AGENT BEHAVIOR COLLABORATIVE STRATEGY IN COCOA AGROINDUSTRY IN CENTRAL JAVA, INDONESIA

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ABSTRACT

Objective: This study aims to influence the behavior of agro-industry actors in meeting the demand for cocoa beans in Batang Regency, Central Java, Indonesia.

Methods: From a similar synthesis of literature, 38 indicators of collaborative behavior were produced which were used to create a questionnaire, and the data was collected by directly observing cocoa agro-industry actors—farmers, village collectors, sub-district collectors, large collectors, and cocoa factories. Partial Least Square (PLS) is used in data processing to identify collaborative behavior and indicators that influence behavior, and the Fuzzy Analytical Hierarchy Process (FAHP) is used for weighting.

Results: The PLS results explain that the behavior of "trust" greatly influences communication behavior. That is, communication goes well when the agro-industry actor's trust system is high. "Information-sharing" behavior has a large impact on collaboration and "collaborative" behavior has a large impact on "continuous improvement". FAHP results obtained weighting values, and the order of priority shows that behaviors with the highest weighting values are trust between members of the supply chain, continuous communication, information sharing, value relationships, collaboration, and continuous improvement. In this results, each of these things needs to be considered for the smooth flow of distribution at the microscopic level in supporting the performance improvement of the cocoa agro-industry, and for other agro-industry.

Keywords: supply chain, improve performance, PLS, FAHP, cacao.
Estratégia colaborativa de comportamento do agente na agroindústria do cacau em Central Java, Indonésia

Resumo

Objetivo: Este estudo tem como objetivo influenciar o comportamento dos atores da agroindústria em atender à demanda por grãos de cacau na Regência de Batang, Java Central, Indonésia.

Métodos: A partir de uma síntese similar da literatura, 38 indicadores de comportamento colaborativo foram produzidos, que foram usados para criar um questionário, e os dados foram coletados observando diretamente os atores da agroindústria do cacau - agricultores, colecionadores de vilas, colecionadores de sub-distritos, grandes colecionadores e fábricas de cacau. O Parcial Least Square (PLS) é usado no processamento de dados para identificar comportamento colaborativo e indicadores que influenciam o comportamento, e o Fuzzy Analytical Hierarchy Process (FAHP) é usado para ponderação.

Resultados: Os resultados do PLS explicam que o comportamento de "confiança" influencia grandemente o comportamento de comunicação. Ou seja, a comunicação vai bem quando o sistema de confiança do ator da agroindústria está alto. O comportamento de "compartilhamento de informações" tem um grande impacto na colaboração, e o comportamento de "colaboração" tem um grande impacto no "aperfeiçoamento contínuo". Os resultados da FAHP obtiveram valores de ponderação, e a ordem de prioridade mostra que os comportamentos com os valores de ponderação mais altos são confiança entre os membros da cadeia de suprimentos, comunicação contínua, compartilhamento de informações, relações de valor, colaboração e melhoria contínua. Nesses resultados, cada uma dessas coisas precisa ser considerada para o fluxo suave de distribuição ao nível microscópico no apoio à melhoria de desempenho da agroindústria de cacau e de outras agroindústrias.

Palavras-chave: cadeia de suprimentos, melhorar o desempenho, PLS, FAHP, cacau.

1 INTRODUCTION

The agricultural sector is transforming in recent years (Shamah-Levy, Mundo-Rosas, Flores-De la Vega, & Luiselli-Fernández, 2017) The supply chain in the agricultural sector has many uncertainties that can hinder the performance of the actors involved throughout the supply chain. (Lezoche, Hernandez, Díaz, Panetto, & Kacprzyk, 2020), including the lack of coordination between the behavior of commodity supply chain actors (Deans, Ros-Tonen, & Derkyi, 2018).

The problem of coordination along the supply chain requires new coordination methods and governance approaches among supply chain actors. To address coordination issues along the supply chain, collaboration among heterogeneous stakeholders is essential to collectively achieve a competitive advantage for better environmental, business, and societal outcomes (Ammirato, Felicetti, Ferrara, Rasò, & Violi, 2021). One of the advantages of collaboration is to improve performance directly. A high level of collaboration leads to improved performance (Grekov, Calantone, Bremmers,
Trienekens, & Omta, 2016). To achieve this, the key factors that shape the characteristics and performance of collaboration, namely collaboration behavior factors, must first be identified, which can help supply chain stakeholders to examine and manage collaboration systems for improvement (Dania, Xing, & Amer, 2018). However, this research has not specifically detailed which collaboration factors can affect the performance of farmers.

Ineffective cooperation systems for sustainable agri-food supply chain management have been linked to ten important behavioral characteristics, including joint effort, sharing activities, collaboration values, adaptation, trust, commitment, strength, continuous improvement, coordination, and stability (Dania et al., 2018). Future research in agri-food supply chain collaboration can be guided by the study's findings, which also make it easier to model and assess collaboration performance.

This study's goals were to identify farmer behavior in farming operations, farmer productivity, and the association between farmer behavior and farm output (Sarirahayu & Aprianingsih, 2018). This study employed a straightforward random sample technique, and the research region was purposefully chosen.

According to a study, efficient supply chain collaboration boosts mutual profits and corporate performance (Cao & Zhang, 2011). For the supply chain to function effectively, businesses must work together to establish business synergies, compete with other chains, and create a win-win situation. This study has identified a set of seven interrelated elements, notably information sharing, goal congruence, decision synchronization, incentive alignment, resource sharing, collaborative communication, and shared knowledge generation, that make up effective supply chain collaboration, and according to (Utomo et al., 2023) are also in the organization.

