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Confirmatory Factor Analysis of Mathematics Learning Interaction in Google Classroom: A Validation Study at Ciamis Vocational School

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Abstrak
Penelitian ini bertujuan untuk mengidentifikasi indikator yang mempengaruhi keberhasilan interaksi belajar siswa melalui Google Classroom dalam pembelajaran matematika di SMKN 1 Panumbangan. Metode yang digunakan adalah pendekatan kuantitatif dengan analisis faktor konfirmatori (CFA). Instrumen berupa angket tertutup diberikan kepada 85 siswa dari kelas X dan XI program Bisnis Digital dan Pemasaran serta Multimedia. Analisis dilakukan menggunakan SPSS versi 26. Hasil eksplorasi menunjukkan terdapat delapan faktor yang terbentuk: faktor internal dan eksternal, perilaku negatif, self-affirmation, perilaku positif, ketidaktahuan, persepsi terhadap mata pelajaran, lingkungan belajar, dan egois. Enam faktor utama dalam model CFA mampu menjelaskan 68,3% variasi data. Kesimpulannya, interaksi belajar siswa melalui Google Classroom dipengaruhi secara signifikan oleh faktor kesadaran diri dan perilaku positif, perilaku negatif, persepsi kebermanfaatan Google Classroom dalam belajar, egois, internal, dan ketidaktahuan.
Kata Kunci: CFA; Google Classroom; Interaksi Belajar; Matematika; SMK

Abstract
This study aims to identify indicators that influence the success of student learning interactions through Google Classroom in mathematics learning at SMKN 1 Panumbangan. The method employed was a quantitative approach, utilizing confirmatory factor analysis (CFA). The instrument, a closed-ended questionnaire, was administered to 85 students from grades 10 and 11 of the Digital Business and Marketing and Multimedia programs. Analysis was conducted using SPSS version 26. The exploration results revealed eight factors: internal and external factors, negative behavior, self-affirmation, positive behavior, ignorance, perception of the subject, learning environment, and egotism. The six main factors in the CFA model were able to explain 68.3% of the data variation. In conclusion, student learning interactions through Google Classroom are significantly influenced by self-awareness and positive behavior, negative behavior, perceived usefulness of Google Classroom in learning, egotism, internal factors, and ignorance.
Keywords: CFA; Google Classroom; Learning Interaction; Mathematics; SMK

I. INTRODUCTION

All students, including those in Vocational High Schools (SMK), are required to take mathematics. The national curriculum standard says mathematics is an essential part of learning at the vocational high school level. Vocational high schools provide mathematics because it helps students learn the skills and knowledge they need for many jobs and industries. The goal of teaching mathematics in vocational high schools is to help students understand basic math concepts and learn how to use mathematics in the real world (Ozdemir & Onder-Ozdemir, 2017).

The Graduate Competency Standards (Permendikbudristek, 2022) outline what vocational high school students should be able to do after they finish their mathematics courses: (a) having a religious and spiritual disposition that is in line with the teachings of their faith; (b) honoring diversity in society and culture; (c) showing that they can work well with people from different groups; (d) being responsible, taking initiative, designing strategic learning, developing themselves, being adaptable, and being committed to reaching their goals; (e) being cultured, coming up with new ideas, and finding other ways to solve problems; (f) being able to analyze problems, come up with ideas, draw conclusions, and make arguments; (g) being skilled and interested in literacy and engaging with information; (h) using concepts, procedures, facts, and math tools to solve problems related to their job; and (i) becoming an expert in their job to become independent and ready for the workforce (Kemendikbudristek, 2022). SStudents need more hands-on learning related to their job degrees to develop these graduate skills. Students need to learn by interacting with various educational resources and media (Khaled et al., 2014; Wu, 2024).

The COVID-19 pandemic accelerated the adoption of digital platforms in schools, particularly in vocational education where hands-on learning is crucial. Learning Management Systems (LMS) such as Google Classroom became central to remote instruction due to their ease of use and integration with educational tools (Cavus et al., 2021; Habibi et al., 2023). However, challenges remain. In many vocational schools, especially those in underserved areas, internet access and device availability limit the effectiveness of online learning (Dow-Fleisner et al., 2022; Rahiem, 2020) Moreover, teachers and students often underutilize the interactive features of platforms like Google Classroom, which are essential for collaborative and practical learning in vocational contexts (Fahmalatif et al., 2021).

In this study, learning interaction is defined as the dynamic exchange of information, experiences, and responses between learners, instructors, and content. Grounded in Moore (1989) typology, this includes learner–content, learner–instructor, and learner–learner interactions. These forms of interaction are vital in mathematics education to foster conceptual understanding, encourage problem-solving, and maintain student motivation (Dorimana & Uworwabayeho, 2022; Li et al., 2024). Inadequate interaction—especially on digital platforms—can lead to passive learning and hinder educational outcomes.

