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Research Article

Advancing Occupational Health and Safety with Wearable Technologies: An MCDM Framework for HR Strategies in the Manufacturing Sector*

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Abstract: This study develops a novel framework for prioritizing wearable technologies in Occupational Health and Safety (OHS) within the manufacturing sector, addressing both technical performance and workforce integration. The purpose of the framework is twofold: first, to identify the key criteria influencing the adoption and effectiveness of wearable technologies, such as safety impact, cost-effectiveness, reliability, ease of training, and employee adoption; and second, to create a structured decision-making approach that supports HR practitioners, stakeholders, and OHS managers in evaluating and selecting technologies. By integrating Fuzzy DEMATEL to analyze causal relationships among criteria and PROMETHEE to rank alternatives, the study reveals that cost-effectiveness and safety impact are the most influential drivers. The wearable technology alternatives, including Gas Detection Sensors, Fatigue-Monitoring Bands, Smart Helmets, and Exoskeletons, were selected as a simulation for the prioritization process, reflecting a diverse set of use cases and challenges. The findings highlight Gas Detection Sensors as the top-ranked technology due to their superior safety and reliability performance, followed by Fatigue-Monitoring Bands and Smart Helmets, while Exoskeletons rank lowest due to cost and training challenges. This framework emphasizes the alignment of technical solutions with workforce readiness, providing actionable insights for decision-makers, including strategies for enhancing employee adoption and targeted training programs. Grounded in the Technology Acceptance Model (TAM) to explain adoption behavior, the study bridges technical evaluation with human-centric criteria, offering a scalable, practical decision-making framework applicable to other industries aiming to enhance workplace safety through wearable technologies.

Keywords: Occupational Health and Safety (OHS), Wearable Technologies, Manufacturing Sector, Human Resource Strategies
Jel Codes: J81, 033, L60, M50

Giyilebilir Teknolojilerle İş Sağlığı ve Güvenliğini Geliştirme: Üretim Sektöründe İnsan Kaynakları Stratejileri için Çok Kriterli Karar Verme Çerçevesi

Öz: Bu çalışma, üretim sektöründe İş Sağlığı ve Güvenliği (İSG) kapsamında giyilebilir teknolojilerin önceliklendirilmesine yönelik hem teknik performansı hem de iş gücü entegrasyonunu ele alan yenilikçi bir çerçeve geliştirmektedir. Çalışmanın amacı, İlk olarak, güvenlik etkisi, maliyet etkinliği, güvenilirlik, eğitim kolaylığı ve çalışanların benimsenmesi gibi giyilebilir teknolojilerin benimsenmesini ve etkinliğini etkileyen temel kriterleri belirlemek; ikinci olarak ise İnsan Kaynakları (İK) uygulayıcıları, paydaşlar ve İSG yöneticilerinin teknolojileri değerlendirmesini ve seçmesini destekleyen yapılandırılmış bir karar verme yaklaşımı oluşturmaktır. Fuzzy DEMATEL metodolojisi ile kriterler arasındaki nedensel ilişkileri analiz ederken, PROMETHEE metodolojisi alternatifleri sıralamada kullanılmıştır. Önceliklendirme süreci için Gaz Algılama Sensörleri, Yorgunluk İzleme Bantları, Akıllı Kasklar ve Dış İskeletler gibi giyilebilir teknoloji alternatifleri bir simülasyon olarak seçilmiş olup, bu alternatifler çeşitli kullanım alanları ve zorlukları yansıtmaktadır. Çalışma, maliyet etkinliği ve güvenlik etkisinin en etkili faktörler olduğunu ortaya

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koymaktadır. Bulgular, Gaz Algılama Sensörleri'nin, üstün güvenlik ve güvenilirlik performansı nedeniyle en üst sırada yer aldığını, ardından Yorgunluk İzleme Bantları ve Akıllı Kasklar'ın geldiğini, Dış İskeletler'in ise maliyet ve eğitim zorlukları nedeniyle en alt sırada yer aldığını göstermektedir. Çalışma, teknik çözümleri iş gücü hazırlığı ile uyumlu hale getirmeye vurgu yaparak, çalışanların teknolojiyi benimsemesi ve hedefe yönelik eğitim programlarının geliştirilmesi gibi karar vericilere yönelik uygulanabilir öneriler sunmaktadır. Teknoloji Kabul Modeli'ne (TAM) dayanan çalışma, benimseme davranışını açıklamak için insan odaklı kriterlerle teknik değerlendirmeyi birleştirmekte ve diğer sektörlerde iş yeri güvenliğini artırmayı hedefleyen ölçeklenebilir, pratik bir karar verme çerçevesi sunmaktadır.

Anahtar Kelimeler: İş Sağlığı ve Güvenliği (İSG), Giyilebilir Teknolojiler, Üretim Sektörü, İnsan Kaynakları Stratejileri
Jel Kodları: J81, 033, L60, M50

1. Introduction

The manufacturing sector presents a unique set of challenges in occupational health and safety (OHS) due to its inherently high-risk environments. Employees face risks such as physical injuries, repetitive strain, hazardous material exposure, and workplace fatigue, which demand innovative solutions to mitigate these challenges (Patel et al., 2022). Traditional OHS measures, while essential, often fall short in providing real-time and proactive safety interventions. Wearable technologies have emerged as a transformative solution in enhancing workplace safety. These technologies, such as fatigue-monitoring bands, smart helmets, and environmental sensors, offer real-time data collection and feedback, enabling proactive measures to prevent accidents and injuries (Svertoka et al., 2021). For example, smart helmets equipped with sensors can detect harmful gases, while exoskeletons can reduce physical strain during heavy lifting tasks (De Fazio et al., 2022). These advancements align with Industry 4.0 principles, where interconnected systems and real-time analytics redefine operational safety (Balamurugan et al., 2022).

The successful implementation and adoption of wearable technologies in workplaces are strongly influenced by employee perceptions, which are central to the Technology Acceptance Model (TAM) developed by Davis (1989). According to TAM, the adoption of any technology is primarily determined by its perceived usefulness (PU)—the extent to which employees believe the technology enhances their job performance—and perceived ease of use (PEOU)—the degree to which the technology is easy to use. When applied to wearable technologies, PU can be reflected in employees' recognition of these devices' ability to enhance safety and reduce workplace risks, while PEOU is critical in ensuring the devices integrate seamlessly into daily routines without significant learning curves. Extending this theoretical lens to wearable technologies in manufacturing, it becomes evident that HR's role in promoting these technologies involves not only logistical support but also fostering positive employee attitudes toward their use.

Human Resource (HR) departments play a critical role in integrating wearable technologies into OHS strategies. HR responsibilities include ensuring employee training, promoting technology adoption, and aligning wearable solutions with organizational policies. The Technology Acceptance Model provides a useful framework for HR to address barriers to adoption by emphasizing the importance of training programs that improve PEOU and communicating the safety benefits of these technologies to enhance PU. Effective implementation relies on employee acceptance, which is influenced by factors such as ease of use, perceived usefulness, and organizational culture (Wong et al., 2021). Thus, HR strategies are pivotal in overcoming barriers to adoption, such as resistance to change and concerns over privacy (Schall Jr et al., 2018). Moreover, the model highlights how organizational support and transparent communication can alleviate resistance by building trust and confidence in the technology's reliability and effectiveness.