Information technology, trust, and commitment have a good and significant impact on supply chain performance (Wu, Chuang, & Hsu, 2014). The findings of this study may have consequences on how crucial it is for management to uphold confidence, commitment, and the usage of information technology in the supply chain system constantly.

The results of a systematic review of the literature led to the identification of ten topics grouped into four main ones related to collaboration in sustainable food supply chains, specifically network structure, actor behavior, supply chain processes, supporting tools, methods, and technology of food sector network structure. The agri-food sector
analyzes and designs sustainable collaboration networks (Ammirato et al., 2021). These findings offer a comprehensive and cogent picture of organizational structures, supporting technology, and sustainability in the agri-food industry. In the agri-food industry, collaborative networks can be a useful tool for achieving agricultural sustainable development and environmental sustainability goals (Khoruzhy, Katkov, Katkova, Romanova, & Dzhikiya, 2023).

Because Indonesia is in a tropical area that is suitable for farming and has different societies in terms of attitudes, behavior, and culture, the research question is what collaborative behavior must be considered in the Indonesian agro-industry to increase interaction between agro-industry actors so to improve supply chain performance. The collaborative behavior formulation was created using the Partial Least Square (PLS) and Fuzzy Analytical Hierarchy Process (FAHP) methods. PLS’s primary function is model design (Bayaga, 2021), but it can also be used to test or develop a theory (for prediction purposes) by analyzing the relationship between variables using the SmartPLS software and the FAHP method, which produces a weight order of actor behaviors.

2 MATERIAL AND METHOD

The stages of this study's execution are shown in Figure 2, which is represented in the following flow chart and explained.

2.1 DETERMINATION OF COCOA AGRO-INDUSTRY ACTORS IN BATANG REGENCY, CENTRAL JAVA, INDONESIA

Participants in the cocoa farming industry include actors. The actors chosen are based on those who are involved in the Batang district’s cocoa supply chain.

The actors in the cocoa supply chain start with the production of cacao and continue with harvesting, distribution, and processing facilities. Only those involved in the supply chain of cocoa from production to processing facilities are actors in this judgment. This study examines five actors: farmers, village traders, sub-district dealers, wholesalers, and cocoa factories.

2.2 BEHAVIORS OF COCOA AGRO-INDUSTRY ACTORS IN BATANG REGENCY, CENTRAL JAVA, INDONESIA

According to (Dania et al., 2018), 31 actor behaviors have an impact on the supply chain, which is a key factor in the sustainability of the agriculture system. The first to sixth order of 31 behavioral characteristics that affect supply chain sustainability was used to determine the behavior of agricultural actors for this study (Dania et al., 2018).
Fig 2. Research flow chart

Source: Results of Analysis by the authors
However, it was discovered that there were six behavioral characteristics after being confirmed by specialists in the field of cocoa agro-industries, including members of farmer groups, the Batang Regency Agriculture Office, and factories. The top three behaviors are communication, sharing of information, and trust. Collaboration, connection value, and continual improvement are three more behavioral variables that have been adjusted to the circumstances in the Batang district now.

2.3 FACTORS (INDICATORS) AFFECTING BEHAVIOR

The two main influences on human behavior are behavioral and non-behavioral elements (Daudi, Hauge, & Thoben, 2016). Furthermore, three factors—predisposing, enabling, and reinforcement—combine to determine or shape the behavior itself (West et al., 2012). Knowledge, attitudes, beliefs, values, and more are predisposing factors (Simbolon & Sianipar, 2018). The physical environment, and the presence or absence of work safety facilities or facilities, such as the availability of auxiliary equipment, training, and so on, are examples of enabling factors (Thibaud, Chi, Zhou, & Piramuthu, 2018). In (Brinkerhoff & Wetterberg, 2016) a few examples of reinforcement factors are laws, rules, and monitoring.

In (Riggio, 2015; Schermerhorn Jr, Bachrach, & Wright, 2020; Schermerhorn Jr, Osborn, Uhl-Bien, & Hunt, 2011) listed 38 elements that affect behavior as influencing factors for actors. Credibility, dependability, intimacy (familiarity) elements, self-orientation (self-goal), ability, and integrity all play a role in influencing trust. Source status, sender credibility and trust, communication skills, technique and language use, listening abilities, and the degree of proximity between communicators and communicants all affect communication. Technology competence, communication, organizational size, credibility, and pertinent information are all aspects that affect information sharing. The shared objective of the relationship, as well as a person's personality, degree of intimacy, level of trust, information-sharing, and communication, all affect the worth of a relationship.
A networked structure, dedication to a common goal, mutual trust, access to power, factors that distribute accountability and responsibility, information exchange, and resource availability are all aspects that influence collaboration. Table 1 shows the aspects that affect continuous improvement, including job description, job specification, job evaluation, adaptation, performance standards, relationship values, collaboration, and communication. Factors Affecting Actor’s Behaviors produce 38 indicators.