There are many ways to use media in mathematics classes to help students discuss with each other, their teachers, and learning resources. Using this media can make mathematical concepts easier to understand, resulting in more interesting discussions. Some examples are interactive whiteboards (Önal, 2017), specialized mathematics software (Semenikhina & Drushlyak, 2014), interactive mathematical applications (Berdiyorovna & Uktamovna, 2025), mathematics simulations (Aldalalah et al., 2019), educational videos (Sen, 2022) , mathematics modeling with real-world situations (Kohen & Orenstein, 2021), and Google Classroom (Md. Sari et al., 2024; Okeke et al., 2022).

Initial investigation at SMK Negeri 1 Panumbangan shows that students are unlikely to be interested in mathematics classes held through Google Classroom. Only a few students talk or ask questions in the online forum. On the other hand, teachers have difficulty keeping track of student responses and assessing their participation. This problem shows how important it is to evaluate and clearly define the different types of learning exchanges and the factors that affect them (Ward et al., 2012).

Google Classroom is an excellent tool for learning mathematics because it has many different features that make it easy to work together, share content, and rate assignments. The main reasons for using it in mathematics classes are that it is useful, works well with other Google tools, and can make learning more interactive (Gurevych et al., 2020; Sheelavant, 2020). This platform lets teachers share online learning materials, assignments, and other resources, ensuring all students have equal access to information (Beaumont, 2018). Additionally, Google Classroom allows teachers and students to interact with each other in real-time through discussion and comment features, which helps both groups understand mathematics topics better (Abuzant et al., 2021; Dewi & Afriansyah, 2022). Collaborating on mathematics content creation and compilation is improved by linking it to Google Drive, Docs, and Sheets (Stafford, 2021). The ability of the platform to keep track of student progress, give feedback, and grade mathematical tasks online makes learning more effective (Lai & Hwang, 2016). Additionally, Google Classroom makes remote learning much easier, which is important during the COVID-19 pandemic because it allows learning to continue without being limited by location (Octaberlina & Muslimin, 2020).

Several studies have looked into how Google Classroom can be used in schools, mostly from students' point of view, their satisfaction with learning, and the results of their education (Kumar et al., 2020; Quiño, 2022). Not many studies look at the structure of learning interaction factors in Google Classroom using a strong quantitative method like Confirmatory Factor Analysis (CFA). Also, there is currently no validated standard tool to measure the aspects of Google Classroom-based math learning interactions at the vocational education level (SMK). This means that there is a gap in the literature that needs to be filled.

This study addresses this gap by developing and validating an instrument to measure learning interaction in Google Classroom using the CFA method. CFA is used to test whether the data fit a hypothesized measurement model and to confirm the structure of observed variables (Koyuncu & Kılıç, 2019). Grounded in Vygotsky's social constructivist theory, which views learning as a socially mediated process influenced by interaction and tools (Churcher et al., 2014), this study offers theoretical and practical insights for improving online mathematics instruction.

This research aims to:

1. Identify the underlying factors of learning interaction among vocational high school students in mathematics classes using Google Classroom.
2. Confirm the validity and reliability of a newly developed instrument for measuring these interactions.

By addressing these aims, the study contributes to the theoretical understanding of digital learning interactions and supports the development of more effective and measurable online mathematics learning models in vocational education.

II. Method

This study uses a quantitative method, specifically a multivariate analytic approach. This statistical analysis method is used to look at data that has a lot of parts, such as independent and dependent variables (Swanson & Holton, 2005). This study uses confirmatory factor analysis (CFA) on the learning interaction indicators to do a quantitative analysis. After that, SPSS software version 26 was used to analysis the quantitative data.

This study uses a multi-factor CFA model to suggest that the concept of student learning interaction has more than one independent latent factor, which was found through exploratory factor analysis (EFA). There are different observable indicators for each construct, and it is assumed that the connection between the construct and the indicators is reflective.

This study uses a multi-factor CFA model to suggest that the concept of student learning interaction has more than one independent latent factor, which was found through exploratory factor analysis (EFA). There are different observable indicators for each construct, and it is assumed that the connection between the construct and the indicators is reflective. Hierarchical CFA was not employed because the theoretical framework did not support a second-order latent construct; the three types of interaction (Moore, 1989) are conceptually distinct rather than hierarchical. Additionally, there are many goodness of fit indices that are used to check if the CFA model is right, including the Chi-square (χ^2), the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), the Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMR) (Hair Jr et al., 2010; Mosconi et al., 2008).

The CFA used in this study was conducted with SPSS version 26, which has some problems with showing structural models and reporting overall model fit indices. Because of this, it would be best to use specialised software like AMOS, LISREL, or SmartPLS in future research. These programs are better at estimating parameters and checking how well models fit. This technical problem is an important finding that can be looked into in future studies.

