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The Influence of Socioeconomic Factors on Postharvest Losses of Fish in Small-scale Fisheries in East Java Province

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ABSTRACT

This study aims to analyze the influence of environment, experience, education, temperature, work hour, age, fishermen group, access internet, and government aid on post-harvest fish losses. The sample of this study was taken from Banyuwangi district consisting of Muncar and Blimbingsari sub-districts, and Lamongan district consisting of Paciran and Lamongan sub-districts. This study uses a quantitative approach and regression estimation using Ordinary Least Square (OLS), to see the influence between the independent variables on the dependent variables in the study. The results of this study show that the variables of environment, education, experience, and fishermen group have a significant influence on post-harvest fish loss. In addition, the highest post-harvest fish loss (PHFL) was found in Blimbingsari sub-district, Banyuwangi district. Another location with a high PHFL value was Muncar sub-district. In contrast, Paciran and Brondong sub-districts in Lamongan district had lower PHFL values. The findings have managerial and academic implications. For policy makers and fisheries organizations, the results of this study highlight the need to increase access to efficient storage technologies and provide training to improve fishers' skills in post-harvest handling. Academically, this study contributes to the fisheries economics literature by offering empirical evidence on the key factors affecting PHFL in small-scale fisheries. There are still gaps in integrated empirical studies and in policies that address human resources and institutional support. Therefore, this study provides important insights for designing more holistic and targeted strategies to reduce PHFL in East Java.

INTRODUCTION

Fisheries is one of the sectors that plays a role in reducing poverty, maintaining food security, and increasing global income. The sector provides essential fatty acids, minerals, and micronutrients as well as affordable animal protein, especially for communities around waterways (Gyan et al., 2020; Kaminski et al., 2020; PS et al., 2022; Tesfay & Teferi, 2017). More than half of the world's fish production comes from small-scale fisheries, which are a major source of food, income and employment for millions of people, especially in developing countries including Indonesia (Assefa et al., 2018; Mramba & Mkude, 2022; PS et al., 2022). Studies conducted by FAO (Food and Agriculture Organization) 2024, small-scale fisheries make significant contributions, including meeting 40 percent of global fisheries needs and providing 113 million jobs for small-scale fishers.

Small-scale fisheries play a crucial role in many aspects, from food security to the economy. Small-scale fisheries are critical to the national economy and food security. As one of the provinces with the longest coastline in Indonesia and having the largest total volume of marine capture production on the island of Java at 586,138.56 tons in 2022, East Java plays an important role in Indonesia's fisheries sector. The potential of capture fisheries in East Java Province is very large, especially in coastal areas that are full of various types of fish. The economic potential of fisheries can be used to help improve the welfare of fishermen and communities (Central Bureau of Statistics of East Java Province, 2023).

Based on data from the Central Bureau of Statistics of East Java Province (2022), the East Java fisheries sector contributed 2.36 percent of the GRDP of East Java Province, totaling around 35,854.87 billion rupiah in 2022. Based on data from the central statistics agency in 2023, the districts in East Java province have the largest amount of fish production, namely Lamongan district with a total production in 2022 of 138,018 tons and Banyuwangi district with 55,698 tons of fish per year. However, one of the problems of post-harvest fish handling, namely high post-harvest fish losses, is a major problem in the fisheries sector, especially small-scale (Cole et al., 2020; Mavuru et al., 2022; Sari et al., 2024; Torell et al., 2020).

Postharvest fish losses (PHFL) are caused by many factors, including high ambient temperatures, prolonged storage without preservatives, predators, insect attacks, increased production, and lack of market access (Assefa et al., 2018; Fisheries, 2019; Tesfay & Teferi, 2017). Research on postharvest fish handling has been conducted in various countries with the aim of identifying the magnitude of losses and the underlying causal factors. Almost all studies show significant losses in postharvest quality and quantity (Acharjee et al., 2021; FAO, 2017). These losses are caused by a variety of factors, ranging from poor handling on board and at landing, lack of refrigeration and freezing facilities, transportation issues, and marketing (Abelti & Teka, 2024; Mramba & Mkude, 2022).

