	111.678	.000
	School's level	683.511	2	341.756	6.629	.002
	Student's level	1,155.200	1	1,155.200	22.408	.000
2.	**Interactions**					
	The application of the generative learning model and school's level	452.044	2	226.022	4.384	.014
	The application of the generative learning model and student's level	417.089	1	417.089	8.090	.005
	School's level and student's level	64.133	2	32.067	.622	.538
	All variables	73.378	2	36.689	.712	.492
3.	**Within groups**	8,660.933	168	51.553		
	Total	17,263.644	179			

4. Discussion and Conclusion

Using fractional factorial design in social studies, such as learning and teaching research, was very helpful. It was almost impossible to observe the relationship between variables while so many other factors must be considered. If the number of very dominant factors is small or there is only a single dominant factor, the best solution is to focus on those very dominant factors and neglect other insignificant factors. In other words, it is imperative to study the most significant fraction of the full factorial design.

In the current study, the effect of the generative learning model in improving students' mathematical communication skills was evaluated along with two important, lower-order factors in the process of instruction, i.e., the schools' and students' academic achievement in mathematics Such aims to provide a more comprehensive analysis on mathematics education dynamics. The use of four models of interaction in this study was intended to examine how the "school-factor" and "student-factor" might interact with each other and influence the improvement of mathematical communication skills. The school factor was the sum of the school's infrastructures, teachers' professionalism, an engaging learning community, quality assurance, or simply the day-to-day management of class routines. This quality could strongly influence the student factor such as their ability to learn effectively and improve their ability.

The first interaction model (the high-achieving students in high-achieving schools) was the situation in which the talented students found a suitable environment to optimize their ability. On the other hand, the last interaction model (the low-achieving students in low-achieving schools) was the situation in which the low quality of students' achievement might be influenced by the low quality of their school itself. The two other interaction models might reflect the situation in which the school quality failed to transfer significant influence on student quality (to be better or worse). This study proved the effectiveness of the last interaction model (low-quality students in low-quality schools) in limiting students' improvement in mathematical communication skills, despite the significant effect of the generative learning model in improving the skill of the other interaction models.

However, this study also suggests that the effect of the generative learning model was significant enough to improve mathematical communication skills in lowly-achieving schools or for low-achieving students. Because the skill itself could boost the student's conceptual understanding of mathematics, applying the generative learning model could accelerate the improvement in mathematics education in the short or long term, despite the schools' level of mathematics achievement.

5. **Limitations of the Study**

Due to the objective of the study: observing the correlation between students' mathematical communication skills and the application of the generative learning model; various levels of school's academic achievement in mathematics influenced the said correlation, this study was based on a largely qualitative research method. The sample of this study is 30% of 433 teachers in the research site as a population. This study was to observe the effect of an independent variable (the application of the generative learning model as a categorical variable) and two other independent variables (the school's mathematics achievement and the student's mathematics achievement – both are simplified as categorical variables) on a single dependent variable (the improvement in mathematical communication skill as continuous numeric or interval variable). As a result, it was found that there was a common pitfall in computing the difference between pre-and post-test scores. The gain score controls for individual differences in pre-test scores were obtained by measuring the post-test score relative to each student's pre-test score. Moreover, there was an enormity of gain scores in the highly-achieving groups that rose twice beyond expectation, which might reflect students' differences in adapting the pre-test and post-test technical aspects (or other interacting factors) that cannot be easily avoided. It is suggested that a generative learning model could improve students' mathematical communication skills at almost all levels of schools' or students' mathematics achievement, except for the lowly-achieving students in lowly-achieving schools. The same result was also found in interaction models involving the application of the generative learning model. However, there was no significant correlation between interaction models involving the schools and student levels.

6. Future Research

The study's limitations suggest future research issues. A generative learning model could boost the student's conceptual understanding of mathematics. Therefore, the following are some potential future research fields.

- Does the generative learning model affect the overall grade of students?
- What kind of applications positively impact mathematics education?

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