ASSESSING WEARABLE TECHNOLOGY ADOPTION READINESS IN SRI LANKA'S MANUFACTURING INDUSTRY TO ENHANCE SAFETY AND HEALTH OF MAINTENANCE WORKERS

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Abstract. There are growing challenges in the manufacturing sector in Sri Lanka when it comes to improving the safety and health of maintenance workers working under hazardous conditions. Wearable technology, which can be described as electronic equipment worn on the body and containing sensors to gather, process, and transmit real time physiological and environmental information, is a viable solution to enhancing occupational safety all over the world. Although this is possible, the adoption preparedness of manufacturing organizations in Sri Lanka to such technology has not yet been thoroughly studied, which is a significant gap in occupational safety and health studies among developing economies. The research intends to examine the level of wearable technology adoption preparedness among food and beverage manufacturing firms in Sri Lanka, paying special attention to improving the safety and health outcomes of the maintenance workers. Structured interviews were used to collect data based on strategic level decision makers and a systematic review of internal safety performance records of five purposively selected organizations. A multi criteria decision making methodology based on the Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) was used to rank the companies in terms of technological, operational, financial, and organizational preparedness factors. TOPSIS was chosen among other MCDM approaches due to its compensatory approach and ability to use both quantitative and qualitative criteria at the same time. Results indicate that there are notable differences: the greatest readiness score was observed in the dairy manufacturing company (MC1) (C_i = 1.0), and the lowest one was in the bottled water manufacturer (MC5) (C_i = 0.044). The most important determinant of readiness to adopt was found to be digital infrastructure maturity and organizational commitment. The research provides a replicable multidimensional preparedness measurement scale with practical implications to the industry stakeholders and policymakers who desire to promote evidence based wearable technology use in the manufacturing industry in Sri Lanka.

Keywords. *Industry Readiness, Maintenance Safety, Manufacturing Industry, Wearable Technology, Work Environment*

1. Introduction

Wearable technology refers to electronic devices worn on the body that integrate sensors and communication capabilities to continuously monitor and collect data related to human activity, health, or environmental conditions (Dias et al., 2018; Iqbal et al., 2021). The production industry is one of the pillars of the Sri Lankan economy as it makes about 7 % of the national Gross Domestic Product (GDP) and is a crucial source of foreign exchange (Teejay Lanka PLC, 2024). In such a landscape, the maintenance operations play an imperative role in determining the operational availability of the work of complex industrial systems. The magnitude of occupational risk is astounding all over the world. International Labour Organization (ILO) estimates that 2.3 million workers die each year because of work accidents and illnesses, which is analogous to 6,400 deaths per day (ILO,

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2023). In Sri Lanka, the Ministry of Labour shows nearly 2,000 incidences of non-fatal workplace accidents annually, and fatal cases always lie between 60 and 80 (Ministry of Labour, 2025). Such numbers highlight the fact that a long-standing safety gap exists, especially since several industries are still using the Factories Ordinance No. 45 of 1942. This colonial-era law is mostly prescriptive and does not accommodate the fast technological change of the fourth and fourth industrial revolution (Melagoda & Rowlinson, 2022).

Repetitive motions, awkward postures, elevated ambient temperatures, and wet working environments have always been linked to occupational exposure to musculoskeletal disorders and heat strain in the food and beverage industry, especially in the processing and packaging lines. The empirical data also show that wearable sensor technologies may be used to assist with monitoring of ergonomic load and thermal stress in food processing workers and, therefore, prevent and minimize the occurrence of injuries in labour-intensive settings (Chiasson et al., 2012; Zare et al., 2018). Among developing economies like Sri Lanka, however, the uptake of smart occupational safety technologies in the food and beverage industry is still affected by the cost constraint, lack of enforcement of the regulations, and the different levels of workforce digital maturity. All these factors have an impact on the rate and magnitude of the integration of Industry 4.0 (Lakmali et al., 2020). Conversely, wearable technology, a modification of embedded sensors and Internet of Things connectivity into work garments, is a transition toward Maintenance 4.0 practices. These systems can be used to monitor physiological signs and environmental risks in real time and intervene in time before accidents take place (Zelik, 2025). Even though such technologies have high potential to reduce musculoskeletal disorders and thermal stress, their adoption in a developing country context such as Sri Lanka is influenced by a complex sociotechnical environment, including organizational culture, financial capacity, regulatory frameworks, and technological infrastructure. However, despite the growing significance of wearable technology in occupational safety, empirical evidence on organizational preparedness for its adoption in the manufacturing industry, particularly within food and beverage firms in Sri Lanka, remains limited. Hence, this study aims to address this gap by assessing the readiness of selected organizations to implement wearable technology, with the objective of improving the safety and health of maintenance workers. The decision-making approach was based on a quantitative multi-criteria approach to decision-making using Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Five purposely selected companies in technological, operational, financial, and organizational scales were evaluated using this method. This paper adopts a methodology combining a literature review with TOPSIS analysis to assess wearable technology readiness across manufacturing companies. The literature review establishes theoretical foundations, while TOPSIS provides a quantitative, multi-criteria evaluation of company preparedness.

This study aims to assess the wearable technology adoption readiness of food and beverage manufacturing companies in Sri Lanka, with particular focus on the safety and health of maintenance workers.

