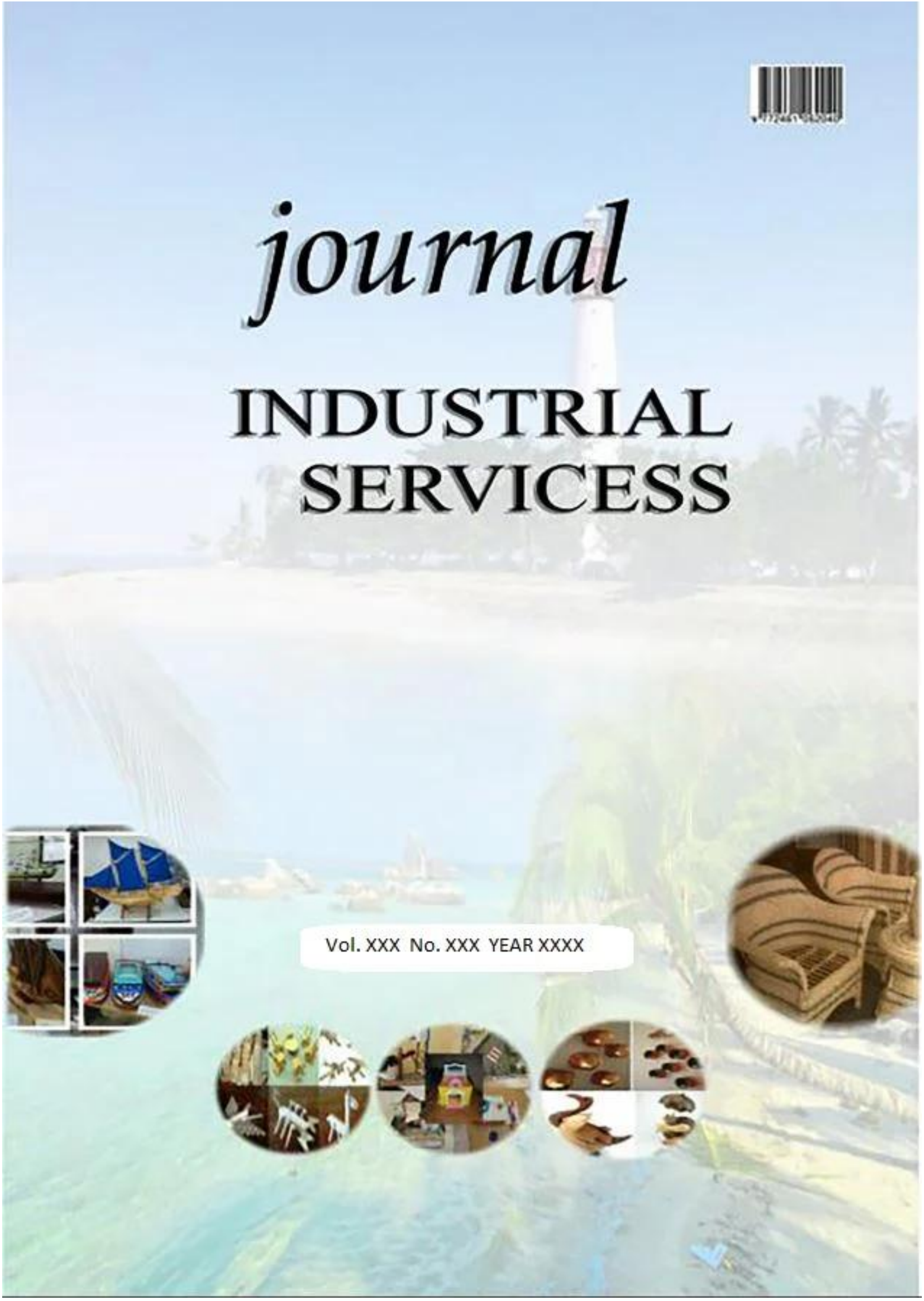
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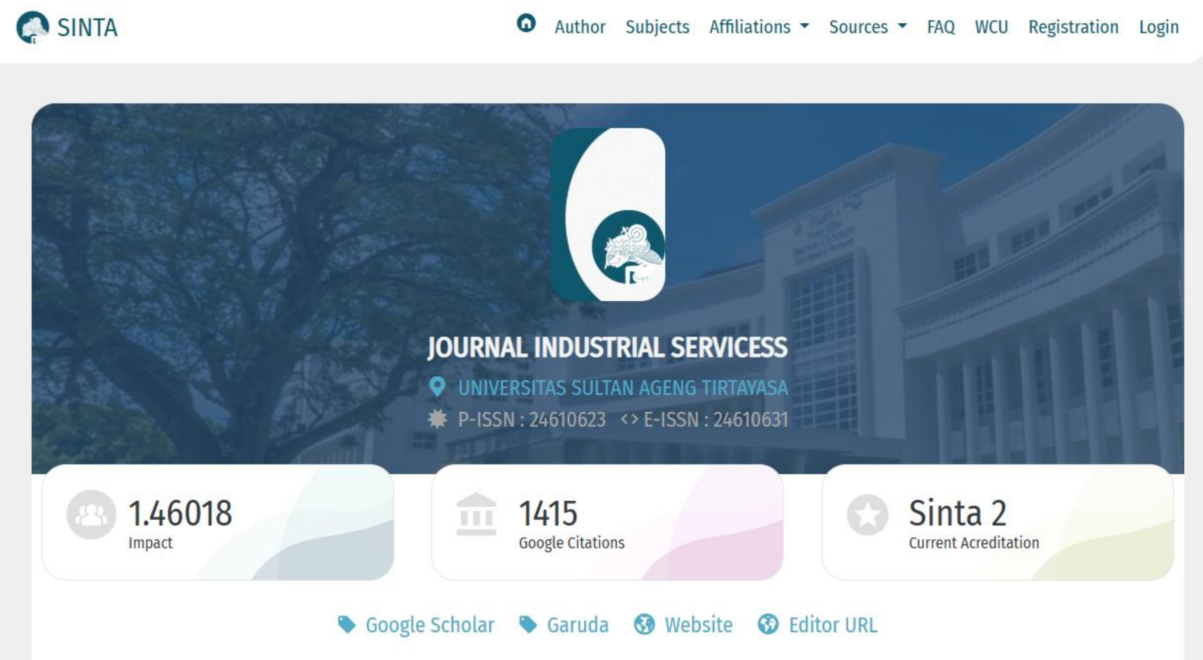
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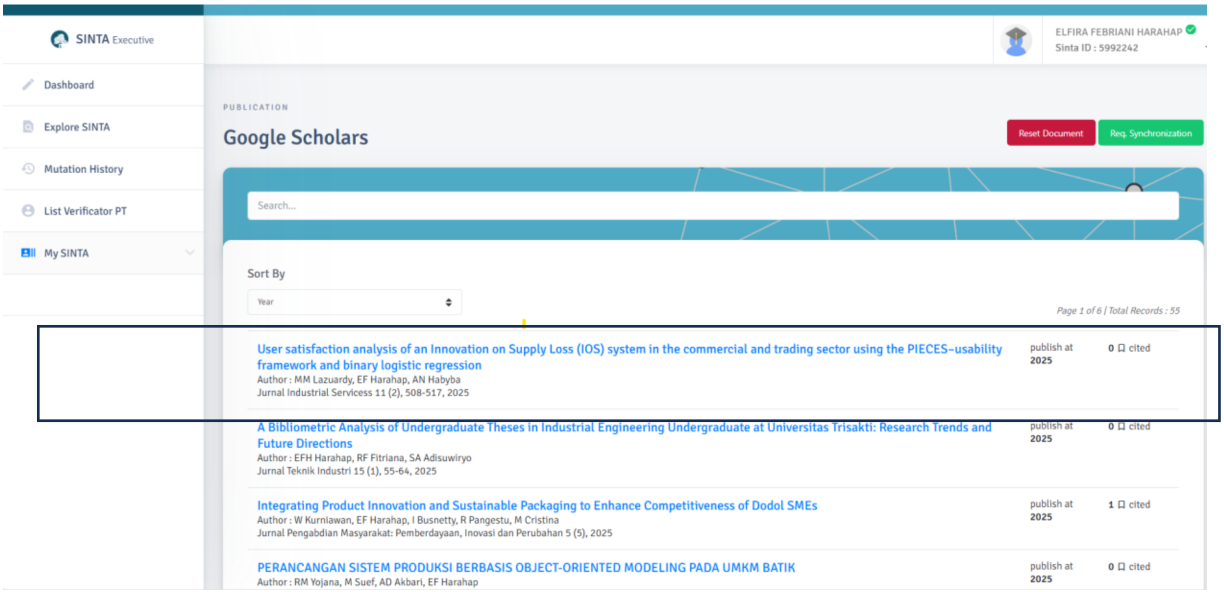