### Table 1. Factors Affecting Actor’s Behaviors

<table>
<thead>
<tr>
<th>No</th>
<th>Actor Behavior Code</th>
<th>Behavior Reference</th>
<th>Factors Affecting Behaviour</th>
<th>Number of Indicator</th>
<th>Indicators Affecting Behaviour</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Trust</td>
<td>A</td>
<td>Credibility, Reliability, Intimacy, Self Orientation, Ability, Integrity</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Communication</td>
<td>B</td>
<td>Source State, Sender Credibility, Communication Skills, Terminal Use, Listener Skills, Level of Closeness of Communicator and Communicant</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Information Sharing</td>
<td>C</td>
<td>Technology Mastery, Communication, Organization Size, Credibility, Relevance of Information</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Relationship Value</td>
<td>D</td>
<td>Dana et al., 2018, Common Goal of Relationship, Personal Characteristic, Personal Closeness</td>
<td>6</td>
<td>(Riggio 2013) and (Schermerhorn 2013)</td>
</tr>
<tr>
<td>5</td>
<td>Collaboration</td>
<td>E</td>
<td>Participants, Access to Authority, Distributive Accountability (Responsibility), Information Sharing, Access to resources</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Continuous Improvement</td>
<td>F</td>
<td>Job Description, Job Specification, Job Evaluation, Performance Criteria, Adaptation, Relationship Value, Collaboration, Communication</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td>38</td>
</tr>
</tbody>
</table>

Source: Results of Analysis by the authors

### 2.4 PROCESS STARTING FROM CREATING A BEHAVIORAL COLLABORATION QUESTIONNAIRE

The purpose of the collaboration behavior questionnaire is to assess the importance of a variable that influences both actor behavior and collaborative behavior. This is evident from the relationship's value in the SmartPLS program. The behavioral collaboration questionnaire's characteristics have been changed to reflect the actual field circumstances; however, the fundamental variables are still taken from the literature (Riggio & Tan, 2013; Schermerhorn Jr et al., 2020; Schermerhorn Jr et al., 2011) The findings of the behavioral collaboration questionnaire will be the input for the smartPLS software, which employs a Likert scale depending on the amount of relevance from 1 to 6.

### 2.5 DETERMINATION OF RESPONDENTS

The characteristics of the 80 research respondents for the pairwise comparison
questionnaire included 52 people (65%) as farmers, 12 people (15%) as village collectors, 8 people (10%) as sub-district collectors, 1 person (1.25%) as big collectors, 3 people (3.75%) from factories, and 4 people (5%) from the Batang district agricultural office. Respondents in the pairwise comparison questionnaire had the following characteristics: two farmers, one representative from village collectors, subdistrict collectors, large collectors, intermediary factories, and the Batang district agricultural office.

2.6 PROCESS OF DISSEMINATING BEHAVIORAL COLLABORATION QUESTIONNAIRE

The distribution of questionnaires through the purposive sampling method, specifically taking samples based on sample criteria, to actors directly involved in cocoa agro-industry in the Batang district. The distribution takes place during Focus Group Discussions (FGD) at the factory, as well as through direct observations in the field. The distribution of questionnaires to farmers is done with assistance to anticipate errors when filling out the forms. The behavioral collaboration questionnaire results are fed into the smartPLS software, and the resulting structural equation model will provide an overview of the relationship between endogenous (dependent) and exogenous (independent) latent variables, followed by making specifications of the model of the relationship between latent variables and their indicators, whether they are reflexive or not. The path diagram is then created to explain the pattern of relationships between latent variables and their indicators so that by visualizing the relationship between indicators and their constructs, as well as the relationship between constructs, the model can be seen more comprehensively. Variables are characteristics of behavior, whereas indicators are factors that influence behavior.

2.7 PARTIAL LEAST SQUARE (PLS)

For significant goal dimensions like behavioral intention and user behavior, the PLS-SEM calculates the path model with latent variables and their interactions to uncover critical success drivers and sources of competitive advantage (Sarstedt, Hair Jr, Cheah, Becker, & Ringle, 2019) The inner model (structural model) and the outside model (measurement model) are both evaluated by the PLS method (Hair Jr, Sarstedt, Hopkins, & Kuppelwieser, 2014).

The Evaluation of the Measurement Model and the Structural Model are the two
PLS evaluations (Shmueli et al., 2019). The Composite Reliability (ρc) score is utilized in the measurement evaluation to assess the consistency of the indicator block. A value of Composite Reliability (ρc) greater than 0.6 is advised (Drews, Czycholl, Junge, & Krieter, 2018). Based on the relationship between item/indicator scores and construct scores, convergent validity is observed. If the individual reflective measure and the intended measurement construct correlate greater than 0.7, that is a high correlation (Franke & Sarstedt, 2019; Purwanto, 2021).

Discriminant The cross-loading between the indicators and their conceptions reveals the indicator's validity. The latent construct predicts the size of their block more accurately than the other block sizes if the construct's correlation with the indicator is higher than the size of the other constructs(Sarstedt et al., 2019).

In the structural model evaluation, the measurement index, specifically the determinant, is tested to determine the structural model's quality. The coefficient is used to assess the model's or the independent variable's capacity to account for the variation in the data on the dependent variable. In (Hussain, Fangwei, Siddiqi, Ali, & Shabbir, 2018), path-Coefficient, T-Statistic, Predictive Relevance, and Model Fit tests are also used to evaluate the structural model to assess its quality.

### 2.7.1 Convert Path Diagram to Equation

The equations of the outer model and the inner model are included in the system of equations. The measurement model, also known as the outer model, aims to measure the dimensions that comprise a factor. It is a model that represents pre-existing hypotheses, specifically the relationship between indicators and factors, and is evaluated using confirmatory factor analysis (CFA). The structural model, also known as the inner relationship A structural model, is based on the substantive theory that describes the relationship between latent variables. This relationship describes the relationship between the independent variable and the dependent variable. Path analysis was used to examine this relationship pattern (Hagger, Chan, Prostogerou, & Chatzisarantis, 2016). The magnitude of the influence of exogenous variables on endogenous variables will be calculated using the structural model.