Despite the evident benefits of wearable technologies, the literature reveals a lack of structured approaches to prioritize these solutions for OHS improvements, particularly from an HR perspective. While prior studies have explored wearable technologies in construction and healthcare (Mejia et al., 2021; Ibrahim et al., 2025), the manufacturing sector remains underexplored. Additionally, limited research exists on integrating HR-driven criteria, such as employee adoption and training requirements, into decision-making frameworks for wearable technology implementation. By incorporating TAM into this study, the emphasis shifts toward understanding the behavioral and psychological dimensions of adoption, ensuring that technical and human resource considerations are aligned. This study addresses the gap by proposing a Multi-Criteria Decision-Making (MCDM) framework that combines Fuzzy DEMATEL for criteria weighting and PROMETHEE for ranking wearable technologies. The integration of HR-specific criteria into the evaluation process, such as employee engagement and ease of training, ensures a holistic approach that aligns with both safety objectives and workforce needs.

The primary objective of this study is to develop a robust decision-making framework to prioritize wearable technologies for OHS in the manufacturing sector. The proposed framework integrates Fuzzy DEMATEL and PROMETHEE methods to evaluate wearable solutions based on both OHS and HR criteria, providing actionable insights for HR and OHS professionals. The inclusion of TAM theory within the framework reinforces the importance of addressing employee perceptions as a critical success factor, highlighting how HR strategies can shape the adoption and sustained use of these technologies.

Several alternative MCDM methods, such as VIKOR, TOPSIS, and AHP, have been used in previous OHS studies to prioritize safety measures and technologies (Gul, 2018; Dabbagh & Yousefi, 2019). For example, VIKOR focuses on compromise solutions but may lack the ability to capture interdependencies among criteria, which is essential for complex evaluations like wearable technology prioritization (La Fata et al., 2021). Similarly, TOPSIS evaluates alternatives based on their proximity to ideal solutions but does not explicitly consider causal relationships between criteria (Badida et al., 2023). In contrast, Fuzzy DEMATEL effectively identifies and weights interdependent criteria, while PROMETHEE provides a robust ranking mechanism that accounts for the weighted criteria and stakeholder preferences. This combination allows for a nuanced analysis of wearable technologies, addressing both the technical and human resource dimensions of OHS challenges.

Prior research underscores the diverse applications and benefits of wearable technologies in OHS. For instance, Awolusi et al. (2018) highlighted the role of wearable sensing devices in monitoring real-time safety metrics, while Nnaji et al. (2021) emphasized their potential to mitigate health risks in construction settings. However, as Aksüt et al. (2024) noted, the adoption of wearable technologies varies significantly across sectors, highlighting the need for sector-specific prioritization frameworks. By focusing on the manufacturing sector and integrating HR criteria, this study contributes to filling this critical research gap.

2. Literature Review

2.1 Wearable Technologies in Occupational Health and Safety (OHS)

Wearable technologies have emerged as transformative tools in occupational health and safety (OHS), offering real-time monitoring, predictive analytics, and enhanced situational awareness. These technologies, which include smart helmets, fatigue-monitoring devices, exoskeletons, and gas detection sensors, are designed to address specific workplace hazards and improve overall safety. The increasing integration of wearable devices in OHS aligns with the principles of Industry 4.0, where interconnected systems, data-driven insights, and automation redefine traditional safety practices.

Smart helmets equipped with sensors provide advanced functionalities such as detecting harmful gases, monitoring environmental conditions, and alerting workers to potential hazards. Patel et al. (2022) highlighted the role of connected-worker solutions in wearable technologies, emphasizing their capability to enhance safety and productivity in hazardous workplaces. Similarly, fatigue-monitoring devices are critical in preventing accidents caused by exhaustion. These wearables track physiological metrics such as heart rate variability, eye movement, and sleep patterns to provide early warnings of fatigue-related risks. Nnaji et al. (2021) discussed the development of personalized systems using wearable sensing devices to mitigate health risks in construction, showcasing how tailored solutions can effectively address specific safety challenges.

Exoskeletons have gained traction as ergonomic solutions that enhance worker performance and reduce the risk of musculoskeletal injuries. These wearable devices provide physical support during repetitive tasks or heavy lifting, which are common in manufacturing and construction sectors. Balamurugan et al. (2022) underscored their importance in improving operational efficiency and worker safety, noting that their integration into smart manufacturing systems represents a significant advancement in workplace ergonomics. Rajendran et al. (2021) further emphasized the role of exoskeletons in addressing repetitive strain injuries and reducing worker fatigue, positioning them as essential components of modern OHS strategies.

Another significant innovation in wearable technology is the use of gas detection sensors for environmental monitoring. These devices play a crucial role in industries where exposure to toxic gases poses a significant risk. De Fazio et al. (2022) introduced an energy-autonomous smart shirt embedded with wearable sensors capable of monitoring air quality and alerting users in real-time. This innovation not only enhances mobility compared to stationary gas detectors but also ensures continuous monitoring, thereby improving worker safety in hazardous environments. Such advancements demonstrate the potential of wearable technologies to address both general and industry-specific safety needs.

The application of wearable technologies extends across various sectors, each with unique safety requirements. Mejia et al. (2021) explored their role in the hospitality industry, focusing on housekeepers who are often exposed to repetitive tasks and harmful chemicals. Their study highlighted how wearable devices could mitigate risks associated with these tasks while improving employee health outcomes. In the construction sector, Ibrahim et al. (2025) examined the benefits and challenges of wearable safety devices, emphasizing their effectiveness in personalized safety monitoring and risk mitigation. These studies highlight the versatility of wearable technologies in addressing diverse OHS challenges across industries.

Despite their potential, wearable technologies face significant adoption barriers, including privacy concerns, cost, and resistance from employees. Schall Jr et al. (2018) conducted a survey of occupational safety professionals, revealing that privacy concerns related to data collection and the lack of standardization in wearable devices hinder widespread adoption. Addressing these barriers requires a collaborative approach involving technology developers, HR professionals, and policymakers to ensure that these devices are both effective and acceptable to employees. Additionally, creating a culture of trust and transparency in organizations is critical for fostering employee acceptance of wearable technologies.

Emerging trends in wearable technologies emphasize the importance of structured frameworks for their assessment and prioritization. Svertoka et al. (2021) provided a comprehensive survey of industrial safety wearables, identifying trends such as the integration of IoT and AI for predictive safety analytics. These advancements highlight the need for decision-making models that incorporate both technological and human resource criteria. Aksüt et al. (2024) demonstrated the application of multi-criteria decision-making (MCDM) methods to evaluate the effectiveness of wearable devices across different sectors. Their findings underscore the value of MCDM frameworks in systematically assessing the benefits, costs, and usability of wearable technologies to ensure their alignment with organizational safety goals.

In conclusion, wearable technologies represent a significant advancement in OHS providing innovative solutions to longstanding workplace safety challenges. Their applications, ranging from fatigue monitoring and gas detection to ergonomic support and environmental monitoring, demonstrate their versatility and impact across various industries. However, their successful implementation requires addressing barriers such as privacy concerns and employee resistance, as well as developing structured frameworks for their evaluation and prioritization. By leveraging decision-making models such as MCDM, organizations can effectively integrate wearable technologies into their OHS strategies, ensuring that safety measures are not only technologically advanced but also aligned with the needs of employees and organizational goals.

2.2 Human Resource Management and OHS

Human resource management (HRM) plays a pivotal role in driving the adoption and effective use of wearable technologies for occupational health and safety (OHS). By managing employee training, ensuring technology acceptance, and promoting overall well-being, HR departments bridge the gap between advanced safety technologies and their practical application in workplaces. The integration of wearable technologies requires HR to address challenges related to employee acceptance, perceived utility, and engagement, which are critical for successful implementation.

