Advanced Engineering Informatics 61 (2024) 102482

Contents lists available at ScienceDirect

Advanced Engineering Informatics

journal homepage: www.elsevier.com/locate/aei

# A multisensory Interaction Framework for Human-Cyber–Physical System based on Graph Convolutional Networks

Wenqian Qi [a,b], Chun-Hsien Chen [b], Tongzhi Niu [c,*], Shuhui Lyu [b], Shouqian Sun [a]

[a] School of Computer Science, Zhejiang University, Lingyin Street, Hangzhou, 310007, China
[b] School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore
[c] School of Mechanical Science and Engineering, Huazhong University of Science and Technology, 1037 Luoyu Road, Wuhan, 430074, Hubei, China

ARTICLE INFO

*Keywords:*
Human-cyber–physical system
Multisensory interaction
Graph convolutional networks
System innovation
Recommendation model

ABSTRACT

Human-Cyber-Physical Systems (HCPS), as an emerging paradigm centered around humans, provide a promising direction for the advancement of various domains, such as intelligent manufacturing and aerospace. In contrast to Cyber-Physical Systems (CPS), the development of HCPS emphasizes the expansion of human capabilities. Humans no longer solely function as operators or agents working in collaboration with computers and machines but extend their roles to include system design and innovation management. This paper proposes a Multisensory Interaction Framework for HCPS (MS-HCPS) that leverages human senses to facilitate system creation and management. Additionally, the introduced Multisensory Graph Convolutional Network (MS-GCN) model calculates recommendation values for multiple senses, elucidating their relevance to system development. Furthermore, the effectiveness of the proposed framework and model is validated through three practical engineering scenarios. This study explores the research on multisensory interaction in HCPS from a human sensory perspective, aiming to facilitate the progress and development of HCPS across various domains.

## 1. Introduction

A Cyber-Physical System (CPS) refers to a coupled system that integrates physical and software components into computational networks and physical processes [1]. The latest iteration of CPS, known as the Human-Cyber-Physical system (HCPS), represents an intelligent composite system with a human core element, aiming to achieve a profound integration of three dimensions for enhanced efficiency and effectiveness. HCPS introduces a human layer that mediates between the physical system and the information system, enabling both direct and indirect control. Direct control entails the user's active engagement with both the physical space and the information space. On the other hand, indirect control involves the system's ability to sense and interpret the user's action, cognition, and attention, thereby facilitating interaction with the information system and subsequently governing the physical system. As a cutting-edge area encompassing intelligent manufacturing, traffic control, and architectural design, HCPS places significant emphasis on human-centricity, unlocking and harnessing human intelligence to a greater extent. The human component, being the most creative, adaptable, and proactive factor within the system, should be actively engaged in the interaction cycle and decision-making process between the physical and information spaces. Human senses serve as the fundamental basis for perception, decision-making, and control, significantly influencing the design and management of physical and information spaces. Therefore, the establishment of HCPS requires deep integration with human multisensory cognition, enhancing users' emotional cognition and establishing an emotional connection between the system and users [2]. Although current HCPS research is often focused on enabling technologies or root technologies, the exploration of user-centered multisensory interaction represents a crucial pathway toward gradually realizing digitalization, networking, and intelligence in a broader range of scenarios and fields.

Enhancing HCPS-oriented multisensory interaction is not only crucial for human perception of external information but also plays a pivotal role in system design and development. Multisensory interaction serves as a conduit through which individuals receive information by utilizing their perceptual organs and experiences, typically encompassing the five senses of vision, hearing, touch, taste, and smell [3]. This field entails a fusion of neurophysiological, psychophysical, mathematical, and computational analyses, along with sensory design. Current research in multisensory technology encompasses sensory substitution and simulation for diverse applications, crossmodal methods for delivering sensory information, and the engineering of multisensory approaches. By optimizing the interaction between individuals and their environment, multisensory stimulation proves crucial in resolving engineering challenges across various domains.

* Corresponding author.
*E-mail address:* tzniu@hust.edu.cn (T. Niu).

https://doi.org/10.1016/j.aei.2024.102482
Received 31 July 2023; Received in revised form 29 February 2024; Accepted 9 March 2024

Nevertheless, there is a dearth of quantitative research pertaining to determining the senses involved in the initial design and the optimal management of engineering projects, including the degree of sensory input and the level of interplay between the senses. Consequently, designers and managers struggle to make informed decisions on which senses should be employed to achieve specific project objectives based on quantitative outcomes. While multisensory interaction is pivotal for the development and optimization of HCPS, the absence of concrete computational models to implement sensory recommendations remains a pressing issue. Employing data-driven outputs and feedback from multiple senses can significantly enhance system efficiency and elevate the user experience, ultimately resulting in the creation of a more captivating system.

Based on the aforementioned challenges, this study aims to assist the system design of HCPS through multisensory interaction, with a particular focus on the human perception aspect. The three questions presented:

(1) How to build HCPS from the perspective of multisensory interaction in order to explore human-centered system design?

(2) How to help system designers get sensory recommendations during the initial design phase to determine the appropriate senses to be incorporated into their research?

(3) How can the proposed recommendations be applied in practical cases?

In this paper, a novel multisensory interaction framework for HCPS is proposed, which includes a recommendation model, and the evaluation of the framework and model is carried out with practical engineering cases. The relationship between HCPS and multisensory interaction is explored from an innovative perspective. Therefore, an HCPS-oriented framework is first established to assist the innovation and management of the system with multisensory design. This approach facilitates the expansion of HCPS research and applications into various domains.

Furthermore, we propose a multisensory recommendation model utilizing Graph Convolutional Networks (GCNs), chosen for their adeptness in processing relational data crucial for depicting the complex network of sensory experiences. In this model, sensory elements are nodes in a graph, with edges representing their interrelations. GCNs effectively capture these dependencies, essential for accurately predicting sensory recommendations in a multisensory context.

This enables effective control of system function development levels corresponding to different senses, as well as clarification of the construction plan and control of input costs for the project. Finally, this study will validate and assess the efficacy of the proposed model by conducting three engineering case studies. This will serve to emphasize the soundness and rationality of the multisensory interaction framework for HCPS. The objective of this paper is to propel various industry domains toward progress by fostering the continuous integration and advancement of multisensory-assisted HCPS. The key contributions of this study can be summarized as follows:

(1) Proposal of an HCPS-oriented multisensory interaction framework (MS-HCPS) that explores the structural relationship between human-centered HCPS and multisensory interaction from a fresh perspective.

(2) Introduction of a multisensory recommendation model (MS-GCN) based on GCNs, enabling designers to achieve system innovation and effective management through sensory integration.

(3) Validation of the framework and model through three case studies encompassing different scenarios.

The subsequent sections of the paper are structured as follows. Section 2 reviews the development of HCPS and surveys the relevant research on the techniques employed in this study. Section 3 presents the system framework of the proposed MS-HCPS. Section 4 delves into the details of the proposed MS-GCN model within the context of the system framework. Subsequently, in Section 5, a case study is conducted, and the implementation and enhancements of the proposed system are discussed. Section 6 concludes the paper by summarizing the key findings and contributions.

## 2. Related works

As a pivotal intelligent system in the context of Industry 5.0, HCPS holds immense potential for tackling forthcoming challenges in both industrial and societal domains [4]. This section briefly reviews the development of HCPS and related research. Subsequently, analysis and investigation of multisensory interaction technology are conducted by surveying the existing literature. And the definition and a brief introduction of GCNs are discussed.

### *2.1. HCPS technology and applications*

HCPS is an intelligent composite system comprising a human, cyber system, and physical system, aimed at addressing various human aspects in system operation and service delivery [5]. The system endeavors to enhance the dynamic interaction between humans and machines in both cyber and physical realms through "intelligent" human-machine interfaces, employing human-machine interaction techniques tailored to the cognitive and physical requirements of the operator. It also seeks to enhance human physical, perceptual, and cognitive capabilities through diverse reinforcement technologies [6].

HCPS, positioned as a key driver in the contemporary industrial revolution, has evolved significantly within innovation systems (see Fig. 1). In the first machine age, Human-Physical Systems (HPS) played a pivotal role, displacing manual labor with mechanical contrivances, and enhancing manufacturing quality, efficiency, and societal productivity. The second machine age, marked by CPS and rapid information technology ascent, saw networked systems assume unparalleled versatility, handling diverse functions, and fostering intense competition in various domains, including computer numerical control, telemedicine, household appliances, and construction site management [7,8]. In the new generation of HCPS, comprising humans, cyber systems, and physical systems, a transformative shift from product-centric to customer-centric manufacturing occurred [9]. The new generation of HCPS is achieved through direct human manipulation of cyber and physical systems or interaction with the cyber system by perceiving human intent to control the physical system. The role of humans as discerning "masters" collaborating harmoniously with operational cyber–physical systems assumed unprecedented prominence in this evolutionary trajectory [10]. On one front, advances in artificial intelligence (AI) promise to introduce human cognitive models, fostering innovation and refinement. Simultaneously, the human workforce transitioned from laborers to creators and managers, engaging in creative pursuits. The heightened emphasis on human perception, learning, and comprehension dramatically bolstered HCPS's capacity for intricate details and complex problem-solving, signaling a transformative wave set to disrupt multiple industries.

The integration of advanced manufacturing technology and new-generation information technology has sparked extensive discussions on HCPS in various domains. In the realm of smart manufacturing, HCPS's development and application can span the entire product lifecycle, manufacturing process, and services, representing the optimal integration of each link and the corresponding system [11]. [12] delves into the application of HCPS in smart manufacturing, encompassing design, production, and service perspectives, and provides key knowledge and reference models. For the context of Assembly Workstation 4.0 (AW4.0), [13] proposes an HCPS framework for AW4.0 systems to facilitate intelligent networks of hyperobjects. Introducing a Temporal Synchronization (ST-Sync) strategy enables coordinated decision-making with heightened flexibility and responsiveness. Additionally, research frameworks exploring the HCPS perspective of Smart Healthy Working (SHW) effectively optimize the people, facilities, and environmental dimensions, offering guidance for the SHW concept [14]. Moreover, HCPS, based on human-in-the-loop, enhances the vertical control of individual vehicles in traffic flow and guides drivers to improve their driving performance [15]. In the realm of smart buildings, a

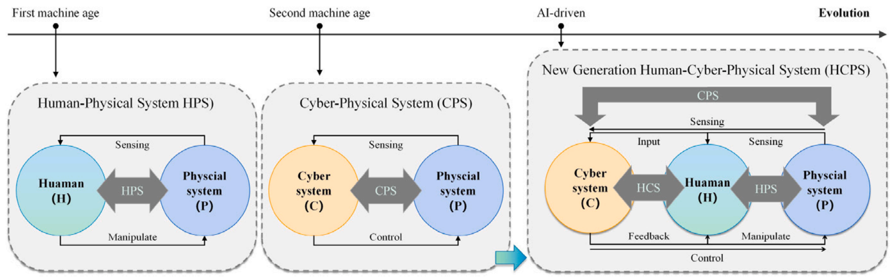


**Fig. 1.** Schematic and evolution of HCPS.

proposed HCPS framework with three dimensions provides an overview of the current research status and potential gaps, further exploring five future research directions for occupant-centered smart buildings [16]. Furthermore, by constructing an HCPS technology system for intelligent coal mines, the human, coal mine information system, and physical system of coal machine equipment interact synergistically. Embracing the concept of human-centeredness, a human-machine synergistic technology pathway is proposed for the new generation of intelligent mines devoid of miners [17]. In summary, it is evident that HCPS has the potential to support the reform and innovation of numerous industries in future societies, leaving ample room for exploration in system innovation across various fields. Whether leveraging the individual strengths of human intelligence and machine intelligence for mutual inspiration or delving into the enhanced experience of human-machine integration, human-centeredness remains an indispensable focal point of the HCPS Institute.

