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WASTE REDUCTION STRATEGY IN A SMALL-SCALE PACKAGING INDUSTRY USING THE WASTE ASSESSMENT MODEL AND PROCESS ACTIVITY MAPPING: A TIME-BASED DIAGNOSTIC APPROACH

Keywords:

Lean Manufacturing; Process Activity Mapping; Small and Medium Enterprises; Packaging Industry; Waste Assessment Model

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Abstract

Small and medium enterprises play a crucial role in manufacturing-based economies but frequently experience operational inefficiencies caused by unmanaged production waste. Unlike large firms, SMEs often operate with manual processes, limited standardization, and restricted data availability, making systematic waste analysis challenging. This study aims to identify the dominant waste drivers and their interrelationships through a case study of a small-scale packaging manufacturing enterprise using a lean manufacturing approach. The study integrates the Waste Assessment Model (WAM) and Process Activity Mapping (PAM) to evaluate waste behavior in the packaging headgear production process. Data were collected through direct observation, time-study measurements, and structured interviews with the enterprise owner. PAM was used to classify activities as value-added (VA), necessary non-value-added (NNVA), or non-value-added (NVA), while WAM was used to quantify the interrelationships among waste categories through a Waste Relationship Matrix (WRM). The results indicate that approximately 40% of total production time consists of NNVA and NVA activities. Overproduction (21.50%), motion (19.63%), and overprocessing (14.02%) were identified as the dominant root wastes, whereas waiting (17.76%) and inventory (16.82%) were the most affected waste categories. The findings demonstrate that waste in small-scale manufacturing systems is structurally interconnected. The integration of WAM and PAM provides a low-resource diagnostic framework to support practical waste reduction strategies in SMEs.

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1. Introduction

Small and medium enterprises (SMEs) increasingly play a central role in national economic development particularly in emerging economies where industrial capacity, labor absorption, and regional resilience strongly depend on their performance (Nazaruddin et al., 2024). In Indonesia, SMEs absorb more than 60% of the national workforce, indicating that improvements in SME operational productivity can generate significant multiplier effects on economic growth (Wicaksono et al., 2024). At the global level, SMEs in developing countries contribute approximately 20–60% of gross domestic product and 38–77% of total employment, with average contributions of 36% and 64%, respectively. Despite this economic importance, SMEs remain highly vulnerable to operational inefficiencies and resource misallocation (Fajarika et al., 2024). Many SMEs rely on manual production systems and exhibit limited technological readiness, which consistently constrains their operational performance (Ghobakhloo, 2020).

Operational inefficiency in SMEs strongly relates to the persistence of production waste, a fundamental concept within the Toyota Production System (TPS). TPS defines waste as any activity that consumes resources without adding value from the customer's perspective (Ohno, 1988). Lean manufacturing literature commonly classifies waste into eight categories: defects, overproduction, waiting, non-utilized talent, transportation, inventory, motion, and overprocessing. Empirical studies have confirmed that these waste categories significantly increase operational costs, disrupt production flow, and reduce manufacturing competitiveness (Hines & Rich, 1997; Liker, 2004; Womack et al., 1991). Longitudinal analyses further demonstrate that even small accumulations of waste can gradually escalate into systemic operational failures (Bhamu & Sangwan, 2014; Shah & Ward, 2007). Researchers have observed these waste dynamics across diverse industrial sectors, ranging from automotive to apparel manufacturing, which suggests that waste behavior remains consistent regardless of organizational scale (Bortolotti et al., 2015).

Field observations at an SME in Indonesia, a micro-scale enterprise specializing in police headgear packaging and uniform accessories, reflect these conditions. Initial assessments show that non-necessary value-added (NNVA) activities account for more than 40% of total production time. These activities include redundant manual operations, excessive operator movement, inefficient material handling, and inventory accumulation caused by inconsistent demand patterns. Previous studies similarly report that SMEs frequently experience operational instability due to the absence of standardized work procedures, heavy reliance on tacit worker knowledge, and limited process visibility (Yusuf & Batubara, 2020; Effendi et al., 2023).