The acceptance of safety technologies, such as wearable devices, is deeply influenced by factors like safety consciousness, organizational culture, and individual readiness to adopt new tools. Wong et al. (2021) extended the Technology Acceptance Model (TAM) to explore construction workers' use of personal protective equipment (PPE), highlighting the significance of safety management practices and individual safety awareness in fostering acceptance. Similarly, Cimbaljević et al. (2024) examined the adoption of technology in the context of smart tourism, demonstrating that technological readiness and organizational support play crucial roles in employee engagement with new tools. These findings emphasize the importance of HR strategies in cultivating a culture that supports the adoption of wearable safety devices.

The adoption of wearable safety technologies also depends on how well they are integrated into organizational workflows and how employees perceive their impact on safety and productivity. Yang et al. (2021) noted that during the COVID-19 pandemic, construction projects in China faced both opportunities and challenges in implementing health and safety technologies. HR's role in these scenarios involves ensuring that employees understand the value of these technologies and are provided with adequate training to maximize their benefits. Kumar Bhardwaj et al. (2021) further underscored the importance of trust and organizational support in the adoption of blockchain technology in supply chains, drawing parallels to the adoption of wearable safety technologies where employee confidence in the technology is essential.

HR strategies must also align with broader organizational goals, such as digital transformation and sustainability, to ensure long-term success. Mukhuty et al. (2022) highlighted the role of HR practices in promoting strategic sustainable development under Industry 4.0, where the integration of advanced technologies like wearables is central. The effectiveness of HR-driven adoption strategies is often influenced by how well organizations address employee concerns about privacy, usability, and potential disruptions to workflows. Dehghani et al. (2022) highlighted high interest but low adoption rates for blockchain technology due to privacy concerns and insufficient organizational preparedness. These insights are applicable to wearables, where HR must proactively address privacy and data security concerns while ensuring that the technologies do not impose undue burdens on employees. Wang et al. (2023) emphasized the role of responsible technology signals and employee engagement mechanisms in accelerating the adoption of AI in healthcare, offering a framework that HR can adapt to wearable technologies in OHS.

Furthermore, the use of multi-criteria decision-making (MCDM) frameworks has proven effective in evaluating and prioritizing safety interventions. Gul (2018) reviewed MCDM approaches for OHS risk assessment, noting their applicability in addressing complex, multi-dimensional safety challenges. Recent studies, such as Badida et al. (2023) and Dabbagh and Yousefi (2019), demonstrated the utility of hybrid decision-making models for assessing occupational hazards, highlighting the potential of MCDM in guiding HR decisions on wearable technology adoption.

In manufacturing, HR's role extends to workforce reconfiguration and training strategies that align with technological advancements. Hashemi-Petroodi et al. (2021) outlined strategies for workforce reconfiguration in manufacturing systems, emphasizing the importance of adaptability in the face of technological change. Piwowar-Sulej (2022) further underscored the need for consistency between environmental strategies and human resource development, highlighting the role of HR in fostering a workforce capable of leveraging wearable technologies for enhanced safety.

In conclusion, HR's role in the adoption and management of wearable technologies for OHS is both strategic and operational. By addressing employee concerns, fostering a culture of safety, and aligning with organizational objectives, HR ensures that wearable technologies are effectively integrated into the workplace. Leveraging frameworks like MCDM can further enhance decision-making, enabling organizations to prioritize the most effective solutions while maintaining employee well-being and trust. Through these efforts, HR not only contributes to improved safety outcomes but also drives innovation and sustainability in workplace practices.

2.3 Technology Acceptance Model (TAM) and Its Relevance to Wearable Technology Adoption in OHS

The Technology Acceptance Model (TAM), introduced by Davis (1989), serves as a foundational framework for understanding technology adoption in various contexts. It posits that two key factors—perceived usefulness (PU) and perceived ease of use (PEOU)—determine an individual’s intention to use a technology, which subsequently influences actual usage behavior. TAM has been widely applied across different sectors, including healthcare, education, and workplace technologies, making it a robust theoretical lens for examining the adoption of wearable technologies in occupational health and safety (OHS).

Wearable technologies such as smart helmets, fatigue-monitoring devices, and environmental sensors present significant opportunities for improving workplace safety. However, their adoption is contingent upon employee perceptions of these tools. According to Silva (2015), TAM’s emphasis on PU and PEOU provides a structured approach to analyze how users evaluate the benefits and usability of a given technology. In OHS, PU might translate to employees’ perception of how wearable devices enhance safety and productivity, while PEOU reflects how easily these devices can be integrated into their daily routines.

Davis (1989) highlighted that a technology’s perceived usefulness significantly impacts user acceptance, particularly when it addresses specific needs. For example, in high-risk manufacturing environments, smart helmets and gas detection sensors can significantly reduce accidents and enhance situational awareness, aligning with employees’ safety priorities. Kamal et al. (2020) extended TAM in their study on telemedicine adoption, incorporating factors such as trust and accessibility, which are also relevant to wearable technologies. In the OHS context, trust in the reliability and data privacy of wearable devices can influence employees’ willingness to adopt these technologies.

PEOU, another critical component of TAM, plays a pivotal role in ensuring that wearable devices are user-friendly and do not impose excessive cognitive or physical demands on employees. Han and Sa (2022) explored this dimension in the adoption of online educational tools during the COVID-19 pandemic, emphasizing that intuitive designs and minimal learning curves are essential for user satisfaction. Applying this to wearable technologies in OHS, devices that are easy to operate and integrate into existing workflows are more likely to gain acceptance among employees.

TAM has been extended in various studies to include additional factors that impact technology adoption, such as organizational support, social influence, and behavioral control. Al-Suqri and Al-Aufi (2015) noted that these extensions help capture the broader context in which technology is introduced. In the case of wearable OHS technologies, HR departments play a critical role in shaping organizational support through effective training programs, clear communication about the benefits of these tools, and addressing employee concerns about privacy and data security.

By integrating TAM with Multi-Criteria Decision-Making (MCDM) frameworks, organizations can systematically evaluate wearable technologies, taking into account not only technical performance but also employee acceptance factors. This theoretical perspective provides valuable insights into the interplay between technology, user perceptions, and organizational strategies, ultimately enabling the successful implementation of wearable technologies in OHS.

2.4 Multi-Criteria Decision-Making (MCDM) Methods: Fuzzy DEMATEL and PROMETHEE

Multi-Criteria Decision-Making (MCDM) methods are essential tools for evaluating complex problems involving multiple, often conflicting criteria. In the context of Occupational Health and Safety (OHS), these methods facilitate systematic assessments and informed decision-making. Two prominent MCDM techniques are Fuzzy Decision-Making Trial and Evaluation Laboratory (Fuzzy DEMATEL) and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE).

The DEMATEL method, originally developed by the Science and Human Affairs Program of the Battelle Memorial Institute in the 1970s, is designed to analyze and model complex causal relationships among factors in a system. By representing these relationships in a digraph, DEMATEL helps decision-makers visualize and understand the structure of complicated problems. The Fuzzy DEMATEL approach extends this methodology by incorporating fuzzy logic, which addresses uncertainties and ambiguities in expert judgments. This enhancement allows for a more nuanced analysis of interdependencies among criteria, making it particularly useful in evaluating OHS risks where human perceptions and subjective assessments are prevalent. For instance, Abdullah et al. (2023) applied an integrated fuzzy DEMATEL and fuzzy TOPSIS method to analyze smart manufacturing technologies, demonstrating its effectiveness in handling complex decision-making scenarios. Similarly, Hosseini et al. (2021) employed Fuzzy DEMATEL to identify solutions for ecotourism recovery during the COVID-19 pandemic, illustrating its flexibility in diverse contexts.