### 2.2. Multisensory interaction and recommendation

The perception and collaboration of multiple senses result from the synergistic activities of various analyzers, enabling individuals to access, interpret, and organize sensory information based on their personal experiences. The integration of these senses enables humans to perceive a cohesive world of perceptual entities [18]. Embracing multisensory experiences, which consider the interconnectedness of human sensory organs during experience design, can foster the creation of novel product and service experiences. This approach also opens up opportunities for immersive storytelling and enhanced user engagement with content [19]. Sensory information is typically acquired through the five fundamental physiological senses visual, auditory, haptic, olfactory, and gustatory. By actively processing and comprehending information observed, heard, and perceived, individuals can gain deeper insights into system functionalities and better grasp user needs, thus fostering the generation of innovative ideas.

Multisensory mixed reality technology holds significant promise for HCPS in intelligent manufacturing. Researchers have explored its application in automotive, food and beverage, and textile industries [20]. The focal point of recent research is on visual and auditory interactions, combined with haptic force feedback technology, to construct systems integrating information and providing physical enhancement [21]. This represents a promising avenue for future multisensory integration, exemplified by the development of a rehabilitation training system for stroke patients [22]. Additionally, olfactory and gustatory technologies have potential applications in specific industries, enhancing human perception and emphasizing material continuity between digital and non-digital practices [23,24]. Multisensory interaction is crucial for anthropomorphic emotional communication, improving user engagement in both physical and virtual environments. However, subjective choices and entrenched habits may limit creative thinking in studying and implementing sensory technologies. The integration of diverse sensory combinations presents a formidable challenge, requiring effective harmonization to align with design objectives for optimal system construction.

Multisensory recommendations strive to enhance user experiences by discerning individual preferences. Employing data analytics, user research, and machine learning, the recommendation system analyzes user intent to deliver personalized suggestions. In visual sensory recommendations, certain studies have enhanced image and visual product recommendations through adversarial learning, fortifying multimedia recommendation models [25]. Additionally, the proposed alert sound recommendation system utilizes a music generation algorithm based on the Generative Adversarial Network (GAN) to achieve real-time sound recommendations [26]. Haptic recommendation research focuses on enhancing user experiences in retail and shopping scenarios, emphasizing tactile interaction with the user interface for more effective recommendations [27]. However, olfactory and gustatory recommendations are still being investigated through human factors experiments due to the challenges in simulating these senses. For instance, using olfactory cues to investigate user preferences and intentions [28]. In the applied research, online perfume systems similarity scores based on user feedback recommend unique perfumes [29]. The “What-To-Taste” food recommendation system suggests dishes based on customers’ tastes, interests, and ordering history [30]. Several studies involve the integration of multiple senses, including vision, haptics, and olfaction. Through comparative experiments, these studies aim to explore variations in user experience across different senses within specific scenarios [31,32]. Overall, current sensory recommendation predominantly targets individual senses to construct tailored product recommendations for specific contexts. Therefore, providing design recommendations for multi-sensory interactions emerges as a novel direction for innovating HCPS.

### 2.3. Graph convolutional networks

The GCNs is a neural network architecture specifically designed for processing data represented as graphs or networks [33]. It extends the concept of convolutional operations from regular grid-like structures to data with graph structures, thereby facilitating the learning of node representations and capturing the relationships between nodes in the graph. In the GCNs architecture, each node in the graph is associated with a feature vector, and the convolution operation is defined based on the aggregation of neighboring node features. GCNs, as a prominent model in Graph Neural Networks (GNNs), has gained significant popularity as a graph analysis method in recent years.

GCNs have demonstrated remarkable capabilities in various tasks of representation learning, such as node classification, link prediction, and graph classification [34]. For node classification, GCNs efficiently learns and propagates information about the entire graph by capturing local and global dependencies between nodes. Consequently, GCNs-based strategies can be effectively applied to career prediction in social network analysis [35]. In terms of link prediction, GCNs enable the prediction of missing or future links between nodes within a graph. Several studies based on the GCNs approach can construct patent-link predictions to predict technology convergence [36]. Regarding graph classification, GCNs aggregate information from all nodes in a graph, allowing it to capture the overall structure and properties of the graph for different levels or classes of classification tasks. To enhance the scalability and efficiency of GCNs, a study proposed a multi-layer coarsening-based GCNs (MLC-GCN) for graph classification. This optimization technique enables the learning of graph representations at multiple levels while preserving both local and global information about the graph [37]. Furthermore, integrating GCNs with other techniques can address specific applications. For instance, combining GCNs with Reinforcement Learning (RL) has proven effective for graph-based recommendation system research [38]. Additionally, GCNs have been successfully combined with generative models like Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) to achieve the structure-aware synthesis of 3D shapes and indoor scenes [39]. Overall, the ability of GCNs to model and analyze graph-structured data has positioned them as valuable tools in various research domains, including computer vision, recommender systems, and knowledge graphs [40]. As ongoing efforts focus on improving modeling capabilities, handling different graph structures, exploring new applications, and addressing practical challenges related to scalability and efficiency, the exploration and application of GCNs in diverse fields will continue to expand.

### 2.4. A brief introduction to GCNs

GNNs are specialized for graph-structured data, adept at representing intricate relationships among nodes and edges [41]. These networks utilize information propagation to derive node representations by incorporating both the node features and its surrounding context. An advanced subtype of GNNs, known as GCNs, employ convolution operations analogous to those in Convolutional Neural Networks. By aggregating feature information from a node's neighbors, GCNs synthesize a comprehensive representation, thereby encapsulating the local structure and inter-node relationships within the graph. In summary, with the ability to model complex interactions in graph data, GCNs represent a potent evolution of GNNs. They offer an effective approach for graph data analysis, skillfully melding the inherent strengths of GNNs with the power of convolution operations.

Formally, we first define a graph.

A graph is $G = (V,\ E,\ A)$, where $V = v_1, \ldots, v_N$ is a set of $N = |V|$ nodes, $E$ is the set of edges, and $A$ is the adjacency matrix of $G$. In a graph, let $v_1 \in V$ to denote a node and $e_{ij} = \left(v_i,\ v_j\right) \in E$ to denote an edge between node $v_i$ and $v_j$. The adjacency matrix $A$ is a $N \times N$ matrix. Every node is assumed to be not connected to itself, $\left(v_i, v_i\right) \notin E$ for any node $v_i \in V$.

Let $H \in R^{N\times d_f}$ be a matrix containing all $N$ nodes with their feature, where $d_f$ is the dimension of the input node features, each row $H_i \in R^{d_f}$ represents the feature vector for node $v_i$. The degree matrix of $A$ is $D$, where $D_{ii} = \sum_j A_{ij}$. $A$ single layer of a GCN can effectively capture information about immediate neighbors. By stacking multiple GCN layers, information from a larger neighborhood, beyond immediate connections, can be incorporated, enhancing the model's understanding of the graph's overall structure. In the context of a graph comprising N nodes, the primary objective of a GCN is to discern structure-aware node representations, thereby ensuring the integration of both local and broader structural details inherent in the graph.

For an L-Layer GCN, each layer can be calculated as a nonlinear function:

$$H^{(j+1)} = \sigma\left(\hat{A}H^{(j)}W^{(j)}\right) \tag{1}$$

where $H^{(0)} = H$, $\hat{A} = D^{-\frac{1}{2}}AD^{-\frac{1}{2}}$ is the normalized symmetric adjacency matrix and $W^{(i)}$ is a weight matrix for the $j$th GCN layer. $\sigma$ is a nonlinear function (e.g. $ReLU\sigma(\bullet) = max(0,\bullet)$). Then, we can obtain a node-level output $Z = H^{(L)}$, which is an $N \times d_g$ representation matrix, where $d_g$ is the dimension of the node representation obtained from $L$th layer of GCN.

Finally, the application of Graph Global Average Pooling is employed to aggregate node-level features, thereby obtaining a holistic representation of the graph's features. This encapsulates the entirety of the graph's inherent structural information in a condensed form:

$$R = \frac{1}{N}\sum_{n=1}^{N} z_n \tag{2}$$

where $z_i \in R^{1\times d_g}$ represents the $i$th vector drawn from $Z \in R^{N\times d_g}$ and $R \in R^{1\times d_g}$ represents the holistic representation of the graph's feature.

## 3. Multisensory interaction framework for HCPS (MS-HCPS)

It is crucial that innovative design research for the next generation of HCPS is human-centered. In addition to facilitating the division of labor and collaboration between humans and machines, it is imperative to fully harness the distinctive capabilities of human ingenuity and machine intelligence to mutually inspire one another and foster shared advancement. The integration of sensory design in system creation and management holds great potential for generating novel and interactive outcomes [42]. Consequently, this study builds the MS-HCPS framework from a user-centric perspective, aiming to develop new avenues for the application and advancement of HCPS.

### 3.1. Description of sensory

Human behavior and consciousness stem from the perception of external information by the sensory system. The sensory system comprises the five main sensory organs: the eyes, ears, nose, tongue, and body, which detect stimuli from the surrounding environment. Fig. 2 illustrates the properties and relationships of these senses. Among the various sensory techniques applied to HCPS, visual and auditory senses are well-suited for objectively capturing rich and nuanced data, owing to their perceptual and rational characteristics and resilience to various types of impairment. Consequently, vision and hearing are commonly utilized and fundamental in HCPS. Moreover, the integration of haptic interaction, which incorporates touch through skin receptors distributed across the body, has emerged as a promising research direction in recent years, enabling a more natural and immersive experience in conjunction with audio-visual interactions. On the other hand, the olfactory and gustatory senses, associated with the sense of smell and taste, present unique challenges due to the difficulty in data collection and flavor simulation. As a result, the development and application of olfactory and gustatory interaction studies remain limited. Nevertheless, the cross-modal associations generated by the interaction of other senses can partially aid in simulating smell and taste [43]. The fusion of these five physiological senses can influence the human experience of the environment in a way that is richer than the sum of the sensations that would result from experiencing each sense independently.