Recent global research trends between 2020 and 2024 increasingly emphasize waste reduction in SMEs. Scholars actively explore the integration of lean manufacturing principles with digital technologies, a concept commonly referred to as "Lean 4.0," to enhance transparency and accuracy in waste identification (Adiawaty & Moeins, 2024; Sony & Naik, 2020). Researchers demonstrate that combining lean practices with Internet of Things (IoT) sensors, cyber-physical systems, and cloud-based monitoring enables real-time, data-driven decision-making that reduces waste occurrence (Frank et al., 2019; Tortorella et al., 2021). However, most SMEs remain poorly prepared to adopt this transition due to limited financial resources, skill gaps, and resistance to digital transformation (Ghobakhloo, 2020; Masood & Sonntag, 2020; Moeuf et al., 2017).

In parallel, sustainability-oriented lean practices continue to gain global attention as industries seek to balance economic performance with environmental responsibility. Studies show that integrating lean and green manufacturing frameworks reduces energy consumption, emissions, and material usage while simultaneously minimizing production waste (Fercoq et al., 2016; Piercy & Rich, 2022). These findings highlight lean manufacturing not only as a productivity-oriented approach but also as a strategic tool for supporting sustainable industrial development.

Despite advances in digital lean tools, researchers consistently emphasize the need for lightweight, low-data waste assessment methods that align with SME constraints. Scholars increasingly develop simplified value stream metrics, waste scoring matrices, rapid diagnostic audits, and visual decision-support tools to assist enterprises that lack comprehensive measurement systems (Hines & Rich, 1997). Among these tools, the Waste Assessment Model (WAM) remains one of the most accessible frameworks for small enterprises.

Rawabdeh (2005) originally introduced WAM as a method for identifying dominant waste types by analyzing interrelationships among different forms of waste in environments with limited data availability (Rawabdeh, 2005). The model employs a Waste Relationship Matrix (WRM) to evaluate the causal strength among waste categories, enabling practitioners to identify primary waste drivers rather than merely addressing observable symptoms. Recent applications in small-scale manufacturing contexts confirm that WAM effectively supports decision-making in job-shop environments characterized by labor-intensive operations and high process variability (Prasetyawan et al., 2021; Muhammad & Yadrifil, 2018).

Contemporary lean manufacturing literature increasingly supports this system-level analysis of waste interactions. Researchers demonstrate that organizations achieve significantly greater operational improvements when they address structural waste drivers instead of implementing isolated, local interventions (Akrami et al., 2021; Buer et al., 2021; Tortorella et al., 2021). Additional empirical evidence further confirms that improvement initiatives should prioritize integrated waste relationships when organizations develop effective improvement roadmaps (Vinodh et al., 2010; Tortorella et al., 2021; Chiarini et al., 2020).

Based on these theoretical and empirical developments, this study establishes a comprehensive foundation for diagnosing waste conditions at SMEs XYZ. By integrating classical lean manufacturing theory, current global research trends, and the Waste Assessment Model, this study justifies the identification of dominant wastes that inhibit productivity in small manufacturing enterprises. The findings aim to support the development of practical, resource-feasible waste reduction strategies suitable for SMEs operating under conditions of labor intensity, low standardization, and high process variability.

Lean manufacturing research has expanded substantially over the past three decades. However, the distribution of research topics and industrial contexts remains heavily concentrated on medium- and large-scale manufacturing systems. Several comprehensive reviews report that more than 75% of published lean studies rely on survey-based methods or case studies conducted in industries such as automotive, plastics, and large-scale packaging (Dieste et al., 2021). These industries typically operate with structured workflows, stable production schedules, and dedicated continuous improvement teams, which naturally facilitate the implementation of formal lean tools. As a result, much

of the existing literature implicitly assumes production environments characterized by high levels of standardization, predictable cycle times, and clearly defined performance baselines.

