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Inventory and Decision Support System for Entrepreneurs Using Computational Algorithms

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Abstract: ***This study presents the development of an inventory and decision support system designed to assist entrepreneurs managing small and medium-sized enterprises. Utilizing computational algorithms, the system incorporates ABC classification, rule association mining, and reorder point analysis to optimize inventory decision-making. The algorithms were evaluated using the F1 score, with rule association and reorder point analyses achieving a perfect score of 1.0, and ABC analysis recording a score of 0.71. The system was further validated through ISO/IEC 25010 standards and a user acceptability test involving 14 participants, including business owners and IT professionals. Evaluation results showed excellent ratings across software quality characteristics, demonstrating the system's reliability, usability, compatibility, and maintainability. These findings highlight the practical applicability of computational algorithms in enhancing smart inventory management for small businesses.***

Keywords: inventory management, decision support system, computational algorithms, f1 score, ISO 25010

1. Introduction

In today's fast-paced business environment, entrepreneurs face a myriad of challenges when it comes to managing their operations effectively. One of the most critical aspects of running a successful business is inventory management, which directly impacts customer satisfaction and overall business performance. Effective inventory management not only ensures optimal stock levels but also enables informed decision-making that drives growth and profitability [1].

However, many small and medium-sized enterprises (SMEs) struggle with implementing effective inventory control systems due to limited resources, lack of expertise, and the sheer complexity of modern markets [2]. These businesses often rely on outdated methods or gut instincts to make crucial decisions, which can lead to suboptimal outcomes and missed opportunities [2].

The advancement of technology has opened up new possibilities for entrepreneurs to streamline their operations and make data-driven decisions. Despite these technological capabilities, the adoption of modern inventory management and decision support systems among businesses remains surprisingly low. This technology gap [2] presents a significant opportunity to develop tailored solutions using appropriate algorithms that address the unique needs and constraints of entrepreneurial ventures.

Recent studies (Analytical Approaches in Inventory Management) have highlighted the potential benefits of integrating various analytical approaches into inventory management systems [2]. Researchers should focus on leveraging descriptive analytics to provide clear insights into historical sales patterns, stock levels, turnover rates, and seasonal trends [3].

Several analytical techniques have shown promise in optimizing inventory management. Such as, ABC analysis that can prioritize inventory items based on their importance and value to the business [4], and computational algorithms have demonstrated advancement in optimizing reorder points and quantities, adapting to changing market conditions in real-time [5].
This study aims to address the identified gap [4] by developing an integrated inventory and decision support system using computational algorithms, specifically tailored to the needs of entrepreneurs. By leveraging a combination of analytical techniques including time ABC analysis, and computational algorithms that seeks to empower business owners with actionable insights and recommendations.

The ultimate goal of this research is to develop a comprehensive system that not only optimizes inventory levels but also serves as an integrated decision support platform. This system aims to help entrepreneurs navigate the complexities of modern business with greater confidence and success, bridging the gap between available technology and practical implementation in small business environments.

This study holds practical significance by providing a tailored digital tool for SMEs to improve inventory decision-making using validated computational techniques. It bridges the gap between theoretical algorithm design and real-world business implementation, promoting data-driven entrepreneurship.

2. Research Objectives

General Objective
This study was conducted to develop an inventory and decision support system for entrepreneurs using computational algorithms to optimize inventory management.

Specific objectives:
Specifically, this study was intended to :
1) Develop an inventory system that can manage store, user, stocks, warehouse, and point of sale.
2) Develop a decision support system for inventory optimization using comparative analysis, association rule, reorder point and abc analysis
3) Evaluate the system using ISO25010 accuracy test and user acceptability test.

3. Methodology

Research Design

This study utilized developmental research design. To achieve the study's objectives, different developmental research methods were employed. This included careful analysis of data and findings. This methodology was deemed appropriate as it aimed to develop a system that will help entrepreneurs optimize inventory management. Descriptive survey results were used to refine the system's functionalities and basis for data-driven improvements.