During the odd semester of the 2023/2024 Academic Year, the study included students in grades X and XI at SMKN 1 Panumbangan. The first trial sample came from four classes of students in grade X Digital Business and Marketing, while the second trial sample was made up of students from two classes of grade XI Digital Business and Marketing and two classes of grade XI Multimedia Given that the instrument consists of 35 indicators, the sample size aligns with the minimum recommendation of 5 to 10 respondents per item for Confirmatory Factor Analysis (CFA), as suggested by Brown (2015). Although this sample meets the lower bound for CFA, further validation with a larger and more diverse sample is recommended for future research to enhance generalizability and model robustness.

The instrument for collecting data is a closed questionnaire. We chose this questionnaire because it has a lot of good points. At first, the fact that respondents have to talk to each other does not get in the way, since they only have to choose from the options given. Second, this questionnaire makes it easy and quick to get answers. Third, participants think the questions are easier to understand and choose answers, which makes them more likely to finish the questionnaire. The organised style makes it easier to code and process data quickly. Using a closed questionnaire means that respondents can fill it out on their own, which means that an interviewer is not needed.

Closed questionnaires, on the other hand, have a lot of problems. One problem is that it is hard to get full answers from participants. Also, this questionnaire cannot take into account new ideas from respondents and assumes that researchers know everything there is to know about all possible answers. The questions need to be worded very carefully to cover all relevant options. On the other hand, the answers given may not accurately reflect the true feelings of the respondents because they can only choose from the options that are available. People who answer the question may also be able to figure out the right answer from the choices given.

This research process encompasses several stages, beginning with the creation and expert validation of instruments, followed by data collection by questionnaire distribution, and concluding with data analysis utilising Confirmatory Factor Analysis (CFA). The full analysis technique has been encapsulated in a procedural chart to offer a visual and comprehensive overview of the stages involved.

This study used a research tool to look at how students interacted with each other while learning maths in Google Classroom. The author made the instrument, which has 35 statements that are labelled X1 through X35. These claims cover how students interact with teachers, classmates, themselves, and how they use digital tools in maths class. Each item was mapped to one of three key factors: Learner–Content, Learner–Instructor, and Learner–Learner, which reflect dimensions of student interaction in online learning environments. Table 1 provides example items representing each factor.

Table 1.
Example Items Representing Each Construct of Student Interaction

Factor	Example item
Learner–Content	X9: I understand that in a team, tasks or responsibilities must be divided.
Learner–Instructor	X20: I believe interaction with the teacher gives me the opportunity to ask questions and discuss during math lessons.
Learner–Learner	X13: I believe supporting friends in difficulty can motivate them to continue learning.

Next, each statement is put in the form of a five-point Likert scale, where people can choose one of five answers: strongly disagree (1), disagree (2), undecided (3), agree (4), or strongly agree (5). The scoring system is the opposite for negative statements. This method is based on the Likert scale principle that Joshi et al. (2015) talked about. It lets us measure attitudes, perceptions, and behavioural tendencies in a way that is both measurable and consistent.

The data analysis in this research was done in steps. At first, professionals checked the instrument to make sure that the material was appropriate for the construct being tested. A field trial was also done by sending out questionnaires to a select group of people. We used Cronbach's Alpha to do an initial reliability check on the instrument to see how well it worked on its own. There was a unidimensionality study that had to be done before confirmatory factor analysis (CFA). In the end, the CFA model was looked at to see if the indicators were appropriate for the construct being measured. The fit indices we talked about before are used to evaluate the model, and all of the analyses were done with SPSS software. During data screening, responses with incomplete answers were removed listwise to maintain model integrity. The proportion of missing data was below 5%, and no imputation was deemed necessary, given the sample size and the use of complete case analysis. This ensures that the parameter estimates and model fit assessments are based on reliable and complete data.

III. Result and Discussion

A. Content Validity Index (CVI) Analysis

The Content Validity Index (CVI) method is used to find out how well the items on an instrument represent the ideas being tested (Isaac & Uwaks, 2022). The idea being looked at is how Student Learning Interaction works in math class using Google Classroom. There are two levels of the Content Validity Index (CVI): the Item-level CVI (I-CVI) and the Scale-level CVI (S-CVI). The I-CVI is based on the number of experts who give each item a score of 3 (very relevant) or 4 (extremely relevant). This study used a single evaluator to check the results. All items that scored 4 were given an I-CVI of 1, which means they were very relevant (F. Wang & Sahid, 2024).