Such assumptions do not adequately represent the operational reality of micro and small enterprises (SMEs). In these settings, firms predominantly rely on manual labor, informal production planning, and flexible task allocation. Operators frequently make decisions based on experience rather than standardized procedures, and process stability often fluctuates with workload variability and resource availability. This mismatch reveals the first major research gap: lean manufacturing scholarship continues to prioritize organized, capital-intensive industrial systems, while small-scale, labor-intensive environments remain systematically underrepresented in empirical research.

A large body of lean literature focuses on identifying and reducing waste using tools such as Value Stream Mapping (VSM), Value Stream Analysis Tools (VALSAT), takt time calculations, fishbone diagrams, and Failure Mode and Effect Analysis (FMEA) (Ramadhani et al., 2023; Sutharsan et al., 2020). Researchers commonly apply these methods to visualize process flows, identify non-value-added activities, and evaluate improvement opportunities. While these tools effectively capture visible inefficiencies and enhance operational performance, they primarily address surface-level manifestations of waste. In contrast, relatively few studies adopt analytical approaches capable of uncovering the underlying structural relationships among different types of waste.

The Waste Assessment Model (WAM), introduced by Rawabdeh (2005), conceptualizes waste as an interconnected system rather than as a set of isolated phenomena. It assumes that waste types rarely occur independently; instead, one type of waste can trigger or amplify others. For example, overproduction frequently leads to excess inventory, unnecessary transportation, and additional motion, while defects generate rework, inspection, and increased waiting time. Although WAM provides a strong theoretical basis for analyzing these interdependencies, researchers have predominantly applied the model in large manufacturing organizations with multi-stage production lines and established data recording systems. This pattern exposes the second research gap: despite the recognized importance of waste interrelationships, empirical investigations of these dynamics in small, manual production environments remain limited.

Studies focusing specifically on the packaging industry also exhibit recurring limitations. Research on plastic, carton, and specialized packaging manufacturing frequently reports measurable improvements, such as reduced cycle time, increased process cycle efficiency, and higher throughput (Effendi et al., 2023; Sari et al., 2025). However, these studies commonly share several characteristics. First, researchers usually conduct them in medium- or large-scale firms equipped with semi-automated machinery. Second, the proposed improvements often involve equipment upgrades, layout redesign, or work-cell restructuring. Third, many studies emphasize before-and-after performance comparisons without examining the upstream mechanisms that generate waste.

These assumptions do not align with the conditions faced by micro and small packaging enterprises. Small-scale packaging processes often rely heavily on manual operations and exhibit high variability due to customized orders, fluctuating demand, and limited workspace. In such environments, waste arises not only from process layout inefficiencies but also from operator fatigue, inconsistent work methods, poor ergonomics, and unstable production volumes. These characteristics produce waste behaviors that differ fundamentally from those documented in larger firms. This discrepancy constitutes the third research gap: existing lean studies in the packaging sector insufficiently address resource-constrained environments where production performance depends largely on manual labor and informal routines.

Several authors emphasize that in small-scale manufacturing systems, inefficiency primarily stems from the interaction and amplification of multiple waste types rather than from the presence of individual waste categories alone. Overproduction often accumulates into inventory and transportation waste, defects propagate additional motion and reprocessing, and inadequate workstation ergonomics extend setup times and increase non-value-added activities. Nevertheless, most published studies continue to categorize waste independently and rarely attempt to quantify the strength of these interdependencies. Although WAM theoretically supports such system-level analysis, researchers seldom apply it as an early-stage diagnostic tool in micro- and small-scale enterprises. This limitation defines the fourth research gap: prior research has not systematically employed waste interrelationship analysis using WAM to diagnose inefficiencies in small, manual packaging industries.

In response to these gaps, the present study positions itself as an integrative contribution to lean manufacturing research. First, it extends empirical investigation into the domain of micro and small enterprises, providing evidence from production systems characterized by low standardization, fluctuating workloads, and minimal capital investment. Second, the study applies the Waste Assessment Model to evaluate the causal structure of waste interactions, enabling the identification of waste categories that exert the strongest influence on overall system inefficiency. Third, it integrates WAM with Process Activity Mapping (PAM) to simultaneously assess process flow efficiency and waste propagation patterns, an approach rarely implemented in SMEs contexts. Finally, the study emphasizes improvement strategies that prioritize feasibility and practicality, avoiding reliance on costly equipment or extensive layout redesign while aligning recommendations with the operational constraints of small enterprises.