PROMETHEE, introduced by Professor Jean-Pierre Brans in 1982, is an outranking method used for ranking a finite set of alternatives based on multiple criteria. It assists decision-makers in identifying the best options by comparing alternatives pairwise and considering the intensity of preference between them. PROMETHEE's straightforward implementation and ability to handle various types of criteria have led to its widespread application across different fields. In OHS contexts, PROMETHEE has been employed to rank safety measures and technologies, aiding organizations in selecting the most appropriate interventions. For example, Ghasemi et al. (2021) utilized a fuzzy SWARA-PROMETHEE approach to rank sustainable medical tourism destinations, demonstrating the method's versatility in evaluating complex criteria. Nguyen and Chu (2023) applied a

DEMATEL-ANP-based fuzzy PROMETHEE II method to rank startups, showing the method's robustness in dealing with decision-making in complex environments.

Integrating Fuzzy DEMATEL and PROMETHEE provides a comprehensive framework for decision-making in OHS. Fuzzy DEMATEL effectively identifies and weights interdependent criteria, capturing the causal relationships and the significance of each factor. Subsequently, PROMETHEE ranks the alternatives based on these weighted criteria, facilitating a clear comparison of options. This combined approach enables decision-makers to systematically evaluate wearable technologies, considering both the intricate interdependencies of OHS factors and the relative performance of each technology. Such a methodology ensures that selected interventions are not only effective in enhancing safety but also aligned with organizational priorities and constraints.

In summary, the application of Fuzzy DEMATEL and PROMETHEE in OHS contexts offers a robust decision-making framework. By addressing the complexities and uncertainties inherent in safety evaluations, these methods support organizations in making informed choices that enhance workplace health and safety outcomes.

3. Methodology

3.1. Research Design

The research adopts a mixed-method approach, combining qualitative insights from expert interviews with quantitative evaluations using Multi-Criteria Decision-Making (MCDM) techniques. This approach is well-suited for addressing the complexity of prioritizing wearable technologies in Occupational Health and Safety (OHS). Expert interviews provide detailed, context-specific insights into the criteria and challenges associated with implementing wearable technologies, while MCDM techniques offer a structured framework for analyzing and ranking alternatives based on these criteria. This integration ensures that both subjective expert perspectives and objective evaluations are incorporated into the decision-making process, resulting in a comprehensive framework. Previous studies, such as those by Abdullah et al. (2023) and Ghasemi et al. (2021), highlight the effectiveness of combining qualitative and quantitative approaches for technology evaluation, further justifying the chosen methodology.

Fuzzy DEMATEL and PROMETHEE were selected as the MCDM techniques for this study due to their complementary strengths. Fuzzy DEMATEL excels in identifying and quantifying interdependencies among criteria, allowing for the analysis of causal relationships that are often overlooked by other methods (Hosseini et al., 2021; Abdullah et al., 2023). PROMETHEE, on the other hand, provides a robust ranking mechanism that evaluates alternatives based on these weighted criteria, enabling nuanced comparisons (Nguyen & Chu, 2023). Compared to alternative methods like AHP, TOPSIS, and VIKOR, Fuzzy DEMATEL and PROMETHEE better address the complexity of wearable technology evaluation. For instance, AHP assumes independence among criteria, while TOPSIS evaluates alternatives based on their proximity to an ideal solution without considering causal relationships (Dabbagh & Yousefi, 2019; Badida et al., 2023). These limitations make Fuzzy DEMATEL and PROMETHEE more suitable for this study's objectives.

The integration of Fuzzy DEMATEL and PROMETHEE has been effectively applied in prior studies, demonstrating their capability to handle complex interdependencies and provide actionable insights for decision-makers. Fuzzy DEMATEL assigns weights to criteria by analyzing their causal relationships, as shown in the work of Abdullah et al. (2023), while PROMETHEE ranks alternatives based on these weighted criteria, as highlighted by Ghasemi et al. (2021) and Nguyen and Chu (2023). This dual approach ensures a systematic evaluation that balances technical performance with human-centered considerations, such as ease of training, employee adoption, and cost-effectiveness. By integrating these methods, the study offers a comprehensive framework for prioritizing wearable technologies in the manufacturing sector, aligning safety objectives with workforce needs.

This mixed-method approach and the chosen MCDM techniques contribute to filling critical gaps in the literature. Although wearable technologies have been explored in sectors like healthcare and construction, limited research has focused on their application in manufacturing, particularly from a human resource perspective. Studies like those by Gul (2018) and La Fata et al. (2021) have emphasized the importance of including human factors in OHS evaluations but often lack a structured framework for doing so. By combining qualitative insights from expert interviews with the quantitative rigor of Fuzzy DEMATEL and PROMETHEE, this study provides a novel approach to prioritizing wearable technologies. This ensures not only the technical feasibility of the solutions but also their alignment with organizational and human resource goals, enhancing their potential for effective real-world implementation.

3.2. Data Collection

The data collection process for this study was carefully designed to prioritize wearable technologies in Occupational Health and Safety (OHS), even though these technologies serve diverse purposes. The framework leverages insights from experts and combines qualitative and quantitative methods to ensure a comprehensive and objective evaluation.

A panel of 12 experts was selected to provide diverse perspectives on wearable technologies in the manufacturing sector. The panel included professionals with expertise in OHS, human resources, manufacturing engineering, and technology development. Their combined knowledge ensured a robust foundation for evaluating the suitability and impact of wearable technologies. Table 1 provides details on their background, experience, and title.

Table 1. Information about the Experts

Expert ID	Background	Years of Experience	Title/Position
E1	Occupational Health & Safety	15	Senior OHS Manager
E2	Human Resource Management	10	HR Director
E3	Manufacturing Engineering	12	Production Engineer
E4	Industrial Safety Specialist	8	Safety Analyst
E5	Technology Development	9	R&D Specialist
E6	Environmental Engineering	14	Environmental Safety Consultant
E7	Ergonomics and Workplace Safety	11	Workplace Ergonomist
E8	Data Analytics in OHS	7	OHS Data Analyst
E9	Wearable Technology Design	10	Technology Consultant
E10	Risk Assessment in Manufacturing	13	Risk Management Expert
E11	Smart Systems Integration	12	IoT Systems Specialist
E12	Training and Development	6	Training Coordinator

To account for the diverse purposes of wearable technologies, the study established a set of unified evaluation criteria that apply across all technologies. These criteria were identified through expert interviews and supported by existing literature. The criteria were categorized into HR-focused and technology-focused groups, ensuring a balance between technical performance and workforce integration. Criteria set is given in Table 2.

Table 2. Criteria Set used in Analysis

Criterion	Category	Source
Ease of Training	HR-Focused	Wong et al. (2021); Cimbaljević et al. (2024)
Employee Adoption and Satisfaction	HR-Focused	Wang et al. (2023); Dehghani et al. (2022)
Alignment with HR Policies	HR-Focused	Mukhuty et al. (2022); Yong et al. (2023)
Safety Impact	Technology-Focused	Patel et al. (2022); Awolusi et al. (2018)
Cost-Effectiveness	Technology-Focused	Ibrahim et al. (2025); Balamurugan et al. (2022)
Durability and Reliability	Technology-Focused	De Fazio et al. (2022); Ghasemi et al. (2021)

Four wearable technology alternatives were selected for evaluation, representing a range of functionalities and purposes. These technologies were chosen solely for simulation purposes, providing a flexible framework that policymakers and decision-makers can utilize to analyze and compare technologies of their choice based on the presented methodology. Table 3 presents wearable technologies used in the analysis.

