




A Roadmap for Deploying Industry 4.0 Technologies in Selected Food Industries Using the Interpretive Structural Modeling (ISM) Technique

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ARTICLE INFO	ABSTRACT
<p>Article History: Received 2 March 2020 Received in revised form 26 May 2020 Accepted 23 June 2020 Available online 27 June 2020</p>	<p>In today's highly competitive business environment, organizations must secure and sustain a competitive advantage in order to ensure long-term survival and growth. The emergence of the Fourth Industrial Revolution (Industry 4.0) has introduced a wide range of advanced technologies that not only enhance productivity but also enable firms to remain innovative, agile, and resilient. Among various sectors, the food industry is increasingly adopting Industry 4.0 technologies to improve efficiency, ensure quality, and respond to dynamic consumer demands. However, the complex interrelationships among these technologies create challenges for managers seeking to prioritize and implement them effectively. The present study investigates the interactive relationships among Industry 4.0 technologies within selected food industries. First, twenty Industry 4.0 technologies were identified through an extensive and systematic literature review. Next, the fuzzy Delphi method was employed to refine and validate this set, resulting in the selection of thirteen technologies most relevant to the food industry. To better understand their hierarchical relationships and interdependencies, the Interpretive Structural Modeling (ISM) technique was applied, leading to the development of a structured roadmap for technology deployment. The findings provide both theoretical and practical contributions by highlighting the critical technologies that should be prioritized and offering guidance for strategic implementation in food industry contexts.</p>
<p>Keywords: Industry 4.0, Internet of Things (IoT), Interpretive Structural Modeling (ISM), Food Industry</p>	

1. INTRODUCTION

The term Industry 4.0 was first introduced at the Hannover Fair in Germany in April 2011. It referred to the integration of physical objects, human actors, intelligent machines, production lines, and processes within organizational boundaries to create a system in which all processes are interconnected and information is shared in real time [1].

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In general, the primary objective of Industry 4.0 is to strengthen digitalization and thereby achieve horizontal and vertical integration of organizational processes. Consequently, all information related to operations, inbound and outbound logistics, market demands, and product–customer interactions will be available in real time. As a result, digital enterprises will cooperate with customers and suppliers in an industrial digital ecosystem that enables better management of interfaces between suppliers and marketing functions [2].

In line with these developments, the present study investigates the interactive relationships of Industry 4.0 technologies in selected food industries. After reviewing the literature and identifying relevant technologies, the fuzzy Delphi method was employed to capture expert opinions and determine the most significant Industry 4.0 technologies for the food sector. Finally, the Interpretive Structural Modeling (ISM) technique was applied to construct a deployment roadmap of Industry 4.0 technologies.

2. Theoretical Foundations and Literature Review

2.1. Industry 4.0

Industry 4.0 is a widely accepted term referring to the Fourth Industrial Revolution. Although there is no universally agreed-upon definition, the expansion of the Internet into manufacturing and service provision marks the beginning of this revolution. The central concept envisions a fully integrated system of suppliers, manufacturers, and customers. Information technology solutions are integrated across all subsystems, processes, resources, supply networks, and customer channels. Consequently, the design of new technological systems integrates supply chains through cyber–physical systems, enabling the execution of new functions and managerial practices in production, logistics, and operations [3].

Key features of Industry 4.0 include increased flexibility, reduced procurement lead time, customized small-batch production, and cost reduction [4].

2.2. Internet of Things (IoT)

The Internet of Things (IoT) refers to the interconnection of physical objects to the global Internet, allowing them to be identified and interact in the virtual world. IoT-enabled objects can sense their environment and influence it. IoT systems function effectively only when devices are securely connected to the communication network, either wired or wireless. Connectivity depends on choosing an appropriate Internet protocol according to specific system requirements such as bandwidth and power consumption [5].

2.3. Additive Manufacturing

Additive manufacturing encompasses technologies that build three-dimensional objects layer by layer under computer control, with 3D printing being the most prominent. The advantages of 3D food printing have been widely highlighted by researchers. However, consumer attitudes toward 3D food printing remain underexplored. Understanding its core value and potential applications is crucial for food industries, markets, and consumers. Moreover, technological advances and practical applications must be continuously monitored to determine how this innovation can meet consumer needs and transform lifestyles. Compared to traditional food production, 3D printing offers several benefits [6].