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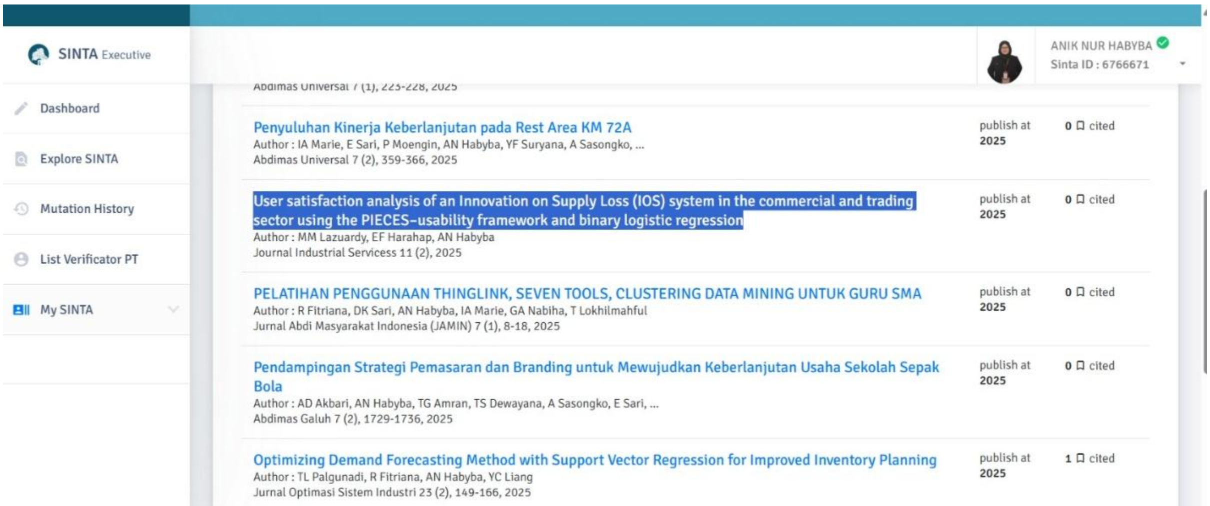