Through this positioning, the study contributes theoretically by deepening the understanding of waste interrelationships in manual production environments and contributes practically by providing an early-stage, data-driven foundation for developing realistic and sustainable waste reduction strategies tailored to small-scale packaging industries.

2. Methods

The methodology adopted in this study follows a structured and sequential approach to identify and analyze waste in the packaging headgear production process at the selected SME. The research commenced with comprehensive on-site observations to understand the actual workflow, operator behavior, workstation configuration, and the emergence of non-value-added activities across the production system. These observations enabled a detailed decomposition of the process into individual work elements, for which setup time, processing time, transportation time, and delay time were measured using standard time-study techniques. This procedure ensured that the collected data accurately represented the operational realities of the shop floor.

To complement observational data, qualitative insights were obtained through an in-depth interview with the owner, who serves as the central decision-maker and possesses complete visibility into all production stages. Given the organizational characteristics of micro-scale manufacturing where operational oversight, scheduling, and quality control are heavily centralized the WAM questionnaire was deliberately administered to the owner. This is consistent with the conceptual foundations of WAM, which stipulate that respondents must have a holistic understanding of process dependencies and waste distribution patterns. Because the owner directly supervises every stage of the packaging headgear workflow, their perspective provides the most valid and reliable basis for assessing inter-waste relationships. This single-respondent approach is treated as a deliberate methodological choice rather than a data-availability constraint; nonetheless, it is acknowledged as a limitation of the present design, and Section 3.C discusses how future studies can complement it with operator-level validation.

Following data collection, a PAM analysis, one of the seven value-stream mapping tools originally formalized by Hines & Rich (1997), was conducted to classify each work element into VA, NNVA, or NVA activities. This mapping revealed clear inefficiencies, including repetitive operator movement due to suboptimal workstation layout, prolonged glue-drying delays, excessive material handling, and redundant preparation activities. These findings provided an empirical foundation for interpreting waste behavior within the production system and establishing the linkage between observed inefficiencies and systemic waste interactions.

The Waste Assessment Model was subsequently employed to quantify the strength of relationships among the seven categories of waste through the development of a Waste Relationship Matrix (WRM). Using Rawabdeh's (Rawabdeh, 2005) scoring criteria Strong (10), Average (8), Weak (4), and No Relation (0) each waste type was evaluated from both the "FROM" and "TO" perspectives. The results showed that overproduction, motion, and overprocessing function as primary drivers that initiate or amplify other forms of waste, thereby acting as structural root causes within the system. Conversely, waiting and inventory emerged as the most affected waste categories, reflecting their dependency on upstream operational inefficiencies. These findings illustrate not only the hierarchical structure of waste interactions but also the systemic nature of inefficiency within the packaging headgear production process.

The integration of PAM and WAM provided a robust analytical framework that enhanced both the interpretive depth and diagnostic accuracy of the study. The convergence of results such as the alignment between WAM's identification of overproduction as a dominant root waste and PAM's observation of excessive work-in-process