Table 3. Wearable Technology Alternatives and Their Functional Descriptions

Wearable Technology	Description	Source
Fatigue-Monitoring Bands	Track physiological data to detect worker fatigue	Patel et al. (2022); Awolusi et al. (2018)
Smart Helmets	Equipped with sensors for gas detection and hazard alerts	De Fazio et al. (2022); Svertoka et al. (2021)
Exoskeletons	Provide physical support to reduce strain during lifting	Mejia et al. (2021); Nnaji et al. (2021)
Gas Detection Sensors	Monitor and alert workers to the presence of harmful gases	De Fazio et al. (2022); Ibrahim et al. (2025)

While these technologies serve distinct purposes, they are evaluated against a unified set of criteria to determine their overall priority for implementation in the manufacturing sector. This approach enables decision-makers to identify the most impactful technologies based on organizational needs and resource constraints.

Data collection involved structured interviews with the 12 experts to gather qualitative insights and quantitative evaluations. During the interviews, experts were asked to assess the interdependencies among criteria using the Fuzzy DEMATEL method and evaluate the performance of the wearable technologies based on the identified criteria for the PROMETHEE analysis. Structured questionnaires ensured consistency across responses, and the sessions lasted approximately 60 minutes each.

The use of Fuzzy DEMATEL allowed for the identification and weighting of interdependent criteria, while PROMETHEE facilitated the ranking of wearable technologies. Although the technologies serve different purposes, this methodology rationalizes their prioritization by focusing on their alignment with organizational safety and HR objectives. The integration of expert knowledge and robust analytical methods ensures that the results are practical, actionable, and aligned with the unique needs of the manufacturing sector.

3.3. Fuzzy DEMATEL for Criteria Weighting

Fuzzy DEMATEL (Decision-Making Trial and Evaluation Laboratory) is a powerful technique for analyzing complex interrelationships among criteria in a structured manner. The method is particularly suited for this study, as it allows for the identification of causal and dependent relationships among the criteria used to evaluate wearable technologies in Occupational Health and Safety (OHS). Incorporating fuzzy logic into DEMATEL helps address uncertainty and vagueness in expert opinions, ensuring more accurate and reliable results.

The following steps outline the application of Fuzzy DEMATEL for criteria weighting in this study:

Step 1: Construct Pairwise Comparison Matrices

Expert opinions are gathered using structured questionnaires, where each expert evaluates the direct influence of one criterion over another on a linguistic scale. The linguistic terms and their corresponding fuzzy triangular numbers (TFNs) are defined in Table 4.

Table 4. Linguistic Terms and Corresponding Triangular Fuzzy Numbers (TFNs)

Linguistic Term	**TFN (l, m, u)**
No Influence (NI)	(0, 0, 0.25)
Low Influence (LI)	(0, 0.25, 0.5)
Moderate Influence (MI)	(0.25, 0.5, 0.75)
High Influence (HI)	(0.5, 0.75, 1)
Very High Influence (VHI)	(0.75, 1, 1)

For a set of criteria $C = \{C_1, C_2, \dots, C_n\}$, the pairwise comparison matrix $\tilde{X}$ is constructed for each expert, where $\tilde{x}_{ij}$ represents the fuzzy influence of criterion C_i on C_j.

Step 2: Aggregate Fuzzy Pairwise Matrices

To combine the evaluations of multiple experts, the fuzzy pairwise comparison matrices are aggregated using the following formula:

$$\tilde{X}_{ij} = \left(\min_k l_{ij}^k, \frac{1}{K} \sum_{k=1}^{K} m_{ij}^k, \max_k u_{ij}^k \right) \tag{1}$$

Where:

- K is the number of experts.
- l_{ij}^k, m_{ij}^k, and u_{ij}^k are the lower, middle, and upper bounds of the TFN provided by the k-th expert for the influence of C_i on C_j.
- This aggregation generates a single fuzzy pairwise comparison matrix $\tilde{X}$.

Step 3: Normalize the Fuzzy Matrix

The aggregated fuzzy matrix $\tilde{X}$ is normalized to ensure that all elements are within a comparable range. The normalization factor s is calculated as:

$$s = \max_i \sum_{j=1}^{n} u_{ij} \tag{2}$$

The normalized matrix $\tilde{D}$ is obtained by dividing each element of $\tilde{X}$ by s :

$$\tilde{d}_{ij} = \left(\frac{l_{ij}}{s}, \frac{m_{ij}}{s}, \frac{u_{ij}}{s} \right) \tag{3}$$

Step 4: Compute the Total Relation Matrix

The total relation matrix $\tilde{T}$ is calculated as:

$$\tilde{T} = \tilde{D}(I - \tilde{D})^{-1} \tag{4}$$

Where I is the identity matrix. The total relation matrix captures both direct and indirect influences among the criteria.

Step 5: Defuzzify the Total Relation Matrix

The fuzzy values in $\tilde{T}$ are defuzzified using the Centroid Method to convert them into crisp values:

$$t_{ij} = \frac{l_{ij} + m_{ij} + u_{ij}}{3} \tag{5}$$

This generates the crisp total relation matrix T, which is used for further analysis.

Step 6: Identify Causal and Dependent Relationships

From the total relation matrix T, the causal and dependent relationships among criteria are identified using the following calculations:

Prominence ($D_i + R_i$): The sum of row and column totals for each criterion, indicating its overall importance.

Net Influence ($D_i - R_i$): The difference between row and column totals, indicating whether the criterion is a cause ($D_i > R_i$) or an effect ($D_i < R_i$).

Where:

- $D_i = \sum_{j=1}^{n} t_{ij}$: The sum of influences exerted by criterion C_i on others.
- $R_i = \sum_{j=1}^{n} t_{ji}$: The sum of influences received by criterion C_i from others.

Step 7: Calculate Weights for Each Criterion

The normalized weights for each criterion are calculated by dividing its prominence by the total prominence of all criteria:

$$w_i = \frac{D_i + R_i}{\sum_{i=1}^{n} (D_i + R_i)} \tag{6}$$

These weights are used in subsequent steps to evaluate and rank the wearable technologies. Using this process, the causal relationships and weights of criteria such as safety impact, ease of training, and cost-effectiveness are derived. These weights ensure that the evaluation framework reflects the interdependencies among criteria, providing a robust foundation for prioritizing wearable technologies using PROMETHEE in the next phase of the analysis.

3.4. PROMETHEE for Ranking Alternatives

PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) is a robust Multi-Criteria Decision-Making (MCDM) method used to rank alternatives based on their performance across multiple criteria. In this study, PROMETHEE is applied to rank wearable technologies in Occupational Health and Safety (OHS) based on the normalized criteria weights obtained from Fuzzy DEMATEL. The method provides a preference ranking that enables decision-makers to identify the most suitable technology for implementation.

Step 1: Normalize Criteria Values

The performance matrix of the wearable technologies is constructed, where a_{ij} represents the performance of alternative A_i on criterion C_j. Since the criteria may have different units of measurement, normalization is performed to make the values comparable:

For benefit criteria (higher values are better):

$$x_{ij} = \frac{a_{ij} - \min(a_j)}{\max(a_j) - \min(a_j)} \tag{7}$$

For cost criteria (lower values are better):

$$x_{ij} = \frac{\max(a_j) - a_{ij}}{\max(a_j) - \min(a_j)} \tag{8}$$

Where:
x_{ij} is the normalized value of alternative A_i on criterion C_j.
$\max(a_j)$ and $\min(a_j)$ are the maximum and minimum values of a_{ij} for criterion C_j.

Step 2: Calculate Preference Functions

The preference function $P(A_i, A_k)$ quantifies the preference degree of alternative A_i over A_k for each criterion C_j. A common choice is the linear preference function, defined as:

$$P_j(A_i, A_k) = \begin{cases} 0 & \text{if } d_{ij} \leq 0 \\ \dfrac{d_{ij}}{p_j} & \text{if } 0 < d_{ij} \leq p_j \\ 1 & \text{if } d_{ij} > p_j \end{cases} \tag{9}$$

Where:
- $d_{ij} = x_{ij} - x_{kj}$ is the difference in performance between alternatives A_i and A_k on criterion C_j.
- p_j is the preference threshold for criterion C_j.