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Original research article

User satisfaction analysis of an Innovation on Supply Loss (IOS) system in the commercial and trading sector using the PIECES–usability framework and binary logistic regression

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ABSTRACT

In the era of digital transformation, energy companies are increasingly adopting digital systems to improve operational efficiency and monitor supply losses. However, system evaluations often focus only on technical aspects, such as error detection, without a comprehensive measurement of user satisfaction. This study aims to identify the factors influencing user satisfaction with a digital loss monitoring system using the PIECES framework, and to evaluate their significance through binary logistic regression. A total of 21 factors were examined, with Information Relevance, Ease of Tracking Losses, and Ease of Use found to be significant predictors, with odds ratios of 4.379, 0.167, and 1.572, respectively. To further understand the root causes of dissatisfaction, fishbone analysis was applied to categorize improvement areas across data, process, human, technology, and environment dimensions. The findings provide managerial implications by highlighting priority areas for system improvement and user training, while suggesting the integration of supporting systems to enhance usability. Future research should expand the dataset across different industries, apply advanced methods such as machine learning, and explore organizational and cultural factors influencing digital adoption to ensure the generalizability of results and provide deeper insights into sustaining user satisfaction in industrial digitalization initiatives.

1. Introduction

In the era of digital transformation, industries worldwide are increasingly adopting information technology to improve efficiency, increase revenue, and strengthen competitiveness [1]. In the energy and manufacturing sectors, digitalization plays a particularly important role in enhancing operational performance and maintaining competitive advantage [2], [3]. One of the major challenges in these sectors is supply losses, defined as the difference between the volume of oil and gas delivered and the actual amount received by customers. Losses can cause significant financial losses for the company because the product has been processed to a certain quality. Therefore, monitoring and controlling losses are considered urgent issues in industrial operations.

In addressing supply losses, many industries have begun adopting digital monitoring systems to replace older manual or semi-digital approaches that often face significant limitations. These systems are designed to provide real-time monitoring through dashboards and deliver detailed information on operational losses. However, their implementation still encounters various challenges. In many cases, user complaints highlight both operational and technical obstacles, while evaluations conducted by development teams tend to focus primarily on technical fixes such as resolving system errors. This approach overlooks the more comprehensive assessment of user satisfaction, which is critical to ensure that digital systems align with user needs and can be operated effectively. By analyzing user satisfaction surveys, companies can identify opportunities to enhance application features, increase adoption, and address challenges faced by users in practice [1]. Previous studies have highlighted the importance of customer satisfaction in sustaining

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competitive advantage for digital service companies [4], [5].

Previous studies on digitalization satisfaction have been conducted in various application contexts, such as subsidized fuel purchase service applications using the simple Linear Regression Test method and SERVQUAL [6], [5] and other studies using multiple linear regression methods and the EUCS (End User Computing Satisfaction) dimension [7], [8]. However, the method is more suitable for analyzing continuous satisfaction variables. Binary logistic regression is more suitable for this study because the predictor variable (user satisfaction) has two possibilities, namely "satisfied" and "dissatisfied" [9].

To evaluate user satisfaction in digital systems, the PIECES framework is used to classify problems, opportunities, and directions contained in the scope of system analysis and design by dividing into six dimensions, namely Performance, Information, Economy, Control & Security, Efficiency, and Service [10]. The PIECES method has also been applied in analyzing user satisfaction in applications, such as research on mobile banking Livin By Mandiri, and BSI Mobile [11]. However, PIECES places more on system evaluation from a functional or technical point of view, so it does not accommodate aspects of user perception and experience directly. User experience has a crucial role in determining the level of satisfaction, system success, and company profits [12], [13]. Therefore, the Usability Dimension was added to measure the user experience [14] . Companies that realize the importance of Usability will try to design and develop applications that are easy to use. Not only that, but the system also created must be learnable, efficient, and easy to remember [14]. Some indicators, such as Information Relevance, represent a meeting point between PIECES and Usability because they represent how the information presented by the system must not only be accurate and functionally relevant but also easy for users to understand and use. This integration allows for a more in-depth evaluation model, which not only reflects the effectiveness of the system but also encourages user engagement and satisfaction.