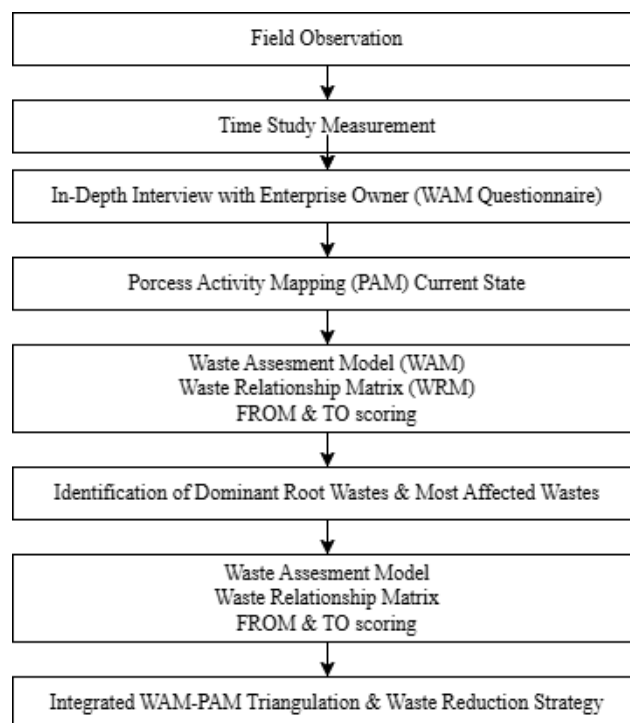


Figure 1. Research Methodology Flowchart

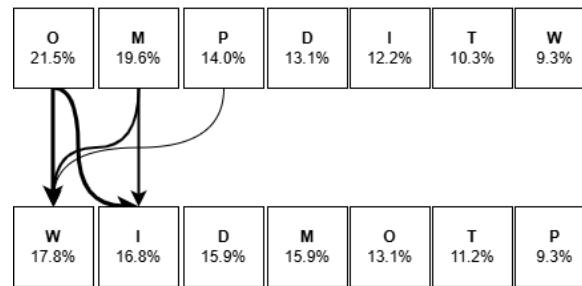
Table 1. Waste Relationship Matrix (WRM) Questionnaire Responses

F/T	O	I	D	M	T	P	W
O	A	O	O	E	A	X	A
I	I	A	I	U	U	X	X
D	O	O	A	U	U	X	I
M	X	E	O	A	X	A	A
T	U	U	O	U	A	X	U
P	X	O	I	A	X	A	X
W	I	O	O	X	X	X	A

Table 2. Waste Assessment Model Score – FROM Perspective (Root Waste Ranking)

From	Total	Percentage (%)
O – Overproduction	46	21.50
M – Motion	42	19.63
P – Overprocessing/Process	30	14.02
D – Defect	28	13.08
I – Inventory	26	12.15
T – Transportation	22	10.28
W – Waiting	20	9.35

FROM (Root Waste)



TO (Affected Waste)

Figure 2. Waste Relationship Diagram (FROM → TO)

accumulation strengthens the internal validity of the analysis. Similarly, the prominence of motion waste in both methods highlights persistent issues in layout design and operator ergonomics. This multi-method triangulation ensures that the derived insights are not only theoretically grounded but also empirically substantiated.

Overall, the methodological approach in this study comprises a coherent sequence of observation, time measurement, expert elicitation, process mapping, waste interrelationship analysis, and integrated triangulation. The sequence of these stages and their analytical connections are summarized in **Figure 1**, which shows how field observation and time-study measurements lead to PAM and WAM analyses before the results are integrated into a waste-reduction strategy. The design of the methodology deliberately accounts for the constraints, informality, and dynamic variability characteristic of micro-scale manufacturing. Consequently, the methodological framework not only supports a precise diagnosis of the dominant waste drivers within SMEs XYZ but also provides a rigorous foundation for formulating practical, context-appropriate, and sustainable improvement strategies.

3. Results and Discussions

3.1 Waste Assessment Model (WAM)

Table 1 presents the coded relationships among waste categories. The scores derived from the matrix are used to assess the influence of each waste category on others (FROM perspective) and the extent to which each category is affected by others (TO perspective). The resulting scores are then converted into percentages to facilitate the ranking of waste categories.

The Waste Assessment Model (WAM) results reveal a clear hierarchy of waste interactions within the packaging headgear production process. The FROM-perspective results summarized in **Table 2** show a clear hierarchy of root wastes. Overproduction emerged as the dominant causal waste, accounting for 21.50% of the total influence, indicating its central role in triggering downstream inefficiencies such as inventory accumulation and additional handling. Motion ranked second with 19.63%, reflecting structural issues related to inefficient workstation layout and excessive operator movement, which further propagate waiting and overprocessing. Overprocessing, contributing 14.02%, also acted as a significant root waste, driven by redundant scoring, folding, and handling activities that extend cycle time without adding value. The overall direction of these relationships is visualized in **Figure 2**, which connects the root wastes identified in the FROM perspective with the waste categories most affected in the TO perspective.