Participants of the Study

Fourteen participants were included in the study and evaluated the Inventory and Decision Support System for Entrepreneurs using Computational Algorithms. The selection considered the nature of the study, participants conducted a pilot testing of the study and were informed of the evaluation test and data confidentiality.

Participants included three business owners, three warehouse managers, three cashiers, and five IT experts.

The number of participants was deemed sufficient for a pilot evaluation considering the targeted end-users and the developmental scope of the study.

Data Gathering Procedure

The data gathering commenced with the interview of the evaluators of the study, to provide necessary information in the development of the system. Moreover, the researcher gathered and analyzed literature to develop insights about inventory optimization and identified possible research gaps. Another data gathering tool was a researcher-made Evaluation Instrument for End-User Evaluation using the ISO/IEC 25010 Software Quality Model Characteristics that underwent validity and reliability testing. And the researcher made sure that the algorithm used were tested with accuracy using F1 score metrics.

Statistical Tools Used

The data gathering instrument was designed similar to the characteristics of the system based on the ISO 25010 which were analyzed using weighted mean and standard deviation. Moreover, uses F1 score metrics to validate algorithm accuracy.

Weighted Mean

The weighted mean for a particular characteristic was computed by taking the sum of the products of each indicator's assigned weight and the number of respondents who selected that response, divided by the total number of respondents.

$$\bar{x}_w = \frac{\sum fx}{n}$$

Where:
$\bar{x}_w$= weighted mean
f = frequency x = scores
n = total number of participants
$\sum$ = summation symbol

Likert Scale

The data gathering instrument was in the form of a 5-point Likert scale from where the weighted mean was derived. Adjectival interpretation of the weighted mean is shown below:

Table 1: Weighted Mean and its Verbal Interpretation

Range	Interpretation
1.00 – 1.80	Poor
1.81 – 2.60	Fair
2.61 – 3.40	Good
3.41 – 4.20	Very Good
4.21 – 5.00	Excellent

F1 Score Metrics

The F1 score serves as a comprehensive performance metric for evaluating the accuracy and reliability of three critical inventory management algorithms: association rule mining, reorder point analysis, and ABC classification. As a harmonic mean of precision and recall, the F1 score provides a balanced assessment that accounts for both false positives and false negatives, making it particularly suitable for inventory management contexts where both over-prediction and under-prediction carry significant operational costs.

Software Model

This area presents a description of the software model used in developing the system. The researcher utilized the Agile Model because it was specifically designed and justified by its alignment with entrepreneurial environments, which are characterized by uncertainty, rapid change, and the need for quick adaptation to market feedback. In addition, the application requirement is well documented, fixed, and clear. The following are the stages of Agile Methodology: (1) Requirements Planning, (2) User Design, (3) Development, (4) Testing, (5) Deployment, and (6) Review.

4. Results and Discussion

This section presents the analysis and interpretation of the data.

Table 2: Mean and Standard Deviation of the Functional Suitability of the System

Criteria	Mean	Description	Standard Deviation
A. Functional Completeness	4.71	Excellent	0.45
B. Functional Correctness	4.64	Excellent	0.47
C. Functional Appropriateness	4.64	Excellent	0.47
Average Mean	4.67	Excellent	0.03

The system met the required functionality standard in terms of functional completeness. The experts evaluated it as "Excellent" (M=4.71, SD=0.45). This implies that the system covers all the specified tasks and objectives. Meanwhile, functional correctness was described as "Excellent" (M=4.64, SD=0.47). This means that the system provided the correct results with the needed degree of precision. Lastly, functional appropriateness was described as "Excellent" (M=4.64, SD=0.47) which means that the system provided appropriate functions to facilitate the accomplishment of specified tasks and objectives.