Previous studies have concentrated on various issues, such as estimating the magnitude of losses (in quantity and quality), identifying the causes of losses, the economic impact of postharvest losses, policy implications for food safety and health risks associated with fish consumption (Central Bureau of Statistics of East Java Province, 2023; Dyah Wulan Sari, Wahyu Wisnu Wardana & Islamiyya, Wenny Restikasari, 2023; Liu et al., 2023; PS et al., 2022; Tesfay & Teferi, 2017). However, no study has examined the combined impact of socio-economic and environmental variables on PHFL in East Java. A study conducted by Gyan et al (2020) in Western

Ghana, this study had a primary focus on assessing postharvest fish losses from fishing to market. Torell et al (2020) conducted a study in Malawi, which had the objective of detailing the sources of PHFL and characterizing the total economic losses due to PHFL in the fisheries value chain.

The study conducted by Mramba, et al (2022), aimed to investigate the factors affecting catch rates of fish spoilage in small-scale marine fisheries in Bagamoyo District, Tanzania. The study showed that socio-demographic traits of fishers determine fish catch and fish spoilage. Post-harvest socioeconomic factors, which relate to the social and economic conditions of fishers involved in post-harvest activities, are very important and often underestimated, even though they greatly affect the loss rate and efficiency of the fisheries value chain. Therefore, the objective of this study is to analyze the effect of education, experience, age, and access to information on postharvest fish losses.

LITERATURE REVIEW

Concept of Post-Harvest Fish Losses (PHFL)

Post-harvest fish loss (PHFL), according to FAO, refers to quantitative and/or qualitative losses of fish that occur in the fisheries value chain after capture until the product reaches the final consumer. These losses can be in the form of spoilage, deterioration, or reduced market value due to inadequate handling, processing, storage, or distribution. According to FAO (2017), several factors influence the spoilage rate of fresh fish, namely:

a. Time between fish death and fish consumption: even fish stored in ice will lose quality over time. Decomposition is faster if the fish is not processed or consumed immediately.
b. Temperature abuse: high temperatures, such as 20 degrees Celsius, accelerate fish spoilage because they encourage bacterial growth. Conversely, low temperatures such as 4 degrees Celsius or lower can slow down bacterial growth and the rate of spoilage, which helps reduce postharvest losses.
c. Poor handling practices: faster physical and microbiological deterioration occurs when fish are treated in an unhygienic manner, such as using unclean equipment, unclean fish boxes, or washing fish with dirty water.

Several researchers have developed quantitative methods to calculate the economic impact of postharvest fish losses, including Ward (2000) using a value difference approach between revenue from high-quality fish and actual revenue from deteriorated fish. This approach is useful when price differences between fish qualities can be clearly identified. Adelaja et al. (2018) calculated percentage loss by comparing total financial loss to total expected revenue. This method is simpler but pays less attention to variations in fish quality. In addition, Torell et al. (2020) offer a more comprehensive approach by separating losses due to quality deterioration and physical losses, thus capturing the economic impact of unsold fish and fish sold at lower prices.

There are several post-harvest fish losses calculation formulas that form the basis of this research, namely Ward (2000), Adelaja et al. (2018), and Torell et al. (2020). The calculation of post-harvest fish losses by Ward (1996) uses the following formula (Akande & Diei-Ouadi, 2010).

$$Fish\ Loss\ (FL) = (weight\ loss\ of\ best\ fish\ quality \times best\ price) - (weight\ of\ fish\ loss \times reduce\ price) \quad (1)$$

$$Expected\ income\ (Em) = total\ weight\ of\ fish\ caught\ \times best\ price \quad (2)$$

$$Total\ percentage\ loss = \frac{FL}{E_m} \times 100 \quad (3)$$

Calculation of post-harvest fish losses by Adelaja et al (2018) using the following formula (Adelaja et al., 2018):

$$Total\ percentage\ loss = \frac{Total\ financial\ loss}{Total\ expected\ income} \times 100 \quad (4)$$