2. Literature review

2.1. WEARABLE TECHNOLOGIES IN MANUFACTURING INDUSTRIES

The industrial wearables market grows very fast throughout the world, and it is projected to grow to 64 billion USD in 2025 due to the imperative to increase operational efficiency and protect workers (Svertoka et al., 2021). In the manufacturing industry, there are four main functional areas of such technologies, namely, monitoring, supporting, training, and tracking (GAO, 2024; Ramesh N, 2025). The most common are monitoring devices, which include smartwatches and wristbands that control almost half of the market share and monitor 12 body related indicators, including Electrocardiogram (ECG) and Electromyography (EMG) signals (Svertoka et al., 2021).

Physical augmentation wearables, such as active or passive exoskeletons, reduce back muscle fatigue by 20 to 60 % and enhance productivity by up to 59.5 % in high intensity tasks (Zelik, 2025). State of the art developments in 2025 focus on integrating Artificial Intelligence (AI) and 5G connectivity to enable predictive safety analytics. The latest smart personal protective equipment incorporates intrinsically safe designs certified under ATEX (ATmosphères EXplosibles) and IECEx (International Electrotechnical Commission for Explosive Atmospheres) standards for use in hazardous zones. Other platforms integrate multiple sensor types, including 3-channel PPG (Photoplethysmography), IMU (Inertial Measurement Unit), and temperature sensing, into a single system for continuous long term health logging. Moreover, augmented reality (AR) glasses are increasingly deployed in maintenance training to guide technicians through safety protocols via AI driven visual overlays (GAO, 2024).

2.2. THEORETICAL TAXONOMY OF INDUSTRIAL WEARABLES

Wearable technology in the industrial context defines the body worn electronic devices that use advanced sensors to gather, process and transfer data about the health and safety of the workers (GAO, 2024). Within the Industry 4.0 framework, these devices are divided into four main functional areas. It includes monitoring features that track physiological parameters, such as heart rate, electrocardiogram, and blood oxygen saturation, as well as environmental conditions, including exposure to toxic gases and hand-arm vibration (HAV) (GAO, 2024). On top of these, supporting functions are supplied with active or passive exoskeletons, which will support workers in heavy lifting activities. Occupational safety research shows that technologies that provide real-time feedback, like augmented reality (AR) glasses and haptic sensors, can potentially reduce muscle fatigue by as much as 60 % (Zelik, 2025). Wearable technologies are another important technology in training because AR glasses and haptic systems are used to guide the technician through the intricate maintenance process and enhance ergonomic positioning (GAO, 2024). Moreover, the ability to track objects with GPS and proximity sensors can facilitate the coordination of emergency evacuation efforts and help navigate the complex operations environment (GAO, 2024). This need is especially acute in the context of Sri Lanka, as a study carried out in Export Processing Zones (EPZs) revealed that 78.3 % of workstations were registered by more than 85 dB of noise over an eight-hour shift.

2.3 DIFFERENT WEARABLE TECHNOLOGIES, CURRENT CHALLENGES AND ADVANTAGES.

The wearable technology industry has undergone a paradigm shift between 2020 and 2026 based on the transition of unsophisticated fitness trackers to advanced multimodal sensing technologies. More modern taxonomies now include physiological sensors, such as single electrode electrocardiogram (ECG) patches to monitor the heart over time (longitudinal) and photoplethysmography (PPG) devices on smart rings and watches to measure heart rate variability (HRV) and blood oxygen saturation (Roos & Slavich, 2023). Secondly, with the invention of biochemical sensors, non invasive continuous glucose monitoring (CGM) has been feasible, and biomarkers are measurable in sweat and interstitial fluid, enabling the management of chronic conditions like diabetes and cardiovascular disease (Luo et al., 2024; Perez & Zeadally, 2021). Often, these devices are currently being produced using flexible and stretchable electronics to achieve epidermal compliance, which allows the devices to conform to the wearer and reduce motion artefacts during intense physical exercises (Sazonov & Daoud, 2021). Modern wearables offer continuous, real time, and objective data, making them more effective than traditional periodic clinical measurements. They improve health awareness and promote preventive habits, especially in physical activity and sleep. (Perez & Zeadally, 2021). As an illustration, longitudinal nocturnal activity HRV has been demonstrated to be effective in predicting the risks of relapse in the case of affective disorders and the ability to anticipate stress events before increasing the symptoms (Roos & Slavich, 2023). IMUs are very effective in the specialised field of neurology, where they offer objective gait measurements that are commonly not accessible in conventional clinical exams (Bonanno et al., 2025). Artificial intelligence strengthens biometric systems by turning complex data into simple, personalised lifestyle guidance. The most serious concern is data privacy. Continuous collection of sensitive biometric data raises ethical questions about ownership, user consent, and the risk of unauthorised identification. (Sazonov and Daoud, 2021). There are also technical constraints, as sensor accuracy is often confirmed in the laboratory, but in practice, uncontrolled parameters such as sensor position, different skin tones and noise in the environment introduce data variability and the absence of standard quality indicators (Canali et al., 2022). Besides, the so-called user burden is a significant obstacle, with most feature rich gadgets yet to balance between high processing power and the requirements of ultra-low power consumption and lightweight and breathable designs (Seçkin et al., 2023).