2.4. Rapid Prototyping

In computer-aided design, rapid prototyping based on additive manufacturing translates a design into source code that automatically generates additive production programs, creating a layered prototype of the design. In the food packaging industry, rapid prototyping can be realized in two ways [7]:

- **Indirectly**, through additive manufacturing of prototype molds for short-term packaging.

- **Directly**, by producing prototypes on paper or polymer-based materials.

2.5. Simulation

Simulation technologies such as finite element analysis and computational fluid dynamics enable model-based design of engineering projects and system implementations. These tools simulate integrated models of system properties [8]. In manufacturing, simulations are used to replicate production techniques, allowing operators to test and optimize machine settings for new product lines prior to physical changes [2].

2.6. Production Control

Shop-floor monitoring involves real-time data collection using supervisory control and remote manufacturing systems. This enables short-term adjustments to long-term planning, accounting for existing constraints within manufacturing execution systems (MES). Flexible production lines and digital manufacturing automation with sensors support integration across hierarchical levels. The ultimate aim is to enable product type changes on production lines with minimal effort while generating daily orders from enterprise resource planning systems, considering device-level data constraints [8].

2.7. Digital Sensors

Digital automation with sensors is considered a core standard technology in Industry 4.0. When integrated engineering systems and computer-aided design and manufacturing processes merge product development data with production processes, sensor-enabled flexible manufacturing allows real-time data collection. This data can be used by flexible production lines to reconfigure process sequences, scheduling, and related operations [8].

2.8. Computer-Aided Design and Manufacturing (CAD/CAM)

CAD/CAM refers to the development of projects and workflows for products and manufacturing through computer-based systems. Computer-aided design facilitates development, optimization, and sharing of structural or graphical product designs. These digital designs can be created using various modeling methods with different levels of complexity. Computer-aided manufacturing is a broader term covering production processes supported by computer systems [7].

2.9. Flexible Manufacturing Systems

Digital automation with sensor technologies (e.g., RFID for product components and raw materials) enables reconfigurable manufacturing systems. This facilitates affordable product integration and adaptation in industrial environments. Industry 4.0 concepts allow organizations to establish flexible manufacturing processes, analyze large volumes of real-time data, and enhance both strategic and operational decision-making. Moreover, by analyzing diverse customer needs, organizations can provide improved cost-effective and reliable services supported by flexible manufacturing systems [9].

2.10. Digital Service Systems

Digital services, often connected through industrial cloud systems, represent a global trend in organizations. These services link smart products embedded with sensors, processors, and software to the Internet, enabling new functionalities in monitoring, control, optimization, and autonomy. Such systems contribute significantly to productivity improvements [8].

2.11. Product Lifecycle Management (PLM)

PLM is a business approach that encompasses all managerial practices, collaborative methods, and technological tools used to develop new products. It considers the diverse requirements and challenges of each stage of the product lifecycle and extends beyond factory boundaries [7].

2.12. Radio Frequency Identification (RFID)

RFID technology, particularly in food packaging, uses smart tags to enable product tracking, theft prevention, quality assurance, and safety monitoring of packaged food products [7].

2.13. Integrated Engineering Systems

Integrated engineering systems involve the consolidation of all product lifecycle data, including conceptualization, production, and commercialization. This technology helps overcome communication and coordination barriers in complex product development and plays a key role in connecting people, objects, and systems through digital platforms, thereby facilitating service organization and industrial applications [8].

2.14. Computer-Aided Engineering (CAE)

CAE systems are widely used to evaluate design performance and behavior at the macro level, optimizing manufacturing efficiency and process parameters through silicon-based analysis under various conditions. In food packaging, CAE has two main applications [7]:

- **Process analysis**, which provides manufacturers with insights for improving existing processes or designing new ones.
- **Phenomenon analysis**, which simulates physical phenomena such as fluid flow, heat or mass transfer, and mechanical deformation. For instance, airflow modeling often requires computational fluid dynamics methods.