Table 3. Waste Assessment Model Score – TO Perspective (Most Affected Waste Ranking)

To	Total	Percentage (%)
W – Waiting	38	17.76
I – Inventory	36	16.82
D – Defect	34	15.89
M – Motion	34	15.89
O – Overproduction	28	13.08
T – Transportation	24	11.21
P – Overprocessing/Process	20	9.35

The ranking in **Table 3** presents the TO perspective, which highlights waste categories that are primarily affected by other wastes. Waiting was identified as the most impacted waste, representing 17.76% of the total influence, largely resulting from overproduction-induced work-in-process buildup and prolonged glue-drying delays. Inventory followed closely at 16.82%, confirming that material accumulation is predominantly a consequence of upstream batching behavior rather than an independent inefficiency. Motion and defects, each accounting for approximately 15.89%, indicate feedback effects where congested work areas and repeated handling increase the likelihood of operational errors.

Overall, the WAM results demonstrate that overproduction, motion, and overprocessing function as dominant root wastes, while waiting and inventory represent downstream effects within the system. These findings suggest that sustainable improvement should prioritize flow control, layout optimization, and process simplification rather than addressing symptomatic wastes alone.

3.2 Process Activity Mapping (PAM)

To obtain a clearer understanding of the workflow efficiency and the distribution of activities within the production system, a Process Activity Mapping (PAM) analysis was conducted. This method is used to classify each work element into VA, NNVA, and NVA activities based on its contribution to the final product. The Current State PAM provides a detailed breakdown of the existing process, covering setup time, processing time, transportation, and delays across all workstations involved in manufacturing the product. Through this mapping, several inefficiencies were identified, including excessive transportation, long setup durations, repeated handling, and significant waiting time during the gluing stage.

The insights gained from the current-state analysis serve as the foundation for developing the Future State PAM. By applying waste reduction principles, process simplification, and workstation improvements, the Future State aims to minimize NNVA and NVA activities while increasing the proportion of VA tasks. The following tables present the detailed comparison between the Current State and Future State, highlighting the impact of process enhancements on overall cycle time and production efficiency (**Table 4** and **Table 5**).

Table 4. Process Activity Mapping Current

No	Workstation	Work Element	Activity Type	Setup (Sec)	Processing Time (Sec)	Transportation (Sec)	Delay (Sec)	Total (Sec)
1	Inventory	Moving raw materials to processing area	NNVA	–	–	5	–	5
2	Creasing rule (body)	Placing body paper on marking board	NNVA	–	3	–	–	3
3	Creasing rule (body)	Making scoring line (body 1)	VA	–	56	29	8	93
4	Creasing rule (body)	Making scoring line (body 2)	VA	–	4	17	–	21
5	Folding	Folding body paper	VA	–	21	–	5	26
6	Creasing rule (wings)	Placing wings paper on marking board	NNVA	30	–	59	–	89
7	Creasing rule (wings)	Installing die on marking board	NNVA	–	18	–	–	18
8	Creasing rule (wings)	Making scoring line (wings)	VA	–	8	–	–	8
9	Cutting	Cutting wings	VA	–	17	41	–	58
10	Folding	Folding wings paper	VA	–	29	26	–	55
11	Gluing	Applying glue on wings	VA	–	46	–	–	46

No	Workstation	Work Element	Activity Type	Setup (Sec)	Processing Time (Sec)	Transportation (Sec)	Delay (Sec)	Total (Sec)
12	Gluing	Applying glue on body	VA	–	9	59	–	68
13	Gluing	Waiting for glue to dry (1/2)	NNVA	–	–	–	64	64
14	Assembly	Joining body and wings	VA	–	67	–	59	126
15	Inspection	Inspection	NNVA	–	3	–	–	3
Total								683