#### 3.1.1. Vision

Vision is the perceptual faculty enabling the discernment of various attributes of external objects, such as luminance, chromaticity, and spatial features, through the visual system. Visual perception holds significant importance in human and machine understanding of the world. In the HCPS, the construction of machine and software systems within the designated ambient space is pivotal for visual interaction. The embedded vision platforms show promise for CPS by enabling multimodal perception in outdoor environments [44]. The primary components of machine vision systems include light source lamps, controllers, cameras, image acquisition cards, lenses, and image processing devices. Moreover, through the design of system software and application software, a user interface that is both functional and aesthetically pleasing is presented to create a good visual interaction experience. Visual research is expansive, encompassing critical studies in the realms of computer vision technologies, object detection, three-dimensional reconstruction, and other techniques integral to human–computer Interaction (HCI) [45]. At the forefront of research, visual perception

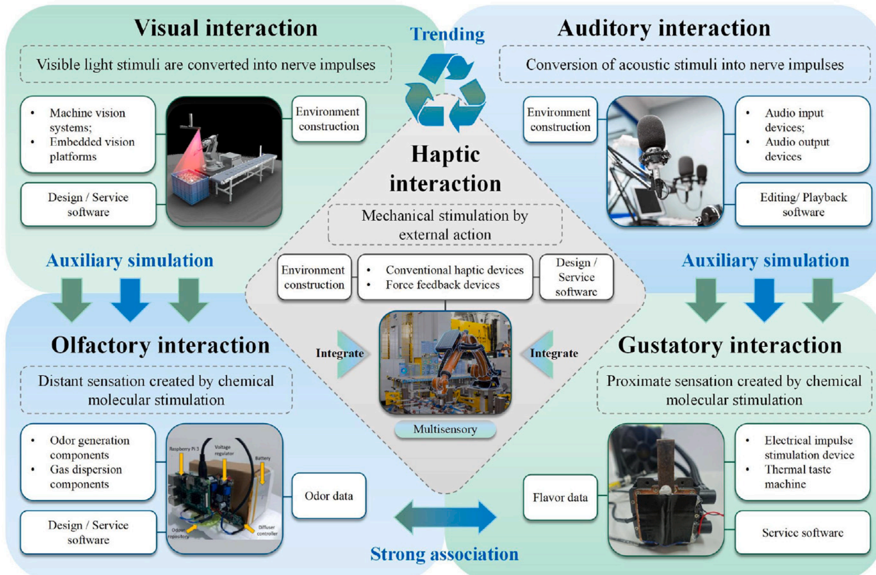


**Fig. 2.** Human sensory technology and relationship organization.

can be stimulated and enhanced by implementing Extended Reality (XR) technologies for simulating environments. The XR technology facilitates virtual experiences and digital sharing of cultural heritage and construction safety training [46–48].

### *3.1.2. Audition*

Auditory perception refers to the sensory experience of sound properties generated by the auditory organs in response to sound waves. Systems conventionally employ sound to achieve functions such as warnings, emphasis, instructions, environmental simulation, and atmospheric rendering. Representative applications of auditory displays, such as smart hearing aids and car audio, enable auditory assistance, enhancement, and design. Within HCPS, constructing auditory interactions requires the incorporation of audio equipment alongside sound processing techniques to realize auditory perception in the specified sound field. This integration aims to actualize auditory perception within the specified sound field. Examples of audio equipment products include speakers, multimedia consoles, digital mixing consoles, audio sampling cards, synthesizers, microphones, headphones, and more. The acoustic software is engineered to extract, truncate, and meticulously edit sound, such as improving audio quality, removing noise, or adding special effects. to realize the synthesis of the intended auditory output. Studies have been conducted to enhance the user experience of unsupervised, highly automated vehicles by innovating new auditory displays [49]. Additionally, investigations have been undertaken into virtual environment training and music therapy, aiming to proficiently restore the brain's capacity for processing and integrating sensory information [50].

### *3.1.3. Haptics*

Haptic receptors establish contacts across the entire expanse of the skin, eliciting sensations encompassing temperature, humidity, texture, pressure, pain, and vibration. They play an indispensable role in the physiological system. Haptic perception involves the operation and use of mechanical devices and serves as a means of providing cues. In the HCPS, haptic interactions stand out prominently, particularly in domains such as medical rehabilitation, intelligent manufacturing, and safety and health training. This prominence is achieved through a meticulous integration of environmental configurations and the thoughtful design of both software and hardware components [51, 52]. Traditional haptic devices include mechanical devices, vibration motors, touch screens, buttons, and switches. Presently, force feedback devices are employed as human-machine interface devices to simulate force feedback in haptic perception. Representative instances of these devices include exoskeleton robots, data gloves, and mechanical handles. Consequently, the experience of force feedback is further facilitated through software simulators. The instructions and feedback provided through haptic interaction significantly influence the user experience of the operator. In recent investigations, wearable bracelets, exoskeleton robots, and mechanical platforms integrated with virtual environments have been utilized to enhance haptic sensations through driving, vibrating, and shaking actions, ultimately providing a more immersive experience [53–55].

### *3.1.4. Olfaction*

Olfaction is a distant sense that perceives chemical stimuli through long distances and is accepted as a suitable stimulus for volatile substances. Olfaction has long been regarded as the most enigmatic sense, thus rendering the simulation and application of this sense to possess a high threshold for development. The current non-intrusive, mobile, low-cost, and wearable olfactory displays primarily consist of an odor generation module and a gas dispersion module. Odors are synthesized from liquid fragrances and atomized, while odor dispersion is achieved through ultrasonic scent emitters [56]. Odor digitization is realized through a software design framework specifically tailored for olfactory simulation, facilitating the emulation of olfactory experiences and the dissemination of odor-related information. Meanwhile, odor data furnishes essential support by encompassing key information, including but not limited to odor molecular details, perceptual attributes, synthetic formulations, and analytical algorithms. In the examination of olfactory interactions, olfaction is often simulated in conjunction with other sensory modalities or employed to augment perceptions in different sensory domains. The delineation of four pivotal olfactory design features serves as a heuristic to inform user preferences in flavor selection [57]. In addition, leveraging virtual reality (VR) technology, olfactory simulation displays have recently been experimentally introduced and implemented within the domains of gaming and redirected walking studies [58,59].

### *3.1.5. Gustation*

Taste involves the proximate sensation experienced when taste organs are stimulated by chemical molecules in food. Taste and smell are often intertwined, but the simulation of taste is still in a rudimentary stage. Virtual taste currently stimulates the oral cavity through direct

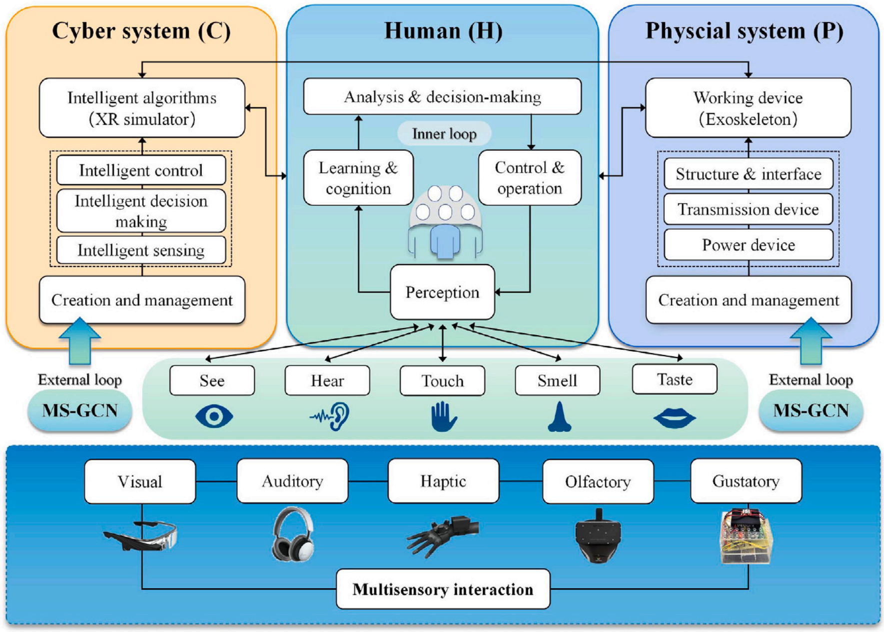


**Fig. 3.** The overview of MS-HCPS.

contact with the tongue using physical devices that provide electrical or thermal stimulation. The production or enhancement of tastes such as saltiness, sourness, sweetness, fatty/oiliness, electric taste, and mint taste is limited in terms of taste experience [60,61]. Software design centered around gustation facilitates the delivery of diet-related functional services and digital flavor simulation. Taste data encompasses information on flavor molecules, flavor descriptions, food recipes, and preparation methods. Gustatory interaction holds the potential to contribute to the design of virtual dining experiences and address issues related to the therapeutic management of dietary disorders. A study has devised a gustatory display capable of replicating flavors as detected by taste sensors. The media further individualizes the taste experience through the integration of effectors and equalizer prototypes [62]. When coupled with VR technology, it can induce distinct gustatory perceptual variations through the manipulation of visual perception using different colors and tactile interactions with samples of varying shapes [63,64].

By stimulating the interaction of multiple senses, it is able to significantly improves the overall awareness of humans in the design, use, management, and optimization of the closed loop. The provision of information displayed in one sense can meet the specific needs of scenarios. The integration of multiple senses not only enriches the system's functionality but also enhances interactive operations. Simultaneous stimulation of one sense triggers the involvement of other sensory channels, leading to a synergistic effect that enhances positive creativity [65]. Therefore, multisensory interaction is based on understanding perceptual experiences, equally empowering the creation of new perceptual experiences.

### 3.2. Framework of MS-HCPS

The trajectory from CPS to HCPS signifies an amplified self-awareness among human beings. In the new generation of HCPS, the human element transcends the traditional notion of operating complex machinery. The role of humans is shifting and evolving, assuming greater prominence, and enabling diverse human types and roles in HCPS. Human ingenuity is used to develop innovative intelligent systems based on information and technology. This fosters a bidirectional closed-loop of perception, control, and innovation, establishing a seamless connection between humans and physical and cyber systems [66].

To explore a human-centric system design approach, the MS-HCPS framework is proposed based on the HCPS model, as illustrated in Fig. 3. The innovation of HCPS is driven by multisensory to form a closed loop of human interaction in the loop [67]. The MS-HCPS comprises humans, cyber systems, and physical systems as its basic elements. The physical system encompasses physical machines endowed with broad cognitive abilities derived from the principles of physics. The cyber system encompasses intelligent algorithms operating within the cyberspace domain, among other components. Furthermore, humans are not only engaged in control and learning tasks but also involved in design and management within the MS-HCPS framework. MS-HCPS expands human perception into five fundamental senses: vision, audition, haptics, olfaction, and gustation, facilitating the perception of information and guiding cyber and physical system design accordingly.

Throughout the sensory perception cycle, individuals employ their senses to apprehend information emanating from cyber and physical systems, and interpret and organize the acquired information, thereby generating corresponding experiences. This process generates further insights and ideas for optimizing or constructing multisensory innovation systems. Ultimately, recommendations from the five sensory interaction modes are used to facilitate the innovative system design.

Within the framework's internal loop, humans develop cognition through perceiving the external world, making decisions regarding information processing in networked systems, and manipulating physical system devices. Cyber systems of HCPS encompass not only communication and storage but also intelligent algorithms derived from intelligent control, intelligent decision-making, and intelligent sensing construction. Physical systems of HCPS extensively cognizant working devices, composed of power devices, transmission devices, and structural and interface design. Exoskeleton robotics technology and XR technology represent popular approaches for systems [68]. Afterward, feedback from cyber and physical systems initiates a new round of user perception, facilitating human perception, learning, decision-making, and system control.