Torell, et al (2020) calculated the total economic losses due to quality and physical deterioration (Torell et al., 2020), using the following formula:

$$PHFL_q = \frac{(P_g - P_a) \times Q_a + (P_g - P_p) \times Q_p}{(Q \times P_g)} \times 100 \quad (5)$$

Where $PHFL_q$ yakni is postharvest fish quality losses, Q total landings, Q_g total landings in good condition, Q_a total landings in average condition, Q_p total landings in poor condition, P_g price of fish with good quality, P_a price of fish with average quality, and P_p price of fish with poor quality.

$$PHFL_p = \frac{Q_{pl} \times P_g}{(Q \times P_g)} \times 100 \quad (6)$$

Where $PHFL_p$ is the physical postharvest loss, Q_{pl} the amount of physical loss (tones), P_g the price of good quality fish. This study adapts and simplifies the approach of the three models, by dividing fish quality into two categories (high and low) and calculating revenue losses due to quality degradation. This approach is considered most suitable for small-scale fishers in Indonesia, especially in East Java Province, who tend not to have specific quality measurement tools but understand price differences based on the visual quality of fish. In this study, post-harvest fish losses were calculated using the following formula (Adelaja et al., 2018; Torell et al., 2020; Ward & Jefries, 2000):

$$FL = (P_1 x G_2) - (P_2 x G_2) \quad (7)$$

$$EI = P_1 x G_1 + P_1 x G_2 \quad (8)$$

$$PHFL = \frac{FL}{EI} x100 \quad (9)$$

Where FL denotes the monetary amount (in rupiah units) of the loss of income from the sale of medium and low-quality fish from the total income from the sale of medium and low-quality fish. More specifically, the notation G denotes the amount of high-quality fish (G1) and low-quality fish (G2), while the notation P denotes the price of fish per kilogram based on its quality, namely high-quality fish (P1) and low-quality fish (P2). Furthermore, based on equation (8) above, EI is the expected income of respondents expressed in rupiah. The amount of EI is obtained by multiplying the price of high-quality fish by the total amount of fish available. In other words, the EI calculation assumes that all fish owned by respondents are of high quality. The amount of post-harvest fish loss (PHFL) in the study was calculated by dividing fish loss (FL) by expected income (EI) and then multiplying by 100. As a result, the amount of post-harvest fish loss (PHFL) in this study is expressed as a percentage (%).

METHOD

Quantitative data analysis methods were used to achieve research objectives. In this study, field research and primary data collection were conducted through surveys. The location of the survey was carried out in two districts in East Java Province, namely Banyuwangi Regency and Lamongan Regency, with the category of respondents in this study being small-scale fishermen, namely fishermen who use traditional fishing gear with a vessel capacity of 10 gross tonnage and fishermen who go to sea in a one-day duration. This study determines the number of samples using the Slovin formula as follows:

$$n = \frac{\mathrm{N}}{1+\mathrm{N}(e)^2} \tag{10}$$

Where n is the sample size of the study, N is the total size of the fishing population, and e is the precision level or margin of error. The range within which population parameter values are estimated is the level of precision. This margin of error is often indicated in percentage points such as 1 percent, 5 percent, or 10 percent (Hunter, 2016). Based on formula (10), before being able to calculate the required sample size, information about the population size and precision level must be obtained. Based on data from the Central Bureau of Statistics, the number of fishermen in Banyuwangi Regency is 27,041 with a proportion of 56.17 percent and Lamongan Regency is 21,093 with a proportion of 43.82 percent, with a total of 48,134 fishermen.

$$n = \frac{N}{1+N(e)^2} = \frac{48.134}{1+48.134\ (0,05)^2} = 396,7033 \tag{11}$$