Table 3: Mean and Standard Deviation of the Performance Efficiency of the System

Criteria	Mean	Description	Standard Deviation
A. Time Behavior	4.36	Excellent	0.48
B. Resource Allocation	4.35	Excellent	0.48
C. Capacity	4.21	Excellent	0.41
Average Mean	4.31	Excellent	0.07

Performance efficiency evaluation result of (M=4.31, SD=0.07) was described as “Excellent.” This means that the system was able to perform its functions efficiently and met the requirements while optimizing the use of resources.

Each criterion in this evaluation; time behavior, resource allocation and capacity, were all described as “Excellent.” These results imply that the system was able to meet the requirements in the following parameters; response and processing times, throughput rates, types of resources and maximum limits.

Table 4: Mean and Standard Deviation of the Compatibility of the System

Criteria	Mean	Description	Standard Deviation
A. Co-existence	4.43	Excellent	0.49
B. Interoperability	4.21	Excellent	0.55
Average Mean	4.32	Excellent	0.10

Compatibility evaluation result (M=4.32, SD=.0.10) was described as “Excellent.” This means that the system was able to exchange information with other systems and operate its required functions while sharing the same hardware or software environment.

The system can be hosted on any server, may it be shared or private, as long it runs on a Windows OS. It was tested and installed on a shared environment and no conflicts or issues found with regards to other software installed in that said environment. This is why the system was evaluated as “Excellent” under the Co-existence criterion. The system was also rated as “Excellent” on Interoperability as it was able to exchange data with other software. One basic example is the use of Excel Files. One of the inputs the system accepts is an Excel file containing upload business plan.

Table 5: Mean and Standard Deviation of the Usability of the System

Criteria	Mean	Description	Standard Deviation
A. Appropriateness Recognizability	4.21	Excellent	0.55
B. Learnability	4.42	Excellent	0.49
C. Operability	4.28	Excellent	0.45
D. User Interface Aesthetics	4.35	Excellent	0.47
E. Accessibility	4.35	Excellent	0.47
F. User Error Protection	4.42	Excellent	0.49
Average Mean	4.34	Excellent	0.07

Usability evaluation result of (M=4.34, SD=0.07) was described as “Excellent.” It implies that the users recognize that the system is appropriate for their needs and that it is very accessible and convenient to use. The result also implies that the interface of the system is well-designed. Users were able to learn in just a short period of time how to use and operate it. They were able to easily communicate with the system, move from one page to another and understand its flow.

Table 6: Mean and Standard Deviation of the Reliability of the System

Criteria	Mean	Description	Standard Deviation
A. Maturity	4.35	Excellent	0.47
B. Availability	4.5	Excellent	0.5
C. Fault Tolerance	4.35	Excellent	0.61
D. Recoverability	4.42	Excellent	0.49
Average Mean	4.41	Excellent	0.05

Reliability evaluation result of (M=4.41, SD=0.05) was described as “Excellent.” This means that the system was able to perform functions that it was designed to do under the condition that it was designed to operate.

The system was able to operate as intended despite the presence of faults. When failures occur, the system can recover the data and re-establish the desired operation. With the use of error logs, users were able to determine what course of action to take to fix the bugs. Moreover, the system gets better and becomes more reliable overtime because of the enhancements made when fixing the bugs that were discovered.

Table 7: Mean and Standard Deviation of the Security of the System

Criteria	Mean	Description	Standard Deviation
A. Confidentiality	4.42	Excellent	0.49
B. Integrity	4.35	Excellent	0.47
C. Non- Repudiation	4.35	Excellent	0.47
D. Accountability	4.35	Excellent	0.47
E. Authenticity	4.21	Excellent	0.41
Average Mean	4.34	Excellent	0.06

Security evaluation result of (M=4.34, SD=0.06) was described as “Excellent.” This means the system was able to protect information and users have the appropriate type of data access depending on the levels of their authorization. The system ensured that the data remain confidential and will only be available to those who are authorized and have access to it

Table 8: Mean and Standard Deviation of the Maintainability of the System

Criteria	Mean	Description	Standard Deviation
A. Modularity	4.21	Excellent	0.41
B. Reusability	4.14	Excellent	0.34
C. Analyzability	4.35	Excellent	0.47
D. Modifiability	4.42	Excellent	0.49
E. Testability	4.35	Excellent	0.47
Average Mean	4.3	Excellent	0.10

Maintainability evaluation result of (M=4.3, SD=0.10) was described as “Excellent.” This means the system can be modified, improve, and adapt to changes in environment, and in requirements.

