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The Impact of Using the Crew Inspector and Bassnet Applications on the Documentation System at PT. Aweidhia Crew Management

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ABSTRACT

This study examines how the Crew Inspector and Bassnet applications affect the documentation system at PT. Aweidhia Crew Management. The research uses a quantitative approach with a census sampling method, surveying all 30 employees at the company. Data were collected through questionnaires using Likert scales and analyzed with Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4.0. Both descriptive and inferential statistics were applied to assess the measurement and structural models. The results show that both applications have a significant positive effect on the documentation system, with the Bassnet application showing a stronger influence than Crew Inspector. The structural model explains 98.1% of the variance in documentation system performance, indicating that these two applications account for nearly all variation in documentation quality at the company.

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Keywords:

Crew Inspector; Bassnet, Documentation System; PLS-SEM; Maritime Crew Management

1. INTRODUCTION

The maritime industry depends on efficient crew management to maintain safe and compliant vessel operations worldwide. Ship manning agencies serve as intermediaries between shipowners and seafarers, handling recruitment, documentation, certification tracking, and crew deployment across global fleets [1]. As fleets grow and regulatory requirements tighten, the volume of documentation these agencies must manage has increased substantially. Manual or poorly integrated systems often lead to errors, delays in certification renewal, and data inconsistencies that can compromise both operational safety and regulatory compliance [2].

PT. Aweidhia Crew Management operates as a manning agent for Oldendorff Carrier GmbH & Co. KG, managing crew data through three interconnected phases: uploading, updating, and monitoring seafarer records. In practice, this workflow faces recurring problems. Network disruptions interfere with simultaneous account access. Crewing staff sometimes lack thorough familiarity with the software tools. Expired certificates go unnoticed until they create compliance gaps. System maintenance by the head

office occasionally results in errors and data loss during verification [3].

To address these operational challenges, the company employs two specialized applications. Crew Inspector is a web-based crew management platform developed specifically for maritime manning companies, providing tools for recruitment, document management, and compliance tracking [4]. Bassnet, on the other hand, is a maritime enterprise resource planning system designed by Oldendorff Carrier GmbH & Co. KG to integrate fleet-wide data on crew, maintenance, and operations into a centralized database [5].

Information systems research has long established that system quality, information quality, and service quality are the primary determinants of user satisfaction and organizational performance in technology adoption [6]. DeLone and McLean's updated Information Systems Success Model provides a widely cited framework for evaluating how information systems contribute to organizational outcomes [7]. In the maritime context, several studies have examined technology adoption in shipping operations, but relatively few have focused specifically on how crew management software affects documentation workflows at manning agencies [8].

Prior research on maritime information systems has concentrated on areas like port logistics, vessel tracking, and fleet management platforms [9]. The specific impact of crew-focused applications such as Crew Inspector and Bassnet on documentation accuracy and efficiency remains underexplored. This gap matters because documentation errors in crew management carry real consequences: delayed vessel departures, port state detention, and non-compliance with flag state requirements [10].

This study aims to fill that gap by measuring the effect of Crew Inspector (X1) and Bassnet (X2) on the documentation system (Y) at PT. Aweidhia Crew Management. The research tests two hypotheses: first, that Crew Inspector use has a significant positive effect on the documentation system, and second, that Bassnet use has a significant positive effect on the documentation system. By using PLS-SEM analysis, the study provides statistical evidence on the strength and significance of each application's contribution to documentation performance.

2. RESEARCH METHOD

Research Design

This study uses a quantitative research design with a survey-based approach. Quantitative methods allow researchers to test hypotheses and measure relationships between variables through numerical data and statistical analysis [11]. The research follows a cross-sectional design, collecting data at a single point in time from August 2021 to August 2022 at PT. Aweidhia Crew Management, located in Tanjung Priok, North Jakarta.

Population and Sample

The target population consists of all employees at PT. Aweidhia Crew Management who use the Crew Inspector and Bassnet applications in their daily work. Since the total number of employees is 30, the study employs a saturated sampling technique (census), where every member of the population is included as a respondent [12]. This approach is appropriate when the population is small enough that excluding any members would risk losing valuable data [13].