3. Literature Review

Campbell et al. (2019), in an article titled “*Industry 4.0 and Lean Manufacturing Practices for Sustainable Organizational Performance in Manufacturing Firms in India*,” examined the direct effects of Industry 4.0 on lean practices and sustainable organizational performance, as well as the mediating role of lean practices in the relationship between Industry 4.0 and sustainable organizational performance. This study is among the early works providing empirical evidence of the relationship between Industry 4.0, lean practices, and sustainable performance. The findings indicated that Industry 4.0 exerts a positive and direct influence on both lean practices and sustainable organizational performance, while also identifying lean practices as an important mediating variable [10].

Yin and Shin (2019), in their article “*An Intelligent Performance Measurement Approach for Co-Design in Industry 4.0*,” proposed an intelligent performance measurement framework based on Industry 4.0 trends. Their approach provides flexible and customized performance evaluation, interoperability, and intelligent real-time feedback to measure, monitor, and improve design team collaboration throughout the product development process [11].

Lucas Santos Dalenguro et al. (2018), in a large-scale survey of 27 industrial sectors representing 2,225 Brazilian companies, investigated the “*Predicted Contribution of Industry 4.0 Technologies to Industrial Performance*.” The study revealed how the adoption of various Industry 4.0 technologies is associated with expected benefits across products, operations, and related dimensions [8].

Tortorella et al. (2018) examined the moderating effect of Industry 4.0 technology adoption on the relationship between lean supply chain management practices and supply chain performance improvement in the Brazilian manufacturing sector. Drawing on data from 147 Brazilian manufacturing firms, the study assessed four performance indicators, the implementation of 17 lean supply chain management practices, and 10 digital technologies associated

with Industry 4.0. Using confirmatory and exploratory factor analysis alongside ordinary least squares regression, the findings demonstrated that Industry 4.0 adoption can moderate the relationship between lean supply chain practices and supply chain performance, though the moderating effect was weaker than expected [9].

Ardito et al. (2018) presented a comprehensive overview of innovative efforts over time to develop digital technologies that connect supply chain management with marketing processes, highlighting their role in maintaining supply chain–marketing integration from an information-processing perspective. Patent analysis and case studies were used for this research. The authors first outlined a subset of enabling technologies linked to Industry 4.0 (e.g., Industrial Internet of Things, cloud computing, big data analytics, customer profiling, cybersecurity), which can foster effective supply chain–marketing integration. Second, they conducted a patent analysis to provide a thorough review of patent activity trends related to these digital technologies, thereby highlighting the dynamics and applications of innovation in this domain [2].

Vanderroost et al. (2017) conducted a study aimed at providing a coherent overview of digitalization in the life cycle of food packaging. Drawing upon reports from the National Institute of Standards and Technology, they identified two major phases—(1) research, design, and production, and (2) quality control and error detection—within the post-procurement life cycle of food packaging, and used this framework to advance their study [7].

4. Methodology

In the first phase, after identifying the technologies applied in Industry 4.0, the subsequent stages involved expert review within the food industry. At this stage, some variables could be removed, added, or merged based on expert judgment. The following criteria were used to select the expert panel:

- Relevant work experience in Industry 4.0 technologies
- Holding managerial positions related to the subject of the study
- Accessibility and willingness to participate in the research

The research focused on the food industry, with experts and specialists from this sector serving as the expert community. A total of seven experts were selected, and the research questionnaire was distributed to all panel members and relevant professionals.

Industry 4.0 technologies were first extracted from the literature and categorized within the preliminary framework of the study. In the second phase, the fuzzy Delphi technique was applied to identify and refine Industry 4.0 technologies most relevant to the food sector by incorporating expert opinions. Finally, the revised DEMATEL technique was used to analyze the interactive relationships among Industry 4.0 technologies.

Table 1. Extracted Industry 4.0 Technologies from the Literature

Industry 4.0 Technologies	Ardito et al. (2018)	Tortorella et al. (2018)	Zhao et al. (2019)	Campbell et al. (2019)	Lucas Santos Dalenguro et al. (2018)	Vanderroost et al. (2017)	Yin & Shin (2019)
Internet of Things (IoT)	✓	✓	✓	✓			✓
Cyber-Physical Systems (CPS)				✓		✓	✓
Cybersecurity	✓			✓			
Additive Manufacturing	✓	✓		✓	✓	✓	
Blockchain			✓				
Rapid Prototyping		✓			✓	✓	
Simulation	✓	✓		✓			
Big Data Analytics	✓	✓		✓	✓		