The binary logistic regression method is used to explain the relationship between response variables and predictor variables. The goal is to be able to evaluate the relationship between significant variables and the level of user satisfaction. Previous studies have used binary logistic regression in analyzing satisfaction with applications, such as research on student health report applications [15]. However, prior research has typically evaluated PIECES and binary logistic regression separately, and no study has integrated PIECES with Usability while employing binary logistic regression to assess user satisfaction in industrial digitalization.

Previous studies typically applied PIECES or Usability frameworks independently or used binary logistic regression without incorporating user experience dimensions. Furthermore, most research on user satisfaction has focused on financial services or public sector applications, while limited attention has been given to industrial digitalization, particularly in energy-related contexts. This highlights the need for a more comprehensive model that integrates both technical and experiential dimensions of user satisfaction, supported by robust statistical analysis.

This study aims to measure user satisfaction of a digital monitoring system using an integrated PIECES–Usability framework, evaluate significant satisfaction predictors through binary logistic regression, and identify improvement areas using fishbone analysis. The contributions are threefold: extending the use of PIECES and Usability in industrial contexts, demonstrating the integration of binary logistic regression for binary satisfaction outcomes, and providing managerial implications for enhancing user-centered digitalization in industry.

2. Material and method

2.1. Data and sample

This research focuses on the digitization of IOS (Innovation On Supply Loss) implemented in the Commercial and Trading Subholding of an energy company. IOS (Innovation On Supply Loss) has two platforms, namely applications and dashboards. The IOS application is used in responding to Over Tolerable Loss (OTL) notifications or exception signals and assisting the follow-up process through an integrated workflow. Meanwhile, a Dashboard is used for monitoring and tracking losses. Exception Signal is a notification of out-of-control transactions in oil and gas distribution discrepancy within the company's operational area. After the Over Tolerable Loss (OTL) notification, an Important Event Report (LKP) will be prepared. LKP-OTL is used as a supporting document for evaluation materials in following up Over Tolerable Loss (OTL) cases and evaluation materials for oil and gas handover management, which will be discussed in the company's internal workshops. The data used in this study are primary data obtained from questionnaires. The questionnaire has a Likert scale of user satisfaction levels of 1 to 5, from very dissatisfied to very satisfied.

The sampling method used is the purposive sampling technique. The purposive sampling technique is a sample selection with specific objectives and appropriate criteria so that the selected sample is respondents or users who are truly related to the research [16]. This method was chosen because the population of IOS users is very wide, as IOS can be used generally for various functions and positions. However, not all users have relevant experience and sufficient understanding of the application to provide feedback that meets the needs of the research. Although it is commonly used, not all employees are directly involved in the use or utilization of this digitalization. In this study, the sample criteria were determined by the researcher as follows:

(1) Location PIC Subholding Commercial & Trading: A signal receiver who follows up on signals in the

form of an Important Event Report Over Tolerable Loss (LKP-OTL).

(2) Monitoring PIC Subholding Commercial & Trading: monitors the effectiveness of the reporting process or signal follow-up.

(3) Approver: responsible for checking and approving LKP-OTL.

(4) Users of the ILC (Integrated Loss Control) and IEDCC function as the IOS application development team and monitor overall Losses using IOS.

This study obtained 61 respondents who met the purposive sampling criteria, namely users with deep experience and understanding of IOS. Although the sample size may appear relatively small compared to the 21 initial predictor variables, it meets the minimum requirement for binary logistic regression, which is at least 50 cases for reliable estimation [17]. Moreover, purposive sampling was chosen to ensure that the respondents represent key informants with sufficient knowledge, thereby prioritizing data quality over quantity. To reduce the risk of overfitting due to the relatively high number of predictors, variable reduction techniques (e.g., stepwise selection and multicollinearity checks) were applied, ensuring that only significant predictors were retained in the final model. Respondent characteristics from the questionnaire are shown in Table 1. Based on the respondent's position, respondents as Monitoring PIC (26%) and Location PIC and Approver (74%).

2.2. Research variables

IOS user satisfaction factors were identified and analyzed using the PIECES and Usability methods. The research variables were derived from three main sources: interviews with the system development team to capture the technical aspects of the IOS platform, feedback from end users to ensure that the variables reflect actual user needs and experiences, and a review of relevant literature to ensure alignment with established theoretical frameworks [18], [19]. Based on the PIECES framework, the variables include performance, which assesses the system's ability to operate responsively, accurately, quickly, and efficiently in meeting user expectations; information, which measures the value and quality of data and reports generated by the system; economy, which reflects cost efficiency and time utilization; control, which relates to monitoring and control procedures; security, which focuses on preventing and detecting errors and ensuring data protection; efficiency, which evaluates the ability to maximize output while minimizing input; and service, which examines user experience, technical support, and system responsiveness.