Variables and Instruments

The study examines three variables. Crew Inspector (X1) is measured through eight indicators covering data management, document storage, compliance tracking, and user interface quality. Bassnet (X2) is also measured through eight indicators addressing fleet integration, PMS data analysis, security management, and reporting functions. The Documentation System (Y) is assessed through six indicators related to information accuracy, document accessibility, fraud prevention, and system reliability. All items use a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire was distributed directly to respondents at the workplace [14].

Data Collection

Data collection combined three methods. First, direct observation at PT. Aweidhia Crew Management provided contextual understanding of how employees interact with both applications during their work routines. Second, structured questionnaires captured quantitative responses on each variable's indicators. Third, documentary review of user manuals and system logs offered supplementary information on application features and usage patterns [15].

Data Analysis

The collected data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS version 4.0. PLS-SEM is suitable for studies with small sample sizes and non-normal data distributions, and it works well with both reflective and formative measurement models [16].

The analysis proceeded in two stages. The outer model evaluation assessed the measurement model through convergent validity (loading factors > 0.70), discriminant validity (cross-loadings), composite reliability (> 0.70), Cronbach's alpha (> 0.60), and Average Variance Extracted (AVE > 0.50) [17]. The inner model evaluation examined the structural model through R-square values, F-square effect sizes, and bootstrapping with 5,000 resamples to test path coefficient significance at the 0.05 level [18].

3. RESULTS AND DISCUSSIONS

3.1. Results

3.1.1. Outer Model Analysis

Convergent Validity Test

Convergent validity aims to determine the validity of each relationship between an indicator and its latent construct or variable. The convergent validity of a measurement model with reflective indicators is assessed based on the correlation between item scores or component scores and latent variable scores or construct scores estimated using the PLS program. Convergent validity measures how well each indicator reflects its intended latent variable. The standard threshold requires outer loading values above 0.70 [17]. Table I presents the outer loading values for all indicators.