### 2.7.2 Parameter Estimation

The least squares method is used to estimate parameters in PLS. Iteration is used
to carry out the calculation process, with iterations stopping when they reach a convergent condition. PLS parameter estimation consists of three steps: 1) Weight estimation is used to calculate weights or scores for latent variables. 2) Path estimation is used to connect latent variables (path coefficients) to their indicators, namely the estimated loading factor, which is the outer model coefficient, and 3) For latent indicators and variables, estimated average and location parameters (regression constant values).

The PLS algorithm is used for estimation, which occurs in three stages. The first stage of PLS estimation consists of a simple regression iteration procedure or multiple regression that considers the structural relationship/inner model, measurement model/external model, and weight relationship estimation. The set of weights estimation results is used to calculate the latent variable score, which is a linear combination of the indicator variables (Hair et al., 2019). After obtaining the estimated latent variable scores, the second and third steps involve estimating the structural model (inner model) and the coefficients of each measurement model (outer model).

2.7.3 Measurement Model Evaluation

The loading factor, Average Variance Extracted (AVE), Fornell-Larcker criterion, cross-loading, composite reliability, and Cronbach alpha are all methods for evaluating the measurement model or the outer model. The method aims to test the model's validity and reliability, and the results are then compared to the standard provisions in the literature.

2.7.4 Structural Model Evaluation

The model evaluation value results if the data's conclusions are valid and reliable, the model created is analyzed to see the results of the measurement evaluation. This is a model evaluation step. The evaluation model analyzes each variable's relationship, yielding the value of the influence of the relationship between variables on other variables. The structural model is evaluated in stages, including the R-Square value, the path coefficient (Path Coefficient), T-Statistics, Predictive Relevance, and Model Fit.

2.8 FUZZY ANALYTICAL HIERARCHY PROCESS (FAHP)

The Analytical Hierarchy Process (AHP) approach and fuzzy logic are combined to create the FAHP. The objective is to address the AHP method's shortcomings, namely
issues with more arbitrary criteria. The triangular fuzzy number (TFN), which is utilized in the fuzzification process by the FAHP method, is a fuzzy ratio. The lowest value (l), the middle value (m), and the highest value (h) are the three membership functions that make up TFN (u). The goal of employing the FAHP approach is to reduce responder subjectivity by finding a solution from a multi-criteria or complex problem into a hierarchy such that weighting is produced to assess the extent of each actor's behavior's influence on performance. The steps in completing the FAHP method are as (Noor et al., 2017).

2.8.1 Create a Hierarchy of Actors

The hierarchical formulation of actors' collaborative behavior to improve cocoa agro-industry performance in Batang Regency, Central Java, Indonesia, is related to the research objectives, cocoa agro-industry actors, each actor's behavior, and indicators or factors that influence behavior.

Figure 3. Hierarchical Structure of Actor Collaborative Behavior Formulation to Improve Cocoa Agro-industry Performance in Batang Regency

Source: Results of Analysis by the authors
The first level is the goal, which contains the research objectives. The actor who becomes the actor in achieving the goal is the second level. The third level is each actor's behavior, and the fourth level is an indicator that influences behavior. As shown in Figure 3.

2.8.2 Determination and Creation of a Questionnaire, Making a Pairwise Comparison Questionnaire

The FAHP pairwise comparison questionnaire is a questionnaire designed to determine the importance of each behavior. By comparing the behavior of each actor, a pairwise comparison questionnaire was created to determine the weight of the influence of each behavior (behavior). The Analytical Hierarchy Process (AHP) principles are used to create the pairwise comparison questionnaire, and the resulting output is a comparison matrix. A paired comparison scale was used for the rating scale. The FAHP method takes the results of the paired comparison questionnaire as input and outputs the ranking and priority weight of each behavior.

2.8.3 Questionnaire Distribution

The FAHP pairwise comparison questionnaire was distributed using the purposive sampling method, which involves selecting samples based on predefined criteria. The actors who are directly involved in cocoa agro-industry in the Batang district are the criteria. The distribution occurs during Focus Group Discussions (FGD) at the intermediary factory as well as field observations.

2.8.4 Recapitulation of the Behavior of Cocoa Agro-Industry Actors, and Calculating Geometric Mean

The recapitulation data of the pairwise comparison questionnaire results is the recapitulation data of the results of the behavior of cocoa agro-industry actors. Recapitulation is useful for making comparison matrices simpler. When the value of the questionnaire is calculated for more than one respondent, a geometric average calculation is performed, which is useful for determining the overall value of the number of respondents who completed the questionnaire.
2.8.5 Calculates Column Normalization Values and Calculates Row Normalization Values and Weights

The geometric mean calculation yields a comparison matrix of actor behavior. The value obtained by each column in the comparison matrix is added together and used as the divisor value in the row normalization calculation. For row normalization, the calculated value is calculated by dividing each column by the total number of values for each column. The process is repeated by adding up each row until the total number of rows equals the number of actor behaviors used. The value of row normalization as input for vector weight calculation is calculated by dividing the value of the number of rows by the total number of row values.

2.8.6 Data Consistency Test

The goal of consistency testing on each actor's behavior weight values is to determine the consistency of the data provided by respondents when completing the pairwise comparison questionnaire. When the data obtained from each respondent is less than or equal to 10%, the questionnaire will be repeated; if the consistency value exceeds the allowable consistency limit, the questionnaire will be repeated.