2.4 ORGANIZATIONAL READINESS DIMENSIONS

The introduction of wearables is not a technical issue but an organizational one. Multi-Criteria Decision Making (MCDM) and TOPSIS Technology selection in the manufacturing industry is a non-similar, multi objective issue with competing criteria (Singh & Sushil, 1990). The People dimension evaluates both management awareness and the technological readiness of the workforce, encompassing factors such as optimism, innovativeness, discomfort, and insecurity (Patel et al., 2022). Meanwhile, the Process dimension assesses the degree of vertical and horizontal integration within the supply chain. One effective method for analysing and ranking alternatives in this context is the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), which orders options based on their Euclidean distance from the Positive Ideal Solution (PIS) and the Negative Ideal Solution (NIS) (Bertolini et al., 2020). The new Employment Act is expected to consolidate 12 existing laws into one framework containing a chapter on Occupational Safety, Health, and Welfare (Ministry of Labour, 2024). In 2025, significant changes in labour regulations are set to impact workplace practices, particularly regarding wearable technology. The maximum limit for injury compensation will increase by 550,000, reaching a total of 2 million, providing a strong incentive for employers and workers to carefully consider the ethical and privacy implications of data collected through wearable devices (Ministry of Labour, 2024). Additionally, the designation of hazardous jobs will expand to cover 80 occupations, up from the current figure of 55,000, creating further economic motivation for stakeholders to address and manage the ethical and privacy concerns associated with wearable information. These changes highlight the growing importance of balancing technological advancement with worker rights and data protection.

3. Methodology

This study employs a quantitative approach based on a multi criteria decision making framework to determine the readiness of the manufacturing sector in Sri Lanka to adopt wearable technologies. Accordingly, five organizations in the food and beverage manufacturing sector were selected as the research sample, including a dairy production company (MC 1), a rice milling company (MC 2), a culinary products company (MC 3), a tea manufacturing company (MC 4), and a bottled water manufacturing company (MC 5). The food and beverage sector is very important since it constitutes a good portion of the economy of Sri Lanka, offering employment to the GDP, and to home consumption, as well as to exports. Furthermore, it has complex production processes, the efficiency, safety, and real time monitoring of which can greatly improve productivity and quality assurance using wearable technologies and similar devices (Ghobakhloo et al., 2019; Kumar et al., 2021). The methodology chosen in data collection was multistage, which included structured interviews with strategic level decision makers and a systematic review of the internal safety performance records. All the options were rated on a five-point Likert scale on four major readiness dimensions: Technology Readiness, Operational Readiness, Cost Readiness, and Organizational Readiness. A multistage approach combining structured interviews with strategic decision makers and a systematic review of internal performance records enhances data validity by integrating stakeholder perspectives with empirical evidence (Creswell & Plano Clark, 2017; Petticrew & Roberts, 2006). The five point Likert scale offers a reliable standard measure for subjective readiness constructs, widely used in organizational research (Likert, 1932; Boone & Boone, 2012). Assessing readiness across technology, operations, cost, and organization reflects established multidimensional readiness models in implementation science (Weiner, 2009; Holt et al., 2007).

To achieve the aim of this study, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was used as the analysis tool. Unlike other methods, TOPSIS is favoured for its "compromise" logic—identifying a solution that is simultaneously closest to the ideal and furthest from the anti-ideal (Behzadian et al., 2012). This logic is particularly effective in industrial assessments where technical readiness must be balanced against economic constraints, as seen in similar sustainability and safety technology evaluations (Zyoud & Fuchs Hanusch, 2017). The TOPSIS process started with the creation of a decision matrix, the rows of which used the manufacturing fields as their names, and the columns used the readiness criteria as their names. To achieve comparison of the parameters under different units of measurement, a normalization process was undertaken to convert the raw scores into a non-dimensional matrix.

The selection of these five organizations was purposive and each company represents a distinct sub sector of food and beverage manufacturing with a unique occupational hazard profile: dairy processing involves ammonia refrigerant exposure and thermal stress; rice milling poses silica dust and vibration risks; tea manufacturing presents ergonomic and chemical hazards; culinary production entails high temperature operations and repetitive motion injuries; and bottled water manufacturing involves chemical handling and hygiene critical processes. Organizations were further selected based on their willingness to participate, their representation of different operational scales within the sector, and the presence of documented occupational health and safety incidents or formal safety management systems, which ensured that readiness was assessed in organizations with demonstrable OHS exposure and relevance. Data were collected from two or three strategic level decision makers in each organization, yielding thirteen respondents in total. Access to the occupational safety and health division was obtained to support data validation. While no single respondent held complete knowledge of all aspects, their inputs were collectively reviewed and confirmed by safety division professionals to ensure reliability. These individuals occupied roles including Health and Safety Manager, Safety engineers, Occupational Health Officer. Emphasis was placed on occupational health and safety personnel, as these individuals are directly responsible for hazard identification, risk assessment, and the implementation of safety interventions, including the adoption of protective technologies for maintenance workers. Strategic level respondents were targeted because they hold authority over technology adoption decisions, capital allocation, and organizational safety policy formulation (Creswell and Plano Clark, 2017). The five point Likert scale was anchored as follows: 1 = Not at all ready, 2 = Slightly ready, 3 = Moderately ready, 4 = Ready, and 5 = Highly ready. Structured interviews were conducted to capture decision makers' perceptions of organizational preparedness across the four readiness dimensions.

