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TOWARDS HIGHER PERSONALIZATION: AN AI-DRIVEN CONTEXT-AWARE SMART PRODUCT-SERVICE SYSTEM DEVELOPMENT APPROACH COMBINED WITH MULTI-CRITERIA DECISION-MAKING

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ABSTRACT
Transformative technologies such as artificial intelligence, big data, and cloud computing are significantly influencing and reshaping daily life. In alignment with digital transformation principles, the objects of design have shifted from industrial and single-function products to digital service systems. Consequently, data-driven Smart Product-Service Systems (SPSS) have emerged. However, despite the widespread deployment and application of SCP and ICT products, current SPSS development methods are limited in their capacity to handle large volumes of structured and unstructured user-generated data, and an effective development paradigm has yet to be fully established. Meanwhile, artificial intelligence technologies—including large language models, image recognition models, and video generation models—have demonstrated advanced intelligence capability, leading users to expect SPSS to integrate these AI capabilities to achieve enhanced product and service functionalities. As a result, personalization and adaptability in service systems have become increasingly important objectives.
To address these challenges, this study presents a novel SPSS development approach that integrates context-aware artificial intelligence (AI) with multi-criteria decision-making (MCDM) methods, enhancing the system's capacity to process large amounts of user-generated data and configure personalized services. Specifically, a data-driven user state inference module is proposed, which collects multi-source contextual data and constructs AI models to infer users' physical and emotional states. Additionally, personalized service solutions are generated by applying MCDM techniques to represent, configure, and optimize service parameters based on users' states. To validate the proposed approach, two case studies were conducted to assess its effectiveness in real-world systems. The results indicate that SPSS integrated with AI technologies is highly effective, and that the automatic configuration of personalized services significantly enhances user satisfaction.

Keywords: Smart PSS, Context-aware system, Artificial intelligence, Multi-criteria decision-making

1 INTRODUCTION

The growing market for Smart Connected Products (SCPs) has led to increasing interest in concepts like Cyber-Physical Systems (CPS), and Smart Product-Service Systems (SPSS). SCPs, aided by digital servitization, allow companies to create innovative services and business models. This digital transformation enables value co-creation within dynamic digital ecosystems. The development of SPSS involves complex factors, including real-time responsiveness to changing user contexts. The development of SPSS follows the systematic approach, placing emphasis on "data-driven", "personalized services" and "value creation"[1, 2].
Integrating context-aware artificial intelligence(AI) into SPSS could enhance understanding of user needs, improve human-machine interaction, and generate tailored service solutions. In this regard, scholars have proposed diverse development methods for data-driven personalized services, leveraging various data sources such as context data[3], Internet of Things (IoT) sensor data[4], physiological data[5], and others. On the other hand, propelled by vast datasets and extensive computational resources, artificial intelligence technologies, exemplified by large language models[6], image recognition models[7], and video generation models, have exhibited higher- order intelligent capabilities. Therefore, it is worthwhile to explore in greater depth the mapping relationship between big data-driven artificial intelligence and intelligent service applications.

In addition, many scholars have delved into researching personalized services value. Demirkan et al. revealed the importance of collecting multi-source data and fostering co-created value between customers and businesses[8]. Chiu and Tsai introduced a multi-agent-based personalized product service system designed for swift adaptation to external changes and customer demands[9]. Some researchers have opted for method such as ontology-based knowledge reasoning[10], multi-objective optimization, and multi-criteria decision-making to orchestrate service value propositions across diverse entities within the system.
Given the abundance of both structured and unstructured data in the intelligent, interconnected cyber-physical space, data-driven paradigms are expected to integrate with multi-criteria decision-making methods to create an efficient and agile approach to personalized SPSS development. However, this area remains largely underexplored.
This study introduces a context-aware AI integrated with MCDM framework for developing Smart Personalized Service Systems (SPSS). The framework consists of three modules: multi-source context acquisition, user modality reasoning, and service recommendation. It collects data from sensors and wearable devices, processes it on a cloud platform, and analyzes user physical and emotional states for personalization. The service recommendation module employs MCDM methods like DEMATEL and TOPSIS to rank services based on user modalities, optimizing resource allocation. This approach enhances SPSS adaptability and effectiveness by aligning services with user needs through iterative decision-making processes.