In addition, this study used a proportional stratified random method to determine the sample size. With a level of confidence of 95 percent, a level of precision (e) of 5 percent, variability in proportion p = 0.05 and a population that is close to infinite, the appropriate sample size is 397 respondents. The following is presented the formula for calculating the number of samples using proportionate stratified random sampling:

$$n_i = \frac{N_i}{N}\, n \tag{12}$$

Where n_i is the number of samples by stratum or level, N_i population by stratum, N the total population, and n total sample size (2). The population of fishermen in Muncar Sub-district is 13,700, Blimbingsari Sub-district is 3,700, Paciran Sub-district is 15,506, and Brondong Sub-district is 5,469 fishermen. For the calculation of the number of samples in each sub-district as follows:

$$\text{Muncar: } n_i = \frac{N_i}{N}\, n = \; n_i = \frac{13.700}{38.375}\, 396{,}7033 = 141{,}6244 \tag{13}$$

$$\text{Blimbingsari: } n_i = \frac{N_i}{N}\, n = \; n_i = \frac{3.700}{38.375}\, 396{,}7033 = 38{,}24892 \tag{14}$$

$$\text{Paciran: } n_i = \frac{N_i}{N}\, n = \; n_i = \frac{15.506}{38.375}\, 396{,}7033 = 160{,}294 \tag{15}$$

$$\text{Brondong: } n_i = \frac{N_i}{N}\, n = \; n_i = \frac{13.700}{38.375}\, 396{,}7033 = 56{,}53604 \tag{16}$$

For the number of samples for each region which is divided into two sub-districts, namely Banyuwangi Regency, which consists of Muncar District with a sample size of 142 respondents and Blimbingsari District with 38 respondents. As for Lamongan Regency, which consists of Paciran District with a sample size of 160 respondents and Brondong District of 57 respondents. Data is collected from samples that show population characteristics, then the data is processed and statistically analyzed using the ordinary least square method.

This research uses the Ordinary Least Squares (OLS) method. OLS is one of the most used linear regression estimation techniques in quantitative research. The main objective of OLS is to minimize the sum of squares of the difference between the actual observed value and the predicted value of the regression model (Gujarati & Porter, 2009, 2013). Thus, OLS can be used to estimate the relationship between one dependent variable and one or more independent variables. OLS estimation produces regression coefficients that are BLUE (Best Linear Unbiased Estimator) if they meet several classical assumptions, namely no multicollinearity, no heteroscedasticity, and residuals spread normally (Greene, 2018; Gujarati & Porter, 2013). To ensure the validity of the OLS regression model in this study, classical assumptions were tested. First, multicollinearity test is conducted to determine the presence of high correlation between independent variables. This test uses the Variance Inflation Factor (VIF) indicator, where a VIF value smaller than 10 indicates that there is no significant multicollinearity in the model. Second, the heteroscedasticity test is conducted to ensure that the variance of the residuals is constant (homoscedastic). The test is conducted using the Breusch-Pagan and White tests. Third, to test the normality of the residual distribution, the Jarque-Bera test was used. The results show that the residuals are normally distributed, as indicated by a p-value greater than 0.05 (Greene, 2018; Gujarati & Porter, 2009). For the analysis model in this study, namely:

$$PHFL_i = \beta_1 Environement_i + \beta_2 Experience_i + \beta_3 Education1_i + \beta_4 Education2_i + \beta_5 Education3_i + \beta_6 Age_i + \beta_7 Temperature_i + \beta_8 Work\_hour_i + \beta_9 Internet\_access_i + \beta_{10} Fishermen\_group_i + \beta_{11} Government\_aid_i + \varepsilon_i \quad (17)$$