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a Multi Criteria Decision Making (MCDM) method that ranks alternatives by measuring their Euclidean distance from both the Positive Ideal Solution and the Negative Ideal Solution, identifying the option simultaneously closest to the best and furthest from the worst outcome (Hwang & Yoon, 1981). TOPSIS was selected over alternative Multi Criteria Decision Making (MCDM) approaches, including the Analytic Hierarchy Process (AHP), and the Elimination and Choice Translating Reality (ELECTRE) for three principal reasons. First, TOPSIS applies compensatory logic, meaning that a lower score on one readiness dimension can be balanced by a higher score on another. This is particularly relevant when assessing wearable technology adoption, where organizations may demonstrate strong financial capacity but weak digital infrastructure, or vice versa. Such trade-offs are common in developing economy contexts and must be captured rather than masked. Second, TOPSIS handles both quantitative and qualitative data that have been converted to cardinal scales, making it well suited to the composite readiness constructs measured in this study (Opricovic and Tzeng, 2004). Third, TOPSIS has been validated extensively in industrial technology assessment studies (Behzadian et al., 2012; Zyoud & Fuchs Hanusch, 2017), demonstrating robustness for the present context.

4. Analysis, Findings and Discussion

4.1. MULTI CRITERIA READINESS ASSESSMENT USING TOPSIS

The decision matrix evaluates the five manufacturing sectors against the four primary dimensions. For this analysis, Technology Readiness, Operational Readiness, and Organizational Readiness are treated as benefit criteria, while Cost Readiness is evaluated based on the burden of investment required. Within each dimension, there were several criteria that had certain sub items, and the scores were gathered and averaged to create a composite readiness score. Technology readiness (C1) was assessed based on the compatibility of wearable systems with existing digital infrastructure, the reliability of sensor data, the robustness of connection networks, and the potential for real time monitoring. Averaging these factors provided an overall view of the organization's preparedness from a technological standpoint. Operational readiness (C2) considered the availability of operational integration, data analytics capabilities, user acceptance and usability, and process adaptability, with the composite score reflecting the organization's ability to incorporate wearable technologies into everyday activities. Cost readiness (C3) examined the financial aspects, including the availability of funds to procure wearable devices, long term support capabilities, and investment in training, with the averaged results indicating the financial feasibility of adoption. Finally, organizational readiness (C4) encompassed top management commitment, workforce digital skill levels, and change management capability, with the combined evaluation offering insight into the in-house capacity to support and facilitate the integration of new technology.

Table 1,Integrated criterion with companies

Manufacturing Company	**C1 – Technology Readiness**				**C2 – Operational Readiness**				**C3 – Financial Readiness**				**C4 – Organizational Readiness**		
	Compatibility with System	Sensor data Reliability	Connectivity	Real-Time Monitoring	Operation Integration	Data Analytics capability	User Acceptance	Process Adaptability	Budget Availability	Readiness for System Integration	Long term support	Training Investment	Top Management Commitment	Workforce Digital Skills	Change Management
MC 1	4	5	3	4	4	3	4	4	5	4	4	5	4	4	5
Average	**4.00**				**3.75**				**4.50**				**4.33**		
MC 2	3	2	3	2	3	2	3	4	4	3	3	4	4	3	4
Average	**2.50**				**3.00**				**3.50**				**3.67**		
MC 3	1	1	1	1	2	1	1	3	2	2	2	2	1	1	3
Average	**1.00**				**1.75**				**2.00**				**1.67**		
MC 4	2	1	2	1	2	1	2	3	2	2	2	3	3	2	3
Average	**1.50**				**2.00**				**2.25**				**2.67**		
MC 5	1	1	1	1	1	1	1	3	1	1	1	1	1	1	2
Average	**1.00**				**1.50**				**1.00**				**1.33**		

The above table illustrates the company wise overall ratings for each readiness parameter, as provided by the interviewed organizational decision makers in the health and safety domain. According to these initial ratings, MC1 shows the most preparedness in all four dimensions, having a good technological infrastructure, well integrated operations, good financial capability and definite top management support. MC2 is moderately prepared, with sufficient financial and organizational resources and apparent technological deficiencies. On the contrary, MC3 and MC5 score remarkably low on all the dimensions, implying that there are serious shortcomings in digital systems, operational flexibility, and investment in finances. MC3 and MC5 are slightly less effective than MC4 but at the same time, MC4 is at a relatively low level of preparedness. All in all, the findings provide a clear ranking of the companies as MC1, MC2, MC4, MC3, and MC5, with MC1 being the company most suited to adopt wearable technology in the short term, as the rest of the companies will need different levels of structural, technological, and financial enhancement before they can consider adopting wearable technology. Normalization converts criteria with different units into a common scale, usually 0–1, to make them comparable across alternatives (Hwang & Yoon, 1981). In this study, it was applied to readiness scores before weighting to ensure balanced evaluation.