Within the external loop of this framework, human perception and interaction based on multiple senses drive innovation and management in HCPS. As shown in Fig. 4, by utilizing the MS-GCN model, numerical

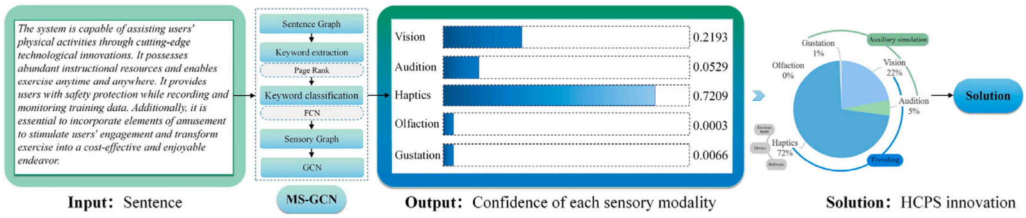


**Fig. 4.** The flowchart of MS-GCN.

values for confidence and relevance can be computed for each sensory modality, including visual, auditory, tactile, olfactory, and gustatory. The numerical values reflect the proportion of correlation of each sensory modality within the system project. These ratios can serve as a reference for determining the priority level of design for each sensory interaction in the target system. Initially, the system requirements sentences inputted by the users are segmented into individual words, following which a sentence graph is constructed based on the similarity of word vectors. Utilizing the PageRank algorithm, we extract the top 8 most significant keywords that effectively represent the sentence. Subsequently, these keywords are classified through a fully connected neural network. This process aids in constructing a sensory graph based on categorical relationships. The sensory graph is then fed into a Graph Convolutional Network (GCN) [69] to derive the recommendation confidence for each sensory modality. This facilitates designers in achieving integrated innovation of both cyber and physical systems, such as human-machine hybrid augmented intelligence based on intelligent algorithms and work devices. Additionally, it aids managers in organizing, managing, and iteratively optimizing systems on an imperfect foundation. Humans will transcend the role of mere operators and assume the roles of creators, managers, and leaders, establishing closer and deeper connections with the system.

The framework proposes leveraging human perception to stimulate creativity and develop intelligent systems that exhibit effectiveness and innovation, thereby enhancing human sensory and cognitive capabilities. The seamless integration of multiple sensory interactions will facilitate the application of HCPS in diverse scenarios, including employee training, perfume factories, medical rehabilitation, and other unexplored domains.

## 4. Multisensory graph convolutional network model (MS-GCN)

We propose a multisensory recommendation model based on GCNs, which assimilates the knowledge from large models in the field of Natural Language Processing (NLP) along with the insights derived from our constructed Commonsense Knowledge Graphs (CKGs). This approach enables the quantification of multisensory recommendations, thereby providing a valuable reference for the design of the HCPS system.

### 4.1. Commonsense Knowledge Graphs of MS-GCN

The sensory data were collected through comprehensive literature and encyclopedia search, resulting in a total of 3850 valid keywords encompassing the five senses: sight, hearing, touch, smell, and taste. The proposed CKGs for sensory interactions is organized into four categories, further divided into eight sub-categories (see Fig. 5). The construction of the CKGs initiates from human requirements analysis, providing a comprehensive depiction of each sense and facilitating the construction of data pertaining to sensory interactions. The first category is user intention, which encompasses three sub-categories: thing, environment, and behavior related to sensory experiences. The collection of data from these sub-categories enables the identification of user intent. Additionally, explicit descriptions of sensory needs are provided under the categories of user need and system need. The user need category encompasses two subcategories: physiological and psychological. Data collection from perspectives of physiological characteristics and psychological states captures the user's instinctive needs and elucidates the impact of various senses on the user. On the other hand, the category of system need comprises two subcategories: usage scenario and core technology. This category integrates technical data related to each sense and expresses the user's non-functional requirements for the system. The final category, sensory definition, directly describes the sensory-related data. The three categories of user intention, user need, and system need to contribute to the expansion of sensory description, ultimately enhancing multisensory interaction for optimal user experience.

Upon acquiring the keywords, we developed CKGs by systematically traversing these keywords, focusing on category relationships and semantic similarity. Specifically, leveraging the large-scale semantic model, pre-trained BERT, we extracted the semantic vectors of each keyword. Subsequently, we navigated through keywords of related categories, guided by their categorization (as illustrated in Fig. 8 of the manuscript). During this process, we calculated the similarity between keywords, established a threshold for linkage, and thus constructed the inter-relationships within the CKGs (similar with Algorithm 2).

CKGs construction facilitates knowledge management, representation, as well as query and recommendation of solutions [70]. The division based on these four categories allows for accurate and effective retrieval of multisensory domain knowledge, thereby assisting in predicting the user's design and management intentions for the system. Building CKGs centered around human sensory interactions effectively optimizes the manipulation of physical and cyberspace, enhancing human's own emotional perception.

Based on this framework, CKGs were constructed for five senses, namely visual-CKG, auditory-CKG, haptic-CKG, olfactory-CKG and gustatory-CKG. The visual-CKG (919 nodes/6123 relations), auditory-CKG (849 nodes/1842 relations), haptic-CKG (674 nodes/2443 relations), olfactory-CKG (730 nodes/3443 relations) and gustatory-KG. (678 nodes/2424 relations), visualized and presented using Cytoscape software, as shown in Fig. 6.

### 4.2. Our proposed method

In this section, a detailed introduction is provided to our MS-GCN model, a novel approach to sensory recommendation. The architecture of this model is shown in Fig. 7. Specifically, Section 4.2.1 commences with a description of the embedding layer. Subsequently, Section 4.2.2 elaborates on our method of keywords extraction to construct a sensory graph, which involves the application of a Keyword Extraction Algorithm Based on Graph Ranking (KEAGR). After that, A fully connected neural network is used to classify keywords in Section 4.2.3. Finally, the process of sensory graph construction is then explained in Section 4.2.4, leading up to a comprehensive introduction of our GCN for MS-GCN model in Section 4.2.5. On the mathematical front, we present the multisensory recommendation as a classic sensory task. Upon preprocessing a given sentence – including tasks such as punctuation removal, stop word elimination, and lemmatization – we derive a set of $S = \{w_1, w_2, \dots, w_n\}$. The objective of multisensory recommendation is to predict a sensory category $c \in \{0, 1, 2, 3, 4\}$, where 0, 1, 2, 3, and 4 symbolize 'visual', 'auditory', 'haptic', 'olfactory', and 'gustatory', respectively.

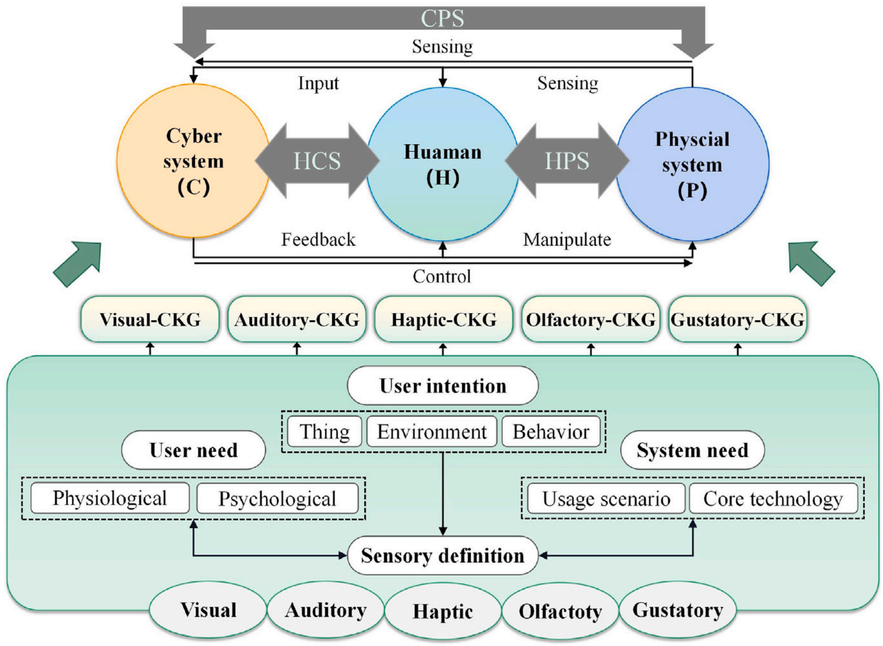


**Fig. 5.** The CKGs framework for multisensory interaction.

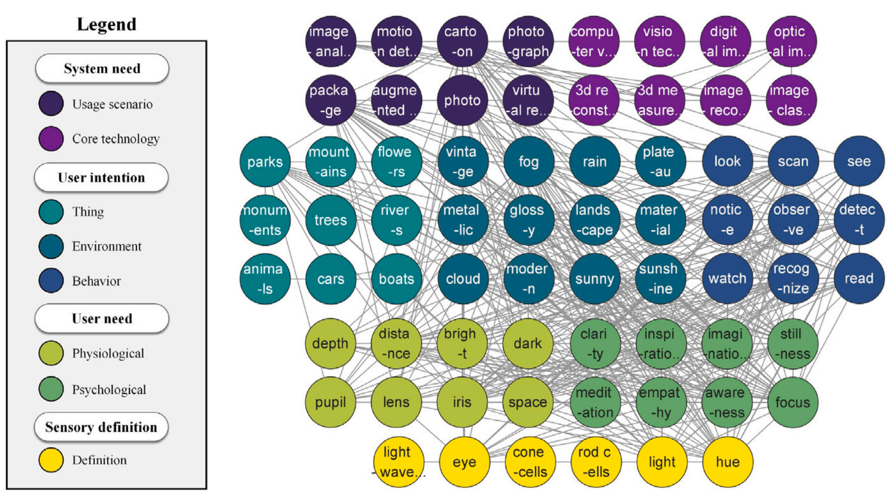


**Fig. 6.** Partial CKGs of MS-GCN (visual-CKG as an example).

#### 4.2.1. Embedding layer

In this section, we provide a concise description of our embedding layer—BERT [71] embedding—which translates each word into a high-dimensional vector space.

BERT represents a significant advancement in the field of contextualized representation learning. There are two variants of BERT, $ERT_{base}$ and $BERT_{large}$, both of which are resource-intensive due to the large number of parameters. For all our experiments, we opt for $BERT_{base}$, featuring 12 layers, 768 hidden dimensions, and 12 attention heads, with a total of 110M parameters.

Given a sentence $S = \{w_1, w_2, \dots, w_n\}$, it can be transformed into a high-dimensional representation $X = BERT(S) \in \mathbb{R}^{n \times d_{bert}}$, where $d_{bert}$ represents the size of the hidden dimension. Consequently, the vector representation of a particular word, $w_i\ is\ x_i \in \mathbb{R}^{d_{bert}}$. Thus, BERT allows for a rich, contextually sensitive mapping of words into a high-dimensional vector space.

#### 4.2.2. Keyword extraction algorithm based on graph ranking

In this section, we first construct a word graph $G_w = (V_w, E_w, A_w)$ from the words extracted from the sentence, and then extract keywords that can represent the meaning of the sentence through the PageRank-based graph ranking method. Initially, we incorporate $X = x_1, x_2, \dots, x_n$ into the nodes of the graph. Following this, edges are established based on the cosine similarity of the vectors contained within X. For a more detailed understanding of this construction process, please refer to Algorithm 1. It is important to note that $\sigma$ serves as a threshold in this context, and for the purpose of this paper, we set $\sigma = 0.8$. This methodology allows for the generation of a graph that encapsulates both the individual characteristics of nodes and the relational dynamics between them.