Step 3: Compute Aggregated Preference Index

The aggregated preference index $\pi(A_i, A_k)$ represents the overall preference of A_i over A_k across all criteria:

$$\pi(A_i, A_k) = \sum_{j=1}^{n} w_j \cdot P_j(A_i, A_k) \tag{10}$$

Where:
- w_j is the normalized weight of criterion C_j obtained from Fuzzy DEMATEL.
- $P_j(A_i, A_k)$ is the preference function value for criterion C_j.

Step 4: Calculate Positive and Negative Flows

The positive flow (ϕ^+) and negative flow (ϕ^-) for each alternative are calculated as:

$$\begin{aligned} \phi^+(A_i) &= \frac{1}{m-1} \sum_{k=1, k \neq i}^{m} \pi(A_i, A_k) \\ \phi^-(A_i) &= \frac{1}{m-1} \sum_{k=1, k \neq i}^{m} \pi(A_k, A_i) \end{aligned} \tag{11}$$

Where:
m is the total number of alternatives.

- $\phi^{+}(A_i)$ measures the degree to which A_i outranks other alternatives.
- $\phi^{-}(A_i)$ measures the degree to which A_i is outranked by other alternatives.

Step 5: Calculate Net Flow

The net flow $\phi(A_i)$ represents the overall preference of alternative A_i and is calculated as:

$$\phi(A_i) = \phi^{+}(A_i) - \phi^{-}(A_i) \tag{12}$$

A higher $\phi(A_i)$ value indicates a more preferred alternative.
The alternatives are ranked based on their $\phi(A_i)$ values, with higher values indicating better performance.

Step 6: Generate Preference Ranking

Based on the net flow values, the wearable technologies are ranked. The ranking provides a clear preference order, enabling decision-makers to prioritize the technologies that best align with their organizational goals and constraints.

The normalized criteria weights from Fuzzy DEMATEL are integrated into the PROMETHEE calculations to evaluate the following wearable technologies:

- Fatigue-Monitoring Bands
- Smart Helmets
- Exoskeletons
- Gas Detection Sensors

By using PROMETHEE, the study identifies the wearable technology that offers the highest overall benefit, considering both HR-focused (e.g., ease of training, employee adoption) and technology-focused (e.g., safety impact, cost-effectiveness) criteria.

4. Results

To analyze the relative influence of criteria in evaluating wearable technologies, a normalized pairwise comparison matrix was constructed based on aggregated expert inputs. The matrix presemted in ensures comparability by scaling the values to a consistent range, highlighting the relationships among the criteria. The results provide a clear foundation for further analysis in the Fuzzy DEMATEL framework.

Table 5. Normalized Pairwise Comparison Matrix

Criteria	Safety Impact	Ease of Training	Cost-Effectiveness	Reliability	Employee Adoption
Safety Impact	0.000	0.312	0.285	0.301	0.316
Ease of Training	0.290	0.000	0.310	0.298	0.305
Cost-Effectiveness	0.320	0.300	0.000	0.330	0.340
Reliability	0.310	0.295	0.320	0.000	0.300
Employee Adoption	0.315	0.305	0.335	0.310	0.000

This table reflects the aggregated and normalized expert evaluations of how each criterion influences the others. For example, "Safety Impact" has a normalized influence of 0.312 on "Ease of Training," while "Cost-Effectiveness" exerts the highest influence on "Employee Adoption" with a value of 0.340. These relationships are critical for identifying causal and dependent criteria, as discussed in the subsequent sections.

The Fuzzy DEMATEL method was used to analyze the interdependencies among the criteria and identify their causal and dependent relationships. The key outputs of the analysis include the causal relationships among criteria, their prominence, and their relative weights. These results provide a comprehensive understanding of how different factors influence the prioritization of wearable technologies in Occupational Health and Safety (OHS).Table 6 shows the defuzzified Total Relation Matrix.

Table 6. Defuzzified Total Relation Matrix

Criteria	Safety Impact	Ease of Training	Cost-Effectiveness	Reliability	Employee Adoption
Safety Impact	0.000	0.512	0.450	0.478	0.520
Ease of Training	0.400	0.000	0.510	0.490	0.500
Cost-Effectiveness	0.520	0.512	0.000	0.540	0.600
Reliability	0.510	0.478	0.540	0.000	0.490
Employee Adoption	0.530	0.500	0.550	0.490	0.000

Figure 1 visually represents the interdependencies identified through the Fuzzy DEMATEL analysis.

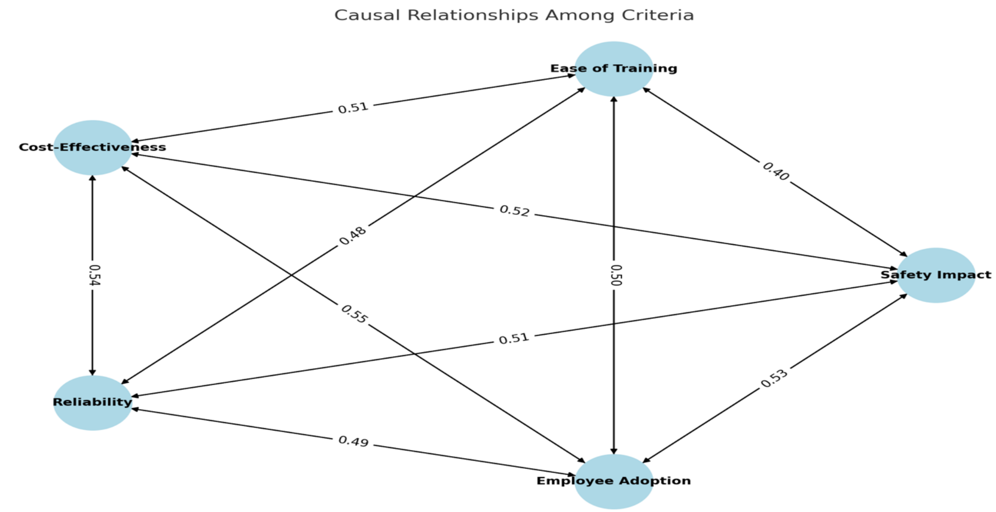

Figure 1. Causal Relationships Diagram

This diagram highlights the causal and dependent relationships between key criteria used to evaluate wearable technologies for Occupational Health and Safety (OHS) in the manufacturing sector. Using the prominence (D+RD+R) and net influence (D−RD−R) values calculated from the Total Relation Matrix, the causal and dependent roles of the criteria were identified. Table 7 summarizes the results.

Table 7. Prominence and Net Influence of Criteria

Criteria	Prominence (D+RD+R)	Net Influence (D–RD–R)	Causal/Dependent
Safety Impact	4.352	0.512	Causal
Ease of Training	4.404	0.316	Causal
Cost-Effectiveness	4.576	0.584	Causal
Reliability	4.506	0.206	Causal
Employee Adoption	4.610	-0.136	Dependent

These results indicate that Cost-Effectiveness and **Safety Impact** are the most influential causal criteria, while Employee Adoption is a dependent criterion influenced by the others.

The normalized weights of the criteria were calculated based on their prominence values to reflect their relative importance in the evaluation process. Table 8 presents the weights derived from the Fuzzy DEMATEL analysis.