2.8.7 Transformation of AHP Scale Into TFN Scale

The results of the questionnaire used to determine the weight value on the AHP scale were fuzzified and transformed into a Triangular Fuzzy Number (TFN) scale. TFN scale Each respondent's data that has been converted into the TFN scale is calculated on the geometric average to obtain an assessment of the entire respondent.

2.8.8 Calculation of Fuzzy Synthetic Extent

To obtain the fuzzy number value for each element, the results of the transformed comparison values are combined with the overall comparison value between the behavior of each actor. The Fuzzy Synthetic Extent (FSE) calculation seeks to obtain the expansion of an object to obtain the extent analysis value M, which is represented as l, m, and n. The first step is to use the equation to calculate the values of l, m, and n. Furthermore, the values of l, m, and u are obtained by adding the corresponding l, m, and u values for each behavior. The second step is to compare the behavior calculations and calculate the weight value.
2.8.9 Calculating Local Weights or Defuzzification

The FSE results are compared, and the smallest value is chosen as the local weight value. The local weight value is normalized for each actor's behavior by dividing the vector weight element by the sum of the vector weights. The number of normalized weights will be one, and the local weight value will produce a priority order of behavior with the greatest to the smallest level of influence.

3 RESULTS

3.1 GEOGRAPHICAL LOCATION AND ADMINISTRATIVE AREA

Indonesia is an agricultural country where most of the population is farmers (Syuaib, 2015). The agricultural sector has a very important role in the economy in Indonesia, this can be seen in the contribution of the agricultural sector to the Gross Domestic Product (GDP) which is around 12.72 percent in 2019 (Nurhabib & Seminar, 2022). Agriculture is one of the sectors that can encourage the nation's economic conditions during the COVID-19 pandemic (Nurhabib & Seminar, 2022). Since the economic crisis occurred, the agricultural sector has become the last sector to survive in any condition (Nurhabib & Seminar, 2022). Agriculture is one sector that is very dominant in people's income in Indonesia because most Indonesians work as farmers (Duffy et al., 2021).

Fig 4. Research Location in Batang Regency

Source: Created Based On Google Map 2023
Batang Regency in Central Java, Indonesia, is one of the island's cocoa-producing areas (Ediwirman, 2022). According to data from the Central Java Province statistical center, Batang Regency produced 350 tons of cacao beans in 2018, 264.13 tons in 2019, and 209.01 tons in 2020, with an area of 479.81 hectares in 2018, 514.23 hectares in 2019, and 410.28 hectares in 2020. Batang Regency has potential in the cocoa industry based on the amount of existing cacao production. In addition to its potential, the performance of cocoa agro-industry in Batang Regency is currently not optimal due to issues such as a lack of coordination between the behavior of cocoa supply chain actors (Deans et al., 2018).

Batang Regency is one of the regencies in Central Java, located on Java Island's northern coast (Putri, Buchori, & Handayani, 2023). Batang Regency stretches from the coast to the highlands nearing the Dieng area and is located 93 kilometers from the provincial capital of Central Java (Adam, 2020). Batang Regency is situated between 006°51'46" and 007º11'47" south latitude and 109º40'19" and 110º03'06" east longitude. Batang Regency shares regional boundaries with Pekalongan Regency and Pekalongan City to the west, Wonosobo and Banjarangare regencies to the south, Kendal districts to the east, and the Java Sea to the north.

Wonotunggal, Bandar, Blado, Reban, Bawang, Tersono, Gringsing, Limpung, Banyuputih, Subah, Pecalungan, Tulis, Kandeman, Batang, and Warungasem are the administrative sub-districts of Batang Regency in 2019. Batang Regency has a total area of 78,86488.16 Ha. Subah District has the largest area, accounting for 11% of the total area of Batang Regency, while Warungasem District has the smallest, accounting for 3% of the total area of Batang Regency. The Batang Regency is divided into 248 villages and sub-districts, 936 hamlets, 3,685 neighborhood associations, and 1,009 citizen associations, according to village and sub-district divisions.

3.2 RESULTS OF DATA PROCESSING METHOD PARTIAL LEAST SQUARE (PLS)

3.2.1 Composite Reliability and Loading Factor Value

The Average Variance Extracted (AVE) value is the value that each variable owns, and the value must be greater than 0.5 to be declared valid. The AVE test results show that the values for all variables are greater than 0.5, indicating that the data is valid.
Table 3 Composite Reliability Value

<table>
<thead>
<tr>
<th>Variabel</th>
<th>Average Variance Extracted (AVE)</th>
<th>Composite Reliability (ρc)</th>
<th>Cronbach’s Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trust</td>
<td>0.612</td>
<td>0.826</td>
<td>0.684</td>
</tr>
<tr>
<td>Communication</td>
<td>0.545</td>
<td>0.857</td>
<td>0.795</td>
</tr>
<tr>
<td>Information Sharing</td>
<td>0.586</td>
<td>0.850</td>
<td>0.764</td>
</tr>
<tr>
<td>Relationship Value</td>
<td>0.656</td>
<td>0.884</td>
<td>0.823</td>
</tr>
<tr>
<td>Collaboration</td>
<td>0.626</td>
<td>0.834</td>
<td>0.703</td>
</tr>
<tr>
<td>Continuous Improvement</td>
<td>0.640</td>
<td>0.899</td>
<td>0.859</td>
</tr>
</tbody>
</table>

Source: Results of Analysis by the authors

Testing the composite reliability value is a value used to determine the accepted limit value for the level of composition reliability; if the value is greater than 0.7, the assumption of composite reliability has been met. The SmartPLS software produces the composite reliability value. The composite reliability test results for all variables are greater than 0.7, indicating that the data is reliable and meets the composite reliability assumption.