2 RELATED WORKS

Significant advancements in internet deployment, computational intelligence, and network technologies have driven the rise of a new generation of SPSS[11]. Chang et al. introduced the concept of user-centric SPSS (UC-SPSS) and provided a development approach for UC-SPSS[12]. Zheng et al. stressed the need for a systematic method in Smart PSS development, concentrating on two key elements: the "data-driven" model and the "value co-creation" process[2].
The data-driven approach to SPSS development has become a major research focus. Wang et al. devised a context-aware concept assessment method for Smart PSS iterations that integrates natural language processing (NLP) tools and takes user experience into account[13]. Multi-agent systems[9] and knowledge graphs[14, 15] have been applied to construct SPSS. Yuan et al. utilized data from wearable sensors to assess users' physical states, using this data to personalize SPSS services[3].
In terms of service configuration, Song et al. proposed a systematic method that integrated a correlation matrix to identify configuration parameters, optimized multiple service objectives, and used the NSGA-II algorithm to achieve these objectives[16]. Chen et al. presented a framework to optimize SPSS configuration with two main goals: enhancing intelligent capability efficiency and value symbiosis efficiency, supported by corresponding optimization algorithms[1].
The SCPs in SPSS enable the acquisition of large volumes of heterogeneous, multi-source data. Given the advantages of context-aware artificial intelligence (AI) in self-adaptation and implicit requirement mining, it becomes possible to gather comprehensive user and contextual data, perceive user needs, and characterize service scenarios. In this context, a comprehensive personalized service generation method that integrates context-aware AI with multi-criteria decision-making processes warrants further exploration.

3 METHODOLOGY

This study proposes a context-aware artificial intelligence (AI) combined with multi-criteria decision-making(MCMD) Smart Product-Service Systems (SPSS) development approach. The proposed method is composed of three key modules: multi-source context acquisition, user modality reasoning, and service recommendation.

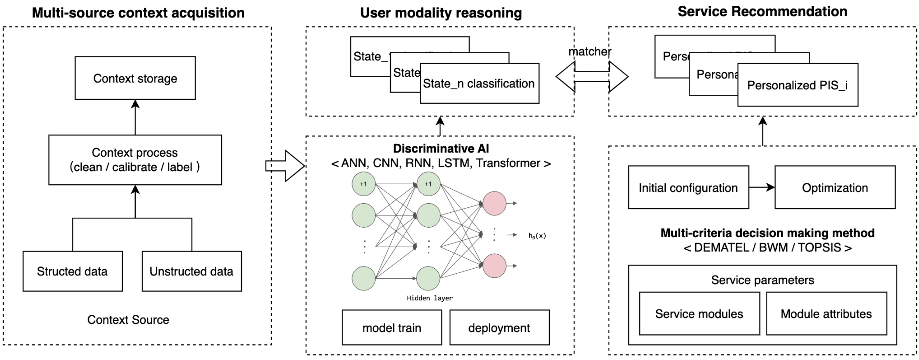

Figure 1. The overall framework of proposed approach

3.1 Multi-source context acquisition

Recent advancements in sensors, computer vision, and networking have led to the generation of extensive structured and unstructured data. For example, user identity data can be acquired through direct methods like surveys and indirect methods such as public datasets and mobile applications. Physical data is gathered from environmental sensors that monitor variables like location and temperature, while real-time sensed context is captured via wearable devices that track metrics like heart rate and blood oxygen levels. Additional data sources include IoT sensors, medical records, and biomedical images.