Augmented Reality (AR)	✓	✓		✓	✓		
Production Control		✓			✓		
Digital Sensors		✓		✓	✓		
Cloud Computing	✓	✓	✓	✓	✓		✓
Computer-Aided Design/Manufacture (CAD/CAM)					✓	✓	
Flexible Manufacturing Systems		✓			✓		
Virtual Reality (VR)				✓		✓	✓
Digital Service Systems		✓			✓		
Product Lifecycle Management (PLM)						✓	
Radio Frequency Identification (RFID)			✓		✓	✓	
Integrated Engineering Systems		✓			✓		
Computer Engineering						✓	

4.1. Interpretive Structural Modeling (ISM) Technique

This method is an interactive learning process in which a set of interconnected elements is systematically structured within a comprehensive model. The methodology helps establish and direct the complex relationships among the elements of a system. One of the main rationales behind this approach is that elements exerting greater influence on other elements of the system are of higher importance.

The model developed through this methodology represents the structure of a complex problem, system, or research domain, designed with a carefully constructed pattern. Consequently, Interpretive Structural Modeling not only provides insights into the interrelationships among the elements of a system but also offers a structured framework based on the relative importance or influence of these elements, depending on the type of contextual relationships defined.

This approach is termed interpretive because the existence of relationships among elements is determined by the collective judgment of experts, and structural because the relationships are organized into an overall structure extracted from a complex set of variables. In practice, ISM is a modeling technique in which specific relationships and the overall structure are represented through a directed graph (digraph).

The ISM methodology has been widely applied in various domains. Its core idea is to decompose a complex system into several subsystems (elements) by leveraging the practical experience and knowledge of experts in order to build a multilevel structural model [12].

The main steps of the ISM technique are as follows:

1. Listing of criteria or elements of interest
2. Defining contextual relationships between the identified elements, based on pairwise comparisons
3. Developing the Structural Self-Interaction Matrix (SSIM)
4. Constructing the Initial Reachability Matrix
5. Deriving the Final Reachability Matrix
6. Level partitioning of the final reachability matrix
7. Developing the ISM digraph
8. Classifying the elements based on driving power and dependence

↓ Penetration Power					
1					
2		Region 4		Region 3	
...					
n-1					
n		Region 1		Region 2	
→ The power of Dependence	1	2	...	n-1	n

Fig. 1. Classification of criteria based on driving power and dependence [12]

5. FINDINGS

After distributing the questionnaire among experts, conducting the necessary calculations, and processing the data in Excel, those technologies whose aggregated fuzzy expert opinions—after defuzzification—exceeded the threshold value of 0.7 (as suggested in previous studies) were selected. Ultimately, following data analysis, thirteen Industry 4.0 technologies applicable to the food industry were identified. These technologies and their corresponding codes are presented in Table 2.

Table 2. Industry 4.0 technologies and their corresponding codes

Industry 4.0 Technology	Code
Internet of Things (IoT)	C1
Additive Manufacturing	C2
Rapid Prototyping	C3
Simulation	C4
Production Control	C5
Digital Sensors	C6
Computer-Aided Design and Manufacturing	C7
Flexible Production Lines	C8
Digital Service Systems	C9
Product Lifecycle Management (PLM)	C10
Radio Frequency Identification (RFID)	C11
Integrated Engineering Systems	C12
Computer Engineering	C13

To construct the deployment roadmap of Industry 4.0 technologies, the Interpretive Structural Modeling (ISM) technique was employed. For this purpose, experts were asked to perform pairwise comparisons of the criteria using the following scale:

- 4: Very high influence

- **3:** High influence
- **2:** Moderate influence
- **1:** Low influence
- **0:** No influence

In cases where the number of experts exceeds one, different methods may be used to aggregate pairwise comparisons. In the present study, the relationships between criteria were assessed using the above scale and the following steps [13]:

- If the row factor significantly influences the column factor, the corresponding weight (0–4) is assigned.
- The results of all experts were then aggregated to form the Structural Self-Interaction Matrix (SSIM).
- A numerical scale was computed according to Equation (1), where n represents the number of experts. Since the influence is determined relative to the average of the scale, the number of experts was multiplied by 2. The resulting numerical value, denoted as M , was then compared with the entries of the SSIM.
- If M was greater than or equal to the corresponding SSIM entry, a value of 1 was assigned in the Initial Reachability Matrix (binary form). Otherwise, a value of 0 was assigned.