To construct graph data of sentences across 8 dimensions, we filter 8 keywords employing the PageRank algorithm [72]. In the context of the internet, this algorithm views web pages as vertices of a graph and hyperlinks between pages as edges connecting these vertices, thereby computing the importance scores of vertices in the graph. The function of the PageRank algorithm is defined as follows. Here, $x_i$ denotes a vertex, $X$ symbolizes a set of vertices that point toward $x_i$, $N_x$ represents the number of links attached to $x$, and $c$ stands for a regularization factor. Through the utilization of PageRank, we extract keywords that

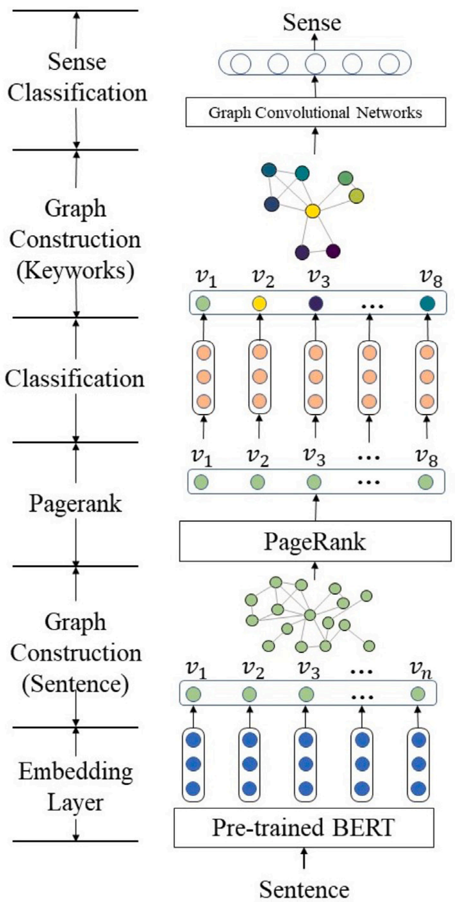


**Fig. 7.** The architecture of our proposed methods.

**Algorithm 1** Pseudo code of constructing word graph

**Input:** sentence $S = \{w_1, w_2, \ldots, w_n\}$, words vector $X = BERT(S) \in \mathbb{R}^{n \times d_{bert}}$, $X = x_1, x_2, \ldots, x_n$, $w_i$ *is* $x_i \in \mathbb{R}^{d_{bert}}$, similarity threshold $\sigma$

**for** $i \leftarrow 1$, $j \leftarrow 1$ to $n$ do **do**
  $cos(x_i, x_j) \leftarrow \frac{x_i \times x_j}{\|x_i\| \times \|x_j\|}$
  **if** $cos(x_i, x_j) > \sigma$ **then**
    **if** $x_i, x_j \in V_w$ **then**
      $e_{i,j} \leftarrow e_{i,j} + 1$
    **else**
      $V_w \leftarrow x_i, x_j$, $e_{i,j} \leftarrow 1$
    **end if**
  **end if**
**end for**

**Output:** word graph $G_w = (V_w,\ E_w,\ A_w)$

bear high importance and relevance to the sentence, thereby efficiently filtering the most informative elements for the graph's construction across multiple dimensions.

$$R(x) = c \sum_{v \in X} \frac{R(v)}{N(v)} \tag{3}$$

Finally, we got the 8 keywords most related to the sentence $S := kw_1, kw_2, \ldots, kw_8$ and the corresponding vectors $X_{kw} = x_1, x_2, \ldots, x_8$, $x_i \in \mathbb{R}^{d_{bert}}$.

#### 4.2.3. Fully-connected neural network

We use multi-layer fully-connected neural network [73] to classify keywords into 8 categories $c_{kw} = 0, 1, \ldots, 7$, where $0, 1, \ldots, 7$, symbolize 'Sensory definition', 'Physiological', 'Psychological', 'Thing', 'Environment', 'Behavior', 'Usage scenario', and 'Core technology', respectively. For each layer of fully connected neural network, there are two parameters $W_j$, $b_j$ that can be learned. The calculation process of the $j$th layer is as follows:

$$x_i^{j+1} = W_j x_i^j + b_j \tag{4}$$

Assuming that the last layer is the $J$th layer, the calculation process is as follows:

$$p_i = Softmax\left(W_J x_i^J + b_J\right) \tag{5}$$

The loss function is defined by the cross-entropy of the predicted and true label distributions for training:

$$L_1 = -\frac{1}{8} \sum_{i}^{8} log\left(p_i\right) \tag{6}$$

#### 4.2.4. Sensory graph construction

In this section, the sensory graph $G_s = \left(V_s, E_s, A_s\right)$ construction is introduced in detail. The keywords vectors $X_{kw} = \{x_1, x_2, \ldots, x_8\}$ is used as the nodes of $G_s$. The weight between the word nodes $x_j$ and $x_k$ is defined as:

$$a_{jk} = \begin{cases} cos(x_j, x_k) & c_j = 0 \ or \ c_k = 0 \\ cos(x_j, x_k) & c_j = c_k \\ 0 \quad otherwise & \end{cases} \tag{7}$$

**Algorithm 2** Pseudo code of constructing sensory graph

**Input:** keywords vectors $X_{kw} = \{x_1, x_2, \ldots, x_8\}$, $x_i \in \mathbb{R}^{d_{bert}}$, the corresponding category through $c_{kw} = \{c_1, c_2, \ldots, c_8\}$, similarity threshold $\sigma$.

**for** $i \leftarrow 1$, $j \leftarrow 1$ to 8 **do**
  $V_s \leftarrow x_i$
**end for**
**for** $j \leftarrow 1$, $k \leftarrow 1$ to 8, 8 **do**
  $cos\left(x_j, x_k\right) \leftarrow \frac{x_j \times x_k}{\|x_j\| \times \|x_k\|}$
  **if** $cos\left(x_j, x_k\right) > \sigma$ **then**
    **if** $c_j = 0$ or $c_k = 0$ or $c_j = c_k$ **then**
      $a_{j,k} \leftarrow cos\left(x_j, x_k\right)$
    **end if**
  **end if**
**end for**

**Output:** sensory graph$G_s = \left(V_s,\ E_s,\ A_s\right)$

For a detailed understanding of the construction process, please refer to Algorithm 2. A visual representation of the adjacency matrix can be found in Fig. 8.

#### 4.2.5. Graph Convolutional Network (GCN) for MS-GCN

In this section, we detail the structure, training and testing process of GCN.

As shown in Fig. 9, the structure of GCN contains input layer, three hidden layers, global mean pool and output layer. The calculation process of three hidden layers and global mean pool are shown in Section 4.1.

$$H^{(j+1)} = \sigma\left(\hat{A} H^{(j)} W^{(j)}\right) \tag{8}$$

where $H^{(0)} = H$, $\hat{A} = D^{-\frac{1}{2}} A D^{-\frac{1}{2}}$ is the normalized symmetric adjacency matrix and $W^{(i)}$ is a weight matrix for the $j$th GCN layer. $\sigma$ is a non-linear function (e.g. $ReLU\sigma(\bullet) = max(0, \bullet)$). Then, we can obtain a node-level output $Z = H^{(L)}$, which is an $N \times d_g$ representation matrix, where $d_g$ is the dimension of the node representation obtained from $L$th layer of GCN.

| | Sensory definition | Physiological | Psychological | Thing | Environment | Behavior | Usage scenario | Core technology |
|---|---|---|---|---|---|---|---|---|
| Sensory definition | Cos | Cos | Cos | Cos | Cos | Cos | Cos | Cos |
| Physiological | Cos | Cos | Cos | | | | | |
| Psychological | Cos | Cos | Cos | | | | | |
| Thing | Cos | | | Cos | Cos | Cos | | |
| Environment | Cos | | | Cos | Cos | Cos | | |
| Behavior | Cos | | | Cos | Cos | Cos | | |
| Usage scenario | Cos | | | | | | Cos | Cos |
| Core technology | Cos | | | | | | Cos | Cos |

**Fig. 8.** The adjacency matrix of $G_s$.

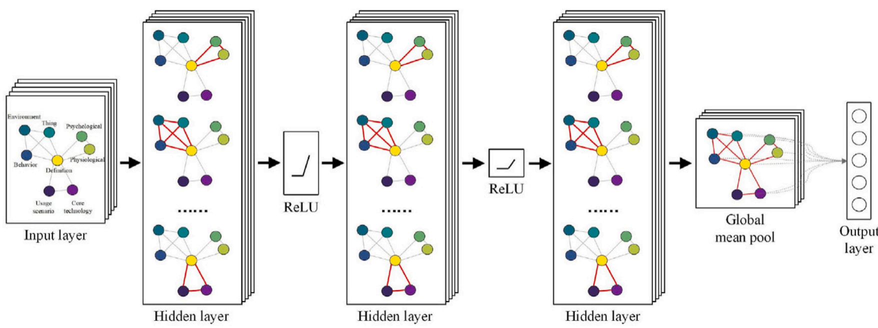


**Fig. 9.** Graph convolutional network for MS-GCN.

Then the application of Graph Global Average Pooling is employed to aggregate node-level features, thereby obtaining a holistic representation of the graph's features. This encapsulates the entirety of the graph's inherent structural information in a condensed form:

$$R = \frac{1}{N}\sum_{n=1}^{N} z_n \tag{9}$$

where $z_i \in \mathbb{R}^{1\times d_g}$ represents the $i$th vector drawn from $Z \in \mathbb{R}^{N\times d_g}$ and $R \in \mathbb{R}^{1\times d_g}$ represents the holistic representation of the graph's feature.

Finally, the output layer is fully-connected neural networks.

$$p = Softmax\,(W R + b) \tag{10}$$

where $W$ and $b$ are learn-able parameters, $p \in \mathbb{R}^5$. The objective of multisensory recommendation is to predict a sensory category $c \in \{0, 1, 2, 3, 4\}$, where 0, 1, 2, 3, and 4 symbolize "visual", "auditory", "haptic", "olfactory", and "gustatory", respectively.

During the training phase, our data is sourced from the Commonsense Knowledge Graph, as detailed in Section 4.2. We randomly select one instance from each of the 8 categories to compose a sensory graph, the construction of which is depicted in Algorithm 2. From this process, we accumulate a total of 2970 sensory graphs, consisting of 275 "visual", 726 "auditory", 209 "haptic", 869 "olfactory", and 891 "gustatory" graphs respectively. These datasets are then randomly partitioned into a training set and a test set, following an 8 : 2 ratio. This methodology ensures a comprehensive coverage of all sensory categories while maintaining a balanced distribution for effective model training and testing. For an in-depth understanding of the specific training process, Algorithm 3 is hereby referred to, which provides a comprehensive overview.

**Algorithm 3** Training phase of GCN

**Input:** Training set $\{(G_s^i, y^i)\}_{i=1}^N$, Test set $\{(\hat{G}_s^i, \hat{y}^i)\}_{i=1}^M$, model $f_\theta$, the maximum number of iterations $T$

```
Initialization: f_θ, training loss ℓ ⟵ 0, test loss ℓ̂ ⟵ 0, best test loss ℓ̂_best ⟵ 1
for t = 1 ⋯ T do
  ℓ ⟵ 1/N Σ_{i=1}^N −y^i log(f_θ(G_s^i)) − (1 − y^i) log(1 − f_θ(G_s^i))
  Update f_θ to minimize ℓ :  θ ⟵ ∇_θ ℓ
  if t%10 = 0 then
    ℓ̂ ⟵ 1/M Σ_{i=1}^M −ŷ^i log(f_θ(Ĝ_s^i)) − (1 − ŷ^i) log(1 − f_θ(G_s^i))
    if ℓ̂ < ℓ̂_best then
      Save f_θ
      ℓ̂_best ← ℓ̂
    end if
  end if
end for
```

**Output:** Updated model $f_\theta$

To accurately pinpoint the most highly recommended senses, we employ one-hot vector labeling. As an exploration of the interrelations among different senses, we utilize soft labels, on the basis of which multi-sensory recommendations are facilitated. Thus, in the research presented in Section 5, we derived the results of both single-sensory and multi-sensory recommendations using two distinct models. In the testing phase, the input derives from the sensory graph acquired as per Section 4.3.4.

