International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Intelligent E-Cigarette: An IoT-Driven Semantic Approach for Managing Smoking Habits and Promoting Healthier Behaviours

[1]Khaled Halimi, [2]Abdelhalim Hadjadj

Submitted : 04/05/2024 **Revised**: 15/06/2024 **Accepted**: 22/06/2024

Abstract: This research presents an innovative approach aimed at designing an intelligent connected e-cigarette. The approach involves seamlessly integrating Semantic Web, Internet of Things (IoT) technologies and vital signs monitoring to effectively reduce tobacco consumption. The design of the smart connected e-cigarette is rooted within the IoT architecture incorporating edge, fog, and cloud layers to ensure both efficiency and scalability in handling real-time data, it incorporates also a sophisticated array of sensors and wearable devices. The integration of diverse devices results in a holistic data aggregation under different contexts. This comprehensive dataset becomes a cornerstone for improved analysis, precise inference, and personalized interventions. In addition, the design adopts a semantic modelling framework, including an ontology, semantic properties and SWRL rules, to strengthen the intelligence and responsiveness of the e-cigarette by uncovering hidden patterns within smokers' behaviour. A key element which is the smoker's RDF model is highlighted, it contains all knowledge about smoker allowing a transparent exchange of data between different stakeholders. Furthermore, a prediction model for smoking cessation based on the Health Belief Model is presented, anticipating the possible impact on smokers' beliefs and behaviours. The experimental study carried out along with this research confirms technical feasibility and widespread acceptance of this innovative design among smokers and demonstrates that they are more likely to reduce smoking habits if the device consistently informs them regarding deviations in their health status. The suggested Semantic IoT-based smart e-cigarette stands as a promising contribution to the ever-evolving landscape of smoking cessation solutions.

Keywords*: *Internet of Things, Sensors; Semantic Web, e-Cigarettes, Vital Signs, Health.

1. Introduction

Quitting smoking has always been a critical public health challenge worldwide due to its deep impact on individuals' health and society well-being. Traditional smoking cessation methods, such as assisting and medical interventions, have shown varying levels of efficacy [1]. Smoking risks are well known, varying from cardiovascular diseases to respiratory complications and even cancer [2]. As a result, lot of initiatives were adopted to reduce tobacco consumption, therefore, moving from these dangers to efforts aimed at reducing consumption requires new approaches that incorporate permanent monitoring of health. For example, the World Health Organization report [3] highlights the need for innovative approaches to help individuals stop tobacco use and reduce the global burden of smoking diseases. Several contributions emphasizing the imperative adoption of personalized approaches. Meanwhile, other seek to discover possible innovative strategies that affect the fight against smoking [4].

The prevalence of e-cigarettes is growing rapidly as a substitute for ordinary cigarettes [5], however most of these devices lack the flexibility to obtain immediate insights about smokers' habits. Current e-cigarettes function independently without being linked to smokers' health status, making it challenging for them to quit [6]. These devices also fail to address triggers and contextual factors influencing smoking behavior [7]. These limitations highlight the need for innovative design that can facilitate data integration in order to improve smoking cessation.

New directions in computing technologies can offer a chance to support smoking cessation effort by redesigning e-cigarettes to effectively control tobacco consumption. One of these modern technologies is the Internet of Things (IoT) and Semantic Web technologies, which present a promising solution for addressing the complex challenges of tobacco addiction. By harnessing IoT's rich data nature and the intelligence of the semantic web, these technologies have the potential to revolutionize smoking cessation strategies [8].

Recent advancements in health monitoring through IoT devices and smart sensors have shown feasibility in tracking users' physical parameters and lifestyle behaviours with precision, including vital signs analysis which provides insights into the immediate physiological impact of smoking [9]. Integrating vital signs monitoring with semantic IoT technologies offers real-time insights into smoking behavior analysis and physiological responses, enabling tailored support and advanced

[1]*Department of computer science, LabSTIC laboratory, University 8 Mai 1945 Guelma, Algeria, https://orcid.org/0000-0002-0047-2986. E-mail: halimi.khaled@univ-guelma.dz*
[2]*Department of computer science, University 8 Mai 1945 Guelma, Algeria, https://orcid.org/0000-0003-2270-9830, E-mail: hadjadji.abdelhalim@univ-guelma.dz*

interventions. This innovative approach envisions a future where personalized assistance intersects seamlessly with advanced technology, transforming the landscape of smoking cessation strategies. Furthermore, the proposed design outlined in the paper holds promise for various stakeholders, including healthcare sector, tobacco industry, and government entities, offering opportunities for proactive healthcare management, reshaping product development and marketing strategies, and informing public health policies and interventions. The aim is to establish a model for smoking cessation compatible with the digital age, leveraging IoT's transformative capabilities to enhance public health.