Since the number of experts is $n=7$, the numerical scale is calculated as:

$$M = 2 \times n \tag{1}$$

Thus, the threshold value for comparison is 14. Table 3 presents the Structural Self-Interaction Matrix (SSIM), while Table 4 displays the Initial Reachability Matrix derived from it.

Table 3. Structural Self-Interaction Matrix (SSIM)

	C13	C12	C11	C10	C9	C8	C7	C6	C5	C4	C3	C2	C1
C1	5.00	13.00	15.00	10.00	12.00	14.00	12.00	19.00	12.00	12.00	15.00	14.00	0.00
C2	13.00	14.00	15.00	11.00	14.00	11.00	7.00	16.00	13.00	7.00	10.00	0.00	7.00
C3	14.00	11.00	11.00	12.00	12.00	16.00	15.00	12.00	12.00	11.00	0.00	11.00	14.00
C4	15.00	14.00	16.00	13.00	16.00	11.00	8.00	14.00	10.00	0.00	9.00	14.00	14.00
C5	14.00	12.00	15.00	13.00	16.00	16.00	10.00	13.00	0.00	13.00	12.00	10.00	12.00
C6	11.00	14.00	15.00	9.00	14.00	14.00	12.00	0.00	9.00	12.00	12.00	14.00	7.00
C7	10.00	9.00	14.00	11.00	9.00	13.00	0.00	10.00	11.00	13.00	12.00	11.00	12.00
C8	11.00	19.00	17.00	19.00	17.00	0.00	10.00	15.00	11.00	12.00	13.00	11.00	11.00
C9	7.00	14.00	13.00	13.00	0.00	16.00	13.00	17.00	8.00	10.00	10.00	7.00	13.00
C10	15.00	16.00	15.00	0.00	15.00	14.00	10.00	16.00	14.00	13.00	13.00	14.00	15.00
C11	13.00	16.00	0.00	16.00	17.00	17.00	12.00	12.00	10.00	11.00	11.00	12.00	13.00
C12	12.00	0.00	16.00	9.00	13.00	12.00	14.00	15.00	13.00	11.00	11.00	12.00	16.00
C13	0.00	20.00	10.00	7.00	16.00	18.00	11.00	13.00	19.00	12.00	13.00	14.00	11.00

Table 4. Initial Reachability Matrix

	C13	C12	C11	C10	C9	C8	C7	C6	C5	C4	C3	C2	C1
C1	0	0	1	0	0	1	0	1	0	0	1	1	0
C2	0	1	1	0	1	0	0	1	0	0	0	0	0
C3	1	0	0	0	0	1	1	0	0	0	0	0	1
C4	1	1	1	0	1	0	0	1	0	0	0	1	1
C5	1	0	1	0	1	1	0	0	0	0	0	0	0
C6	0	1	1	0	1	1	0	0	0	0	0	1	0
C7	0	0	1	0	0	0	0	0	0	0	0	0	0
C8	0	1	1	1	1	0	0	1	0	0	0	0	0
C9	0	1	0	0	0	1	0	1	0	0	0	0	0
C10	1	1	1	0	1	1	0	1	1	0	0	1	1
C11	0	1	0	1	1	1	0	0	0	0	0	0	0
C12	0	0	1	0	0	0	1	1	0	0	0	0	1
C13	0	1	0	0	1	1	0	0	1	0	0	1	0

The Final Reachability Matrix for the criteria is obtained by considering the transitivity of relationships, which is a fundamental assumption in Interpretive Structural Modeling (ISM). Transitivity implies that if variable *A* is related to variable *B*, and variable *B* is related to variable *C*, then variable *A* is also considered to be related to variable *C*.

To align the Structural Self-Interaction Matrix (SSIM) with the Final Reachability Matrix, the SSIM is raised to the power of *k*+1 until a steady state is achieved ($M^{k+1}=M^k$), where *M* denotes the Final Reachability Matrix. Through this process, some zero elements are converted to ones, which are marked as (*1).