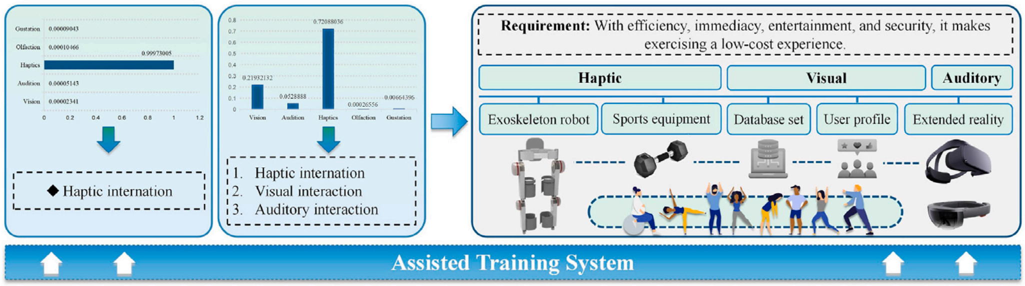


**Fig. 10.** Illustration of case one assisted training system.

## 5. Case study

In this section, we have discussed three practical case studies. Based on the input of the target system's requirement description, the MS-GCN model is utilized to derive quantitative recommendations for sensory interaction. The quantitative results are then integrated with the framework concept of MS-HCPS to develop preliminary system solutions.

### *5.1. Assisted training system*

In the current fast-paced and sedentary lifestyle, there is a growing demand for innovative sports and fitness methods. With the increase in desk-bound work, reliance on technology, and limited cost of exercise, individuals are seeking new ways to stay active and maintain a healthy lifestyle. To address these challenges, there is a need for the development of advanced training systems that can provide effective and personalized support. Traditional exercise methods, such as going to the gym or participating in organized sports, may not always align with the preferences of modern individuals. Additionally, many people face barriers such as lack of motivation, time constraints, or limited access to exercise facilities. This necessitates exploring alternative approaches to provide flexibility, convenience, and motivation for regular physical activities.

In order to address these challenges, an innovative assistive training system is required to aid users in their physical activities through cutting-edge technological innovations. The input system requirement description states: *"The system is capable of assisting users' physical activities through cutting-edge technological innovations. It possesses abundant instructional resources and enables exercise anytime and anywhere. It provides users with safety protection while recording and monitoring training data. Additionally, it is essential to incorporate elements of amusement to stimulate users' engagement and transform exercise into a cost-effective and enjoyable endeavor".*

Based on the provided input, the key extracted keywords are: *"instructional", "training", "teaching", "exercise", "transform", "video", "recording", "sport".*

The recommended sensory interaction results and system solutions have been obtained, as present in Fig. 10. The results obtained firstly by MS-GCN indicate a high confidence level of 0.99 for the tactile sense, suggesting a strong correlation with the given task. In the second step, MS-GCN explored the multisensory matching values for this task revealing significant matching values for the haptic, visual, and auditory senses. Combined with the MS-HCPS conceptual framework, corresponding system solutions can be designed for further exploration and implementation: The system aims to enhance locomotion by configuring an exoskeleton equipped with pressure sensors and heart rate sensors, as well as exercise equipment, with multimodal force feedback for haptic interactions. Moreover, the incorporation of machine learning-driven motion datasets and user profiles enables the amalgamation of pertinent physiological data, thereby affording the user rich sports action resources and a comprehensive visual representation of the physiological state. Additionally, the system's capabilities extend to the XR simulator, simulating intricate virtual environments and virtual instructional guides. Thereby augmenting the training experience within virtual spaces by seamlessly simulating both visual and auditory interactions.

The system affords users an immersive and interactive exercise experience. By assisting in transforming the way individuals engage in physical exercise, pioneering assisted training systems render physical exertion markedly more captivating, personalized, and accessible. The innovative system introduces novel paradigms and orientations poised to catalyze a paradigm shift within the sports realm.

### *5.2. Perfume development system*

Perfumes have long been used as a means of personal expression, with individuals increasingly seeking fragrances that match their personalities, preferences, and lifestyles. As the demand for personalized and unique experiences in all aspects of life grows, this changing consumer landscape requires the development of innovative perfume research and development systems to meet these individual needs and preferences. Traditional approaches to perfume development often rely on standardized and mass-produced methods, resulting in a limited range of options that may not fully satisfy the diverse tastes of individuals. In addition, the process of creating and refining perfumes has traditionally been limited to a small number of experts, making it inaccessible to a wider audience. These limitations have created a gap between the perfume industry and consumer aspirations, leading to a growing demand for more customized and personalized perfume experiences [74].

To bridge this gap, a new paradigm for perfume research and development is needed. The input system requirement description states: *"The system is able to provide one-on-one service to customers, thus providing exclusive perfume design solutions. Through this system, innovation and development of perfumes can be achieved, while constructing customized visual packaging and delivery schemes based on user preferences. It allows users to enjoy exclusive customized services and technical support for convenient fragrance sniffing with sensor technology. And build a perfume museum based on the user's image profile".*

The key keywords extracted based on the input are: *"perfume", "customized", "design", "packaging", "fragrance", "development", "visual", "technology".*

As shown in Fig. 11, the results obtained from MS-GCN exhibit a strong correlation with the olfactory sense, with a confidence level of 0.75. Furthermore, further computations reveal significant matching values for the five senses, particularly in terms of olfaction, vision, and audition. Capitalizing on the framework of MS-HCPS, a preliminary systemic solution can be designed as follows: At the olfactory stratum, the foundational infrastructure of smart devices and odor data analytics is employed to orchestrate perfume apparatus and formulations that cater to individual unique preferences. Simultaneously, services pre-distributing perfume packages and samples with customer's personal images are harnessed at the visual and auditory dimensions, manifesting as potent tools for heightening customer contentment and fostering

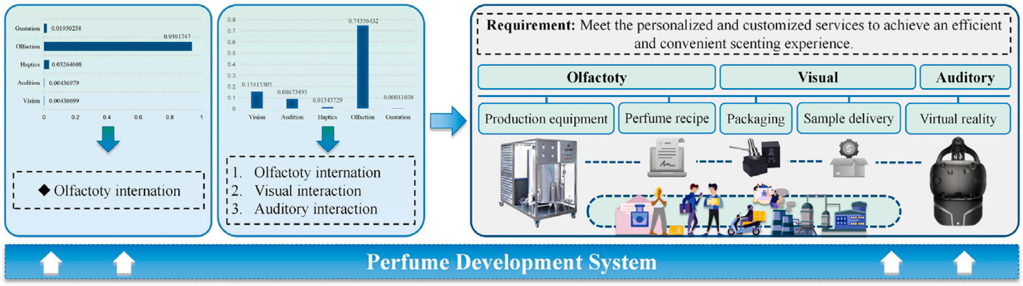


**Fig. 11.** Illustration of case two perfume development system.

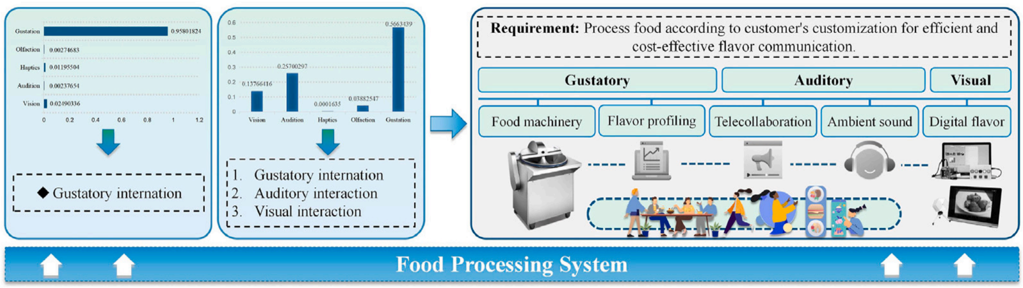


**Fig. 12.** Illustration of case three food processing system.

brand loyalty, thereby engendering an augmentation of brand equity and the propagation of favorable commendations. Furthermore, the micro heaters and scent generator fan modules of VR impart a synergistic and conveniently distinctive olfactory encounter, epitomizing the synergy that can be harnessed to amplify user engagement.

The perfume development system can build the perfect service with intelligent equipment and technology to enhance user perception on the olfactory, visual, and auditory three levels, providing an exclusive and customized perfume. Such innovative systems are expected to revolutionize the perfume industry, heralding a transformative era of more all-encompassing and immersive olfactory exploration and personalization.

### 5.3. Food processing system

The food industry is involved in the production and processing of various types of food, beverages, and dietary supplements, making it a multidimensional and challenging industry [75]. In today's interconnected world, customers are seeking convenient and efficient ways to experience food and interact with it. Traditional methods of food processing and communication often require physical presence, resulting in time-consuming processes and limitations in reaching a wider audience. To address these challenges, there is an increasing need for innovative food processing systems that enable remote tasting experiences, reduce communication time, and enhance customer satisfaction.

To deliver higher quality services, food processing systems need to meet the demands of efficient and cost-effective communication. The input system requirement description states: *"The system is capable of processing beef in various ways, such as pan-frying and boiling, according to customer preferences. Additionally, it allows customers to remotely experience the flavor of the beef to confirm if their requirements are met. The user experience of beef taste needs to be convenient, fast, and cost-effective in order to save time and costs associated with order fulfillment".*

The key keywords extracted by the input are: *"beef", "boiling", "customer", "processing", "associated", "cost", "requirement", "taste".*

As present in Fig. 12, the results obtained from MS-GCN exhibit a strong correlation with the sense of taste, with a confidence level of 0.96. Furthermore, the computation of multisensory matching reveals significant matching values for gustatory, auditory, and visual. In conjunction with the MS-HCPS framework, a preliminary system solution can be strategically formulated: The system synergizes cutting-edge automated machinery with flavor analysis technology to surmount the intrinsic constraints inherent in conventional culinary techniques. This strategic fusion empowers the system to facilitate streamlined, multimodal food processing, thereby elevating the overall quality of the taste experience. In the realm of auditory engagement, telecollaboration technologies for simulating environmental and food processing sounds offer a heightened level of fidelity and efficiency to remote interactions. Furthermore, the ability to capture and simulate taste sensations can be realized through the orchestration of coordinating beef food information encompassing both auditory and visual interaction, thereby affording patrons the immersive opportunity to virtually partake in their desired gastronomic experiences.

This food processing system serves to augment the interactive dynamics between consumers and their desired culinary offerings. Through its commitment to flavor fidelity and the optimization of order placement methodologies, effectively bridges the geographic and temporal gaps between consumers and food producers, and represents a transformative shift in the food processing service paradigm.

### 5.4. Quantitative analysis

Our approach began with collecting a diverse range of user data across various scenarios, resulting in a dataset that reflects real user needs in system design. This dataset, detailed in Table 1, comprises a diverse set of 12 sensory instances: 2 for vision, 2 for auditory, 3 for haptic, 2 for olfactory, and 3 for gustatory cases.

Utilizing this dataset in our trained Multisensory Graph Convolutional Network (MS-GCN), we performed keyword extraction and classification, followed by the construction of sensory graphs and the prediction of sensory recommendation confidence.