The data processing steps involve feature extraction, handling missing data, and validating datasets to remove anomalies. Data formats are standardized using various structures like key-value, tagged encoding, ontology-based, and hybrid formats. Data modeling, which aids in understanding data characteristics and relationships, is managed on a cloud platform. This enables the collection, storage, and analysis of large context datasets, ensuring safety, reliability, and flexibility. The process focuses on data source quality and context-specific feature extraction, with data being standardized and cleaned for better visualization and analysis capabilities.

In the data storage phase, a robust cloud-based database structure is established to accommodate concurrent access by multiple devices, particularly in healthcare settings. Cloud databases, favored for their accessibility and resource efficiency, support communication between various rehabilitation devices. The structure incorporates different types of databases, including relational (e.g., MySQL, Oracle, PostgreSQL), non-relational (e.g., MongoDB, Redis), and graph databases (e.g., Neo4J, InfoGrid), offering flexibility and scalability in managing multi-source data.

3.2 User modality reasoning

Modality reasoning is essential for extracting insights from data, especially in identifying user modalities, such as physical and emotional states, to enhance personalized experiences. By analyzing user contexts, SPSS can deduce these modalities, enabling the delivery of tailored product-service bundles. Context reasoning involves inferring high-level insights from general data through logical inference and probability calculations, addressing the challenge of associating and transforming raw data into meaningful context.

The reasoning process generates user modality, representing advanced attributes like exercise intensity, emotions, and service experiences. This concept draws from the term modality, meaning 'something exists, is experienced or expressed in a certain mode' [17]. User modality is linked to the entity's state (e.g., physical and mental), particularization (e.g., spatial perception and experience), and mobility (e.g., vehicle condition)[18]. With these understandings, SPSS can deliver enhanced environments, such as intelligent technology scenarios, value co-creation networks, and customized service packages.

The reasoning process is divided into three key modules: input, reasoning, and output. The input module gathers various context data—such as user identity, environmental context, and sensor data—through cloud-based middleware. In the reasoning module, supervised learning techniques, particularly neural networks, are used to predict new data from labeled datasets. The network processes multi-source data through an input, hidden, and output layer configuration, using backpropagation optimization to reduce errors and improve performance. The cost function incorporates regularization, and the model parameters are refined through continuous iterations. The output module generates user modalities, representing key characteristics like exercise intensity and emotional state.

Regarding model architectures, artificial neural networks (ANNs) are considered classic frameworks for machine learning inference[19]. Building on these foundations are deep learning architectures, including convolutional neural networks (CNNs)[20], recurrent neural networks (RNNs)[21], long short-term memory (LSTM) networks[22], and transformers[23]. CNNs are particularly well-suited for processing image data, while RNNs and LSTMs excel at handling sequential data. The transformer architecture, nowadays, is increasingly applied to multimodal data fusion and inference tasks.

3.3 Service recommendation

This section examines how context-aware AI systems can develop service strategies for identified user modalities through a multi-criteria decision-making (MCDM) process. The selection and ranking of service elements are based on established MCDM methods such as DEMATEL, TOPSIS, and BWM, which assign weights to service components like staff, equipment, and consumables. Each service element has associated weights and costs, forming a decision matrix that helps service providers optimize their allocation strategies. Service elements are ranked based on their influence, and optimal service combinations are identified through an iterative optimization process.

The process begins with identifying user modality, followed by the creation of a personalized service strategy. MCDM method is used to assign weights to service elements, generating a comprehensive relationship matrix to evaluate inter-element influence. Service elements are then allocated based on utility value, and the system iterates to optimize resource distribution. This matrix leads to optimized service configurations by balancing utility against costs. Providers can select service strategies tailored to specific user modalities, ensuring personalized service bundle (PSB) recommendations. After segmentation, users' personalized requirements are matched with tailored service strategies using a logic-based matcher. By using fuzzy numbers and an evolutionary algorithm to refine service configurations, improving the alignment between user needs and service modules. Additionally, evolutionary algorithms are employed to optimize weight matrices, ensuring service configurations remain objective despite expert biases.