2. Motivation & research questions

This research aims to address the limitations of existing e-cigarettes and contribute to the advancement of smoking cessation technologies. By designing innovative electronic cigarettes, the goal is to develop a comprehensive system that does not only exceed the current market restrictions but also enhances health awareness and supports efforts towards tobacco cessation. The study explores the utilization of sensor-based technologies, semantic modelling, and vital signs monitoring to develop an intelligent system capable of capturing, interpreting and interacting with data meaningfully. Our research primarily focuses on assessing smokers' acceptance of the smart connected e-cigarette design. Additionally, we seek to gauge the effectiveness of the underlying system in guiding smokers to decrease their smoking habits, in line with the Health Belief Model. To guide the research, several key questions are posed: Which smoker's health-related data should be monitored to help in smoking cessation? How can e-cigarette be seamlessly integrated into a connected ecosystem? What sensors can optimize the e-cigarette's performance? How can data interoperability be achieved within the ecosystem? How can latent patterns in smokers' habits be discovered through data analysis? In what ways can the implementation of a smart e-cigarette improve health awareness and facilitate smoking cessation? These questions serve as the motivation for developing a foundational framework for a smart connected e-cigarette system.

3. Background Knowledge

There is no doubt that smoking cause deaths of millions of people and creates different diseases all over the world, it has a direct relation with life-threatening health problems [10]. Reducing nicotine addiction is a difficult mission, especially when the tobacco industry aggravates the problem by actively targeting young people through aggressive marketing techniques [11]. While healthcare systems bear very large economic burdens due to smoking-related diseases, in return, the financial impact of the tobacco industry, social acceptance and regularities raises obstacles to effective implementation of the anti-smoking policies. To effectively address the harms associated with tobacco, it's imperative to embrace holistic strategies that engage governments, public health organizations and communities collaboratively [12].

Recently, e-cigarettes have emerged as a promising alternative to traditional tobacco products, some supporters see the possibility of this type of devices to reduce or quit consumption [13]. However, this issue is a subject of hot discussion between experts and health policy makers. While e-cigarettes can eliminate the harmful combustion process that characterizes traditional cigarettes, anxiety about its long-term health effects and high use by young people raised doubts about its effectiveness. Unlike traditional cigarettes, e-cigarettes do not produce harmful tar and many toxic chemicals similar to that in tobacco smoke [14]. Experts argue that while e-cigarettes might aid smoking cessation through gradual nicotine reduction, their effectiveness remains uncertain. "Double use" of e-cigarettes alongside traditional ones could eliminate potential benefits. Furthermore, concerns arise over the popularity of e-cigarettes among youth, raising fears of future nicotine addiction [15].

It is obvious that taking into account the smokers' health is a priority in any smoking cessation strategy, this will inevitably lead us to delve into the complex relationship between e-cigarettes and smoker's vital signs.

Vital signs play a crucial role in the evaluation of individuals' health since they provide valuable indications on the physiological functioning of the body, in particular with regard to parameters such as oxygen saturation, stress and blood pressure, etc. To better interpret these signs, standardized scoring systems have been developed, defining values considered normal and abnormal [16]. Differences in relation to these references can report potential health problems, ranging from a minor imbalance under serious medical conditions [17].

In the field of public health, the Health Belief Model rises as a conceptual useful framework to understand how individuals perceive and react to these vital signs [18]. According to this model, the perception of susceptibility to a disease and the severity of its consequences, as well as the perception of the effectiveness of preventive actions, influence health behaviours. Thus, persons aware of the harmful effects of e-cigarettes on their vital signs will be more inclined to consider abandonment of this habit, motivated by the desire to preserve their health.

By using wearable devices, we can now monitor important parameters in real time. Equipped with advanced sensors, these devices provide precise data and precious information on individuals' health. Transparent data sharing allows healthcare providers to monitor the individuals' vital signs, to early discover health problems and to create personal care plans [19]. In recent years, using wearable devices, such as smart watches, bracelets and rings, has increased significantly where statistics show an increasing trend in their use by different age groups around the world. Their smooth integration in daily life, along with its advanced capabilities, places them as pivotal tools in effective health monitoring strategies.