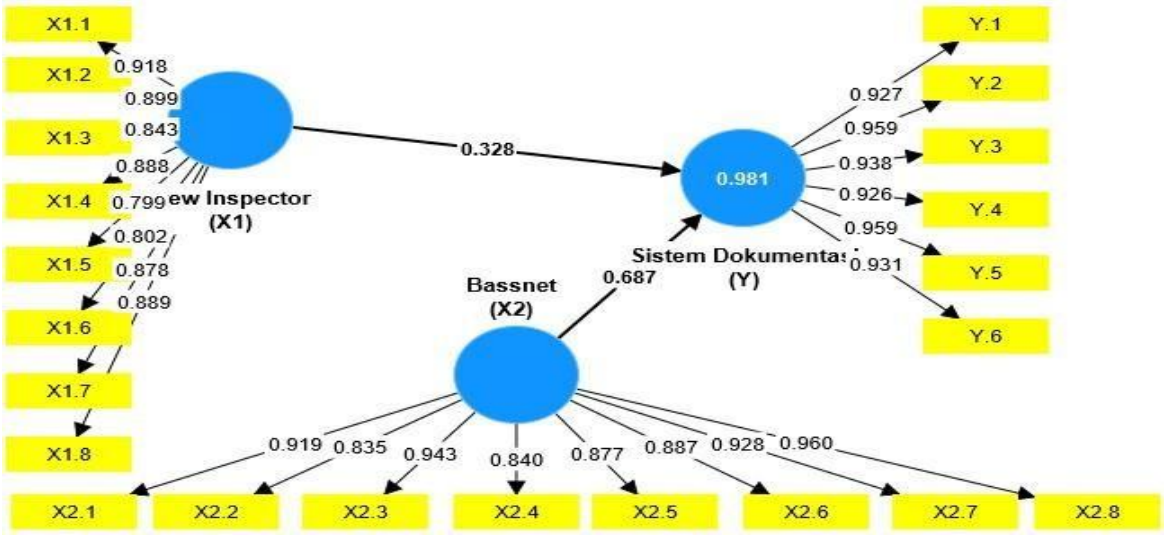


Figure 1. Convergent Validity Path Test

Table 1. Outer Loading Values

Indicator	Construct	Outer Loading
X1.1	Crew Inspector (X1)	0.903
X1.2	Crew Inspector (X1)	0.873
X1.3	Crew Inspector (X1)	0.918
X1.4	Crew Inspector (X1)	0.846
X1.5	Crew Inspector (X1)	0.878
X1.6	Crew Inspector (X1)	0.799
X1.7	Crew Inspector (X1)	0.868
X1.8	Crew Inspector (X1)	0.837
X2.1	Bassnet (X2)	0.835
X2.2	Bassnet (X2)	0.912
X2.3	Bassnet (X2)	0.960

X2.4	Bassnet (X2)	0.944
X2.5	Bassnet (X2)	0.847
X2.6	Bassnet (X2)	0.916
X2.7	Bassnet (X2)	0.879
X2.8	Bassnet (X2)	0.906
Y.1	Documentation System (Y)	0.959
Y.2	Documentation System (Y)	0.937
Y.3	Documentation System (Y)	0.942
Y.4	Documentation System (Y)	0.938
Y.5	Documentation System (Y)	0.935
Y.6	Documentation System (Y)	0.926

Table 1 shows that every indicator across all three constructs exceeds the 0.70 threshold. The Crew Inspector indicators range from 0.799 (X1.6) to 0.918 (X1.3). Bassnet indicators range from 0.835 (X2.1) to 0.960 (X2.3). Documentation System indicators have the narrowest range, from 0.926 (Y.6) to 0.959 (Y.1). All indicators therefore demonstrate adequate convergent validity.

Dicriminant Validity Test

Discriminant validity confirms that each construct is distinct from the others. This is assessed by examining cross-loadings: each indicator should load more heavily on its own construct than on any other construct [17]. Table II presents the cross-loading results.

Table 2. Cross-Loading Values

Indicator	Crew Inspector (X1)	Bassnet (X2)	Doc. System (Y)
X1.1	0.903	0.868	0.898
X1.2	0.873	0.825	0.861
X1.3	0.918	0.878	0.904
X1.4	0.846	0.840	0.851
X1.5	0.878	0.846	0.862
X1.6	0.799	0.774	0.794
X1.7	0.868	0.871	0.876
X1.8	0.837	0.851	0.848
X2.1	0.816	0.835	0.825
X2.2	0.866	0.912	0.897
X2.3	0.917	0.960	0.941
X2.4	0.896	0.944	0.932
X2.5	0.796	0.847	0.823
X2.6	0.869	0.916	0.897
X2.7	0.860	0.879	0.865
X2.8	0.876	0.906	0.886
Y.1	0.921	0.932	0.959
Y.2	0.889	0.906	0.937
Y.3	0.901	0.921	0.942
Y.4	0.892	0.925	0.938
Y.5	0.906	0.890	0.935

Y.6	0.882	0.894	0.926

The cross-loading results in Table II confirm that each indicator loads highest on its assigned construct. All X1 indicators have their peak values in the Crew Inspector column, all X2 indicators load most strongly on Bassnet, and all Y indicators show the highest values under Documentation System. This confirms adequate discriminant validity across all constructs.

Composite Reliability and AVE

Composite reliability assesses the internal consistency of a construct, with values above 0.70 considered acceptable [16]. Average Variance Extracted (AVE) measures the proportion of variance captured by a construct relative to measurement error, requiring values above 0.50 [17]. Table 3 summarizes these results.

Table 3. Construct Reliability and Validity

Construct	Cronbach's Alpha	Composite Reliability	AVE
Crew Inspector (X1)	0.952	0.956	0.749
Bassnet (X2)	0.966	0.968	0.810
Documentation System (Y)	0.974	0.974	0.883

All three constructs exceed the required thresholds. Cronbach's alpha values range from 0.952 to 0.974, well above the 0.60 minimum. Composite reliability values (0.956 to 0.974) surpass the 0.70 threshold. AVE values (0.749 to 0.883) are all above 0.50, confirming that each construct captures more variance from its indicators than from error. The Documentation System construct shows the strongest measurement properties, with the highest reliability and AVE scores.