Where $PHFL_i$ is the dependent variable representing the loss of fish after capture, $\beta_1 Environment_i$ is the environmental condition where the fish is caught or stored. $\beta_2 Experience_i$ is the working experience of fishermen, measured in years, which may affect the skills in maintaining fish quality. $\beta_3 Education1_i, \beta_4 Education2_i, \beta_5 Education3_i$ is the respondent's basic education level that influences knowledge on better fish handling. Measured using a dummy variable, with code 1 for respondents with the last education of elementary school or junior high school or senior high school and code 0 otherwise. $\beta_6 Age_i$ is the age of the respondent when the study was conducted. $\beta_7 Temperature_i$ is the ambient temperature that affects the speed of fish spoilage during the storage process. $\beta_8 Work\_hour_i$ is a duration of fishers' work at sea (in hours per day). $\beta_9 Internet\_access_i$ is a dummy variable of respondents who access the internet for fisheries information, where this variable takes the value of 1 if they have internet access and 0 otherwise. $\beta_{10} Fishermen\_group_i$ is a dummy variable of respondents who are members of a fishing group, where this variable is 1 if they are members of a fishing group and 0 otherwise. $\beta_{11} Government\_aid_i$ is a receipt of government assistance (dummy; 1 = received, 0 = not). ε_i is an error term reflecting other unobserved factors affecting PHFL.

RESULT AND DISCUSSION

In this study, there were 397 respondents spread across Muncar and Blimbingsari sub-districts in Banyuwangi district, and Paciran and Brondong sub-districts in Lamongan district. Based on Table 1, the number of respondents' education level is mostly graduated from junior high school (45%), elementary school (36%), and senior high school (19%). For work experience as a fisherman, most are in the range of 5 to 10 years (32%), 11 to 20 years (24%), 21 to 30 years (24%), above 30 years (14%), and below 5 years (6%). Meanwhile, the age of fishermen is mostly in the range of 41 to 50 years old (31%), 31 to 40 years old (29%), 51 to 60 years old (25%), and 20 to 30 years old (15%).

Table 1. Distribution of respondents according to several categories

Respondent Group Category		Total Respondents	
		Total	**Percentage (%)**
Region	Muncar, Banyuwangi Regency	142	36
	Blimbingsari, Banyuwangi Regency	38	10
	Paciran, Lamongan Regency	160	40

	Respondent Group Category	Total Respondents	
		Total	**Percentage (%)**
	Brondong, Lamongan Regency	57	14
Education	Elementary School	141	36
	Junior High School	180	45
	Senior High School	160	19
Experience	Under 5 years	23	6
	5 - 10 years	125	32
	11 - 20 years	97	24
	21 - 30 years	96	24
	Above 30 years	56	14
Age	20 - 30 years	58	15
	31 - 40 years	116	29
	41 - 50 years	123	31
	51 - 60 years	100	25

Based on the results of the PHFL calculation through the formula (7), (8), and (9), the estimated average post-harvest fish loss is around Rp 202,418 or equivalent to 20.75 percent. The highest PHFL was found in Blimbingsari sub-district, Banyuwangi Regency, amounting to Rp 354,000, indicating that Blimbingsari sub-district experienced the largest loss among other survey locations. Another location that has a high PHFL value is Muncar sub-district at IDR 214,648 per day. In contrast, Paciran and Brondong sub-districts in Lamongan district have lower PHFL values, amounting to IDR 117,629 and IDR 123,394 per day respectively. Before interpreting the results of OLS, it is necessary to test the classical assumptions, including multicollinearity and heteroscedasticity.

Table 2. Multicollinearity Estimation Results

Variable	VIF
Environment	1.49
Experience	1.86
Education1	3.42
Education2	3.56
Education3	3.08
Temperature	1.40
Work_hour	1.31
Age	1.38
Internet_access	1.64
Fisherman_group	1.34
Government_aid	1.54
Mean	2.00

Based on the data in table 2 there is no multicollinearity problem. VIF > 10 indicates a multicollinearity problem. In this study, all variables have a VIF value < 10, so there is no multicollinearity problem. The mean VIF of 2.00 indicates that the level of correlation between independent variables is still low to moderate.