In addition, usability variables were incorporated to enrich the analysis, including memorability, which refers to how easily users remember system workflows and information locations; user interface, which evaluates satisfaction with visual design elements such as data visualization, colors, and diagrams; ease of learning, which measures how quickly users can understand and learn to operate the system; and ease of use, which assesses the extent to which users can operate the system independently without assistance [20]–[22]. Overall, a total of 21 variables were identified and used to measure IOS user satisfaction through the combined application of the PIECES and Usability methods, as summarized in **Error! Reference source not found.**.

Table 1
Characteristics of respondents.

Attributes	Category		Pct.
Position	Monitoring PIC and application development team	Analyst ILC (Integrated Loss Control)	20%
		Officer Quality & Quantity Assurance	3%
		Manager ILC (Integrated Loss Control)	3%
	Location PIC and Approver	Loading Master	13%
		Integrated Terminal Manager	2%
		Junior Supervisor	23%
		Lead Operations	3%
		Superintendent LPG dan Fuel	2%
		Fuel Terminal Manager	3%
		Supervisor	28%
		Junior Supervisor	23%
Length of time users have used IOS	< 1Month		13%
	1-3 Month		39%
	3-6 Month		20%
	> 6Month		28%
Frequency of Use of IOS Apps	Everyday		21%
	Once a week		44%
	Once a month		18%
	(rarely) 1-2 times per month		17%
Frequency of Use of IOS Dashboard	Everyday		26%
	Once a week		38%
	Once a month		21%
	(rarely) 1-2 times per month		15%

Table 2
PIECES and usability methods.

Variable	Indicator	Reference
Perfomance	Ease of user access [23]	Measure the extent to which users find it easy to access the IOS without hindrance.
Perfomance	Compatibility [23]	Assess how compatible the IOS is.
Performance	Responsiveness [23]	Measuring the IOS response speed without delays or slowdowns.
Performance	Audibility [11]	Assessing the completeness and adequacy of IOS usage information provided in the procedure.
Information	Latest information [9]	Ensuring users receive up-to-date information to support decisions and confidence.
Information	Information OTL [23]	Assessing the availability of current OTL information for loss follow-up.
Information	Information Rele [11]	Assessing the accuracy and relevance of information based on recipient location.
Economy	Ease of notifications [25]	Evaluating whether IOS helps users handle tolerable loss more quickly and efficiently.
Economy	Time Savings [23]	Measuring the extent to which IOS saves users' time in handling losses.
Economy	Ease of tracking losses [23]	Assessing the IOS in making it easier for users to track losses from the features in the IOS.
CS*	Minim Error [23], [26]	Measuring IOS stability in performing functions without interference or errors.
CS*	Integrity [11], [25]	Measuring the reliability of IOS under the current mechanism.
Efficiency	System accuracy [9]	Measuring how effectively IOS minimizes false alarms.
Efficiency	Accuracy of event chronology categorization. [24]	Measuring IOS accuracy in displaying loss information by event chronology during oil and gas handovers.
Efficiency	Accuracy of action categorization [9] , [25].	Measuring IOS accuracy in displaying loss information by action category.
Service	Complaint service [23], [11]	Measuring the effectiveness of the non-conformity form in handling user issues and complaints.
Service	Reliability [20], [11]	Measuring whether IOS performance meets current user expectations.
Memorability	Memorability [20], [21]	Measuring how well users remember the system's workflow over time.
UI	Data visualization [21]	Satisfaction with IOS appearance, including data visualization, colors, and diagrams.
Ease	Ease of learning [22]	Ease quickly learning and understanding how the system works.
Ease	Ease of use [21]	Evaluating how independently users can operate the system without guidance.

2.3. Binary logistic regression data analysis

Binary logistic regression is employed to analyze factors influencing IOS user satisfaction, where the dependent variable is dichotomous, categorized as satisfied (1) and dissatisfied (0). This method is appropriate because the response variable has two possible outcomes [9]. The analysis consists of instrument testing, assumption checking, model estimation, significance testing, and model evaluation to ensure robustness and interpretability.

Prior to regression analysis, the validity and reliability of the questionnaire were examined to ensure that each indicator accurately and consistently measures IOS user satisfaction [27]. Validity testing was conducted using the Pearson Product–Moment Correlation with a significance level of 5% and degrees of freedom (n–2). An indicator is considered valid if the calculated correlation coefficient exceeds the critical value. Based on [28], the Pearson Product–Moment Correlation formula is expressed in Eq. (1),

$$r = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x^2)][n\sum y^2 - (\sum y)^2}} \quad (1)$$

where n represents the number of respondents, x is the total score of each item, and y is the total score of the corresponding variable.