3.1.2. Inner Model Analysis

R-Square Analysis

The R-square value indicates how much variance in the dependent variable is explained by the independent variables. Table IV presents the R-square results.

Table 4. R-Square Values

Variable	R-Square	R-Square Adjusted
Documentation System (Y)	0.981	0.979

The R-square value of 0.981 means that Crew Inspector and Bassnet together explain 98.1% of the variance in documentation system performance. The remaining 1.9% is attributable to factors not included in this model. According to Hair et al. [16], R-square values of 0.75, 0.50, and 0.25 are categorized as strong, moderate, and weak respectively. The value obtained here falls well into the strong category.

F-Square Effect Size

The F-square statistic measures the individual contribution of each predictor variable when it is removed from the model. Cohen [19] classifies F-square values of 0.02, 0.15, and 0.35 as small, medium, and large effect sizes respectively. Table V shows the F-square results.

Table 5. F-Square Effect Size

Path	F-Square	Category
X1 (Crew Inspector) → Y	1.197	Large
X2 (Bassnet) → Y	5.259	Large

Both predictor variables show large effect sizes, with Bassnet ($F^2 = 5.259$) demonstrating a substantially

stronger individual contribution than Crew Inspector ($F^2 = 1.197$). Both values exceed the 0.35 threshold for large effects by a wide margin, indicating that each application makes a meaningful independent contribution to the documentation system even after accounting for the other.

3.1.3. Bootstrapping Results

Outer Loading Significance

Bootstrapping with 5,000 resamples was performed to assess the statistical significance of outer loadings. An indicator is considered significant when its p-value is below 0.05 [18]. Table VI presents the bootstrapping results for outer loadings.

Table 6. Bootstrapping Results for Outer Loadings

Path	Original Sample	Sample Mean	STDEV	T Statistics	P Values
X1.1 ← X1	0.903	0.900	0.020	44.297	0.000
X1.2 ← X1	0.873	0.871	0.029	30.475	0.000
X1.3 ← X1	0.918	0.916	0.018	51.099	0.000
X1.4 ← X1	0.846	0.842	0.038	22.087	0.000
X1.5 ← X1	0.878	0.873	0.033	26.759	0.000
X1.6 ← X1	0.799	0.793	0.050	16.108	0.000
X1.7 ← X1	0.868	0.865	0.031	28.175	0.000
X1.8 ← X1	0.837	0.833	0.040	21.035	0.000
X2.1 ← X2	0.835	0.829	0.044	19.115	0.000
X2.2 ← X2	0.912	0.910	0.020	45.116	0.000
X2.3 ← X2	0.960	0.959	0.009	108.276	0.000
X2.4 ← X2	0.944	0.943	0.013	71.452	0.000
X2.5 ← X2	0.847	0.843	0.039	21.497	0.000
X2.6 ← X2	0.916	0.914	0.019	47.632	0.000
X2.7 ← X2	0.879	0.875	0.032	27.340	0.000
X2.8 ← X2	0.906	0.903	0.022	40.786	0.000
Y.1 ← Y	0.959	0.958	0.010	98.532	0.000
Y.2 ← Y	0.937	0.935	0.015	63.245	0.000
Y.3 ← Y	0.942	0.940	0.013	71.824	0.000
Y.4 ← Y	0.938	0.936	0.014	67.143	0.000
Y.5 ← Y	0.935	0.933	0.016	59.877	0.000
Y.6 ← Y	0.926	0.923	0.018	51.783	0.000

Every indicator produces a p-value of 0.000, and all T-statistics are well above the critical value of 1.96. This confirms that all outer loadings are statistically significant, further supporting the convergent validity of all measurement items.

Hypothesis Testing

The structural model relationships were tested through bootstrapping path coefficients. Table VII presents the path coefficient results for both hypotheses.