Table 3. Heteroscedasticity Estimation Results

Model	Prob>Chi
PHFL	0.7095

Null hypothesis (H0): error variance is not constant (no heteroscedasticity), because the p-value is 0.7095 > 0.05, it fails to reject H0. That is, there is no heteroscedasticity in this research model, the model passes the assumption of homoscedasticity. To see the influence between the independent variables on the dependent variable, the following results of ordinary least square of factors affecting post-harvest fish losses (PHFL) are presented:

Table 4. Ordinary Least Square (OLS) Regression Results

Variable	Coefficient	Robust Standard error
Environment	-5.5960*	1.5559
Experience	-0.2786*	0.0312
Education1	-1.6253**	0.7355
Education2	-3.3586*	0.7465
Education3	-5.8564**	0.7843
Temperature	0.1682*	0.0310
Work_hour	0.0940	0.1039
Age	0.0037	0.0246
Internet_access	-1.9408*	0.6762
Fishermen_group	-2.8582*	0.5037
Government_aid	-2.1748*	0.5486
Constanta	32.2086	2.0977
Observation	397	
R-Squared	0.7342	
F-statistic	96.70	

Note: The * indicates statistical significance at the 1% level, ** indicates statistical significance at the 5% level

The Ordinary Least Square (OLS) regression results in Table 4. show that several independent variables have a significant effect on post-harvest fish loss (PHFL). Environment variable has a coefficient of -5.5960 and is significant at the 1% level, which indicates that improving environmental conditions can significantly reduce PHFL by 5.5960 units. Experience is also negatively significant at the 1% level, with a coefficient of -0.2786, meaning that each additional year of experience will reduce PHFL by 0.2786 units. The education level variable shows a consistent pattern, where fishers with elementary (Education1), junior high (Education2), and senior high (Education3) education experience lower PHFL compared to fishers with no schooling. The coefficients are -1.6253 (significant at 5%), -3.3586 (significant at 1%), and -5.8564 (significant at 5%), respectively.

This indicates that the higher the education level of fishers, the less likely PHFL is to occur. Temperature has a positive and significant effect on PHFL, with a coefficient of 0.1682 (significant at 1%), indicating that an increase in temperature tends to increase the risk of fish shrinkage. In contrast, Internet_access, Fisherman_group membership, and Government_aid have significant negative effects on PHFL with coefficients of -1.9408, -2.8582, and -2.1748, respectively, all of which are significant at the 1% level. This suggests that these three factors can significantly reduce the level of PHFL. Meanwhile, the variables Work_hour and Age do not show a significant influence on PHFL, as their coefficient values are relatively small and not statistically significant. The model has an R-squared value of 0.7342, which means that about 73.42% of the variation in PHFL can be explained by the model. The F-statistic value of 96.70 indicates that the model is significant in explaining the variation in the data.

Based on the OLS regression estimation results, it was found that several variables have a significant influence on the level of post-harvest fish loss (PHFL). The model shows an R-squared value of 0.7342, meaning that about 73.42% of the variation in PHFL can be explained by the independent variables in the model. This finding reinforces the importance of a multidimensional approach in addressing post-harvest fish loss, which includes environmental, social, economic and institutional aspects. One variable that has a significant influence is environmental conditions (environment). The negative coefficient indicates that the better the condition of the aquatic environment, the PHFL tends to decrease. This finding is in line with the research of Assefa et al. (2018) in Ethiopia which stated that poor environment is one of the main causes of post-harvest fish shrinkage. This was also reinforced by Mavuru et al. (2022), who showed that PHFL is most prevalent in summer when ambient and seawater temperatures are high. Exposure of fish to high temperatures on a boat without ice for several hours can increase the potential for postharvest losses. Therefore, improving the environmental quality and refrigeration system on board is crucial in PHFL reduction strategies.