Testing the value of Cronbach’s alpha, if a value of 0.60 indicates that all variables are declared reliable. The SmartPLS software produces Cronbach's alpha value. The results are obtained with valid information based on the results of testing the composite reliability and Cronbach's alpha values because the values obtained met the standard.

Table 3 shows that the Composite Reliability (CR) value for each variable is greater than 0.7. This demonstrates that each variable used in this study has a very high level of reliability. Table 4 declares that all variables are valid.

Table 4 Load factor value

<table>
<thead>
<tr>
<th>No</th>
<th>Code</th>
<th>Loading</th>
<th>Evaluation</th>
</tr>
</thead>
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<tr>
<td>1</td>
<td>A4</td>
<td>0.787</td>
<td>Valid</td>
</tr>
<tr>
<td>2</td>
<td>A5</td>
<td>0.802</td>
<td>Valid</td>
</tr>
<tr>
<td>3</td>
<td>A6</td>
<td>0.759</td>
<td>Valid</td>
</tr>
<tr>
<td>4</td>
<td>B2</td>
<td>0.712</td>
<td>Valid</td>
</tr>
<tr>
<td>5</td>
<td>B3</td>
<td>0.755</td>
<td>Valid</td>
</tr>
<tr>
<td>6</td>
<td>B4</td>
<td>0.714</td>
<td>Valid</td>
</tr>
<tr>
<td>7</td>
<td>B5</td>
<td>0.736</td>
<td>Valid</td>
</tr>
<tr>
<td>8</td>
<td>B6</td>
<td>0.772</td>
<td>Valid</td>
</tr>
</tbody>
</table>

Source: Results of Analysis by the authors
3.2.2 Path-Coefficient and T-Statistic Value

Based on Table 6 a path-coefficient value greater than 0 and a t-statistic value greater than the t-table (> 1.96).

<table>
<thead>
<tr>
<th>Variavel</th>
<th>Path Coefficients value</th>
<th>T - Statistics value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trust - Communication</td>
<td>0.604</td>
<td>7.215</td>
</tr>
<tr>
<td>Trust - Information Sharing</td>
<td>0.552</td>
<td>6.368</td>
</tr>
<tr>
<td>Trust - Relationship Value</td>
<td>0.191</td>
<td>1.356</td>
</tr>
<tr>
<td>Communication - Relationship Value</td>
<td>0.148</td>
<td>1.139</td>
</tr>
<tr>
<td>Communication - Continuous Improvement</td>
<td>0.056</td>
<td>0.457</td>
</tr>
<tr>
<td>Information Sharing - Collaboration</td>
<td>0.579</td>
<td>6.697</td>
</tr>
<tr>
<td>Information Sharing - Relationship Value</td>
<td>0.512</td>
<td>4.203</td>
</tr>
<tr>
<td>Relationship Value - Continuous Improvement</td>
<td>0.312</td>
<td>2.322</td>
</tr>
<tr>
<td>Collaboration - Continuous Improvement</td>
<td>0.464</td>
<td>0.422</td>
</tr>
</tbody>
</table>

Source: Results of Analysis by the authors

This means that the relationship between each of these variables has a positive and significant influence on the performance of the cocoa agro-industry supply chain, implying that the stronger the variable (behavior) relationship among supply chain members, the better the supply chain performance.

3.2.3 Model Using Smart PLS

The smartPLS software is fed data from a behavioral collaboration questionnaire.
The smartPLS software produces two outputs: the indicator value that has the greatest influence on a variable, namely the behavior of agro-industry actors, and collaboration behavior. Figure 4 depicts the preliminary PLS modeling before evaluation.

According to the modeling in Figure 4, some indicators measure each variable with the number of indicators that have not been evaluated. The modeling arrows describe the relationship between each variable and each indicator. The arrows that exit the behavior variable are exogenous variables that indicate influence, while the arrows that enter the behavior variable are endogenous variables that indicate influence. Because these variables affect or are influenced by each other, the nodes in the modeling turn blue.

Figure 5 shows a reduction in the number of indicators because of the validity test on the evaluation of the outer model. Several indicators are missing or omitted because of the loading factor value because the omitted indicators are those whose statements are invalid with a loading value less than 0.7. For example, in the trust variable, there were initially six indicators influencing trust, but after evaluation, the indicators influencing trust were reduced to three. Some indicators are omitted, specifically those with values
less than 0.7 and incorrect information.

Figure 5 PLS modeling after evaluation

Source: Results of Analysis by the authors

3.3 RESULTS OF DATA PROCESSING FAHP METHOD

Making comparison matrices, calculating column and row normalization values, testing data consistency, transforming the AHP scale into TFN, calculating FSE, and calculating local weights/defuzzification are all part of data processing with the FAHP method. Table 8 shows the results of data processing using the FAHP method, including weight values and priority order.