A single validator with expertise in Math education and experience in creating and evaluating research tools uses an expert judgment process to check the content validity. We ask validators to rate the relevance of each item on a scale of 1 to 4, with 1 indicating "not relevant," 2 indicating "less relevant," 3 indicating "very relevant," and 4 indicating "extremely relevant". Then, the evaluation results show that all 35 items

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got a score of 4, which means that the validator thought each one was very relevant. The validator also gave editorial suggestions on many things to make the sentence clearer and the instrument easier to read. One suggestion is to change the word "jobdesk" to its Indonesian equivalent and change "enthusiastic" to "spirited" to make it more appropriate for students.

The Content Validity Index (CVI) is a numerical way to measure agreement among validators. It does this by calculating the Item-level CVI (I-CVI) and the Scale-level CVI (S-CVI). There was only one validator in this study, so each item had an I-CVI value of 1. This means that the results reflect the opinion of one person rather than a group. The CVI value is written down as an expert opinion, with a focus on the qualitative substantive validity of the validators' ideas.

The table below shows a summary of the validators' suggestions for changes:

Table 2.
Summary of the Validators' Suggestions

Item number	Item summary	Suggestions/ revisions
2	The significance of interaction	Clarify whether the interaction is academic or social.
9	Dividing up tasks/job desk	Change the term "jobdesk" to Indonesian
14	Not caring about friends who are having a hard time	"Experience" is used instead of "in".
21	Depending on the examination answers, without practicing dishonesty	Get rid of the word "daily".
28	Object if the group has students who are not performing well	"Passion" is used instead of "weak."
35	Excitement when teachers use fun methods	Change "enthusiastic" to "spirited".

The results of this content validation indicate that the instrument is fundamentally in line with the construct being measured and that the validator thinks it is very relevant. The input that was sent in is mostly editorial and has no impact on the item's content. As a result, the instrument is ready to move on to the next step of checking its empirical validity, which will be done through Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Pearson correlation analysis.

B. Instrument Validity Test

The Pearson Product-Moment correlation method was used to do a validity test and make sure that each statement item in the study instrument accurately measures the desired construct. This method looks at how the score of each item relates to the overall score of the instrument (Aletras et al., 2010). The criteria used are based on comparing the r-calculated value to the r-table. The item is real if the r-calculated, denoted as r-c, value is higher than the r-table value. The r-table, denoted as r-t, value at a 5% significance level is 0.213 for 100 students who answered. The following are the results of the validity test for all 35 statement items developed in the research instrument:

Table 3.
Validity Test Result

Item	r-c	Validity	Item	r-c	Validity
X1	0.614	valid	X19	0.505	valid

Item	r-c	Validity	Item	r-c	Validity
X2	0.513	valid	X20	0.696	valid
X3	0.436	valid	X21	0.616	valid
X4	0.434	valid	X22	0.256	valid
X5	0.525	valid	X23	0.752	valid
X6	0.453	valid	X24	0.469	valid
X7	0.646	valid	X25	0.335	valid
X8	0.445	valid	X26	0.718	valid
X9	0.634	valid	X27	0.730	valid
X10	0.677	valid	X28	0.391	valid
X11	0.757	valid	X29	0.379	valid
X12	0.323	valid	X30	0.319	valid
X13	0.713	valid	X31	0.575	valid
X14	0.484	valid	X32	0.575	valid
X15	0.358	valid	X33	0.373	valid
X16	0.711	valid	X34	0.435	valid
X17	0.628	valid	X35	0.683	valid
X18	0.467	valid			

The r-calculated value for all the items in the research instrument was higher than the r-table value, which means that all the items are valid. This means that every question on the student learning interaction questionnaire accurately measures the traits that fit with the theoretical construct created by the researcher.

The r-c values ranged from 0.256 (X22) to 0.757 (X11). The data shows that the quality of the items is mostly the same at a high level of validity, and a lot of the items have a lot of discrimination power (r-c > 0.7), such as X11, X13, X23, X26, and X27. These questions do a good job of defining the idea of learning interaction. They are the main indicators for each factor in the model that will be tested by exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

Items with correlation values close to the minimum threshold, like X22 (r-c = 0.256), are still valid, but we should be careful when interpreting them because the relationship between the item and the construct is not as strong as it is for other items. Even so, no items should be thrown away because all of the r values are higher than the r-t value of 0.213. So, the whole research tool has met the requirements for content validity and preliminary construct validity, and it is ready to collect data for the main study. The fact that this event was valid shows that the item compilation process was done correctly and in line with the rules of psychometric measurement.

C. Instrument Reliability Test

We used Cronbach's Alpha to do a reliability test on the student learning interaction questionnaire to make sure it was consistent inside. This test is very important for checking how consistent and stable the statement items in the questionnaire are when measured multiple times (Bonett & Wright, 2015). We used SPSS version 26 to do the assessment, and the results are shown in the table below:

Table 4.
Results of the Reliability Test for the Learning Interaction Instrument

Aspect	Value
Number of Valid Respondents	85 (100%)
Number of Excluded Cases	0 (0%)
Total Number of Cases	85
Cronbach's Alpha	0.915
Number of Items	35

Note: Listwise deletion was applied based on all variables included in the procedure.