Table 2, Normalization readiness score

Company	**Technology**	**Operational**	**Financial**	**Organizational**
MC 1	4/5.568 ≈ 0.718	4/5.678 ≈ 0.705	4.5/6.396 ≈ 0.704	4.33/6.490 ≈ 0.667
MC 2	3/5.568 ≈ 0.539	3/5.678 ≈ 0.529	3.25/6.396 ≈ 0.508	3.67/6.490 ≈ 0.565
MC 3	1/5.568 ≈ 0.180	1.5/5.678 ≈ 0.264	2/6.396 ≈ 0.313	1/6.490 ≈ 0.154
MC 4	2/5.568 ≈ 0.359	2/5.678 ≈ 0.352	2.25/6.396 ≈ 0.352	2.67/6.490 ≈ 0.411
MC 5	1/5.568 ≈ 0.180	1/5.678 ≈ 0.176	1/6.396 ≈ 0.156	1.33/6.490 ≈ 0.205

The table shows the normalized readiness scores in every company in four dimensions which are Technology Fit, Operational Readiness, Financial Readiness, and Organizational Readiness. All the scores have been divided using the square root value applied during the normalization process of TOPSIS, which generates similar values with 0 1. The use of weights in a multi criteria decision making process is done to indicate the relative weight of each criterion. Not every factor has the same impact on a decision, and as a result, the normalized scores are weighted in such a way that more significant criteria will make a bigger contribution to the overall assessment. This action will enable the analysis to generate a balanced and significant evaluation that reflects the concerns of the decision situation well.

Table 3, Applied weights

Company	***Technology***	***Operational***	***Financial***	***Organizational***
MC 1	*0.718*0.25= 0.180*	*0.705*0.25= 0.176*	*0.704*0.25= 0.176*	*0.667*0.25 =0.167*
MC 2	*0.539*0.25= 0.135*	*0.529*0.25= 0.132*	*0.508*0.25= 0.127*	*0.565*0.25 =0.141*
MC 3	*0.180*0.25= 0.045*	*0.264*0.25= 0.066*	*0.313*0.25= 0.078*	*0.154*0.25 =0.039*
MC 4	*0.359*0.25= 0.090*	*0.352*0.25= 0.088*	*0.352*0.25= 0.088*	*0.411*0.25 =0.103*
MC 5	*0.180*0.25= 0.045*	*0.176*0.25= 0.044*	*0.156*0.25= 0.039*	*0.205*0.25 =0.051*

The equal weight of 0.25 for each dimension ensures a balanced evaluation of company readiness. When there is no strong empirical basis to prioritize one factor, studies often assign equal weights so that technological, operational, financial, and organizational capacities are considered equally important in technology adoption. This approach is consistent with the Technology–Organization–Environment (TOE) Framework, which explains that multiple organizational factors jointly influence the adoption of new technologies (Tornatzky & Fleischer, 1990).

Table 4, Identify Ideal Best (A^+) and Ideal Worst (A^-)

Criteria	A^+	A^-
Tech Fit	0.180	0.045
Operational	0.176	0.044
Financial	0.176	0.039
Organizational	0.167	0.039

The ideal best (A^+) and ideal worst (A^-) values represent the most favourable and least favourable scores for each readiness criterion. Here, Technology Fit has the highest ideal best at 0.180, while Organisational Readiness has the lowest ideal worst at 0.039, indicating varying levels of performance potential across the criteria.

Table 5, Evaluating Relative Closeness to Ideal Solution

Company	S^+	S^-	C_i
MC 1	0	0.265	0.265/(0+0.265) =1.0
MC 2	0.084	0.184	0.184 / (0.084+0.184) ≈ 0.687
MC 3	0.237	0.045	0.045 / (0.237+0.045) ≈ 0.160
MC 4	0.167	0.102	0.102 / (0.167+0.102) ≈ 0.379
MC 5	0.259	0.012	0.012 / (0.259+0.012) ≈ 0.044

Table 6: Ranking

Rank	Company	C_i
1	MC 1	1.00
2	MC 2	0.687
3	MC 3	0.379
4	MC 4	0.160
5	MC 5	0.044

The TOPSIS analysis gives a numerical classification of five companies on four dimensions, namely Technology Fit, Operational Readiness, Financial Readiness and Organizational Readiness. The average data was normalized, and equal weights were given to the distances to the ideal and the worst solutions and a relative closeness score (C 0) was obtained to indicate the extent to which each company is similar to the ideal wearable ready model. The findings reveal that MC 1 has the greatest score (C 1 = 1.0), hence it is the closest to the best answer. This is an indication of high technology compatibility, good sensor preparedness, consistent systems integration, well developed processes, adequate financial capability and dynamic leadership. The next one is MC 2 with a lower score (C 0.687), which means moderate readiness. It exhibits partial digitality and partial process elasticity, yet encounters connectivity, sensor validation, and systematic financial planning issues. On the contrary, MC 3, MC 4, and MC 5 have much lower scores (C 3 0.044 to 0.379), which indicates that they are not as prepared. The limiting factors of these companies include poor digital infrastructure, connectivity problems, unreliable sensor networks, manual processes, and poor analytic capabilities. They are further diminished by financial constraints and organizational factors, including low digital competence and experience in change management. The results of the TOPSIS clearly give MC 1 the first position as the most ready to adopt wearable technology, and then MC 2. The other companies will need a lot of investment and organizational restructuring before they can effectively implement it. This ranking offers a systematic and evidence-based basis for prioritizing the adoption of wearable technology.