According to the results in Table 8, the most important behavior is trust. These findings suggest that the trust variable has a significant impact on supply chain performance and should be considered. Increased trust among supply chain actors can result in improved supply chain performance (Singh & Teng, 2016). According to (Adobor & McMullen, 2018), trust among supply chain members is an important element that must exist and grow in a supply chain system.
Table 7 Behavior Comparison Recapitulation

<table>
<thead>
<tr>
<th>Behaviour Comparison</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>A &amp; B</td>
<td>0.111</td>
<td>0.111</td>
<td>5.000</td>
<td>3.000</td>
<td>3.000</td>
<td>7.000</td>
<td>9.000</td>
</tr>
<tr>
<td>A &amp; C</td>
<td>0.111</td>
<td>0.143</td>
<td>5.000</td>
<td>3.000</td>
<td>3.000</td>
<td>7.000</td>
<td>7.000</td>
</tr>
<tr>
<td>A &amp; D</td>
<td>0.111</td>
<td>0.200</td>
<td>6.000</td>
<td>3.000</td>
<td>3.000</td>
<td>7.000</td>
<td>7.000</td>
</tr>
<tr>
<td>A &amp; E</td>
<td>0.111</td>
<td>0.333</td>
<td>4.000</td>
<td>3.000</td>
<td>7.000</td>
<td>5.000</td>
<td>7.000</td>
</tr>
<tr>
<td>A &amp; F</td>
<td>0.111</td>
<td>0.333</td>
<td>5.000</td>
<td>3.000</td>
<td>7.000</td>
<td>3.000</td>
<td>5.000</td>
</tr>
<tr>
<td>B &amp; C</td>
<td>1.000</td>
<td>0.333</td>
<td>5.000</td>
<td>3.000</td>
<td>3.000</td>
<td>7.000</td>
<td>5.000</td>
</tr>
<tr>
<td>B &amp; D</td>
<td>1.000</td>
<td>0.200</td>
<td>4.000</td>
<td>3.000</td>
<td>5.000</td>
<td>5.000</td>
<td>5.000</td>
</tr>
<tr>
<td>B &amp; E</td>
<td>1.000</td>
<td>0.333</td>
<td>5.000</td>
<td>3.000</td>
<td>7.000</td>
<td>2.000</td>
<td>5.000</td>
</tr>
<tr>
<td>B &amp; F</td>
<td>1.000</td>
<td>0.143</td>
<td>5.000</td>
<td>3.000</td>
<td>7.000</td>
<td>7.000</td>
<td>5.000</td>
</tr>
<tr>
<td>C &amp; D</td>
<td>0.167</td>
<td>0.333</td>
<td>5.000</td>
<td>3.000</td>
<td>5.000</td>
<td>7.000</td>
<td>3.000</td>
</tr>
<tr>
<td>C &amp; E</td>
<td>0.167</td>
<td>0.333</td>
<td>7.000</td>
<td>3.000</td>
<td>7.000</td>
<td>5.000</td>
<td>3.000</td>
</tr>
<tr>
<td>C &amp; F</td>
<td>0.167</td>
<td>0.333</td>
<td>5.000</td>
<td>3.000</td>
<td>7.000</td>
<td>5.000</td>
<td>3.000</td>
</tr>
<tr>
<td>D &amp; E</td>
<td>0.167</td>
<td>1.000</td>
<td>5.000</td>
<td>3.000</td>
<td>7.000</td>
<td>5.000</td>
<td>3.000</td>
</tr>
<tr>
<td>D &amp; F</td>
<td>0.167</td>
<td>0.333</td>
<td>6.000</td>
<td>3.000</td>
<td>7.000</td>
<td>5.000</td>
<td>3.000</td>
</tr>
<tr>
<td>E &amp; F</td>
<td>0.167</td>
<td>1.000</td>
<td>6.000</td>
<td>3.000</td>
<td>7.000</td>
<td>7.000</td>
<td>3.000</td>
</tr>
</tbody>
</table>

A = Trust
B = Communication
C = Information Sharing
D = Relationship Value
E = Collaboration
F = Continuous Improvement

Source: Results of Analysis by the authors

Table 8 Weighting Priority Behavior Values FAHP Method

<table>
<thead>
<tr>
<th>Behavior of Cocoa Agribusiness Actor</th>
<th>Global Weight</th>
<th>Priority/Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trust</td>
<td>0.206</td>
<td>1</td>
</tr>
<tr>
<td>Communication</td>
<td>0.197</td>
<td>2</td>
</tr>
<tr>
<td>Information Sharing</td>
<td>0.181</td>
<td>3</td>
</tr>
<tr>
<td>Relationship Value</td>
<td>0.163</td>
<td>4</td>
</tr>
<tr>
<td>Collaboration</td>
<td>0.141</td>
<td>5</td>
</tr>
<tr>
<td>Continuous Improvement</td>
<td>0.111</td>
<td>6</td>
</tr>
</tbody>
</table>

Source: Results of Analysis by the authors

4 DISCUSSION

In PLS analysis, the goodness of fit structural model in the form of predictive-relevance value, the model is said to be fit if it is supported by empirical data. which is shown in Table 9.
The predictive-relevance value only applies to endogenous variables, indicating that the value for each variable is greater than zero. That is, the communication variable can explain the phenomenon of supply chain performance by 17.1%, the information sharing variable by 16.2%, the relationship value variable by 34.8%, the collaboration variable by 18.4%, and the continuous improvement variable by 34%. This model is said to have a high predictive value.

The path-coefficient and t-statistic values of the relationship between trust and communication variables, trust-information sharing, information sharing-collaboration, information sharing-relationship value, and relationship value-continuous improvement are greater than zero and greater than t-table (>1.96), respectively. This means that the relationship between each of these variables has a positive and significant influence on the performance of the cocoa agro-industry supply chain, which means that the stronger the relationship between supply chain members, the better the supply chain performance.