As these smart devices become more sophisticated and integrate advanced sensors, they naturally approach the wider landscape of the IoT. The latter fundamentally transforms how we interact with technology, extending beyond traditional devices to everyday objects [20]. It enables seamless communication and data analysis on a vast scale. IoT architecture comprises four layers: perception, network, middleware, and application, facilitating data collection, transfer, processing, and application. Edge, fog, and cloud layers are pivotal in optimizing IoT efficiency, balancing real-time processing and data analysis, while sensors form the backbone of IoT, they capture diverse data with energy efficiency and security measures. The combination of connected devices not only speeds up automation but also encourages a data-driven approach, empowering sectors to make well-informed decisions and significantly enhance their operational efficiency. As the IoT continues to evolve, its potential for transformation continues to unfold, offering a wide range of benefits that reshape the landscape of modern industries which will inevitably contribute to the development of health monitoring [21]. Through these capabilities, IoT presents a promising solution for the development of future e-cigarettes, offering potential to support and promote healthier habits among smokers.

But, the proliferation of several brands of e-cigarettes, each with its own technology, protocol and data format, actually poses an important challenge in terms of data interoperability. The absence of a standardized data format makes it difficult for e-cigarettes to communicate and share smoking data with other devices or platforms consistently. This fragmentation can limit the potential for comprehensive health monitoring and personalized interventions [22]. Integrating the Semantic Web holds great promise for resolving data interoperability resulting from diversity of e-cigarette brands and other IoT devices.

The Semantic Web, is an extension of the World Wide Web, emphasizes creating data readable by both humans and machines, facilitating significant connections and interoperability across diverse information sources. Key components such as linked data and ontologies enable seamless connections between datasets and structured representations of knowledge and the Resource Description Framework (RDF) triples underpin linked data, promoting interconnected and meaningful data structures [23]. RDF enhances e-cigarette interoperability, enabling the representation and exchange of smoking data in a universally understandable format [24]. Ontologies further advance e-cigarette capabilities by formalizing domain knowledge and organizing relationships among entities and concepts while Semantic reasoning enables intelligent recommendations, contributing to personalized risk assessments and health predictions [25].

To establish a robust foundation for our research, we reviewed existing literature on e-cigarettes and vape devices. This thorough examination is vital for contextualizing our study within the current field, allowing us to recognize trends, pinpoint gaps, and grasp the shortcomings of smoking technologies. **Table 1** showcases a set of studied e-cigarettes identified in the literature. Within this table, we have distilled a range of features and options offered by these entities, aiming to provide a comprehensive overview of the diverse technological landscape in the field.

Table 1. Overview of Studied E-cigarettes and Approaches in the Literature

e-Cigarette / Key Features and Options	VapeTracker [26]	JULL [27]	Vaporcade [28]	VOOPOO [29]	G Pen [30]	SmokRPM [31]	Enovap [32]	Smokio [33]	Ploom Tech [34]	Vype ePen [35]	Pax 3 [36]	Pact [37]	mPuff [38]
Smart Inhalation Sensors	✓												
Adjustable Nicotine Levels			✓					✓		✓			
Temperature Control				✓	✓						✓		
Aerosol Sensor													
Puff number	✓		✓			✓	✓	✓					
Customizable Flavours			✓	✓			✓				✓	✓	
Accelerometer & Gyroscope												✓	✓

Location detection (GPS)				✓									
Battery life control		✓	✓	✓	✓	✓		✓	✓	✓			
Vape Analytics								✓		✓			
Connectivity to Mobile	✓	✓	✓	✓				✓	✓	✓	✓		
Real-time Monitoring	✓	✓	✓	✓			✓		✓		✓	✓	✓
Tracking Behaviour	✓	✓					✓			✓			
Support Smoking Cessation													
Safety Features		✓									✓		
Alerts & Warnings													
Personalized Quit Plans			✓				✓			✓			
Goal Achievement	✓		✓					✓					
Social Support				✓									

In our study of different e-cigarettes brands, we have identified a significant gap in their design, particularly in terms of health monitoring features. Many devices lack comprehensive health monitoring capabilities, representing a missed opportunity to prioritize user well-being. While they often provide basic connectivity to mobile phones and offer tracking features like puff counts, battery levels, and device temperature, they typically offer limited data visualizations. Furthermore, there's a notable lack of interoperability among different brands, hindering seamless communication and data exchange. To address these shortcomings, we propose a solution that integrate IoT, semantic web technologies and vital signs monitoring to provide users with comprehensive health insights and personalized smoking experiences beyond basic metrics. In the following section, we will delve into the detailed design of a smart connected e-cigarette. This design aims to create a comprehensive system that not only enhances awareness about health but also actively contributes to tobacco cessation efforts.