The Final Reachability Matrix is derived from the SSIM using the following relationship, where *DDD* is the Structural Self-Interaction Matrix and *III* is the identity matrix [12]:

$$M = D + I \tag{2}$$

$$M^* = M^k = M^{k+1}, K > 1 \tag{3}$$

Table 5. Final Reachability Matrix

	C13	C12	C11	C10	C9	C8	C7	C6	C5	C4	C3	C2	C1
C1	1*	1*	1	1*	1*	1	1*	1	1*	0	1	1	1
C2	1*	1	1	1*	1	1*	1*	1	1*	0	1*	1	1*
C3	1	1*	1*	1*	1*	1	1	1*	1*	0	1	1*	1
C4	1	1	1	1*	1	1*	1*	1	1*	1	1*	1	1
C5	1	1*	1	1*	1	1	1*	1*	1	0	1*	1*	1*
C6	1*	1	1	1*	1	1	1*	1	1*	0	1*	1	1*
C7	1*	1*	1	1*	1*	1*	1	1*	1*	0	1*	1*	1*
C8	1*	1	1	1	1	1	1*	1	1*	0	1*	1*	1*
C9	1*	1	1*	1*	1	1	1*	1	1*	0	1*	1*	1*
C10	1	1	1	1	1	1	1*	1	1	0	1*	1	1
C11	1*	1	1	1	1	1	1*	1*	1*	0	1*	1*	1*
C12	1*	1	1	1*	1*	1*	1	1	1*	0	1*	1*	1
C13	1	1	1*	1*	1	1	1*	1*	1	0	1*	1	1*

Note: Entries marked with (*) indicate transitive relationships added during the ISM process. *

5.1. Level Partitioning of the Final Reachability Matrix

After forming the Final Reachability Matrix, level partitioning is performed. For each criterion, the Antecedent Set and Reachable Set are determined, and their intersection defines the criterion’s level.

- The Antecedent Set of a criterion includes all criteria that lead to or influence that criterion. In other words, criteria that have a “1” in the column corresponding to a given criterion form its Antecedent Set. For example, if criteria C2, C3, and C4 influence C1, then these criteria constitute the Antecedent Set of C1.
- The Reachable Set represents all criteria that are affected by a given criterion. For instance, if C1 influences C2, C3, C4, and C5, then these criteria form the Reachable Set of C1.

By finding the intersection of the Antecedent Set and Reachable Set, the Intersection Set is obtained. Criteria whose Intersection Set matches their Reachable Set are assigned Level 1 priority. After removing these criteria and repeating the process for the remaining criteria, the levels of all other criteria are determined [12]. Table 6 illustrates the level partitioning process, and the placement of Industry 4.0 variables is shown in Figure 2.

Table 6. Level Partitioning of Criteria

Level 1 Confirmation	Intersection Set	Reachable Set	Antecedent Set	Criterion
✓	C ₁ ,C ₂ ,C ₃ ,C ₅ ,C ₆ ,C ₇ ,C ₈ ,C ₉ , C ₁₀ ,C ₁₁ ,C ₁₂ ,C ₁₃	C ₁ ,C ₂ ,C ₃ ,C ₅ ,C ₆ ,C ₇ ,C ₈ ,C ₉ , C ₁₀ ,C ₁₁ ,C ₁₂ ,C ₁₃	C ₁ , ... , C ₁₃	C ₁
✓	C ₁ ,C ₂ ,C ₃ ,C ₅ ,C ₆ ,C ₇ ,C ₈ ,C ₉ , C ₁₀ ,C ₁₁ ,C ₁₂ ,C ₁₃	C ₁ ,C ₂ ,C ₃ ,C ₅ ,C ₆ ,C ₇ ,C ₈ ,C ₉ , C ₁₀ ,C ₁₁ ,C ₁₂ ,C ₁₃	C ₁ , ... , C ₁₃	C ₂
✓	C ₁ ,C ₂ ,C ₃ ,C ₅ ,C ₆ ,C ₇ ,C ₈ ,C ₉ , C ₁₀ ,C ₁₁ ,C ₁₂ ,C ₁₃	C ₁ ,C ₂ ,C ₃ ,C ₅ ,C ₆ ,C ₇ ,C ₈ ,C ₉ , C ₁₀ ,C ₁₁ ,C ₁₂ ,C ₁₃	C ₁ , ... , C ₁₃	C ₃

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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