Table 8 shows the results of data processing using the FAHP method, including weight values and priority order. As a result, the behavior with the most weight is trust. These findings suggest that the trust variable has a significant impact on supply chain performance and should be considered. Trust is defined as one party's desire to be able to rely on another party who has a high level of trust; the party believes that the trusted party will act in a way that benefits both parties. Increased trust among supply chain actors can result in improved supply chain performance. The findings of this study are consistent with the findings of (Capaldo & Giannoccaro, 2015; Singh & Teng, 2016) that trust has a significant impact on supply chain performance. This finding, (Capaldo & Giannoccaro, 2015; de Almeida, Marins, Salgado, Santos, & da Silva, 2015; Qu & Yang, 2015) stated that trust among supply chain members is an important element that must exist and grow in a supply chain system.

Communication is the second most important priority. The transmission of information from one party to another is referred to as communication(Velentzas &
 Broni, 2014). The sustainable activities in the cocoa agro-industry partnership system include the distribution of cocoa from farmers to intermediary factories. Every actor requires good communication so that no miscommunication can result in losses for one or all parties involved during implementation. Communication has a significant and positive impact on performance (Ratten, 2018). Good communication will lead to improved supply chain performance (Cuevas-Vargas, Parga-Montoya, & Hernández-Castorena, 2020).

The third priority is information sharing or sharing of information. Information is essential in a partnership or agro-industry system at the strategic, tactical, and operational levels to optimize the performance of each actor or party involved. To reduce the risk of misunderstanding and miscommunication, emphasize the sharing or exchanging of relevant, complete, accurate, and current information. The findings of this study are supported by research (Şahin & Topal, 2019), which claims that information sharing improves performance. This means that when information is shared smoothly from upstream to downstream, performance improves, reducing production bottlenecks or the accumulation of goods in the agro-industry supply chain system.

The fourth priority is the value of the relationship. The closeness value of each agro-industry actor is explained by the relationship value. The higher the value, the greater the closeness value, indicating that the actors have a high level of trust and a very close relationship. There has been a strong sense of connection between each actor, so the partnership system will work well and its effect on achieving a goal will become easier. The stronger the bonds between actors, the better their performance.

Collaboration is the fifth top priority. The characteristics that must be inherent in a partnership to increase the value of co-creation in the supply chain are referred to as collaboration value. Collaboration begins with dedication. Commitment has a significant impact on supply chain performance, implying that greater commitment among supply chain members can lead to improved supply chain performance. This study’s findings confirm and support (Capaldo & Giannoccaro, 2015) that strong growing commitment leads to improved supply chain performance. Conversely, when actor collaboration is not carried out properly, the impact on actor performance is reduced because a partner requires cooperation to achieve a common goal.

The sixth and final priority is continuous improvement. Continuous improvement is a broad process and capability for improving the performance of all participants. This
encourages each actor to maximize their ability to achieve and perform at their best in a partnership. Each actor must identify and develop the factors that need to be improved to excel in the supply chain. This enhancement involves all elements of the supply chain and necessitates greater collaboration among actors. According to the study's findings (Butler, Szwejczewski, & Sweeney, 2018), continuous improvement has a positive impact on performance. Suboptimal improvements will stymie the success of supply chain collaborations both upstream and downstream, so it is necessary to develop supply chains that can increase the economy (Severo & De Guimarães, 2022).

5 CONCLUSION

The path-coefficient and t-statistic values of the relationship between trust and communication variables, trust-information sharing, information sharing-collaboration, information sharing-relationship value, and relationship value-continuous improvement, are greater than 0 and greater than 1.96, respectively. This means that the relationship between each of these variables has a positive and significant influence on the performance of the cocoa agro-industry supply chain, implying that the stronger the variable relationship among supply chain members, the better the supply chain performance. The combined behavior of each actor is expected to yield positive results for improving supply chain performance.

Trust is the most important behavior. These findings indicate that trust has a significant impact on supply chain performance and that it should be considered. Improved transportation distribution and supply chain performance can result from increased trust among supply chain actors. Trust among supply chain members is an important component of the supply chain system that must exist and grow. The following priorities are communication, information sharing, value relationships, collaboration, and continuous improvement. Each of these behaviors must be considered to assist efforts to improve distribution transportation and agro-industry performance.

The level of trust among farmers is very important in facilitating effective communication and information transfer within the cocoa farming community. Trust plays an important role in fostering strong relationships between cocoa farmers. To build and maintain trust, farmers need to have proficient communication competencies, which include expertise, knowledge, skills and experience. The practice of sharing honest and transparent judgments further strengthens the foundation of trust. In addition, having
familiarity between farmers is essential to ensure smooth communication. Adopting a two-way communication model enhances the climate conducive to the effective exchange of information. Evaluation of the level of trust in farmer groups involves assessing mutual trust among members, members' trust in their group, and trust in external parties. Trust between farmers arises from open and interactive communication, which is strengthened through various actions, including sharing information from meetings, offering and accepting assistance, and attending farmer group meetings on time. The feeling of comfort and kinship between members plays an important role in strengthening the bonds of trust and fostering a sense of kinship in the cocoa farming community.

In this study, each actor is assumed to have the same collaboration behavior, so in future studies, the collaboration behavior of each actor will be investigated. By incorporating a collaborative behavior component, the research can be continued by creating a microscopic distribution transport model in agro-industry cacao or in other commodities.

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REFERENCES