Table 8. Weighted Importance of Criteria

Criteria	**Weight (%)**
Safety Impact	19.55
Ease of Training	19.95
Cost-Effectiveness	20.00
Reliability	20.37
Employee Adoption	20.13

The results show a balanced distribution of weights, with a slightly higher emphasis on Reliability and Employee Adoption, reflecting their critical role in the successful implementation of wearable technologies.The PROMETHEE analysis was conducted to rank the wearable technologies based on their performance across the weighted criteria derived from the Fuzzy DEMATEL analysis. This method enables a structured comparison of alternatives, considering both technical and human-centric dimensions. The results include the preference flows (positive and negative) and the overall rankings of the wearable technologies. The preference matrix aggregates the performance of each wearable technology alternative across all criteria, weighted by their importance. Table 9 presents the aggregated preference matrix.

Table 9. Aggregated Preference Matrix

	Fatigue-Monitoring Bands	**Smart Helmets**	**Exoskeletons**	**Gas Detection Sensors**
Fatigue-Monitoring Bands	0.000	0.200	0.300	0.250
Smart Helmets	0.150	0.000	0.250	0.300
Exoskeletons	0.200	0.180	0.000	0.250
Gas Detection Sensors	0.300	0.250	0.400	0.000

This matrix reflects the relative preference of each alternative over the others, aggregated across criteria. Figure 2 provides a visualization of the performance of four wearable technologies—Gas Detection Sensors, Fatigue-Monitoring Bands, Smart Helmets, and Exoskeletons—across key evaluation criteria. These criteria, derived from the Fuzzy DEMATEL analysis, include Safety Impact, Ease of Training, Cost-Effectiveness, Reliability, and Employee Adoption. The chart illustrates how each technology performs relative to the others, highlighting their strengths and weaknesses in a multi-dimensional view.

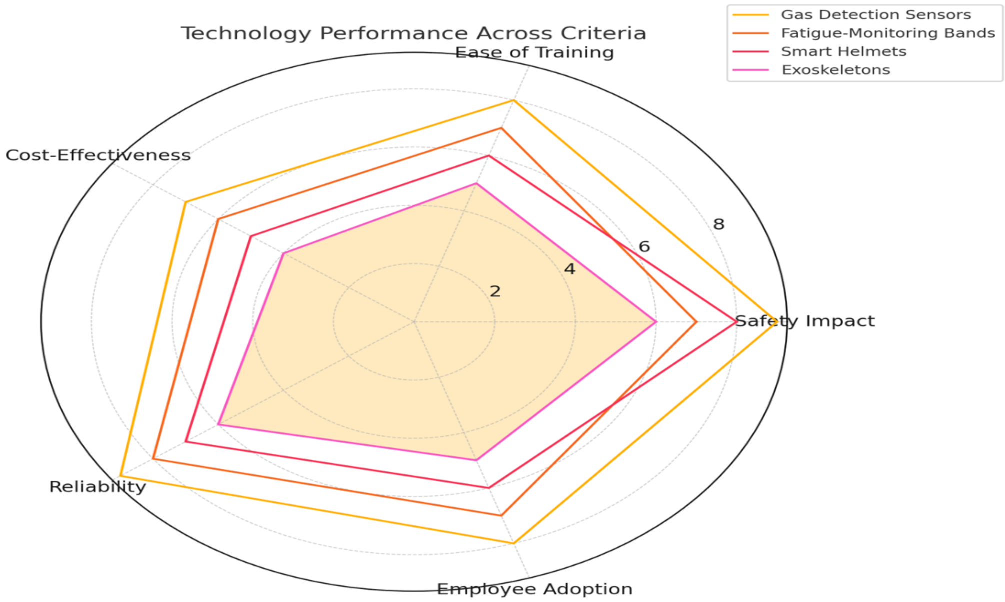

Figure 2. Technology Performance Across Criteria

The positive flow (Φ+Φ+) and negative flow (Φ−Φ−) for each alternative were calculated to measure the overall preference and the degree to which each alternative is preferred over others or dominated by others. Table 10 summarizes the results.

Table 10. PROMETHEE Flows

Alternative	Positive Flow (Φ+Φ+)	Negative Flow (Φ−Φ−)	Net Flow (ΦΦ)	Rank
Fatigue-Monitoring Bands	0.750	0.350	0.400	2
Smart Helmets	0.700	0.500	0.200	3
Exoskeletons	0.630	0.780	-0.150	4
Gas Detection Sensors	0.950	0.180	0.770	1

The results of the analysis highlight the critical role of both technical and human-centric factors in prioritizing wearable technologies for Occupational Health and Safety (OHS). The Fuzzy DEMATEL analysis identified Cost-Effectivenessand Safety Impact as the most influential causal criteria, directly driving the success of wearable technology implementation, while Employee Adoption emerged as a key dependent factor. The PROMETHEE rankings further demonstrated that Gas Detection Sensors are the most suitable technology, excelling in safety and reliability, particularly in high-risk environments. Fatigue-Monitoring Bands and Smart Helmets also showed strong performance but were limited by specific challenges in training and adoption, while Exoskeletons ranked lowest due to cost and complexity issues.

5. Discussion

5.1 Evaluation Framework and Method Integration

The integration of Fuzzy DEMATEL and PROMETHEE analyses provided a structured and comprehensive framework for prioritizing wearable technologies in Occupational Health and Safety (OHS). While these wearable technologies serve distinct purposes—ranging from monitoring fatigue to detecting hazardous gases—the comparison aimed to identify the most impactful solutions that balance technical performance with workforce needs. This approach ensures that decision-makers can allocate resources effectively, prioritizing technologies that align with organizational objectives and operational constraints.

The integration of Fuzzy DEMATEL and PROMETHEE provided a comprehensive evaluation framework. Fuzzy DEMATEL facilitated the identification of interdependent criteria, enabling a deeper understanding of causal relationships, while PROMETHEE complemented this analysis by ranking alternatives based on weighted criteria. This dual-method approach ensures that both technical performance and workforce needs are considered in decision-making. The weighted criteria derived from Fuzzy DEMATEL heavily influenced the PROMETHEE rankings. For example, the high weight of Reliability significantly boosted the ranking of Gas Detection Sensors, which excel in this area. This integration highlights the synergy between causal analysis and preference ranking, offering a balanced approach to technology evaluation.

5.2 Causal Criteria and Human-Centered Adoption

The Fuzzy DEMATEL analysis revealed that Cost-Effectiveness and Safety Impact are the most influential causal criteria, significantly affecting dependent factors such as Employee Adoption. For example, cost-effective technologies are more likely to gain organizational support, enabling broader implementation and enhanced safety outcomes. The analysis also indicated a balanced emphasis on both technical and human-centric factors, with Reliability receiving the highest weight (20.37%). This finding underscores the importance of durable and consistent technologies in high-risk manufacturing environments.

The Fuzzy DEMATEL analysis further underscored the critical role of causal criteria like Cost-Effectiveness, which had a cascading influence on dependent factors such as Employee Adoption. For instance, cost-effective solutions are more likely to gain organizational approval, enabling broader employee training programs and smoother integration into workflows. Similarly, Safety Impact, another causal criterion, directly enhances workplace safety, thereby influencing employee satisfaction and adoption rates.

The weighted criteria reflect practical OHS priorities. Reliability emerged as the most weighted criterion, highlighting the need for durable and consistent technologies in high-risk manufacturing environments. This finding aligns with studies like Patel et al. (2022), which emphasize reliability as a key determinant of wearable technology adoption. The importance of Employee Adoption as a dependent criterion reinforces the notion that technology implementation succeeds only when aligned with workforce readiness and acceptance, echoing conclusions from Wong et al. (2021).