Table 5. Process Activity Mapping Future

No	Work Station	Work Element	Activity Type	Setup (Sec)	Processing Time (Sec)	Transportation (Sec)	Delay (Sec)	Total (Sec)
1	Inventory	Moving raw materials (shortened distance)	T	–	–	2	–	2
2	Creasing rule (body)	Placing body paper	NNVA (reduced)	1	–	–	–	1
3	Creasing rule (body)	Scoring line (body combined process)	VA	–	56	–	3	59
4	Creasing rule (body)	Scoring line body 2 (merged flow)	VA	–	17	–	2	19
5	Folding	Folding body	VA	–	21	–	2	23
6	Creasing rule (wings)	Placing wings paper	NNVA (reduced)	10	–	–	–	10
7	Creasing rule (wings)	Installing die	NNVA (reduced)	5	–	–	–	5
8	Creasing rule (wings)	Scoring wings	VA	–	8	–	–	8
9	Cutting	Cutting wings	VA	–	41	–	10	51
10	Folding	Folding wings	VA	–	26	–	5	31
11	Gluing	Gluing wings	VA	–	46	–	–	46
12	Gluing	Gluing body	VA	–	59	–	5	64
13	Drying	Glue drying (with fan)	NNVA (reduced)	–	–	–	30	30
14	Assembly	Joining body and wings	VA	–	67	–	30	97
15	Inspection	Inspection (streamlined)	NNVA (reduced)	–	–	–	1	1
Total								452

Table 4 details the current-state Process Activity Mapping (PAM), which identifies the distribution of VA, NNVA, and NVA activities within the production process. The total cycle time required to produce one unit is 683 seconds, consisting of 59.59% VA, 21.23% NNVA, and 19.18% NVA activities. Several activities that contribute significantly to inefficiency include material transportation, setup time during creasing operations, and prolonged drying time during the gluing process. Additionally, there are repeated motions in scoring and folding steps as well as unnecessary material movement due to the distance between workstations. These findings indicate that the production flow still contains considerable waste that affects overall cycle time and productivity.

Based on the problems identified in the current state, a Future State PAM was developed to eliminate or reduce NVA activities and streamline NNVA activities. Improvements were carried out by rearranging workstation layout to shorten transportation distance, standardizing paper placement, reducing setup time through marking guides, and introducing simple tools such as folding jigs and cutting templates. The drying process was improved by using an external fan to accelerate the glue-drying time, significantly reducing delay. Several steps, such as scoring processes for body components, were combined into a single continuous operation to reduce repetitive motion.

The proposed future-state activities and their estimated durations are presented in **Table 5**, allowing them to be compared with the current-state activities in **Table 4**. As a result of these proposed improvements, the total cycle time decreases from 683 seconds to 452 seconds, representing a projected cycle-time reduction of 33.8%. NNVA time was reduced by more than half, particularly in setup and inspection activities, while delay time decreased by 56% due to

accelerated drying. The Future State design demonstrates a more streamlined and efficient process flow, emphasizing the reduction of waste and the enhancement of value-added activities throughout production.

3.3 Discussion

The improvement scenario projected in the Future State PAM was derived through a desk-based time-motion re-estimation of the proposed interventions (workstation re-layout, marking guides, folding and cutting aids, and fan-assisted drying) rather than through a physical pilot implementation. Consequently, the reported reduction from 683 to 452 seconds per unit (33.8%) should be interpreted as a theoretically achievable target rather than a field-validated outcome. This projected cycle time reduction is comparable in magnitude to cycle-time reductions reported in other MSME packaging studies that applied lean interventions without capital-intensive automation (Effendi et al., 2023; Sari et al., 2025), and is consistent with prior applications of WAM-based diagnostics that identified overproduction and motion as leverage points for improvement in job-shop and small-batch environments (Muhammad & Yadrifil, 2018; Prasetyawan et al., 2021). Future work should validate the Future State design through a supervised pilot run or discrete-event simulation before full adoption on the shop floor.