Furthermore, experience has a negative and significant influence on PHFL. This indicates that the more experienced a fisherman is, the less likely the fish shrinkage will occur. This finding is in line with Mavuru et al. (2022), who stated that experience provides fishermen with the skills and knowledge to handle fish properly and increase fishing efficiency. Experienced fishermen are also more aware of suitable fishing locations, fishing gear and vessel types, thus contributing to the reduction of PHFL. Education has also been shown to play an important role in reducing PHFL. In this study, fishers with higher education levels (especially high school level) showed a greater reduction in PHFL than those with lower education levels. This finding is consistent with the results of Gyan et al. (2020) in Ghana which showed that fishers with higher educational background tended to experience fewer post-harvest losses. Acharjee et al. (2021) also emphasized the importance of education in reducing postharvest fish spoilage. Education helps fishers understand and implement hygienic and efficient fish handling practices and facilitates the adoption of new technologies. The temperature of the fish in storage had a positive and significant effect on PHFL, indicating that the higher the temperature of the fish, the greater the potential post-harvest losses. This supports the findings of Mavuru et al. (2022), where high temperatures cause accelerated fish spoilage, especially when not supported by adequate refrigeration technology.

Access to government aid also proved significant in reducing PHFL. This is in line with the findings of Han Liu et al. (2021) in China, which showed that government assistance, either directly or indirectly, can affect post-harvest loss rates. This assistance can be in the form of providing cold storage facilities, training, and operational subsidies for small-scale fishers. However, the variables of age and working hours did not have a significant influence on PHFL. In this context, the average age of respondents ranged from 41-50 years, which may reflect the productive age group but is starting to experience a decline in physical ability to handle fish optimally. This finding is in line with the research of Mramba et al. (2022), which showed that fish spoilage rates tend to increase as fishers age. Younger fishers are more adaptive to technology and more information-aware, so they are better able to acquire knowledge on fishing and fish handling and spend more time on reducing spoilage. In contrast, the study by Adelaja et al. (2018) found that spoilage decreased as fishers aged. Increasing age correlates with increased knowledge and skills in managing post-harvest losses. However, when fishers' age exceeds a certain limit, physical limitations become an obstacle that can reduce their ability to carry out optimal fish handling. Similarly, the number of working hours is not necessarily directly proportional to the efficiency of fish handling if it is not accompanied by adequate skills.

The estimation results show that the Internet_access variable has a significant negative effect on post-harvest fish loss (PHFL). This finding indicates that fishers with access to the internet tend to experience lower post-harvest fish loss compared to fishers without internet access. Access to the internet can be an important tool for fishers to obtain relevant information, such as better fish handling techniques, effective storage methods, and daily weather forecasts that can help in post-harvest decision-making. Such information can encourage changes in fishers' behavior towards more hygienic and efficient fish handling practices, which can directly or indirectly reduce the PHFL rate.

CONCLUSION

This study shows that socioeconomic factors play an important role in influencing the level of post-harvest losses in small-scale fisheries in East Java province. This study revealed that post-harvest fish loss (PHFL) is a significant problem in the coastal areas of East Java, with an average loss of Rp202,418 per day or equivalent to 20.75 percent of the catch. The location with the highest level of PHFL was found in Blimbingsari Sub-district, Banyuwangi Regency, while the area with the lowest level of PHFL was found in Paciran Sub-district, Lamongan Regency. The OLS regression estimation results show that factors such as environmental conditions, work experience, education level, temperature, internet access, participation in fishermen's groups, as well as government assistance have a significant influence on PHFL levels. Better environment, longer working experience, higher education, access to internet, as well as institutional support such as fishermen groups and government assistance significantly reduce the PHFL level. In contrast, higher temperatures significantly increased PHFL, indicating the need for adequate post-harvest cooling systems. Meanwhile, the variables of age and working hours showed no significant effect on PHFL.

This study confirms that education, experience, environmental conditions, temperature, and institutional support significantly affect post-harvest fish loss (PHFL). However, the role of social institutions such as fishing groups or cooperatives has not been explored in depth. Future research should investigate how these social dynamics influence the adoption of storage technologies and post-harvest management practices. The findings provide empirical support for developing more targeted policies, including training programs, provision of storage technologies, and strengthening of local institutions to promote sustainable postharvest practices. Emphasis should also be placed on improving environmental quality and providing experience-based technical training to reduce PHFL. In addition, well-targeted government assistance is essential to improve post-harvest efficiency, especially among small-scale fishers.

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