The classification performance, illustrated in a confusion matrix in Fig. 13, shows remarkable accuracy of our model in classifying sensory data. Notably, the predicted values were found to be completely consistent with the true values, exhibiting precise accuracy across all sensory categories. Although our experimental dataset is somewhat limited, its well-distributed categories encompass predictions for each

**Table 1**
Quantitative datasets.

| | System | Sensory | Label |
|---|---|---|---|
| 1 | Flower purchase system | Visual | 0 |
| 2 | Bird watching system | Visual | 0 |
| 3 | Sound simulation system | Auditory | 1 |
| 4 | Music playback system | Auditory | 1 |
| 5 | Assisted training system | Haptic | 2 |
| 6 | Exoskeleton system | Haptic | 2 |
| 7 | Weightlifting system | Haptic | 2 |
| 8 | Perfume development system | Olfactory | 3 |
| 9 | Odor generation system | Olfactory | 3 |
| 10 | Food processing system | Gustatory | 4 |
| 11 | Orange production system | Gustatory | 4 |
| 12 | Soup preparation system | Gustatory | 4 |

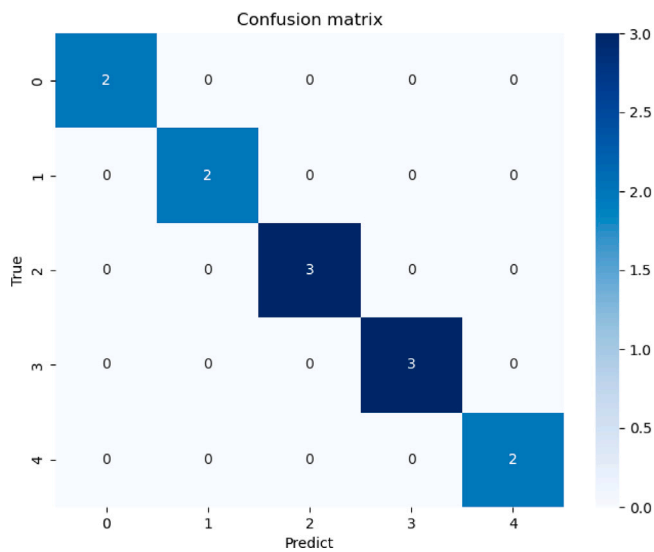


**Fig. 13.** Confusion matrix.

case, highlighting the model's robustness. This even distribution and consistent prediction accuracy across various sensory modalities provide significant evidence supporting the robustness of our method, despite the dataset's limited size.

Constrained by the challenges inherent in data collection, the current number of verification cases, and the scope of knowledge within the CKG, our research faces certain limitations. Moving forward, we plan to substantially broaden the knowledge base of the CKG. Simultaneously, we intend to seek out and incorporate a wider array of cases for verification, with the aim of continually refining and enhancing the algorithm's efficacy.

### *5.5. Prototype design*

To further advance the systematic design of the case studies, we have developed a prototype for case one, employing the MS-HCPS framework and MS-GCN model. This prototype entails an assisted training system aimed at facilitating daily exercise routines, as present in Fig. 14. It utilizes the HoloLens MR HMDs developer edition as the platform for information system development, alongside a physical platform for lower limb exoskeletons. Through the information system's operation, users can partake in standardized exercise routines guided by virtual coaches within virtual environments. Integrated with the physical system, the exoskeleton robot assists users in performing stretching, extension, fixation, and coordination exercises using exercise equipment. Subsequently, users' physiological data are collected upon completing the training session, allowing for visualization of exercise performance. The prototype of the assisted training system implemented the solution derived from the MS-HCPS framework, prioritizing tactile, visual, and auditory interactions in the system design. This system prototype, comprising an exoskeleton robot, XR simulator, action dataset, user profile, and sports equipment, has been effectively deployed in the domain of assisted locomotion.

In the physical system, users adjust and lock joint angles by rotating knobs on the outer side of the exoskeleton robot, coupled with other sports equipment for lower limb stretching exercises. The outer side of the hip joint of the exoskeleton is designed with two sets of gear-adjustable joints, providing two rotational degrees of freedom in the X and Y directions of the thigh exoskeleton. The locking mechanism of gear-adjustable joints operates on the principle of unidirectional rotation of the ratchet wheel. An electromagnetic switch regulates the pawl, which is actuated by a gear reduction unit linked to it. In addition, users' physiological data collection is facilitated by pressure and pulse sensors embedded within the exoskeleton. In the cyber system, users engage in target action practice by following virtual coaches within the XR simulator. The simulator supports various natural interactions such as gestures and speech, complemented by visual and auditory cues to enhance tactile experiences. Users can immerse themselves in the details of the virtual coach's movements and adjust the angle and speed of actions. Additionally, the display provides information on training and remaining time for time management purposes. During this process, exoskeleton robot can be utilized for corrective actions. Bidirectional communication between the cyber and physical systems is enabled through the bluetooth modules, allowing for the updating of motion datasets and user profiles.

## 6. Conclusion and discussion

The present study proposes MS-HCPS as a multisensory interactive framework for exploring HCPS. The sensory description and overall framework are introduced, allowing creators and managers to approach system design, management, and operation from a new perspective. Additionally, this paper presents the MS-GCN model for sensory recommendation computation. The GCNs are briefly introduced, followed by the construction of CKGs corresponding to five senses, and a detailed explanation of the MS-GCN model construction process. Finally, the effectiveness of this research is validated through three practical case scenarios.

The contributions of this paper can be demonstrated in three aspects. Firstly, MS-HCPS explores a system interaction framework centered around human senses by integrating features from different senses, thus promoting the research and application of HCPS systems on a broader scale. Secondly, MS-GCN is capable of deriving the most relevant senses and specific recommendation indices for the target system based on user-input demand text. This model practically facilitates the design and management of systems in MS-HCPS, enabling rational allocation of research and development resources. The organization and optimization of HCPS system inspiration, design, and innovation are systematically enhanced. Thirdly, case conceptualization and design requirements are proposed to address the research gaps in HCPS, specifically in the areas of training assistance, perfume development, and food processing. System framework design discussions are conducted based on the computational results of this study.

The case studies demonstrate that this research effectively enhances the efficiency of decision-making and execution in the early stages of system development. However, MS-HCPS can further investigate the implementation methods of various sensory interaction technologies in more detail. Additionally, MS-GCN has the potential for further expansion. We will try to establish the interconnections among the five senses using the Knowledge Graph, and employ the MS-GCN for quantitatively articulating the relationships between senses as well as potential synesthesia interaction methodologies.


**Fig. 14.** Prototype of case one assisted training system.

## CRediT authorship contribution statement

**Wenqian Qi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Chun-Hsien Chen:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Tongzhi Niu:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology. **Shuhui Lyu:** Writing – review & editing, Visualization. **Shouqian Sun:** Writing – review & editing, Supervision, Funding acquisition.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

## Acknowledgments

The authors would like to thank the editors and the anonymous reviewers for their valuable comments and suggestions, which have led to a substantical improvement of this paper. This work was supported by the National Key R&D Program of China (No. 2020YFC1523301-2).

## References

[1] T. Fitz, M. Theiler, K. Smarsly, A metamodel for cyber-physical systems, Adv. Eng. Inform. 41 (2019) 100930.
[2] W. Qi, S. Sun, T. Niu, D. Zhao, Research and prospects of virtual reality systems applying exoskeleton technology, Univers. Access Inf. Soc. (2022) 1–22.
[3] P. Cornelio, C. Velasco, M. Obrist, Multisensory integration as per technological advances: A review, Front. Neurosci. 15 (2021) 652611.
[4] D.K. Baroroh, C.-H. Chu, L. Wang, Systematic literature review on augmented reality in smart manufacturing: Collaboration between human and computational intelligence, J. Manuf. Syst. 61 (2021) 696–711.
[5] C.F. Cheung, K.M. Lee, P. Zheng, W.B. Lee, Digital manufacturing systems, in: Springer Handbook of Automation, Springer, 2023, pp. 805–827.
[6] H. Wang, M. Liu, W. Shen, Industrial-generative pre-trained transformer for intelligent manufacturing systems, IET Collab. Intell. Manuf. 5 (2) (2023) e12078.
[7] J. Pang, N. Zhang, Q. Xiao, F. Qi, X. Xue, A new intelligent and data-driven product quality control system of industrial valve manufacturing process in CPS, Comput. Commun. 175 (2021) 25–34.
[8] J. Xiao, W. Zhang, R.Y. Zhong, Blockchain-enabled cyber-physical system for construction site management: A pilot implementation, Adv. Eng. Inform. 57 (2023) 102102.
[9] J. Zhou, Y. Zhou, B. Wang, J. Zang, Human–cyber–physical systems (HCPSs) in the context of new-generation intelligent manufacturing, Engineering 5 (4) (2019) 624–636.
[10] S.K. Sowe, E. Simmon, K. Zettsu, F. De Vaulx, I. Bojanova, Cyber-physical-human systems: Putting people in the loop, IT Prof. 18 (1) (2016) 10–13.
[11] W. Baicun, Z. Jiyuan, Q. Xianming, D. Jingchen, Z. Yanhong, Research on new-generation intelligent manufacturing based on human-cyber-physical systems, Strateg. Study Chin. Acad. Eng. 20 (4) (2018) 29–34.
[12] B. Wang, P. Zheng, Y. Yin, A. Shih, L. Wang, Toward human-centric smart manufacturing: A human-cyber-physical systems (HCPS) perspective, J. Manuf. Syst. 63 (2022) 471–490.
[13] S. Ling, D. Guo, Y. Rong, G.Q. Huang, Spatio-temporal synchronisation for human-cyber-physical assembly workstation 4.0 systems, Int. J. Prod. Res. 60 (2) (2022) 704–722.
[14] H. Qiqi, Z. Xiangying, L. Dai, Z. Xujun, Z. Xujun, W. Baicun, T. Renzhong, Smart healthy working from human-cyber-physical system(HCPS) perspective, J. Mech. Eng. 58 (18) (2022) 229–239.
[15] M. Nice, S. Elmadani, R. Bhadani, M. Bunting, J. Sprinkle, D. Work, CAN coach: vehicular control through human cyber-physical systems, in: Proceedings of the ACM/IEEE 12th International Conference on Cyber-Physical Systems, 2021, pp. 132–142.
[16] P. Li, Y. Lu, D. Yan, J. Xiao, H. Wu, Scientometric mapping of smart building research: Towards a framework of human-cyber-physical system (HCPS), Autom. Constr. 129 (2021) 103776.
[17] J. Zhixin, W. Hongwei, F. Xiang, Development path of new generation intelligent coal mine under HCPS theory system, J. Mine Autom. 48 (10) (2022).
[18] D.J. Lewkowicz, A.A. Ghazanfar, The emergence of multisensory systems through perceptual narrowing, Trends Cogn. Sci. 13 (11) (2009) 470–478.
[19] M. Obrist, E. Gatti, E. Maggioni, C.T. Vi, C. Velasco, Multisensory experiences in HCI, IEEE MultiMed. 24 (2) (2017) 9–13.
[20] H. Santoso, D.K. Baroroh, A. Darmawan, Future application of multisensory mixed reality in the human cyber—Physical system, South Afr. J. Ind. Eng. 32 (4) (2021) 44–56.
[21] J. Qu, Y. Zhang, W. Tang, W. Cheng, Y. Zhang, L. Bu, Developing a virtual reality healthcare product based on data-driven concepts: A case study, Adv. Eng. Inform. 57 (2023) 102118.
[22] A.V. Zakharov, V.A. Bulanov, E.V. Khivintseva, A.V. Kolsanov, Y.V. Bushkova, G.E. Ivanova, Stroke affected lower limbs rehabilitation combining virtual reality with tactile feedback, Front. Robot. AI 7 (2020) 81.
[23] J. Lin, L. Cao, N. Li, Assessing the influence of repeated exposures and mental stress on human wayfinding performance in indoor environments using virtual reality technology, Adv. Eng. Inform. 39 (2019) 53–61.
[24] E. Kerruish, Arranging sensations: smell and taste in augmented and virtual reality, Senses Soc. 14 (1) (2019) 31–45.