4.2. RADAR VISUALISATION

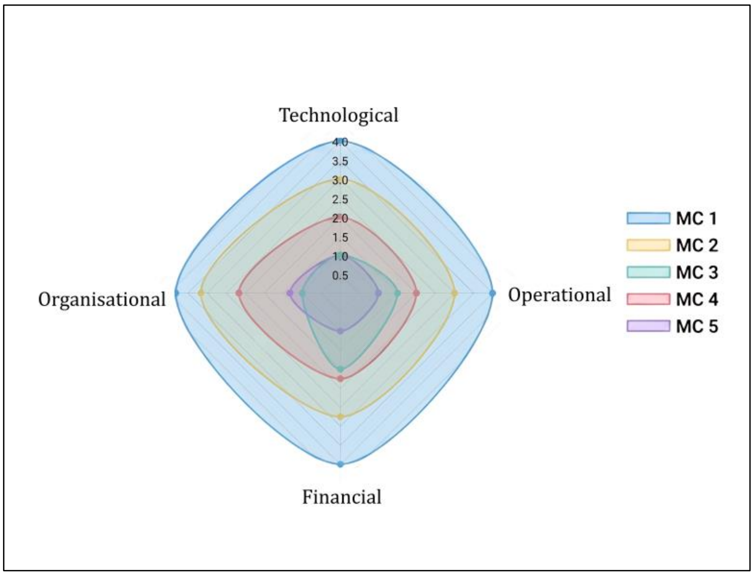

Figure 1, Radar Chart Generated from TOPSIS findings (Author Constructed-Python executed)

To better interpret the results, the radar chart above depicts the wearable technology readiness of the five companies across the four assessed dimensions. MC1 occupies the largest area in the chart, confirming its superior readiness across all four dimensions and its position as the most prepared organization for wearable technology adoption. MC2 displays a balanced but moderate profile, indicating sufficient foundational capacity that could be strengthened through targeted investment in digital connectivity and workflow integration. MC3, MC4, and MC5 cluster near the centre of the chart, reflecting their low scores, particularly in Technology Fit and Financial Readiness, indicating insufficient digital infrastructure and inadequate budget allocation for adoption. The visualization thus confirms the TOPSIS rankings: MC1 is the most adoption ready, MC2 is moderately equipped, and the remaining three organizations require substantial foundational improvements before viable deployment.

The chart underlines that MC1 has the biggest area, as it has a good performance in all four dimensions and is the best prepared organization to pursue the use of wearable technology. MC2 has a moderate but even profile, which means that it has a decent background that may be enhanced with a specific focus on enhancing the digital connectivity and integration of workflows. Conversely, MC3, MC4 and MC5 fall into the middle with significantly lower scores, especially in Technology Fit and Financial Readiness. This implies poor digital infrastructure and inadequate financial abilities to facilitate adoption. On the whole, the visualization itself proves the ranking of TOPSIS, MC1 is the most prepared, MC2 is moderately prepared, and the rest of the firms need extensive underlying development prior to successful deployment. The TOPSIS findings also indicate the evident disparities in readiness of the five food and beverage manufacturing companies. MC1 is closest to the optimal solution, which is high relative to the ideal solution, is technologically capable, operationally integrated, financially strong, and organizationally committed. MC2 is moderately prepared, MC3, MC4 and MC5 are much less prepared. These differences indicate bigger trends in the adoption of technology and digital transformation in the manufacturing industry. The most prominent performance of MC1 indicates that the maturity of infrastructure and compatibility of the system are key success factors.

This finding is consistent with the Technology Acceptance Model of Fred Davis (1989), which has placed the factors of perceived usefulness and ease of use as major adoption factors. The degree of preparedness at MC1 implies that wearable technologies can easily fit into its current digital systems and maintenance practices without creating uncertainty and resistance. This compatibility is particularly significant in food and beverage processing, where there are stringent requirements concerning hygiene, equipment reliability, and traceability. To this end, Agri food digitalization studies reveal that sensor networks and embedded monitoring systems enhance safety performance and transparency in operations (Verdouw et al., 2016). It is also found to be in line with the Unified Theory of Acceptance and Use of Technology developed by Viswanath Venkatesh et al. (2003) that pointed out facilitating conditions and managerial support as critical determinants of adoption behaviour. The high organizational preparedness of MC1 indicates good leadership and labour ability, which are necessary in a highly controlled industry like dairy, tea and processed food production. Research into the adoption of Industry 4.0 in the food industry once again confirms the more effective results of digital transformation with the help of strategic management and cross functional integration (Kamble et al., 2018). This is supported by the organizational readiness theory as explicated by Bryan J. Weiner (2009), which places emphasis on shared commitment and collective capability as key to successful change. The high score of MC1 indicates a high level of internal alignment, whereas low scores of MC3 and MC5 imply weak links in organizational cohesion.

The main obstacle is still resistance to change and a lack of training, especially in food processing industries where safety and inspection regulations are essential. The reports by the Food and Agriculture Organization (2022) highlight that digital transformation does not only entail the use of technology but also workforce development and capacity building. Financial preparedness is also a determining factor. Gary M. Koenig et al. (2020) state that the key to a successful implementation of wearable safety technologies is the ongoing employee training and organizational learning, especially in high-risk industrial settings. Fred D. Davis (1989) notes that perceived usefulness and ease of use, which have sufficient training and resources to support them, are critical factors in user acceptance and sustained adoption of new technologies. The theory of diffusion of innovation by Everett M. Rogers (2003) suggests that the availability of resources, as well as perceived economic benefit, has a strong effect on the preference to adopt or not. In price sensitive food and beverage markets, low margins and variable input prices may inhibit investment. The reduced financial preparedness of MC3 and MC5 implies limited resources in terms of purchasing and updating wearable technologies. This is in line with the results of Louis G. Tornatzky & Mitchell Fleischer (1990), which reveal that adoption in emerging economies can be hindered by financial risk and budget constraints. Equally, the International Labour Organization (2020) indicates that both financial and skill limitations frequently slow down the adoption of digital safety technologies in industries.