4 CASE STUDY

4.1 A context-aware SPSS for supporting non-professional sports competitions

Non-professional sports events, such as marathons, pose higher risks for participants due to a lack of systematic training, leading to incidents like sudden cardiac death (SCD). The risk of cardiac arrest during vigorous exercise is significantly higher for individuals with low daily activity. Current preventive measures, including screenings and AED services, are inadequate for long-distance events. To address this, the Context-Aware Smart Product-Service System (CA-SPSS) framework[3] was implemented in the 2021 Shanghai Jiao Tong University long-distance race. Using wearable devices, the system monitors athletes' real-time physical states, offering personalized services and helping reduce on-field risks.

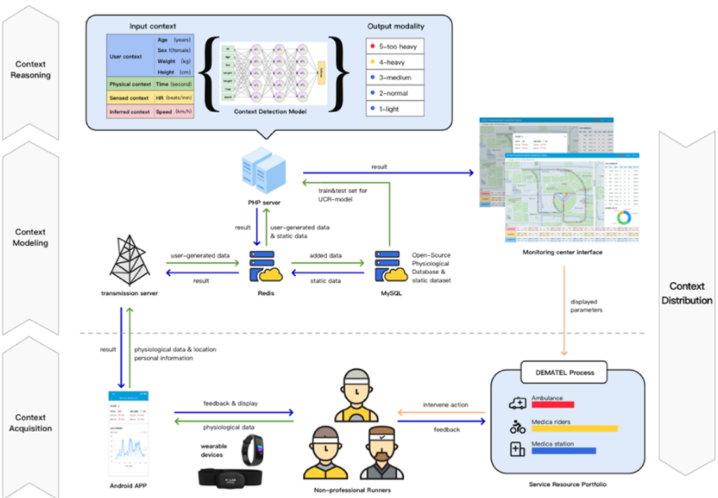

Figure 2. Overview of CA-SPSS for supporting Non-Professional Sports Competitions

The Context-Aware Smart Personalized Service System (CA-SPSS) for Non-Professional Sports Competitions (NPSC) gathers contextual data via a wireless sensor network that includes runners, wearable devices, and mobile phones. The system collects four types of context: user context (e.g., age, sex, height, weight) during registration, physical context (e.g., time and location) from mobile phone sensors, inferred context (e.g., speed), and sensed context (e.g., heart rate) through wearable devices. Heart rate data from devices like Polar H7 is collected via an Android app and transmitted through Bluetooth BLE, while location data is obtained using Baidu Maps SDK, all sent to the cloud for real-time analysis.On the cloud, the system models data using Redis for real-time context and MySQL for static user data. A PHP server processes data to detect exercise intensity, utilizing a modality-detection model that continuously updates with new data. The context reasoning process begins with clustering an open-source physiological dataset via K-means, followed by classifying exercise intensity based on the Metabolic Equivalent of Energy (MET) theory. A neural network model trained on 200 user profiles achieved 83.9% accuracy and an AUC of 0.94 in detecting five exercise intensity levels, forming the basis for personalized service recommendations in NPSC applications.

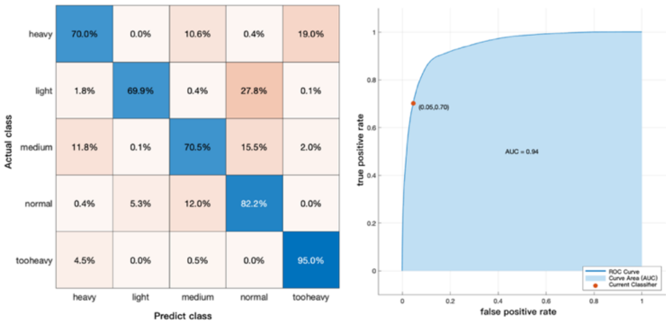

Figure 3 Exercise intensity modality-detection neural network model

In the model deployment phase, the exercise intensity modality-detection model was implemented using the PyTorch framework and integrated into a cloud platform with a PHP backend. The model processed real-time data from runners, including heart rate, speed, and time, formatted as JSON and linked to identity data stored in a MySQL database. It produced exercise intensity modality levels, which were sent to a context distribution layer for personalized service recommendations.