The data processing gave a Cronbach's Alpha value of 0.915, which is much higher than the usual minimum reliability threshold of 0.6 for instruments (Hair Jr et al., 2010). The questionnaire, which has 35 statement items, shows a high level of internal consistency, which means it is a reliable way to measure the idea of student learning interactions. The high reliability rating means that each question on the questionnaire is consistently related to the

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others when measuring the same construct, with little to no interference or inconsistencies between items. This maintains the internal validity of the measurement instruments. Also, all of the data used in the reliability test is valid (N = 85), with no exclusions (excluded = 0). This means that the data collection process was done correctly and there are no incomplete responses, which makes the Cronbach's Alpha value more accurate.

D. Results of Exploratory Factor Analysis

The first step in making the student learning interaction questionnaire was to use Exploratory Factor Analysis (EFA) on the Google Classroom app for math at the vocational school where the research was done. We used a 35-item learning interaction questionnaire with a 5-point Likert scale to gather data. The results showed that EFA found eight factors from a list of 35 items.

Before doing exploratory factor analysis, it is important to test its feasibility to make sure it is good enough for further study. The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity are used to check if the project is possible. The KMO value checks how good the sample is, and Bartlett's Test checks how important the correlation matrix is across items. This is what factor analysis is based on. The next results are from the KMO and Bartlett's Test on the student learning interaction questionnaire data from Google Classroom for math classes at SMKN 1 Panumbangan in Ciamis:

Table 5.
Results of KMO and Bartlett's Test

Test	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO)	0.768
Bartlett's Test of Sphericity:	
Approx. Chi-Square	2201.148
df (degree of freedom)	595
Sig. (p-value)	0.000

The KMO MSA value of 0.768 is greater than 0.5, and the significance value of 0.000 is less than 0.05. This means that the variables are related, and the factor analysis can proceed (Zeynivandnezhad et al., 2019).

Principal Component Analysis (PCA) was used to look at the Total Variance Explained and figure out how many factors could be taken out of the instrument (Jollife & Cadima, 2016). This analysis discovers components with eigenvalues higher than 1, which is what the Kaiser Criterion looks for. The table below shows the first eigenvalues, the percentage of variance that each component explains, and the total percentage of variance.

The table above shows that eight things affect how well students learn in Google Classroom. These things make up 71.366% of the differences in the data. There are other things that make up the other 28.634% that this study overlooked at. Also, the results showed that these eight components had eigenvalues greater than 1 and together explained a large part of the total variance. This means that the level of explained variance was high enough to warrant more analysis.

The Total Variance Explained showed that eight factors could be found that together explained 71.366% of the total variance. Using the Varimax method, a factor rotation was done to make it easier to understand these factors. The goal of factor rotation is to make the loading structure clearer and easier to understand by maximizing the variance of each factor. This makes it easier to see which items have the biggest effect on each factor. The table below shows the factors that were created after rotation, along with their items, factor loadings, eigenvalues, percentage of variance explained, and cumulative percentage.

Table 6.
Rotated Factor Structure

Factor	Item Description	Loading
Internal and external	Interaction with teacher (X1)	0.642
	Interaction with others (X2)	0.685
	Group study (X7)	0.845
	Task distribution in team (X9)	0.677
	Cooperation without self-interest (X10)	0.795
	Benefit of discussion (X11)	0.880
	Support for friends (X13)	0.732
	Self-reflection (X16)	0.774
	Expected outcome from teacher interaction (X20)	0.640
	Honesty (X23)	0.807
	Being a pleasant person (X26)	0.726
	Socializing with anyone (X27)	0.838
Negative behavior	Chatting during class (X4)	0.633
	Pretending not to know (X6)	0.703
	Passive toward friends (X14)	0.888
	Sarcasm toward friends (X18)	0.818
	Honesty is annoying (X24)	0.862
	Letting friends argue (X25)	0.739
	Confidence in self (X21)	0.627
Self-affirmation	Understanding Google Classroom from teacher (X32)	0.748
Positive behavior	Not interrupting others (X29)	0.850
	Not accusing friends unfairly (X30)	0.866
Ignorance	Unaware of Google Classroom (X33)	0.733
Subject importance	Importance of math (X34)	0.875
Learning environment	Conducive classroom (X19)	0.715
Selfishness	Selfishness (X12)	0.696