The high operational preparedness of MC1 allows the efficient utilization of wearable data to make safety and maintenance decisions, but MC3 and MC5 are not as effective since the companies use manual operations and have low analytical capabilities. The analysis is enhanced by the use of the TOPSIS method, which was proposed by Ching Lai Hwang and Kwangsun Yoon (1981), allowing the systematic ranking of alternatives depending on how close they are to an ideal solution. It has been proven to be effective in the assessment of complex industrial choices (Behzadian et al., 2012). The numerical difference between MC1 and the other companies is clear, which proves the strength of this method to describe the trade-offs during the technological, financial, operational, and organizational factors. The findings also indicate the socio technical systems theory, which emerged as a result of the work of Eric Trist & Ken Bamforth (1951), that highlights the necessity of the match between the technological systems and the structures of human beings. Implementation of wearable technology is not just about placing a device; it involves orchestrated investment in infrastructure, work processes, financial management and leadership involvement. The poorer results of MC3, MC4, and MC5 demonstrate how the lack of any of these interdependent areas can decrease overall preparedness.

In a more general view of digital transformation, George Westerman, Didier Bonnet & Andrew McAfee (2014) point out that organizations perform better when technology efforts are coordinated with the governance and long-term strategy. This trend can be seen in MC1, which demonstrates the role of integrated digital systems and structured safety management in the creation of a favourable environment to support the adoption of wearables. MC2 seems to be at a transition stage, and better connectivity, analytics capability, and financial planning may have a tremendous impact on preparedness. Wearable technology implementation in the Sri Lankan food and beverage production industry is an institutional change and not a mere technological enhancement. Existence of readiness is due to the interaction between infrastructure maturity, operational coordination, financial capacity, and organizational culture. With readiness assessment and multi criteria decision making, this methodology presents a systematic and theoretically informed model on how to prioritize digital safety investments in the emerging industrial settings.

5. Conclusion

This was research done to determine the level of readiness of five food and beverage manufacturing companies in Sri Lanka with regard to wearable technology adoption by applying a multi criteria decision making model based on TOPSIS. The results reveal that there is a considerable difference in the preparedness of organizations on four dimensions measured, which include technological, operational, financial, and organizational readiness. One of the main findings of the study is that the most decisive aspects in determining readiness are the digital infrastructure maturity and organizational leadership commitment, as opposed to the financial capacity alone. The example of the dairy manufacturer (MC1) demonstrates how an enabling environment for wearables adoption exists due to existing digital systems and a proactive safety culture, which is especially relevant to OHS critical workplaces, such as ammonia exposure and thermal stress. In comparison, the low scores of MC3, MC4, and MC5, which do not change over the years, indicate that the presence of fragmented digital systems, lack of digital literacy of the workforce, and reactive safety cultures are systemic issues that are not solvable by technology procurement alone. The research also indicates that TOPSIS based readiness profiling is an effective, evidence-based instrument to prioritize investments in safety technologies in small organizations.

The results provide practical recommendations to industry players and policymakers. Moderately prepared companies (e.g. MC2) ought to focus on implementing pilot rollouts in high-risk maintenance zones, backed by structured training and incremental financial budget. Companies with lower readiness levels (MC3 MC5) need foundational investments of digital infrastructure and regulatory compliance before they can adopt it. On the policy front, the results support the existence of specific government incentives, such as the availability of wearable technologies at subsidized prices and occupational safety reform to fast track the uptake of wearables in the manufacturing industries in Sri Lanka. There are a number of limitations in this study. The sample is limited to five food and beverage companies, which restricts generalizability. The data based on a Likert scale, which is self-reported, presents a possibility of response bias, even when it is triangulated with internal records. Equal criterion weighting is not necessarily representative of sector specific priorities; future studies ought to take into account empirically determined weights through techniques like AHP. Empirical studies of readiness change after intervention over a longitudinal time frame, and more general cross sectoral research, would considerably expand the empirical base created with this study.

6. References

Attaran, M. (2020). The impact of wearable technology on the digitalization of supply chain. *International Journal of Production Economics*.

Bandara, W. A. A. M., & Athapaththu, J. C. (2025). Factors influencing digitization of procurement in tea processing factories in Sri Lanka. *International Journal of Supply Chain and Logistics*.

Behzadian, M., Otaghsara, S. K., Yazdani, M., & Ignatius, J. (2012). A state-of-the-art survey of TOPSIS applications. *Expert Systems with Applications, 39*(17), 13051–13069. https://doi.org/10.1016/j.eswa.2012.05.056

Bertolini, M., Esposito, G., & Romagnoli, G. (2020). A TOPSIS-based approach for advanced manufacturing technology selection. *Expert Systems with Applications, 159*, 113610.

Bonanno, M., Ielo, A., De Pasquale, P., et al. (2025). Use of wearable sensors to assess fall risk in neurological disorders: A systematic review. *JMIR mHealth and uHealth*.

Boone, H. N., & Boone, D. A. (2012). Analyzing Likert data. *Journal of Extension*.

Canali, S., Schiaffonati, V., & Aliverti, A. (2022). Challenges and recommendations for wearable devices in digital health: Data quality, interoperability, health equity, and fairness. *PLOS Digital Health, 1*(10), e0000104. https://doi.org/10.1371/journal.pdig.0000104

Chiasson, M. E., Imbeau, D., Major, J., Aubry, K., & Delisle, A. (2012). Influence of musculoskeletal pain on workers' ergonomic risk exposure in food processing plants. *Applied Ergonomics, 43*(2), 322–330.