4. The Conceptual Model of the Smart Connected E-Cigarette

In the next section, we detail our approach of the connected smart e-cigarettes design. This approach transcends traditional smoking cessation methods, harnessing the power of modern technology to create a dynamic and responsive solution. By incorporating Semantic Web, IoT principles, our goal is to overcome challenges related to data heterogeneity, personalized interactions, and real-time health and behavior monitoring while using smoking devices.

The system architecture of the Semantic IoT-based e-Cigarette involves the integration of various hardware and software components to allow real time data collection, semantic analysis and personalized interventions. Figure 1 presents an outline of the key elements of the system's architecture. In essence, the system comprises a holistic ecosystem centred around the smoker representing the edge layer, a fog gateway and a cloud layer. Additionally, the engagement of various stakeholders completes the system's intricate architecture, fostering collaboration and shared insights within the dynamic realm of smoking cessation.

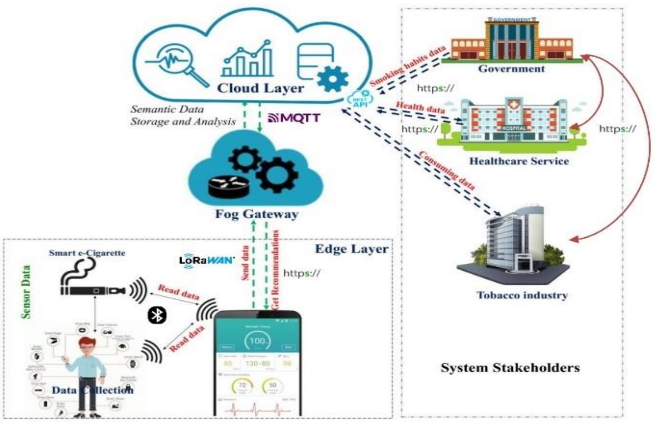

Fig. 1. Architecture of the system.

4.1 The smoker's device ecosystem

The smoker's device ecosystem comprises three key components:

Smartphone: the central hub for data aggregating and visualizing, it interacts with smokers, collects information from wearable devices and e-cigarette. It provides a user interface to access real information about smoking habits, vital signs and personal recommendations.

Wearable devices: including smart watches, smart rings and fitness tracking, these devices complement the e-cigarette by providing vital data constantly. Equipped with sensors, it provides measures such as heart rate, respiratory rate, blood pressure and sleep habits, etc.

Smart Connected e-cigarette: equipped with a set of sensors, this device collects detailed information about users' smoking behavior and contextual information. For example, Puff sensors track puff frequency, duration and intensity, while temperature sensors monitor e-liquid vaporization, etc.

4.2 The smart connected e-cigarette components

The design of the smart connected e-cigarette adopts the same principles of conventional e-cigarettes. A conventional e-cigarette operates in a simple mechanical way, consisting of a battery, atomizer and an e-liquid-filled cartridge. When the user launches it, either by inhalation or a button press, the battery powers the atomizer, which heats a coil within. This process vaporizes the e-liquid providing a satisfying experience for the vaper. By seamlessly integrating cutting-edge technologies, such as sensors and actuators, the new design preserves the simplicity of the conventional one while introducing advanced features. Figure 2 encapsulates the new e-cigarette design. Through the incorporation of sensors and actuators, it transforms into a dynamic entity, not only to deliver vape but also adapting its functionalities in real-time. This augmentation embodies the envisioned intelligence and connectivity within the system.

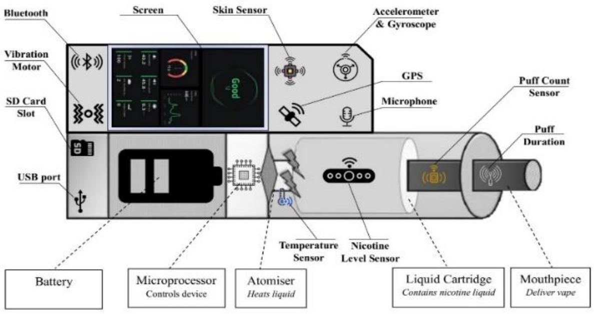

Fig. 2. Components of the Smart Connected E-Cigarette.