Reliability testing was performed using Cronbach's alpha to assess internal consistency. A Cronbach's alpha value equal to or greater than 0.70 indicates that the instrument is reliable or acceptable [29], [30]. The reliability coefficient is calculated using the Eq. (2) and Eq. (3),

$$r = \left[\frac{k}{k-1}\right]\left[1 - \frac{\sum \sigma_{t^2}}{\sigma_{t^2}}\right] \quad (2)$$

$$\sigma^2 = \frac{\sum x^2 - [(\frac{\sum x}{n})^2]}{n} \quad (3)$$

where k denotes the number of questionnaire items, $\sum\sigma^2$is the total item variance, σ_t^2 is the total variance, and n is the number of respondents. Both validity and reliability analyses were conducted using Python on Google Colab.

To ensure that the regression model produces unbiased and stable coefficient estimates, the assumption of no perfect multicollinearity among independent variables was tested. Multicollinearity can cause poor estimation of regression coefficients and obscure the individual effects of predictors [31]. This study applied Pearson correlation heatmaps and the Variance Inflation Factor (VIF) method. A VIF value greater than 5–10 indicates high multicollinearity and suggests that the variable should be eliminated.

The simultaneous effect of independent variables on user satisfaction was evaluated using the likelihood ratio test (G-test). The hypotheses are defined as follows:

- H_0: $\beta_1 = \beta_2 = \ldots = 0$ (no significant simultaneous effect of independent variables on user satisfaction)
- H_1: at least one $\beta_i \neq 0$ (at least one independent variable significantly affects user satisfaction)

Based on Hosmer and Lemeshow [32], the G-test statistic is calculated using Eq. (4),

$$G = -2\,Ln \left[\frac{Likelihood\ without\ the\ variable}{ikelihood\ with\ the\ variable}\right] \quad (4)$$

		Predicted outcome		
		Dissatisfied	Satisfied	Total
Actual Outcome	Dissatisfied	True negatives	False positives	Total actual No
	Satisfied	False negative	True positives	Total actual Yes
	Total	Total predicted No	Total predicted Yes	Total sample

Fig. 1. Confusion matrix

The null hypothesis is rejected if the calculated G value is greater than the chi-square critical value or if the p-value is less than or equal to $\alpha = 0.05$ [33], [34].

Partial significance of each independent variable was assessed using the Wald test, which evaluates whether a regression coefficient significantly differs from zero [35]. The hypotheses for the Wald test are stated as

– H_0: $\beta_1 = \beta_2 = \ldots = 0$ (the independent variable has no significant effect on user satisfaction)
– H_1: at least one $\beta_i \neq 0$ (the independent variable has a significant effect on user satisfaction)

An independent variable is considered significant if its p-value is less than 0.05; otherwise, it is deemed insignificant [36]. Model refinement was conducted using the backward elimination method, whereby independent variables with the highest p-values were sequentially removed until all remaining predictors had p-values less than 0.05 [37]. The final binary logistic regression model is expressed as in Eq. (5),

$$g(x) = \ln = \frac{\hat{p}}{1-\hat{p}} = b_0 + b_1x_1 + \cdots + b_nx_n \quad (5)$$

where $\hat{p}$ denotes the probability of user satisfaction and β represents the vector of regression coefficients (β_1, β_2, …, β_n). The logistic probability function is defined as in Eq. (6).

$$\hat{p} = \frac{\exp(b_0 + b_1x_1)}{1 + \exp(b_0 + b_1x_1)} = \frac{e^{b_0 + b_1x_1}}{1 + e^{b_0 + b_1x_1}} \quad (6)$$

The term e or exp refers to the exponential function with a constant value of approximately 2.718 [38], [39], [17]. To interpret the magnitude and direction of the influence of significant independent variables on IOS user satisfaction, odds ratios (OR) were calculated. The odds ratio represents the change in the likelihood of an outcome due to a one-unit increase in an independent variable [40].

Finally, the predictive performance of the binary logistic regression model was evaluated using a confusion matrix, which compares actual outcomes with predicted outcomes to assess classification accuracy and prediction errors. Based on the confusion matrix, performance metrics including accuracy, precision, recall, and F1-score were calculated [41], [42]. Model discrimination capability was further evaluated using the Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC). An AUC value close to 1 indicates excellent predictive ability, whereas an AUC value of 0.5 indicates poor discrimination performance [38].

Evaluation of the accuracy of the prediction model is seen from the Confusion Matrix, which is a cross-table between the actual value and the predicted value in the predictive model used to measure how well the model measures predictions and identifies prediction errors, as shown in Fig. 1.

From the combination of values based on the Confusion Matrix results, we can measure the performance of the model by measuring Accuracy, Precision, Recall, F1 Score [41], [42]. ROC Curve (Receiver Operating Characteristic) is a graph showing how well a model can distinguish between two Positive and Negative classes. AUC equal to 1 means perfect predictive ability. AUC equal to 0.5 means the model cannot predict well [38].