Factor rotation showed that there were eight different factors. This shows that students use Google Classroom in a lot of different ways to talk to each other. The first factor, "internal and external factors," accounted for 33.398% of the variance (eigenvalue = 11.689). It included things like being honest, open to new people, working with teachers and classmates, studying in groups, and working together. Factor 2, which was the negative behavior factor, accounted for 13.349% of the variance (eigenvalue = 4.672). It included things like talking in class, acting like you cannot comprehend anything, being passive, using sarcasm, getting annoyed with honesty, and letting friends fight. Factor 3, which is the self-affirmation factor, accounted for 5.727% of the variance (eigenvalue = 2.005). It included things like trusting yourself and learning how to use Google Classroom from your teacher. Factor 4, which was the positive behavior factor, made up 4.819% of the variance (eigenvalue = 1.687). It included not interrupting or making false accusations against other people. The fifth factor, "ignorance," explained 4.340% of the variance (eigenvalue = 1.519) and was based on not knowing about Google

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Classroom. Factor 6, which was the subject importance factor, explained 3.560% of the variance (eigenvalue = 1.246) and included how important math is. Factor 7, which was the learning environment factor, explained 3.229% of the variance (eigenvalue = 1.130). It was about having a good classroom environment. The last factor, Factor 8, was called the selfishness factor. It explained 2.945% of the variance (eigenvalue = 1.031) and showed selfish behavior. These eight factors made up 71.366% of the total variance, which shows how complicated student interactions are because of personal, social, and environmental factors.

E. Results of Confirmatory Factor Analysis

The student learning interaction questionnaire for math classes at SMKN 1 Panumbangan was then re-evaluated on different samples and analyzed using Confirmatory Factor Analysis (CFA). CFA is used to check how consistent indicators are when they are grouped by latent variables or constructs (Marsh et al., 2014). The following research tools are the results of exploratory factor analysis:

Table 7.
Statements and Notations

Statement	Notation
I think that talking to teachers can help me feel more confident about learning.	X1
I understand how important it is to talk to other people.	X2
I know that studying with others is important for learning maths.	X3
I know that a team should divide up its work.	X4
I will work with anyone, no matter what our differences are.	X5
Talking about things helps me learn better.	X6
Helping friends who are having a hard time can make them want to learn again.	X7
I know my weaknesses and work to improve myself.	X8
Talking to teachers gives you chances to ask questions and talk about things.	X9
Being honest with my friends and teachers makes me a better person.	X10
When I talk to other people, I try to be nice.	X11
I talk to people of all social classes.	X12
I tell my friends to talk during class.	X13
When my friends have problems, I act like I am clueless.	X14
When my friends are in trouble, I tend to be passive and do nothing.	X15
I directly mock friends who make mistakes.	X16
I know that being honest is the most annoying thing for me.	X17
I avoid becoming involved when friends are fighting.	X18
I trust my own work on math tests without cheating.	X19
My teacher taught me how to use Google Classroom.	X20
I know that no one has the right to interrupt other people.	X21
I know it is inappropriate to blame friends.	X22
I have not heard of or used Google Classroom to learn.	X23
I know that maths is important for learning how to solve problems.	X24
I know that a supportive classroom affects how well I can focus.	X25
When my team disagrees with my ideas, I disagree with it.	X26

The CFA findings were assessed using the following goodness of fit criteria: CFI and TLI values over 0.90 signify a strong model fit; RMSEA values below 0.08 show a low approximation error; and SRMR values under 0.08 reflect a minimal standard residual (Hair Jr et al., 2010).

We used factor analysis and SPSS version 26 to test the learning interaction tool at SMKN 1 Panumbangan to see if it was valid and reliable. The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy had a value of 0.833 (>0.50) and a significance level of 0.000 (<0.05), which means that the sample was good enough for further analysis. We used the Anti-Image Correlation matrix to check for reliability. All items had values above 0.5, which met the Measure of Sampling Adequacy (MSA) standards. The communalities results showed values between 0.415 and 0.843, indicating that most of the items had sufficient common variance to be included in the analysis; moreover, although a sample size of 100 is considered the minimum for factor analysis, the relatively high communalities in this study (most above 0.4 and many above 0.6) suggest that the extracted factors are stable and valid (Costello & Osborne, 2005; Maccallum et al., 1999).

The Total Variance Explained analysis found six factors with eigenvalues greater than 1 that, when combined, explained 68.297% of the total variance in the data. The first factor explained 33.035% of the variance, which was the biggest share. This means that it was the most important factor in describing the underlying structure of learning interaction. The second factor made up 15.292% of the variance, and the third factor made up 6.536%. The fourth and fifth factors explained 4.928% and 4.616% of the variance, respectively, while the sixth factor explained 3.891%. The other factors that were not included in this analysis accounted for 31.703% of the variance. This means that the six factors identified account for a large part of the statistically significant variation, but there may be other factors that affect learning interaction that were not included or measured in this study.