The result of evaluation shows that the system has the capacity to trace or easily identify its flaws and can be fixed and maintained by the developer easily. The system provided a way to handle errors easily by keeping an error log. This log contains useful information about errors, including the time of occurrence, where it occurred and if possible, how it occurred. This information is very useful in diagnosing problems and provides some insights as to what went wrong with system.

Table 9: Mean and Standard Deviation of the Portability of the System

Criteria	Mean	Description	Standard Deviation
A. Adaptability	4.35	Excellent	0.47
B. Installability	4.21	Excellent	0.41
C.Replaceability	4.28	Excellent	0.58
Average Mean	4.28	Excellent	0.05

Portability evaluation result of (M=4.28, SD=0.05) was described as "Excellent." This means the system effectiveness and efficiency with which a system, can be transferred from one hardware, software or other operational or usage environment to another.

Table 10: Evaluate Rule of Association Analysis Algorithm Accuracy using F1 Score

Outcomes	Values
TP	44
FP	0
FN	0
TN	0
TP + FP	44
Precision	1
TP + FN	44
Recall	1
2 × Precision × Recall	2
Precision + Recall	2
F1 Score	**1**

Outcomes	Class A	Class B	Class C	Total
TP	16	10	9	35
FP	0	8	6	14
FN	8	6	0	14
TN	25	25	34	84
TP + FP	16	18	15	49
Precision	1	0.55555556	0.6	0.714285714
TP + FN	24	16	9	49
Recall	0.66666667	0.625	1	0.714285714
2 × Precision × Recall	1.333333333	0.694444444	1.2	1.020408163
Precision + Recall	1.666666667	1.180555556	1.6	1.428571439
F1 Score	0.8	0.588235294	0.75	0.714285714

The association rule mining algorithm demonstrated performance in identifying product relationships within the inventory dataset, achieving a perfect F1 score of 1.0, which represents 100% accuracy in the classification task. The confusion matrix revealed that the algorithm successfully identified 44 true positives, meaning all actual product associations present in the dataset were correctly detected by the system. Remarkably, the analysis produced zero false positives, indicating that the algorithm did not incorrectly identify any non-existent associations as valid relationships, thereby ensuring that all recommended product pairings were based on genuine purchasing patterns rather than spurious correlations.

The precision metric, calculated as TP/(TP+FP), yielded a perfect score of 1.0, demonstrating that every association rule generated by the algorithm was accurate and reliable. This high precision is particularly valuable for inventory management applications, as it ensures that business decisions based on these associations such as bundling strategies, cross-selling recommendations, and coordinated restocking are grounded in authentic customer behavior patterns. Simultaneously, the recall metric, computed as TP/(TP+FN), also achieved a perfect score of 1.0, with zero false negatives recorded. This indicates that the algorithm captured all existing product associations within the dataset without missing any significant relationships, ensuring comprehensive coverage of potential optimization opportunities.

Table 11: Evaluate Reorder Point Analysis Algorithm Accuracy using F1 Score

Outcomes	Values
TP	38
FP	0
FN	0
TN	12
TP + FP	38
Precision	1
TP + FN	38
Recall	1
2 × Precision × Recall	2
Precision + Recall	2
F1 Score	**1**

The Reorder Point (ROP) analysis algorithm using F1 score metrics demonstrates exceptional classification performance, achieving a perfect score of 1.0 (100% accuracy). This outstanding result represents the highest possible level of algorithmic accuracy, indicating that the ROP analysis component of the inventory management system performs flawlessly in identifying optimal reorder thresholds and classifying inventory items according to their reorder requirements. The perfect F1 score was derived from 38 true positives, zero false positives, and zero false negatives, alongside 12 true negatives, demonstrating that the algorithm successfully classified all 50 test cases without any misclassification errors.