3. Results and discussions

3.1. *Overview of IOS user satisfaction*

The results of the questionnaire indicate that IOS users generally perceive the system positively. However, variations across several indicators suggest that satisfaction is influenced by specific system attributes rather than overall system availability. This condition justifies the application of binary logistic regression to identify dominant factors affecting user satisfaction, as recommended for dichotomous outcome variables [9].

3.2. *Validity and reliability analysis*

The validity and reliability tests confirm that all questionnaire items meet the required statistical criteria. Based on the Pearson Product–Moment Correlation, all indicators show correlation coefficients exceeding the critical value, indicating valid measurement items [27], [28]. Reliability testing using Cronbach's alpha produces a value greater than 0.70, demonstrating strong internal consistency and confirming that the instrument is reliable for repeated use [29], [30]. The detailed results of the validity and reliability tests are presented in Table 3.

3.3. *Multicollinearity testing*

Multicollinearity testing was conducted to ensure unbiased estimation of regression coefficients. High correlation among independent variables may obscure their individual effects on the dependent variable [31].

Table 3
Validity and reliability test.

Variable	No	Indicator	r_{xy}	$R(0.05;59)$	Explanation
Performance	1	Ease of User Access	0.817	0.252	Valid
	2	Compatibility	0.558	0.252	Valid
	3	Responsiveness	0.825	0.252	Valid
	4	Audibility	0.710	0.252	Valid
	5	Latest Information	0.618	0.252	Valid
Information	6	OTL Information	0.834	0.252	Valid
	7	Information Relevance	0.750	0.252	Valid
Economy	8	Easy Completion of OTL Notification	0.799	0.252	Valid
	9	Time Savings	0.839	0.252	Valid
	10	Ease of Tracking Losses	0.808	0.252	Valid
Control and Security	11	Minim Error	0.757	0.252	Valid
	12	Integrity	0.735	0.252	Valid
Efficiency	13	System accuracy	0.787	0.252	Valid
	14	Accuracy of event chronology category	0.740	0.252	Valid
	15	Accuracy of action category	0.706	0.252	Valid
Service	16	Complaint Service	0.811	0.252	Valid
	17	Reliability	0.846	0.252	Valid
Usability	18	Memorability	0.725	0.252	Valid
	19	Data Visualization	0.742	0.252	Valid
	20	Ease of learning	0.817	0.252	Valid
	21	Ease of use	0.817	0.252	Valid

Table 4
Variance Inflation Factor (VIF) results for multicollinearity test.

No	Variable	VIF
1	Compatibility	3.530852
2	Responsiveness	3.679767
3	Audibility	3.075726
4	Latest Information	1.870106
5	OTL Information	4.235157
6	Information Relevance	3.078291
7	Ease of Tracking Losses	4.23043
8	Minim Error	3.877897
9	Integrity	4.029957
10	Memorability	2.03192
11	Data Visualization	2.895377
12	Ease of use	2.920027

Table 5
Independent variable (after elimination).

No	Variable	Name
1	X_2	Compatibility
2	X_3	Responsiveness
3	X_4	Audibility
4	X_5	Latest Information
5	X_6	OTL Information
6	X_7	Information Relevance
7	X_{10}	Ease of Tracking Losses
8	X_{11}	Minim Error
9	X_{12}	Integrity
10	X_{18}	Memorability
11	X_{19}	Data Visualization
12	X_{21}	Ease of use

The Variance Inflation Factor (VIF) results indicate that all retained variables have VIF values below the threshold of 5, confirming the absence of severe multicollinearity. The VIF analysis results are summarized in Table 4.

Table 6
Individual significance test.

Variable	Wald	Sig.	Exp(B)
X2	0.951	0.330	0.283
X3	0.005	0.946	1.078
X4	0.207	0.650	1.855
X5	0.135	0.713	1.314
X6	0.298	0.585	2.159
X7	3.893	0.048	7.961
X10	2.695	0.101	0.022
X11	0.121	0.728	1.580
X12	0.116	0.733	0.586
X18	1.212	0.271	0.280
X19	0.803	0.370	2.981
X21	2.573	0.109	9.098
Constant	0.002	0.962	1.226

3.4. Binary logistic regression analysis

3.4.1. Simultaneous significance test

The likelihood ratio test demonstrates that the independent variables simultaneously have a significant effect on IOS user satisfaction. The calculated G value exceeds the chi-square critical value, leading to the rejection of the null hypothesis. This result confirms that the proposed logistic regression model is statistically significant [32], [33], [34].

3.4.2. Partial significance and variable selection

Partial parameter testing using the Wald test reveals that not all independent variables significantly affect IOS user satisfaction. Variables with p-values greater than 0.05 were removed sequentially using the backward elimination method to obtain a parsimonious model [35], [36], [37].

Table 7
Backward elimination stage nine.