The user interface of the Context-Aware Smart Personalized Service System (CA-SPSS) for Non-Professional Sports Competitions (NPSC) displayed key information, categorizing runners into three exercise intensity levels: medium, heavy, and too heavy. This visual interface facilitated competition monitoring and risk detection. During a long-distance race, resource planning and allocation were optimized using the DEMATEL method, focusing on service staff and emergency equipment. Service strategies were tailored to runners' intensity levels, ensuring personalized care and enhancing safety and user satisfaction throughout the event.

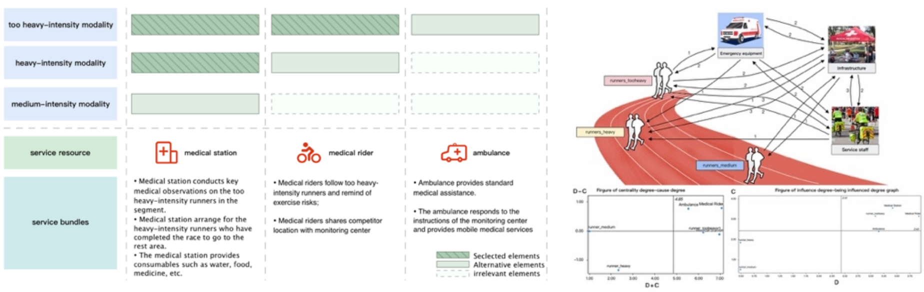

Figure 4. Blueprint with service strategies of CA-SPSS for NPSC

4.2 A context-aware SPSS based on fine-tuned large vision AI model and fuzzy-DEMATEL

Facial palsy, resulting from trauma, infections, or congenital issues, impairs facial muscle movement, affecting chewing, self-esteem, and overall health. Prompt treatment can facilitate recovery, while delays may lead to persistent symptoms. Current assessments, like the House-Brackmann Grading System, are prone to human error. This study suggests utilizing deep learning for automated evaluations.

Treatment varies based on severity; mild cases may improve with medication and exercises, while severe cases often require surgery. The Rehabilitation Management Smart Product-Service System (FPRM-SPSS) enhances patient compliance and exercise experience by integrating advanced human-computer interaction features, including exercise demonstrations and remote physician monitoring[24].