Beyond the cycle-time reduction itself, the projected Future State also carries direct productivity implications. Because completing one unit would require 452 seconds instead of 683 seconds, the same working time could theoretically yield approximately 51% more finished units ($683/452 \approx 1.51$), assuming the redesigned layout and tools perform as estimated and demand is sufficient to absorb the additional output. This figure is offered as a sensitivity indicator rather than a guaranteed capacity gain, since it does not yet account for additional material costs, tooling investment, or operator adaptation time; a formal cost-benefit and capacity-utilization analysis is recommended as SMEs XYZ scales the proposed changes.

The dominance of overproduction, motion, and overprocessing as root wastes (**Table 2**) is consistent with the operational characteristics commonly reported for micro and small enterprises, where informal production planning, demand uncertainty, and the absence of standardized work instructions typically drive batch-based overproduction and unplanned material handling (Effendi et al., 2023; Yusuf & Batubara, 2020). This reinforces the argument that waste in SMEs XYZ is not merely a set of isolated inefficiencies but a structurally reinforced pattern rooted in how the enterprise plans and schedules production, echoing the research gap this study addresses regarding lean diagnostics in manual, low-standardization settings.

Regarding the reliability of the WAM assessment, the questionnaire was administered to a single respondent, the enterprise owner, who holds centralized authority over scheduling, quality control, and daily supervision consistent with the intended use of WAM in environments where one informant possesses holistic process visibility (Rawabdeh, 2005). Nevertheless, single-respondent assessment remains a methodological limitation, since it cannot capture potential discrepancies between managerial perception and operator-level experience. Future studies are encouraged to complement the owner's assessment with a short structured validation session involving line operators to cross-check the perceived severity and causal direction of each waste relationship.

Overall, this study's principal strength lies in combining WAM's structural diagnosis with PAM's activity-level quantification, offering convergent evidence for the same root-cause pattern: overproduction, motion, and overprocessing as drivers, and waiting and inventory as downstream effects. Its main limitations are the single-case, single-respondent design and the desk-based nature of the Future State validation, both of which restrict generalizability and warrant the pilot-scale validation and multi-case replication proposed above.

4. Conclusion

This study identified the dominant waste types and their interrelationships within a micro-scale packaging manufacturing enterprise (SMEs XYZ) by integrating the Waste Assessment Model (WAM) and Process Activity Mapping (PAM). The WAM results (**Table 2**) show that overproduction (21.50%), motion (19.63%), and overprocessing (14.02%) function as the dominant root wastes, cascading into waiting (17.76%) and inventory (16.82%) as the most affected categories, while the PAM analysis shows that value-added activities account for only 59.59% of total cycle time, leaving 40.41% as NNVA/NVA time. The convergence between the two methods confirms that inefficiency in this small-scale packaging process is systemic rather than isolated, and that time-related waste — specifically waiting caused by overproduction-driven work-in-process and prolonged drying — represents the most immediate target for intervention.

Addressing waste at its structural root, particularly overproduction, motion, and overprocessing, through flow control, layout improvement, and low-cost work standardization offers a realistic pathway to reduce time-related waste in micro-scale manufacturing without requiring substantial capital investment; the projected Future State PAM indicates this pathway could reduce cycle time by up to 33.8% (see Discussion, Section 3.C). Together with the theoretical contribution, practical implications, and study limitations elaborated in the Discussion, these findings demonstrate that structured, integrated lean diagnostics can meaningfully guide waste reduction strategies for SMEs operating under manual, resource-constrained conditions.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this manuscript, the authors used generative AI and AI-assisted tools to support language refinement, improve sentence clarity, and enhance the overall readability of the manuscript. The AI tools were not used to generate the research data, conduct the analysis, interpret the results, or draw the conclusions. All intellectual content, methodological decisions, data analysis, interpretation, and final revisions remain the sole responsibility of the authors. The authors have reviewed and edited all AI-assisted outputs and take full responsibility for the content of the manuscript.

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