In order to design the smart connected e-cigarette, we have equipped it with a suite of cutting-edge technologies elevating its functionality to new heights. Here is a set of sensors that can be integrated:

- Puff Duration Sensor: measures the duration of each puff.
- Puff Count Sensor: counts the number of puffs taken, aiding in tracking usage patterns.
- Nicotine Level Sensor: measures concentration of nicotine in e-liquid.
- Temperature Sensor: monitors the temperature of the vapor to stay within safe levels.
- Accelerometer and Gyroscope: providing information on usage gestures and positioning.
- GPS Module: enables location tracking for context-aware health data.
- Bluetooth Module: facilitates wireless communication with smartphones.
- LED Display: provides a visual interface for users to view different information.
- Battery Voltage Sensor: monitors the battery voltage to ensure proper functioning.
- Microphone: captures ambient sounds like coughing.
- Skin Sensor: can be utilized to measure hand trembling or tremors or skin movements.
- Vibration Motor: Provides haptic feedback to the user, alerting them to events.
- SD Card Slot: provides a means for users to store and retrieve data locally.
- USB Port: can be used for charging the device, providing a convenient and widely adopted power source. It facilitates data transfer between the device and a computer.

To enhance the efficiency and power management of the smart e-cigarette system, it is imperative to restrict the continuous tracking of data to moments when it is deemed essential. Continuous monitoring can be resource-intensive, leading to unnecessary power consumption. In order to address this concern, various strategies can be implemented to manage and optimize the tracking process. These strategies aim to strike a balance between accurate monitoring and conserving energy. By adopting interval-based tracking, triggered tracking based on specific events, user-initiated tracking, or context-aware algorithms, the smart e-cigarette can dynamically adjust its monitoring frequency. These approaches not only contribute to a more power-efficient operation but also ensure that the device responds judiciously to user needs and environmental conditions. To manage and optimize the tracking process of the smart e-cigarette system, we proposed a context-aware algorithm.

***Algorithm 1**: Context-Aware Vital Sign Tracking*

```
Parameters:
  activity_threshold (float) = 0.5
  tracking_enabled (boolean) = False
  environmental_conditions (dictionary) = None
Procedure UpdateEnvironmentalConditions(conditions):
  environmental_conditions = conditions
Procedure UpdateActivityLevel(activity_level):
  if activity_level > activity_threshold:
      tracking_enabled = True
```

This algorithm seeks to check updates of environmental conditions and user activity levels. It checks whether vital sign tracking should be enabled based on the user's activity level and environmental conditions. And it uses a simple threshold-based approach where tracking is enabled if the activity level exceeds a predefined threshold.

4.3 Wearable Devices Worn by Smokers

Smokers use wearable devices that significantly contribute to the system's operations. By constantly monitoring their vital signs, these wearables allow smokers to increase their self-confidence by providing them with necessary information about their health. Figure 3 illustrates a smoker wearing wearable devices. For instance, a suite of sensors is deployed: a heart rate monitor for assessing cardiovascular health and blood pressure, an accelerometer for precise activity tracking and movement analysis, a pulse oximeter for monitoring blood oxygen saturation, a temperature sensor for detecting changes in body temperature, and an electrodermal activity sensor for comprehensive stress level assessment. Additionally, there are sensors like the galvanic skin response sensor for tremor detection, a respiration rate monitor and a GPS module for location tracking. Furthermore, the smartwatch features a sleep tracking sensors for monitoring sleep patterns and stages. The smartphone serves as the central hub, gathering all these information from sensors for further analysis and interpretation.

Fig. 3. Smoker wearing wearable devices.

4.4 The Internet of Things Model

The design of the smart connected e-cigarette is founded upon the conventional architecture of an IoT system, comprising three distinct layers: edge, fog, and cloud. This architecture strategically distributes data processing and management responsibilities across these layers, optimizing efficiency and scalability while enhancing the overall functioning of the e-cigarette.

Edge layer: incorporates smart e-cigarette, smartphone, and wearable devices, various sensors and actuators enable continuously monitoring of vital signs in real time. This layer conducts immediate data collection and minor processing, facilitating swift responses to user actions. Immediate feedback is provided to smokers regarding their vaping habits, including notifications and alerts for potentially harmful situations due to critical deviations in vital signs.