With a cut-off loading value above 0.5, the rotated component matrix using Varimax rotation with Kaiser normalization showed a clearer distribution of variables. Based on the results, Factor 1 was called "Awareness and Positive Behavior." It included things like group learning (X3), dividing up tasks (X4), working together (X5), talking about things that are good (X6), making friends with anyone (X12), not interrupting others (X21), and not blaming friends (X22). "Negative Behavior," or Factor 2, included things like talking during class (X13), pretending not to know about friends' problems (X14), being passive (X15), making fun of friends (X16), finding it annoying to tell the truth (X17), and ignoring problems (X18). Factor 3, "Usefulness," included talking to teachers (X1), what students expected from talking to teachers (X9), being honest (X10), and how important math is (X24). "Egoism" was the name of Factor 4, and it was based on selfishness (X26). "Internal Factors" was the fifth factor. It included things like helping friends (X7), thinking about yourself (X8), and being a nice person (X11). Lastly, Factor 6, "Ignorance," included not knowing about Google Classroom (X23).

The standardized factor loadings for all retained items in the CFA model are presented in Table 8. These loadings indicate the strength of the relationship between each observed variable and its corresponding latent factor, providing empirical support for the construct validity of the instrument.

Table 8.
Factor Loadings for Retained Items in the CFA Model

Factor	Item Description	Loading
Awareness and Positive Behavior	Group study (X3)	0.626
	Task distribution in team (X4)	0.659
	working together (X5)	0.792
	talking about things that are good (X6)	0.802
	making friends with anyone (X12)	0.612
	not interrupting others (X21)	0.743
	not blaming friends (X22)	0.780
Negative behavior	Chatting during class (X13)	0.778
	pretending not to know about friends' problems (X14)	0.778
	Passive toward friends (X15)	0.856
	Sarcasm toward friends (X16)	0.604
	Honesty is annoying (X17)	0.839
	ignoring problems (X18)	0.816
Usefulness	Interaction with teacher (X1)	0.767
	Expected outcome from teacher interaction (X9)	0.798
	Honesty (X10)	0.676
	Importance of math (X24)	0.679
Egoism	Selfishness (X26)	0.808
Internal	Support for friends (X7)	0.587
	Self-reflection (X8)	0.572
	Being a pleasant person (X11)	0.586
Ignorance	Unaware of Google Classroom (X23)	0.767

The negative conduct factor is the only one that always matches up with its construct variables when compared to the results of exploratory component analysis. One reason to do confirmatory factor analysis (CFA) is to see if the current factors still match the variables that make them up (Goni et al., 2020; Santor et al., 2011).

F. Discussion

The findings of this research show that the student learning interaction tool for math classes at SMKN 1 Panumbangan using Google Classroom is valid, reliable, and covers all the ways that students interact with each other. The CVI approach showed that the content was valid, the Pearson correlation analysis showed that the empirical validity was good, and the reliability analysis showed that the Cronbach's Alpha value was 0.915, which means that the items were very consistent with each other. The results were even stronger when exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were used together. EFA first found eight factors that accounted for 71.366% of the variance. Then CFA refined and confirmed six main factors that accounted for 68.297% of the total variance, showing that the model was strong and well-structured.

The steps of validation and factor extraction show how the results were found in a systematic and empirical way. The KMO and Bartlett tests showed that the sample was good enough and the data was good for factor analysis. Eigenvalues greater than 1 and communalities above acceptable levels were used to extract factors. This made sure that the factors that were extracted really represented the underlying constructs. Using Varimax rotation made the factor loadings clearer and helped put items into groups that made sense. This further proved that the instrument was structurally valid.

Looking at these results, it seems that student learning interaction has a lot of different parts that are all connected. Awareness and Positive Behavior, the most important factor, shows how important it is to do things like learn in groups, work together, be respectful, be open-minded, and stay away from behaviors that are disruptive. These behaviors are very important for creating a productive and helpful learning environment, especially in online and blended learning settings (Buchs & Butera, 2015; Geletu, 2022). The fact that Negative Behavior has become a separate factor shows how harmful passive attitudes, sarcasm, resistance to honesty, and avoiding conflict resolution can be for learning and group dynamics. This finding is consistent with studies that associate negative peer interaction with reduced social presence and diminished learning motivation (Azmat & Ahmad, 2022; Kasperski & Blau, 2023).

However, it is essential to acknowledge that these negative behaviors may not exclusively represent student dispositions but may also be influenced by cultural norms or pedagogical methodologies. For instance, reluctance to articulate dissent or challenges in self-regulation may emerge in educational settings that prioritize hierarchy, conformity, or examination-focused pedagogy. Previous cross-cultural studies indicate that students' conduct in group contexts is frequently influenced by implicit cultural norms (Shi & Tan, 2020), which educators must take into account when analyzing interaction patterns.