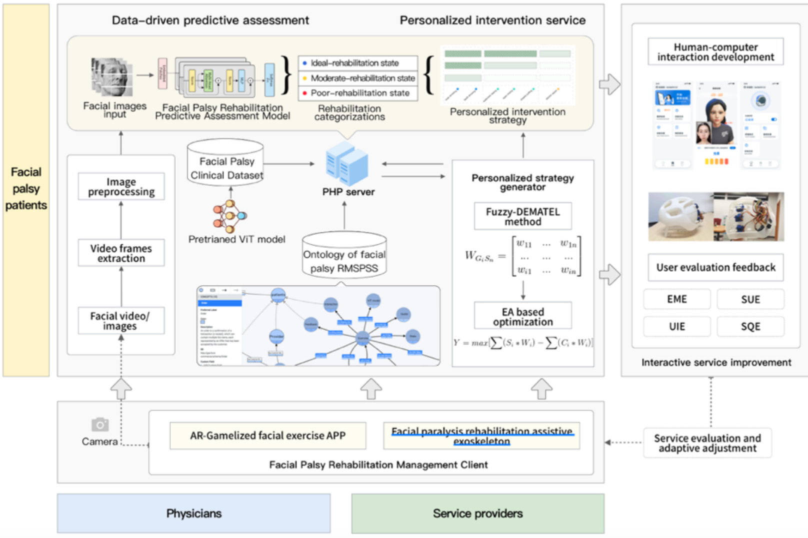

Figure 5. The overall framework of FPRM-SPSS

This study developed a Clinical Facial Palsy (CFP) dataset from clinical cases at a collaborating hospital, collecting 3,744 images of facial videos and images from 52 patients at various intervals (one week to twelve months post-intervention). Each image was preprocessed and annotated by facial nerve specialists, achieving a resolution of 500×500 pixels. The dataset was classified using three clinical grading scales: the House-Brackmann Facial Nerve Grading System (HBGS), Facial Nerve Grading System 2.0 (FNGS 2.0), and the Yanagihara Facial Nerve Grading System, categorizing patients into ideal, moderate, and poor rehabilitation states. Ethics approval and patient consent were obtained for the study. To enhance classification accuracy while reducing costs, the study utilized a pre-trained Vision Transformer (ViT) model for developing a facial palsy rehabilitation predictive assessment model. Training occurred on a cloud server equipped with an NVIDIA T4 GPU. The model demonstrated exceptional performance, achieving a training accuracy of 99.99%. Following pruning and compression, users can obtain predictive assessments by uploading facial images to the system.

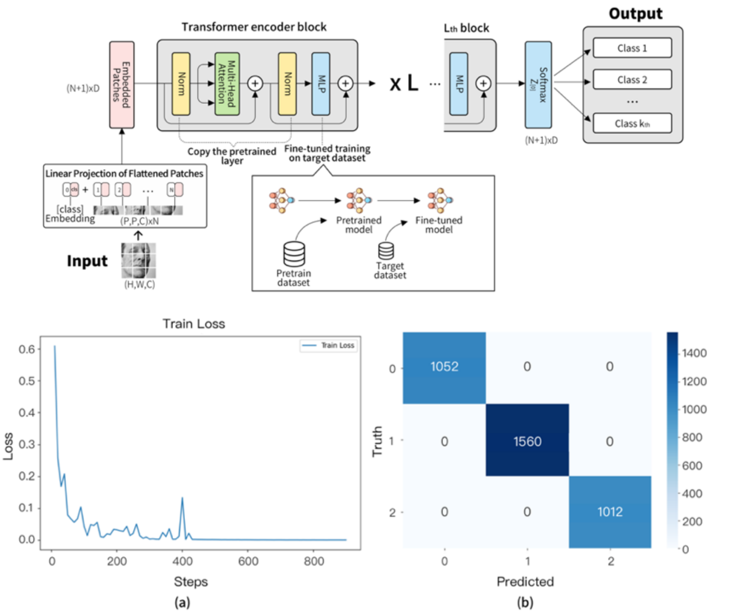

Figure 6. The fine-tuned predictive assessment model

This section outlines the development of a Smart Personalized Service System (SPSS) designed for facial palsy rehabilitation, structured into three layers: the service scope, service modules, and module

attributes. Personalized interventions focus on targeted exercises for specific facial muscles, developed in collaboration with hospitals. The system integrates clinical datasets, Vision Transformer (ViT) models for predictive assessment, and control algorithms for tailored interventions, while the attributes layer encompasses mobile devices and cloud resources. Rehabilitation exercises are categorized into five guidance modules and two exoskeleton-assisted modes, with personalization parameters based on severity levels of facial palsy (mild, moderate, severe). The study employs fuzzy linguistic evaluations and the DEMATEL method for decision-making, assessing rehabilitation scenarios through expert evaluations of service modules. The impact of various facial exercises is quantified and organized into a comprehensive influence matrix, enabling optimization via the NSGA-II evolutionary algorithm.
Furthermore, an interactive feedback system is developed, featuring an augmented reality (AR) gamified app and a rehabilitation exoskeleton. The app enhances engagement by allowing users to upload facial videos for assessment, receive exercise recommendations, and track progress, while the exoskeleton assists with targeted exercises. Together, these innovations significantly improve user experience and rehabilitation outcomes.