The fog layer: acts as a bridge between the edge and the cloud, it processes and aggregates multiple data streams efficiently. It conducts advanced analyses and it reduces data transmission to the cloud. Fog computing enables context-aware recommendations based on localized factors. This layer allows for complex analysis of smoking behavior patterns and uses semantic model to infer relationships between smoking parameters and health impacts.

The cloud layer: serves as the central hub for comprehensive data storage, advanced analytics, and reasoning. It collects data from multiple sources across different areas and securely stores smokers' RDF files with controlled access for stakeholders. Leveraging computational power, this layer conducts complex analyses, semantic reasoning, and personalized interventions. It provides insights into long-term trends, patterns, and correlations in smoking habits and health metrics. Advanced machine learning algorithms detect patterns, anomalies, and trends, developing predictive models for future smoking behaviours and analysing potential health implications over time.

In our context the communication and the flow of data from the smart e-cigarette and wearable devices by the smartphone through the fog to the cloud adheres to a structured process within the IoT architecture. This orchestrated flow, ensured by different communication protocols and standards, guarantees seamless transmission of information:

Bluetooth Low Energy (BLE) technology enables communication between the smart e-cigarette, wearable devices, and smartphones, ensuring efficient data exchange with minimal energy consumption. LoRaWAN protocol facilitates communication from edge to fog layer, optimizing long-range transmission of data securely and reliably. MQTT protocol orchestrates communication from fog to cloud layer, ensuring lightweight and efficient transmission of refined data for analysis and storage. For communication from cloud to edge through fog, a combination of MQTT and HTTP or CoAP protocols is recommended, tailored to the needs of edge devices. HTTPS and RESTful API architecture are employed for secure and standardized communication between cloud and stakeholders' systems. Additionally, communication between stockholders necessitates a secure and collaborative approach. Employing HTTPS ensures the confidentiality and integrity of the shared data. Facilitating communication between healthcare sector and government involves implementing the FHIR (Fast Healthcare Interoperability Resources) standard, promoting interoperability and seamless exchange of health-related information. For communication between the tobacco industry and government, HTTPS serves as the secure transmission protocol, coupled with adherence to industry standards and regulations to maintain data integrity. This multifaceted approach fosters a transparent and compliant flow of information, enabling collaboration and informed decision-making in the realm of smoking cessation.

4.5 The Semantic Web model

The Semantic Web enhances IoT-based smart e-cigarettes by improving interoperability and enabling seamless communication between devices. Standardized formats and protocols ensure compatibility across diverse systems. Semantic technologies allow machines to understand contextual relationships between data points, enhancing the system's ability to offer personalized interventions and recommendations by identifying triggers and patterns in users' behavior. The following section presents the ontology, the smoker's model and Semantic Web Rule Language (SWRL) rules, illustrating an inferential model to enrich the system's capabilities in deriving logical conclusions based on structured knowledge.

We've developed an ontology tailored for smart connected e-cigarettes, providing a structured framework for modelling functional data. This ontology facilitates understanding of elements like user profiles and smoking-related events. It forms the foundation for a context-aware system that analyses usage patterns, alerts, and offers personalized support to smokers. This approach fosters comprehensive and standardized intelligent data management in smoking behavior analysis and health surveillance. Figure 4 outlines the structure of the ontology, including the concepts, properties, and relationships that represent the domain knowledge.

Classes within an ontological framework serve as foundational elements, organizing entities into categories based on shared characteristics. This structured taxonomy enhances semantic clarity, fostering interoperability and knowledge sharing across systems and facilitating effective data management and reasoning processes. For example, the *Smoker* class provides a comprehensive representation of a smoker's characteristics, while the *WearableDevices* class encompasses smart wearables capturing diverse data streams.

Properties define relationships between classes and individuals, allowing for complex attributes representation. These relationships facilitate personalized recommendations and insights, contributing to better understanding of individual smoking behaviours and health patterns. For instance, *hasE-cigarette* linking smokers to specific e-cigarette models, and *hasWearable* connecting smokers to a wearable device that monitors vaping habits or health metrics. The semantic analysis engine can utilize these relationships to provide personalized recommendations and insights to the users, leading to better tobacco consumption control.