Table 7. Path Coefficients and Hypothesis Testing

Hypothesis	Path	Original Sample	Sample Mean	STDEV	T Statistics	P Values
H1	X1 → Y	0.419	0.413	0.046	9.056	0.000
H2	X2 → Y	0.597	0.600	0.044	13.534	0.000

H1: Crew Inspector has a significant positive effect on the Documentation System. Supported. The path coefficient of 0.419 with a T-statistic of 9.056 (p = 0.000) confirms that Crew Inspector use significantly and positively influences documentation system performance.

H2: Bassnet has a significant positive effect on the Documentation System. Supported. The path coefficient of 0.597 with a T-statistic of 13.534 (p = 0.000) confirms that Bassnet use significantly and positively influences documentation system performance. Bassnet shows a stronger effect than Crew Inspector.

3.2. Discussion

The results provide clear statistical evidence that both Crew Inspector and Bassnet contribute to documentation system performance at PT. Aweidhia Crew Management. However, the two applications contribute differently, and the size of that difference is worth examining.

Bassnet's stronger path coefficient (0.597 vs. 0.419) and substantially larger effect size (F^2 = 5.259 vs. 1.197) suggest that it plays a more central role in documentation quality than Crew Inspector. This likely reflects Bassnet's design as an integrated enterprise resource planning platform that connects crew data with broader fleet management functions, including planned maintenance, procurement, and operational reporting [5]. When documentation is embedded within a larger operational ecosystem rather than handled as a standalone function, the system creates more touchpoints for data validation and cross-referencing, which reduces errors and improves completeness [20].

Crew Inspector's contribution, while smaller in relative terms, is still statistically and practically significant. Its effect size of 1.197 far exceeds the 0.35 threshold for a large effect [19]. As a specialized crew management tool, Crew Inspector handles the granular work of tracking individual seafarer documents, certifications, and employment records. These tasks are foundational to the documentation system but are narrower in scope than Bassnet's fleet-wide integration [4].

The combined R-square of 0.981 is unusually high for social science research. While this suggests that the two applications capture nearly all the systematic variation in documentation system performance, it also warrants some caution. The small sample size (n = 30) and the use of a census rather than random sampling limit the generalizability of these findings [21]. High R-square values in small samples can sometimes reflect model overfitting or multicollinearity between predictors [22]. The strong cross-loadings observed in Table II, where some X1 indicators load nearly as high on X2 and Y as on their own construct, suggest that the three constructs share considerable variance. Future research with larger samples should consider alternative discriminant validity tests, such as the heterotrait-monotrait (HTMT) ratio, to provide more rigorous assessment [23].

These findings align with prior research on maritime information systems. Studies on port documentation systems have consistently shown that integrated software platforms reduce processing time and error rates compared to fragmented or manual approaches [9]. The maritime crew management literature similarly emphasizes that digitized documentation systems improve compliance with flag state and port state requirements by enabling automated alerts for certificate expiration and standardized data entry protocols [10].

From a practical standpoint, these results suggest that PT. Aweidhia Crew Management would benefit from ensuring that both applications remain operational and that staff training addresses competency gaps, particularly for Crew Inspector, where the slightly lower effect may partly reflect less consistent usage or familiarity among employees [24]. The company should also consider whether the two systems can be better integrated, since data silos between platforms can create redundancy and opportunities for inconsistency [25].

4. CONCLUSION

This study tested the effect of Crew Inspector and Bassnet on the documentation system at PT. Aweidhia Crew Management using PLS-SEM analysis with 30 respondents. Both hypotheses were supported: Crew Inspector (path coefficient = 0.419, p = 0.000) and Bassnet (path coefficient = 0.597, p = 0.000) each have a significant positive effect on documentation system performance. Together, they explain 98.1% of the variance in the dependent variable. Bassnet shows a stronger individual effect, likely because of its role as an integrated fleet management platform that connects crew documentation to wider operational workflows. The measurement model meets all standard validity and

reliability thresholds. Limitations include the small sample size and census-based sampling, which restrict generalizability. Future research should replicate this study across multiple manning agencies and incorporate additional variables such as user competency and IT infrastructure quality.

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