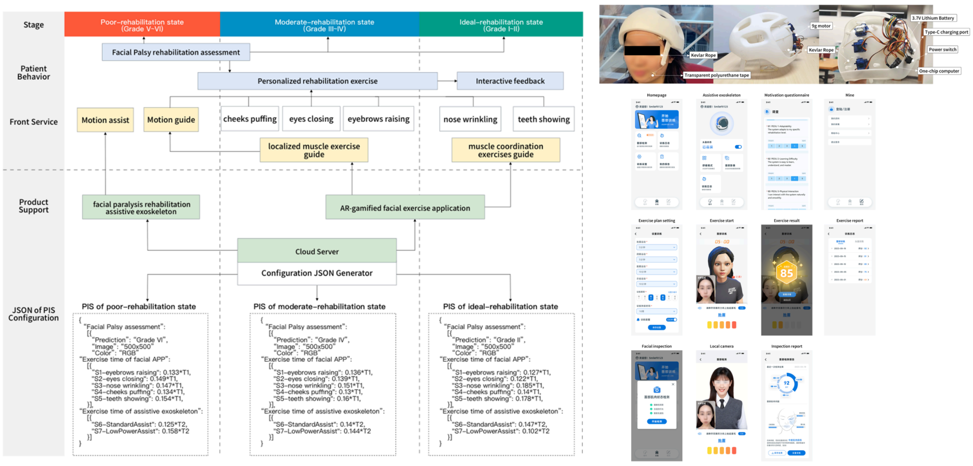

Figure 7. Facial Palsy rehabilitation management client and service strategies

5 DISCUSSION & CONCLUSION

This study explores a context-aware AI framework integrated with MCDM for developing SPSS. The framework aims to add value for stakeholders by improving service efficiency, reducing costs, and promoting sustainability through resource-efficient strategies. It includes three modules: multi-source context acquisition, user modality reasoning, and service recommendation. Multi-source context acquisition collects structured and unstructured data from sensors, processed through cloud-based feature extraction and standardization. Modality reasoning uses neural networks to predict user physical and emotional states, informing personalized service strategies. Service recommendation applies MCDM methods like DEMATEL to optimize resource allocation and tailoring services to user needs.
In comparison to existing research, the proposed approach incorporates context-aware AI to enhance recommendation quality[25].
This approach prioritizes users by focusing on deeply reasoning their needs and experiences. Unlike user-centric SPSS methods, which aim to address technical limitations and rely on qualitative user analysis[12], this study is more time- and cost-efficient in user research, providing a comprehensive data-driven approach. It can autonomously detect and identify user modality, showing promise in understanding implicit needs and offering more tailored PSB recommendations. Additionally, compared to knowledge-based personalized service configuration, this approach strengthens SPSS's ability to handle vast amounts of user data by incorporating advanced AI techniques.
This paper's contributions include: i) A novel conceptual framework for data-driven personalized SPSS, integrating context awareness to improve self-adaptation and implicit requirement mining, enhancing SPSS adaptability and effectiveness through AI and decision-making processes. ii) Two SPSS case studies demonstrating the application of the proposed approach, including a comprehensive evaluation of its effectiveness in real-world scenarios.
Although this study has several benefits, it also presents some limitations. For example, the user dataset used in the research exhibited similar geographic and ethnic traits, negatively impacting data quality.

Additionally, the approach does not fully address users' implicit needs. Integrating context-aware computing with qualitative methods like interviews, questionnaires, and focus groups could enhance future investigations.

Future research should take the following recommendations into account. First, as the convergence of digital and physical environments intensifies, the volume and diversity of user-generated data continue to expand. Therefore, it is crucial for researchers to employ advanced AI technologies, such as multimodal models, to better comprehend and define user needs and conditions. Additionally, the complexity of contemporary commercial ecosystems involves multiple stakeholders in SPSS. Thus, further research is needed to explore modeling techniques capable of addressing the intricacies of dynamic systems from diverse perspectives.

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