[25] J. Tang, X. Du, X. He, F. Yuan, Q. Tian, T.-S. Chua, Adversarial training towards robust multimedia recommender system, IEEE Trans. Knowl. Data Eng. 32 (5) (2019) 855–867.
[26] W. Han, X. Hu, Alarm sound recommendation based on music generating system, in: 5G for Future Wireless Networks: Second EAI International Conference, 5GWN 2019, Changsha, China, February 23-24, 2019, Proceedings 2, Springer, 2019, pp. 86–95.
[27] A. Mishra, A. Shukla, N.P. Rana, Y.K. Dwivedi, From "touch" to a "multisensory" experience: The impact of technology interface and product type on consumer responses, Psychol. Market. 38 (3) (2021) 385–396.
[28] D. Biswas, L.I. Labrecque, D.R. Lehmann, Effects of sequential sensory cues on food taste perception: cross-modal interplay between visual and olfactory stimuli, J. Consum. Psychol. 31 (4) (2021) 746–764.
[29] J.E. Lee, H. Ihm, Implementing a signature perfume recommendation system based on perfume similarity evaluation, in: Proceedings of HCI Korea, 2014, pp. 461–465.
[30] K. Ahuja, M. Goel, S. Sikka, P. Makkar, What-to-taste: a food recommendation system, 2020.
[31] S.A. Macdonald, E. Freeman, S. Brewster, F. Pollick, User preferences for calming affective haptic stimuli in social settings, in: Proceedings of the 2021 International Conference on Multimodal Interaction, 2021, pp. 387–396.
[32] R. Han, Translating scientific content into accessible formats with visually impaired learners: Recommendations and a decision aid based on haptic rules of perception, 2020.
[33] Y. Ma, S. Wang, C.C. Aggarwal, J. Tang, Graph convolutional networks with eigenpooling, in: Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2019, pp. 723–731.
[34] X. Miao, N.M. Gürel, W. Zhang, Z. Han, B. Li, W. Min, S.X. Rao, H. Ren, Y. Shan, Y. Shao, et al., Degnn: Improving graph neural networks with graph decomposition, in: Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining, 2021, pp. 1223–1233.
[35] K.Z. Khanam, G. Srivastava, V. Mago, The homophily principle in social network analysis: A survey, Multimedia Tools Appl. 82 (6) (2023) 8811–8854.
[36] M. Park, Y. Geum, Two-stage technology opportunity discovery for firm-level decision making: GCN-based link-prediction approach, Technol. Forecast. Soc. Change 183 (2022) 121934.
[37] Y. Xie, C. Yao, M. Gong, C. Chen, A.K. Qin, Graph convolutional networks with multi-level coarsening for graph classification, Knowl.-Based Syst. 194 (2020) 105578.
[38] S. Zhou, X. Dai, H. Chen, W. Zhang, K. Ren, R. Tang, X. He, Y. Yu, Interactive recommender system via knowledge graph-enhanced reinforcement learning, in: Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval, 2020, pp. 179–188.
[39] S. Chaudhuri, D. Ritchie, J. Wu, K. Xu, H. Zhang, Learning generative models of 3D structures, in: Computer Graphics Forum, Vol. 39, Wiley Online Library, 2020, pp. 643–666.
[40] C. Wang, H. Wang, M. Liu, A dual-attention feature fusion network for imbalanced fault diagnosis with two-stream hybrid generated data, J. Intell. Manuf. (2023) 1–13.
[41] H. Wang, J. Wang, Y. Zhao, Q. Liu, M. Liu, W. Shen, Few-shot learning for fault diagnosis with a dual graph neural network, IEEE Trans. Ind. Inform. 19 (2) (2022) 1559–1568.
[42] M.L. Lehman, How sensory design brings value to buildings and their occupants, Intell. Build. Int. 3 (1) (2011) 46–54.
[43] F. Huang, J. Huang, X. Wan, Influence of virtual color on taste: Multisensory integration between virtual and real worlds, Comput. Hum. Behav. 95 (2019) 168–174.
[44] B. Brkljač, B. Antić, Z. Mitrović, Potential of embedded vision platforms in development of spatial AI enabled CPS, in: 2022 11th Mediterranean Conference on Embedded Computing, MECO, IEEE, 2022, pp. 1–4.
[45] Y. He, Prioritizing skill action recognition of basketball using decision support system, 2022.
[46] F. Banfi, M. Previtali, Human–computer interaction based on scan-to-BIM models, digital photogrammetry, visual programming language and extended reality (XR), Appl. Sci. 11 (13) (2021) 6109.
[47] J. Goulding, W. Nadim, P. Petridis, M. Alshawi, Construction industry offsite production: A virtual reality interactive training environment prototype, Adv. Eng. Inform. 26 (1) (2012) 103–116.
[48] Y. Han, J. Yang, Y. Diao, R. Jin, B. Guo, Z. Adamu, Process and outcome-based evaluation between virtual reality-driven and traditional construction safety training, Adv. Eng. Inform. 52 (2022) 101634.
[49] P. Larsson, J. Maculewicz, J. Fagerlönn, M. Lachmann, Auditory displays for automated driving—challenges and opportunities, in: The 25th International Conference on Auditory Display, ICAD 2019, Vol. 52, 2019, pp. 299–305.
[50] B.B. Johansson, Multisensory stimulation in stroke rehabilitation, Front. Hum. Neurosci. 6 (2012) 60.
[51] Z. Wang, L. Cui, W. Guo, L. Zhao, X. Yuan, X. Gu, W. Tang, L. Bu, W. Huang, A design method for an intelligent manufacturing and service system for rehabilitation assistive devices and special groups, Adv. Eng. Inform. 51 (2022) 101504.
[52] C.H.J. Li, V. Liang, Y.T.H. Chow, H.-Y. Ng, S.-P. Li, A mixed reality-based platform towards human-cyber-physical systems with IoT wearable device for occupational safety and health training, Appl. Sci. 12 (23) (2022) 12009.
[53] E. Pezent, A. Israr, M. Samad, S. Robinson, P. Agarwal, H. Benko, N. Colonnese, Tasbi: Multisensory squeeze and vibrotactile wrist haptics for augmented and virtual reality, in: 2019 IEEE World Haptics Conference, WHC, IEEE, 2019, pp. 1–6.
[54] R. Lovreglio, V. Gonzalez, Z. Feng, R. Amor, M. Spearpoint, J. Thomas, M. Trotter, R. Sacks, Prototyping virtual reality serious games for building earthquake preparedness: The auckland city hospital case study, Adv. Eng. Inform. 38 (2018) 670–682.
[55] Q. Wu, X. Wang, B. Chen, H. Wu, Patient-active control of a powered exoskeleton targeting upper limb rehabilitation training, Front. Neurol. 9 (2018) 817.
[56] M. de Paiva Guimarães, J.M. Martins, D.R.C. Dias, R.d.F.R. Guimarães, B.B. Gnecco, An olfactory display for virtual reality glasses, Multimedia Syst. 28 (5) (2022) 1573–1583.
[57] E. Maggioni, R. Cobden, D. Dmitrenko, K. Hornbæk, M. Obrist, SMELL space: mapping out the olfactory design space for novel interactions, ACM Trans. Comput.-Hum. Interact. 27 (5) (2020) 1–26.
[58] S. Niedenthal, W. Fredborg, P. Lundén, M. Ehrndal, J.K. Olofsson, A graspable olfactory display for virtual reality, Int. J. Hum.-Comput. Stud. 169 (2023) 102928.
[59] J. Lee, S. Hwang, K. Kim, S. Kim, Auditory and olfactory stimuli-based attractors to induce reorientation in virtual reality forward redirected walking, in: CHI Conference on Human Factors in Computing Systems Extended Abstracts, 2022, pp. 1–7.
[60] N. Ranasinghe, D. Tolley, T.N.T. Nguyen, L. Yan, B. Chew, E.Y.-L. Do, Augmented flavours: Modulation of flavour experiences through electric taste augmentation, Food Res. Int. 117 (2019) 60–68.
[61] K. Karunanayaka, N. Johari, S. Hariri, H. Camelia, K.S. Bielawski, A.D. Cheok, New thermal taste actuation technology for future multisensory virtual reality and internet, IEEE Trans. Visual. Comput. Graph. 24 (4) (2018) 1496–1505.
[62] H. Miyashita, Taste display that reproduces tastes measured by a taste sensor, in: Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology, 2020, pp. 1085–1093.
[63] P. Cornelio, C. Dawes, E. Maggioni, F. Bernardo, M. Schwalk, M. Mai, S. Pawlizak, J. Zhang, G. Nelles, N. Krasteva, et al., Virtually tasty: An investigation of the effect of ambient lighting and 3D-shaped taste stimuli on taste perception in virtual reality, Int. J. Gastron. Food Sci. 30 (2022) 100626.
[64] N.M. Harris, R.W. Lindeman, C.S.F. Bah, D. Gerhard, S. Hoermann, Eliciting real cravings with virtual food: Using immersive technologies to explore the effects of food stimuli in virtual reality, Front. Psychol. 14 (2023) 956585.
[65] D. Nowlan, Synesthesia and creativity: an analysis of human perception, 2021.
[66] M. Gil, M. Albert, J. Fons, V. Pelechano, Designing human-in-the-loop autonomous cyber-physical systems, Int. J. Hum.-Comput. Stud. 130 (2019) 21–39.
[67] B. Wang, H. Zhou, G. Yang, X. Li, H. Yang, Human digital twin (HDT) driven human-cyber-physical systems: Key technologies and applications, Chin. J. Mech. Eng. 35 (1) (2022) 11.
[68] D. Mourtzis, J. Angelopoulos, N. Panopoulos, Operator 5.0: A survey on enabling technologies and a framework for digital manufacturing based on extended reality, J. Mach. Eng. 22 (2022).
[69] T.N. Kipf, M. Welling, Semi-supervised classification with graph convolutional networks, 2016, arXiv preprint arXiv:1609.02907.
[70] L. Dong, M. Ren, Z. Xiang, P. Zheng, J. Cong, C.-H. Chen, A novel smart product-service system configuration method for mass personalization based on knowledge graph, J. Clean. Prod. 382 (2023) 135270.
[71] J. Devlin, M.-W. Chang, K. Lee, K. Toutanova, Bert: Pre-training of deep bidirectional transformers for language understanding, 2018, arXiv preprint arXiv:1810.04805.
[72] L. Page, S. Brin, R. Motwani, T. Winograd, The Pagerank Citation Ranking: Bring Order to the Web, Tech. Rep., Technical Report, Stanford University, 1998.
[73] T.N. Sainath, O. Vinyals, A. Senior, H. Sak, Convolutional, long short-term memory, fully connected deep neural networks, in: 2015 IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP, IEEE, 2015, pp. 4580–4584.
[74] K.J. Begum, J.A. Ibrahim, E. Refaee, Smell sensory system in m-commerce-a case study, in: 2021 International Conference on Software Engineering & Computer Systems and 4th International Conference on Computational Science and Information Management, ICSECS-ICOCSIM, IEEE, 2021, pp. 507–511.
[75] D. Granato, G.F. Branco, A.G. Cruz, J.d.F. Faria, N.P. Shah, Probiotic dairy products as functional foods, Compr. Rev. Food Sci. Food Saf. 9 (5) (2010) 455–470.