Table 11: Evaluate ABC Analysis Algorithm Accuracy using F1 Score

Outcomes	Class A	Class B	Class C	Total
TP	16	10	9	35
FP	0	8	6	14
FN	8	6	0	14
TN	25	25	34	84
TP + FP	16	18	15	49
Precision	1	0.555555556	0.6	0.714285714
TP + FN	24	16	9	49
Recall	0.666666667	0.625	1	0.714285714
2×Precision × Recall	1.333333333	0.694444444	1.2	1.020408163
Precision+ Recall	1.666666667	1.180555556	1.6	1.428571429
F1 Score	0.8	0.58823529	0.75	0.71428571

ABC analysis performance was conducted using F1 score metrics, which provide a comprehensive measure of classification accuracy by balancing precision and recall. This approach validates the algorithm's ability to correctly categorize inventory items into their respective classes (A, B, and C) based on value contribution and importance. The F1 score analysis reveals differentiated performance levels across the three classification categories, offering insights into the algorithm's strengths and areas requiring refinement.

The overall system performance achieved an F1 score of 0.714285714 (approximately 71.43%), indicating that the ABC classification algorithm demonstrates moderately strong accuracy in categorizing inventory items. This aggregate score was calculated from 35 true positives, 14 false positives, and 14 false negatives across all three classes, with overall precision and recall both converging at 71.43%. This balanced precision-recall relationship suggests that the algorithm maintains consistent performance in both identifying correct classifications and capturing all relevant items within each category, without significantly favoring one metric over the other.

Class A items, representing the highest-value inventory components that typically account for approximately 80% of total inventory value, demonstrated the strongest classification performance with an F1 score of 0.8. The algorithm achieved perfect precision (1.0) for Class A items, meaning that every item classified as Class A was correctly identified with zero false positives. This precision is particularly significant given the critical nature of Class A items in inventory management, as misclassifying lower-value items as high-priority would lead to inefficient resource allocation and excessive management attention on less important inventory. However, the recall for Class A was 0.67 (approximately 66.67%), indicating that the algorithm failed to identify 8 items that should have been classified as Class A (false negatives).

Class B items, which represent moderate-value inventory requiring balanced management attention, exhibited the lowest F1 score at 0.588235294 (approximately 58.82%). This category demonstrated the most significant classification challenges, with precision at 0.556 and recall at 0.625. The presence of 8 false positives indicates that items from other classes were incorrectly promoted to Class B status, while 6 false negatives suggest that legitimate Class B items were misclassified into other categories. The relatively lower performance in Class B classification can be attributed to the inherent ambiguity in the boundary zones between high, moderate, and low-value classifications.

Class C items, representing low-value inventory that typically constitutes a large number of items but minimal overall value, achieved an F1 score of 0.75, demonstrating solid classification performance. Notably, Class C exhibited perfect recall (1.0), meaning the algorithm successfully identified all items that truly belonged in this category with zero false negatives. This complete capture of Class C items ensures that no low-priority inventory is mistakenly elevated to higher management priority levels, which could waste resources on items that require minimal oversight. However, the precision for Class C was 0.6, with 6 false positives indicating that some items from higher-value classes were incorrectly relegated to the lowest priority category. While this precision level is acceptable, the misclassification of potentially important items into Class C represents a risk, as these items may receive insufficient management attention and could lead to stockouts if demand patterns change.

5. Conclusion

The developed inventory and decision support system successfully integrates computational algorithms to enhance the inventory practices of entrepreneurs operating small businesses. The use of F1 metrics demonstrated strong algorithmic performance, particularly in rule association and reorder point analysis. Evaluation through ISO/IEC 25010 standards confirmed the system's robustness, usability, and maintainability. These findings suggest that the system offers a viable solution for SMEs seeking to improve their inventory efficiency and data-driven decision-making capabilities.

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