Creswell, J. W., & Plano Clark, V. L. (2017). *Designing and conducting mixed methods research*. Sage Publications.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Dias, D., & Paulo Silva Cunha, J. (2018). Wearable health devices—Vital sign monitoring, systems, and technologies. *Sensors, 18*(8), 2414. https://doi.org/10.3390/s18082414

European Agency for Safety and Health at Work. (2019). *Work-related musculoskeletal disorders: Prevalence, costs and demographics in the EU*. Publications Office of the European Union.

Food and Agriculture Organization. (2022). *The state of food and agriculture: Leveraging digital technologies*. FAO.

Ghobakhloo, M., Fathi, M., & Azar, A. (2019). Adoption of advanced manufacturing technologies: A review of drivers and challenges in food and beverage firms. *Journal of Manufacturing Technology Management, 30*(5), 812–836.

Government Accountability Office. (2024). *Wearable technologies: Implications for workplace safety and health* (GAO-24-107303).

Holt, D. T., Armenakis, A. A., Feild, H. S., & Harris, S. G. (2007). Readiness for organizational change: The systematic development of a scale. *Journal of Applied Behavioral Science, 43*(2), 232–255.

Hwang, C. L., & Yoon, K. (1981). *Multiple attribute decision making: Methods and applications: A state-of-the-art survey*. Springer-Verlag.

International Labour Organization. (2023). *Safety and health at the heart of the future of work*. ILO.

International Labour Organization. (2025). *National occupational safety and health (OSH) policy 2025–2030*. ILO.

Iqbal, S. M. A., Mahgoub, I., Du, E., Leavitt, M. A., & Asghar, W. (2021). Advances in healthcare wearable devices. *npj Flexible Electronics, 5*(1), 9. https://doi.org/10.1038/s41528-021-00107-x

Kamble, S. S., Gunasekaran, A., & Sharma, R. (2018). Analysis of drivers and barriers of Industry 4.0 adoption. *International Journal of Production Research, 56*(8), 2781–2802.

Koenig, G. M., Soper, C., & Hodge, A. (2020). Wearable technologies for occupational safety and health: A review. *Journal of Safety Research, 74*, 101–115. https://doi.org/10.1016/j.jsr.2020.06.004

Kumar, S., Singh, R., & Gupta, P. (2021). Wearable technology adoption in manufacturing: Impacts on efficiency and safety in food processing industries. *International Journal of Production Research, 59*(14), 4285–4302.

Likert, R. (1932). A technique for the measurement of attitudes. *Archives of Psychology*.

Luo, X., Tan, H., & Wen, W. (2024). Recent advances in wearable healthcare devices: From material to application. *Bioengineering, 11*(4), 358. https://doi.org/10.3390/bioengineering11040358

Melagoda, D. G., & Rowlinson, S. (2022). The institutional framework of construction safety management: A case study of Sri Lanka. *IOP Conference Series: Earth and Environmental Science*.

Ministry of Labour. (2024). *Amendment of legislations: Occupational safety, health and welfare act*. Sri Lanka.

Opricovic, S., & Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *European Journal of Operational Research, 156*(2), 445–455. https://doi.org/10.1016/S0377-2217(03)00020-1

Patel, A., et al. (2022). Technology readiness and acceptance model (TRAM) for wearable technology. *Expert Systems with Applications*.

Pearl, D., Intriligator, J., & Liu, X. (2025). Seamless integration: The evolution, design, and future impact of wearable technology. *arXiv*.

Perez, A. J., & Zeadally, S. (2021). Recent advances in wearable sensing technologies. *Sensors, 21*(20), 6828. https://doi.org/10.3390/s21206828

Petticrew, M., & Roberts, H. (2006). *Systematic reviews in the social sciences: A practical guide*. Blackwell Publishing.

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Roos, L. G., & Slavich, G. M. (2023). Wearable technologies for health research: Opportunities, limitations, and practical and conceptual considerations. *Brain, Behavior, and Immunity, 113*, 444–452. https://doi.org/10.1016/j.bbi.2023.08.008

Sazonov, E., & Daoud, W. A. (2021). Grand challenges in wearable electronics. *Frontiers in Electronics, 2*. https://doi.org/10.3389/felec.2021.668619

Seçkin, A. Ç., Ateş, B., & Seçkin, M. (2023). Review on wearable technology in sports: Concepts, challenges, and opportunities. *Applied Sciences, 13*(18), 10399. https://doi.org/10.3390/app131810399

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.

Trist, E. L., & Bamforth, K. W. (1951). Some social and psychological consequences of the longwall method. *Human Relations, 4*(1), 3–38.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

Verdouw, C. N., Wolfert, J., Beulens, A. J. M., & Rialland, A. (2016). Virtualization of food supply chains with the Internet of Things. *Journal of Food Engineering, 176*, 128–136.

Weiner, B. J. (2009). A theory of organizational readiness for change. *Implementation Science, 4*(67).

Westerman, G., Bonnet, D., & McAfee, A. (2014). *Leading digital: Turning technology into business transformation*. Harvard Business Review Press.

Zelik, K. (2025). How wearable technology is helping mitigate the skilled labor shortage. *Occupational Health & Safety*.