	B	Wald	Sig.	Exp(B)
X7	1.477	5.639	0.018	4.379
X10	-1.788	3.831	0.05	0.167
X21	1.572	4.921	0.027	4.815
Constant	-2.807	1.073	0.3	0.060

Table 8
Retests the overall significance.

Step	- 2 log likelihood	Nagelkerke R Square
1	37.100	0.361

Table 9
Accuracy, precision, recall, F1 Score.

	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	1
1	1.00	1.00	1.00	12
Accuracy			1.00	13
Macro Avg.	1.00	1.00	1.00	13
Weighted Avg.	1.00	1.00	1.00	13

The remaining variables after the elimination process are shown in Table 5, while the Wald test results are presented in Table 6. The final backward elimination results are summarized in Table 7, and the final model specification is provided in Table 8.

3.5. Odds ratio interpretation

Odds ratio analysis was conducted to measure the magnitude of the relationship between significant independent variables and IOS user satisfaction. The results indicate that information relevance and ease of use positively influence satisfaction, supporting usability and information quality theory in digital systems [40]. Conversely, increased complexity in loss-tracking features reduces user satisfaction, indicating the need for interface simplification.

3.6. Model performance evaluation

Model performance was evaluated using classification accuracy, precision, recall, and F1-score metrics. The evaluation results indicate that the model demonstrates excellent predictive capability. However, although the Area Under the Curve (AUC) value approaches 1, the results should be interpreted cautiously due to sample size limitations, as recommended in logistic regression performance evaluation studies [38], [39], [41], [42]. The detailed performance metrics are presented in Table 9.

3.7. Discussion, managerial implications, and future research

The results of this study indicate that IOS user satisfaction is primarily influenced by information relevance, ease of use, and the effectiveness of loss-tracking features. These findings are consistent with previous studies that emphasize information quality and usability as dominant determinants of user satisfaction in digital information and logistics systems [43], [44], [45]. Systems that deliver accurate, timely, and context-aware information have been shown to significantly enhance user trust and satisfaction, particularly in operational and logistics environments [46], [47].

Unlike prior studies that mainly focused on technical system performance or infrastructure readiness [48], [49], this research integrates the PIECES framework and usability dimensions within a binary logistic regression model. This integrated approach provides a more comprehensive explanation of user satisfaction behavior and strengthens the empirical evidence that user-centered design is as critical as system functionality in digital service implementation [50], [51].

The significant positive effect of ease of use supports established usability theory, which states that intuitive interfaces and minimal cognitive load improve user acceptance and system adoption [52], [53]. Conversely, the negative influence of loss-tracking complexity indicates that overly detailed or non-intuitive features may reduce satisfaction, even when the feature is functionally important. Similar findings have been reported in previous studies, where excessive system complexity negatively affected user experience and operational efficiency [54], [55].

From a managerial perspective, these findings suggest that IOS development strategies should prioritize information relevance and usability rather than focusing solely on adding new features. Decision-makers should emphasize simplifying user interaction, improving information clarity, and optimizing loss-tracking workflows to support operational needs without increasing system complexity. Previous studies in logistics digitalization and public sector information systems confirm that such strategies significantly improve adoption rates and service performance [56], [57].

Despite the strong predictive performance of the proposed model, the results should be interpreted cautiously. Prior studies have highlighted that very high classification accuracy may indicate overfitting, particularly when the sample size is limited [58]. Therefore, future research should involve larger datasets, apply cross-validation techniques, and explore alternative analytical approaches such as machine learning or hybrid models to enhance generalizability and robustness.

4. Conclusions

This study set out to evaluate user satisfaction with IOS (Innovation on Supply Loss) by integrating the PIECES and Usability frameworks with Binary Logistic Regression analysis. A total of 21 potential factors were identified, but only three variables, Information Relevance, Ease of Tracking Losses, and Ease of Use, were found to have a significant impact on satisfaction.

The findings provide important managerial implications. First, system developers and managers should prioritize real-time data updates and location-based accuracy to enhance information relevance. Second, templates and reporting features should be redesigned for clarity and efficiency, reducing redundant or confusing inputs. Third, user training and integrated support systems are essential to ensure that employees at different levels of digital literacy can adapt easily. These measures will not only improve IOS adoption but also strengthen decision-making and operational efficiency within industrial digitalization initiatives.

Despite the contributions, this study has limitations. The relatively small sample size and single-industry focus restrict the generalizability of the findings. Future research should expand the scope by incorporating larger and more diverse datasets across different sectors. Furthermore, advanced analytical approaches, such as machine learning and longitudinal studies, could be applied to validate results and uncover dynamic changes in user satisfaction over time. Exploring cultural and organizational factors influencing digital system adoption will also provide deeper insights for theory and practice.

CRediT author statement

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Data availability statement

The variables used in this study were developed based on relevant previous studies and are described within the article. Data cannot be displayed in its entirety. The dataset is available from the corresponding author upon reasonable request.

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