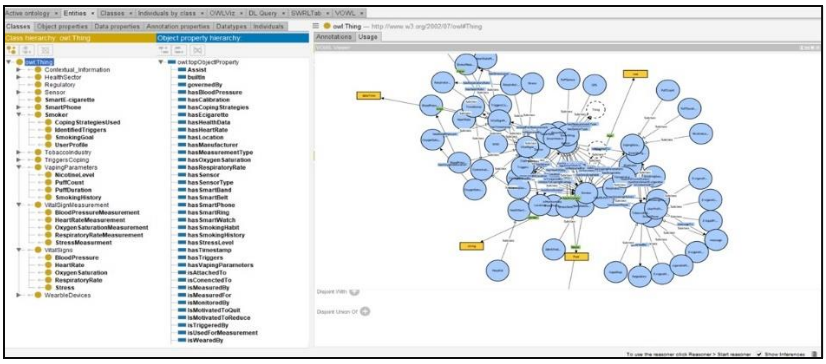

Fig. 4. Ontological Representation of Smart E-Cigarette Data Model

The semantic model of the smoker within the smart connected e-cigarette system serves as a robust repository, consolidating a wealth of knowledge pertaining to each individual user. Presented in the form of an RDF file, this model facilitates structured representation and seamless integration within the system, encompassing personal information, historical profiling, and real-time vital signs relayed by IoT sensors embedded within the e-cigarette. Moreover, the RDF files archive past system recommendations to present a whole view of the user's journey toward healthier habits, alongside records of user acceptance of system guidelines, indicative of engagement and adherence levels. Furthermore, these files incorporate contextual details such as lifestyle factors and environmental influences contributing to a holistic understanding of each user's profile. This structured representation empowers advanced reasoning and inference capabilities helping in discovering hidden smoking patterns and augmenting the system's capacity to deliver personalized interventions tailored to individual needs. These RDF files are securely stored in cloud storage, ensuring accessibility to various stakeholders for efficient utilization in comprehensive analysis and informed decision-making processes. Figure 5 represents the smoker RDF model.

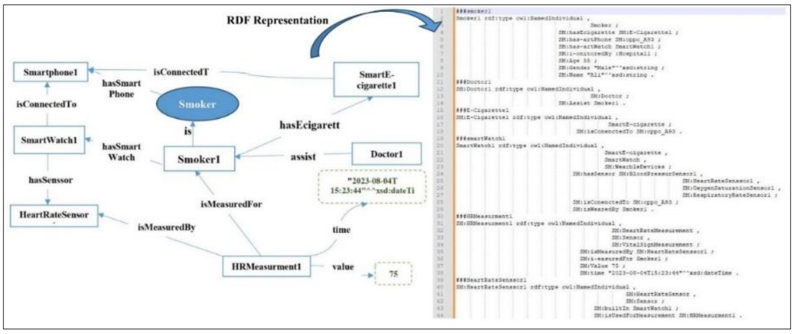

Fig. 5. The semantic model of the smoker and its representation with RDF

RDF representation of the smoker's model offers multiple advantages, including flexibility to adapt to new e-cigarette brands, standardization of measurement units, and comprehension of diverse data transmission protocols. These capabilities ensure uninterrupted health monitoring, facilitating personalized interventions even across international borders. Smoker's model emerges as a pivotal asset for healthcare professionals, allowing standardized data interpretation and fostering global collaboration in comprehending smoking patterns. By harnessing RDF's adaptability, healthcare providers can seamlessly navigate changes in usage preferences and maintain consistency in monitoring different metrics.

Semantic inferring, powered by structured ontologies and Semantic Web Rule Language (SWRL), plays an essential role in extracting meaningful insights from data within a smart connected e-cigarette system. By leveraging relationships and definitions encoded in ontologies, semantic inferring goes beyond surface-level analysis to identify patterns and crucial correlations between smoking data and vital sign measurements. This sophisticated analysis enables the system to make informed decisions, adapt to evolving user needs, and tailor personalized interventions, contributing to more intelligent and user-centric system. SWRL facilitates the formulation of complex rules within ontologies, allowing the system to deduce hidden insights and predict future health trajectories, ultimately empowering users with proactive and personalized support on their journey towards smoking cessation.

We have formulated a set of SWRL rules in consultation with medical professionals, leveraging their expertise and validation to ensure accuracy and effectiveness. This collaborative effort ensures that the rules adeptly capture and leverage crucial health-related information within the context of smoking behavior. To underscore the inherent intelligence embedded in these rules and to clarify the potential of our approach in revealing hidden insights, we have developed a comprehensive set of 50 SWRL rules as this example:

(hasHeartRate(?smoker, ?hr) ∧ swrlb:greaterThan(?hr, 80)) → (hasSmartE-cigarette(?smoker, ?e-cigarette) ∧ swrlb:greaterThan(?hr, 80)) :Smoker(?smoker) ∧ :SmartE-cigarette(?e-cigarette) -> swrl: make_ Recommendation (?smoker, "Consider reducing vaping while monitoring your heart rate.")