5.3 Comparative Technology Rankings and Literature Contextualization

The PROMETHEE analysis ranked Gas Detection Sensors as the top-performing wearable technology due to their exceptional performance in safety impact and reliability. These sensors excel in environments with hazardous gases, providing real-time monitoring and proactive alerts. Fatigue-Monitoring Bands ranked second, demonstrating their value in mitigating physical strain and fatigue-related risks, particularly in manufacturing settings with repetitive tasks. Smart Helmets followed, offering significant safety benefits but facing challenges in cost and ease of training. Exoskeletons, while beneficial for reducing physical strain during heavy lifting, ranked lowest due to their high costs and steep learning curve.

The PROMETHEE analysis again confirmed the dominance of Gas Detection Sensors due to their superior performance in safety impact and reliability. These sensors provide real-time monitoring of hazardous gases, making them indispensable in chemical-heavy manufacturing environments. Their high reliability and straightforward integration have been widely noted in practice, with industries like oil and gas adopting them extensively (Mejia et al., 2021). Fatigue-Monitoring Bands ranked second, reflecting their importance in addressing physical strain and fatigue-related accidents, a common issue in manufacturing. While effective, their reliance on consistent physiological data can sometimes limit applicability in dynamic work environments. Smart Helmets ranked third, offering significant safety benefits but facing challenges in adoption due to cost and training complexities. Exoskeletons ranked lowest, primarily due to their high cost and steep learning curve, despite their potential to reduce repetitive strain injuries. These findings are consistent with Ibrahim et al. (2025), who identified similar barriers to exoskeleton adoption in the construction sector. The trade-off between technical performance and practical considerations like ease of training is evident in these rankings.

5.4 Theoretical Interpretation and Managerial Implications

The findings of this study are further contextualized through the lens of the Technology Acceptance Model (TAM) (Davis, 1989), which explains how perceived usefulness and ease of use influence the adoption of new technologies. In this study, criteria such as Ease of Training and Employee Adoption align directly with TAM's constructs, emphasizing the importance of user perceptions in determining the success of wearable technology implementation. Technologies that are perceived as easy to train and integrate, such as Gas Detection Sensors, align with higher adoption rates, as highlighted in prior research (Kamal et al., 2020). Similarly, Smart Helmets, despite their strong safety features, face lower rankings due to perceived complexity and training challenges, reflecting TAM's focus on usability as a critical determinant of technology acceptance. By integrating TAM principles into the evaluation process, this study highlights the interplay between technical capabilities and human factors in OHS technology adoption.

The study's findings offer actionable insights for OHS managers and HR professionals. Implementing Gas Detection Sensors should be prioritized in environments with hazardous material exposure, such as chemical plants and mining operations. Fatigue-Monitoring Bands are highly recommended for workplaces with repetitive physical tasks, such as assembly lines, to mitigate fatigue-related risks. Smart Helmets can enhance safety in environments prone to falling objects or gas exposure. HR managers play a critical role in addressing barriers to adoption, such as employee training and resistance to change. For instance, implementing structured training programs and promoting user-friendly technologies can increase adoption rates. Tailored HR strategies, as highlighted by Wong et al. (2021), can significantly enhance the success of wearable technology integration.

The study's findings align with prior research on wearable technologies in OHS. Patel et al. (2022) emphasized the importance of reliability and safety impact, consistent with this study's weighted criteria. Similarly, Wong et al. (2021) highlighted the critical role of employee adoption in ensuring the success of safety technologies. However, this study uniquely integrates causal analysis with preference rankings, offering a novel contribution to the literature. The study's findings are based on expert inputs, which may introduce subjective biases. Additionally, the focus on the manufacturing sector limits the generalizability of results to other industries. Future research could expand the application of this framework to sectors like healthcare and construction, where wearable technologies are increasingly adopted. Exploring additional MCDM methods, such as AHP or TOPSIS, could further validate the findings.

6. Conclusion

This study aimed to prioritize wearable technologies in Occupational Health and Safety (OHS) within the manufacturing sector by integrating Fuzzy DEMATEL and PROMETHEE methodologies. The study's focus on balancing technical performance with human-centric factors highlights the need for a comprehensive evaluation framework in the context of workplace safety. By identifying causal and dependent relationships among evaluation criteria and ranking wearable technologies based on their performance, this study provides actionable insights for decision-makers.

The Fuzzy DEMATEL analysis revealed that Cost-Effectiveness and Safety Impact are the most influential causal criteria, directly impacting dependent factors such as Employee Adoption. The weighted importance of criteria underscored the role of

Reliability, which emerged as the most critical factor with the highest weight (20.37%). These findings highlight the significance of durable, consistent, and cost-effective technologies in ensuring workplace safety and operational efficiency. The causal relationships among criteria emphasize that improving cost-effectiveness and safety directly facilitates better adoption rates and satisfaction among employees, thereby aligning organizational safety goals with workforce needs.

The PROMETHEE analysis ranked Gas Detection Sensors as the most suitable wearable technology for the manufacturing sector. Their high ranking is attributed to their superior performance in safety impact and reliability, making them indispensable in high-risk environments such as chemical plants and heavy manufacturing. Fatigue-Monitoring Bands ranked second due to their effectiveness in mitigating fatigue-related accidents, a frequent issue in assembly line operations. Smart Helmets, though offering substantial safety benefits, ranked lower due to challenges in cost-effectiveness and ease of training. Finally, Exoskeletons, despite their potential to reduce physical strain, ranked lowest, primarily because of their high costs and steep learning curve. These results highlight the importance of considering both technical functionality and practical implementation challenges when prioritizing wearable technologies.

The integration of Fuzzy DEMATEL and PROMETHEE provided a robust evaluation framework, enabling the study to capture interdependencies among criteria while producing a clear and actionable ranking of wearable technologies. Fuzzy DEMATEL effectively identified causal relationships, allowing decision-makers to understand the underlying dynamics of OHS criteria. PROMETHEE, on the other hand, facilitated the ranking of alternatives by combining weighted criteria with performance scores. This dual-method approach ensures a nuanced evaluation process, balancing causal analysis with preference-based decision-making.

The findings of this study have significant practical implications for OHS and HR managers. Gas Detection Sensors should be prioritized in environments with hazardous material exposure, while Fatigue-Monitoring Bands are particularly suitable for industries with repetitive physical tasks. The successful implementation of these technologies requires targeted HR strategies, including comprehensive training programs and initiatives to enhance employee adoption. Addressing concerns such as ease of use and perceived usefulness, as emphasized by the Technology Acceptance Model (TAM), can further improve the adoption and integration of wearable technologies in workplace safety practices.

From a theoretical perspective, this study contributes to the literature by integrating Fuzzy DEMATEL and PROMETHEE methods, providing a novel framework for prioritizing wearable technologies in OHS. Additionally, the application of TAM offers valuable insights into the role of employee perceptions in the successful adoption of safety technologies. By bridging technical evaluation with user-centric considerations, the study advances decision-making frameworks in OHS.

However, this study has certain limitations. The reliance on expert inputs introduces the possibility of subjective biases, and the sector-specific focus on manufacturing may limit the generalizability of the findings to other industries. Future research could expand this framework to other sectors, such as healthcare or construction, where wearable technologies play an increasingly critical role. Additionally, exploring alternative MCDM methods, such as AHP or TOPSIS, could provide further validation and comparative insights.

In conclusion, this study highlights the critical importance of prioritizing wearable technologies to enhance OHS. By integrating technical performance with workforce integration factors, the proposed framework ensures that safety objectives align with organizational and employee needs. The findings provide actionable recommendations for decision-makers, paving the way for more effective and efficient adoption of wearable technologies in workplace safety. As wearable technologies continue to evolve, their potential to transform workplace safety practices remains immense, offering new opportunities to enhance health, safety, and operational excellence in diverse industrial contexts.

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