The Usefulness factor shows how important it is for students to feel that math is relevant and that teachers support them. It also shows that when students have positive feelings about math and their interactions with teachers, they are more likely to be active participants. Therefore, how useful people think something is is a big factor in whether or not they will use and adopt technology-based learning environments (Kirkwood, 2014). Likewise, Egoism and Internal Factors examine individual characteristics that may obstruct or facilitate collaborative learning. These dimensions resonate with the Self-Determination Theory framework, particularly the focus on autonomy, competence, and relatedness as indicators of engagement (C. K. J. Wang et al., 2019). The Ignorance factor, which means not knowing how to use Google Classroom, shows an important part of being ready for technology. It supports a study that says optimism, innovativeness, discomfort, and insecurity are the main things that affect whether or not someone will use technology (Álvarez-Marín et al., 2023).

These results support and build on what we already know about how people learn and interact with each other. In the past, studies have always stressed how important it is for students to have good social skills and be able to work together to improve their engagement and learning outcomes (Buchs & Butera, 2015; Geletu, 2022; Malik et al., 2022). The results support the previous study, which says that encouraging interactions that are collaborative and socially meaningful improves cognitive and social outcomes in learning that uses technology (Chen et al., 2018).

Also, finding Internal Factors fits a study that says that autonomy, competence, and relatedness are important for motivating

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learners to engage meaningfully (C. K. J. Wang et al., 2019). Adding technological literacy as a separate factor to traditional interaction models is a big step forward because it recognizes how important digital competence is for getting students involved, which is an area that is becoming more well-known but is still not fully explored.

The refined six-factor model makes a big theoretical contribution by bringing together behavioral, social, and technological aspects into a single framework. This model not only makes it easier to understand how complicated student learning interactions are, but it also gives useful advice on how to make educational policies and interventions. The focus on Ignorance as a key factor shows how important it is to include digital literacy training in school curricula so that students can fully participate in and benefit from online learning environments. At the same time, encouraging good social and internal traits can help make learning spaces that are welcoming and interesting for everyone.

In short, this study gives us a strong, empirically validated tool that captures the many different ways that students learn from each other. This study adds to our understanding of how online and hybrid learning work by providing a useful tool for measuring learning and a new way of thinking about it. It does this by using strict validation methods, advanced factor analysis, and a combination of modern learning theories. The proposed model is a starting point for future research and practice that aims to improve student engagement, the quality of interactions, and learning outcomes in educational settings that use technology.

IV. CONCLUSION

This study shows that the student learning interaction tool for math classes at SMKN 1 Panumbangan through Google Classroom is valid, reliable, and can fully describe the many different ways that students learn from each other. The strict validation process, which includes content validity, empirical validity, and high internal consistency (Cronbach's Alpha = 0.915), makes sure that each item accurately measures the intended construct. The factor analysis found six main factors that explained 68.297% of the total variance: Awareness and Positive Behavior, Negative Behavior, Usefulness, Egoism, Internal Factors, and Ignorance. This shows how complex and rich the patterns of student interaction are in online learning environments.

The rise of these factors shows how social, behavioral, and technological factors all work together to shape learning experiences. The fact that positive behaviors and perceived usefulness are more common shows how important supportive and collaborative practices are for increasing engagement and motivation. By identifying Ignorance as a separate factor, a new theoretical perspective emerges that incorporates technological readiness into the understanding of learning interaction. This is in line with recent trends that see digital literacy as a key part of academic success.

These results not only help us reach the initial objective of creating a strong measurement tool, but they also add to the bigger picture by providing a unified model of how people learn together. This model encourages teachers and policymakers to think about more than just social and behavioral skills when making plans for online learning. They should also think about how important digital skills and each student's mental readiness are. The study therefore gives us new ideas about how to set up and support interactions in hybrid and digital learning environments to improve learning outcomes.

Nonetheless, this study has its limitations. The sample's relative homogeneity, derived from a singular educational context, constrains the generalizability of the results. Moreover, employing a solitary expert validator in the content validation phase may result in bias when assessing item relevance. These limitations indicate that subsequent research should evaluate the instrument in a broader range of educational environments and cultural contexts to improve external validity.

Furthermore, to gain a deeper comprehension of the dynamic characteristics of student interaction, it is advisable for researchers to undertake longitudinal studies to monitor the evolution of interaction patterns over time. Qualitative follow-up studies, including interviews or classroom observations, may yield deeper insights into the personal, cultural, and pedagogical factors that affect student engagement in digital learning environments. Using the tool in more subjects besides math would show that it is useful and make it more useful in a wider range of situations.

In summary, this study presents a comprehensive instrument and a conceptual framework for examining student interaction in technology-mediated education, establishing a basis for ongoing research and practice in the development of inclusive and effective learning environments.

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