This rule suggests that if the smoker's heart rate is elevated, it might be a good idea to cut down smoking, as high heart rate could be associated with various health concerns.

The smart e-cigarette could provide a variety of personalized recommendations based on these inferring rules. These recommendations aren't solely explicit but also implicit, derived from newly discovered knowledge from the smoker's behavior. Such knowledge might remain undiscovered without the aid of this inference mechanism. These recommendations include: suggesting healthier timing for vaping during stressful hours, providing stress management techniques or guided breathing exercises in real-time, sending moderation alerts as users approach their daily puff limit, advising on sleep to avoid late-night vaping, offering tailored support by gradually decreasing nicotine levels, connecting users with health professionals if deviations in vital signs are detected, providing location-specific recommendations to halt vaping in designated non-smoking zones, and incorporating gamification elements to make the process of reducing smoking more and motivating. These personalized recommendations aim to support users in making healthier choices and achieving their smoking cessation goals.

4.6 Bridging Health Belief Model Principles with Smart E-Cigarette

We are confident that aligning with the Health Belief Model principles, the envisioned smart connected e-cigarette will significantly contribute to smoking cessation efforts. In our context, the HBM suggests that smokers are more inclined to take care of their health when they perceive a threat or danger to their health according to their vital signs. It acknowledges the potential health risks associated with excessive vaping, monitored through vital signs and contextual data. By offering health-related recommendations, we address the perceived severity of these risks, emphasizing the importance of healthier alternatives and aligning with perceived benefits of adopting healthier behaviours. Real-time alerts, location-based tips, and personalized interventions serve as cues to action, prompting behavior modification in response to health-related cues. Our approach tailors recommendations based on smokers' profile and vital signs data to optimize the effectiveness of health interventions.

Quantifying this model to predict the behavior of a smoker based on vital signs requires a multifaceted approach. The desired model would integrate variables representing the vital signs and potentially other factors. Since human behavior is complex in nature and the physiological state is determined according to the response factors for smoking, this model will be made of probability rather than determinism. Let's consider a simplified model based on physiological vital signs commonly associated with smoking and its immediate effects: blood oxygen levels (O_2), blood pressure (BP) and heart rate (HR). These are measurable indications that can reflect the state of danger. Here's a formula to illustrate the proposed concept: smokers will decrease consumption in response to a deviation in their vital signs.

$$P(S|R) = 1 / (1 + e^{(-z)}) \tag{1}$$

Equation (1) represents the logistic regression equation, commonly used to model the probability of an event (S) occurring given another event (R) has already happened. This formula introduces the concept of a smokers' reduction or cessation probability based on a perceived danger from their vital signs. When R increases (vital signs are deviating from safe levels), P(S|R), the probability of cessation, goes up. Here's a breakdown of the terms:

- P(S|R): This represents the conditional probability of event S happening.
- 1 / (1 + e^(-z)): This is the logistic function, also known as the sigmoid function, compresses any real number input into a value between 0 and 1, representing a probability.
- e: This is the base of the natural logarithm (approximately 2.718).
- 1: This is added to ensure the function never outputs exactly 0.
- z: This is the linear combination of weighted features associated with events.

$$z=w1^* (O2)^2+w2^* (BP)^2+w3^* (HR)^2 \tag{2}$$

w1, w2, and w3 represent the weight of each vital sign's impact on the likelihood of cessation:

O_2 (w1=0.5), BP(w2=0.3) and HR (w3=0.2)

We have defined the baseline ranges and danger zones for the three vital signs: Blood Oxygen Level: [Normal: 100%; Danger Zone: 85%], Blood Pressure : [Normal : 120/80 mmHg; Danger Zone: 180/120 mmHg] and Heart Rate: [Normal: 60 beats per minute (bpm); Danger Zone: 200 bpm]

The model uses the raw values of the vital signs as features. However, we have to normalize them before feeding them into the model. Normalized O_2: (O2-100)/(85-100); Normalized BP: (BP-120)/(180-120) and Normalized HR: (HR-60)/(200-60)

In the predictive modelling process, a threshold of 0.55 has been established to determine binary predictions based on the conditional probability P(S=1|R). If P(S=1|R) >= 0.55, the model assigns 1 (the smoker will reduce smoking.). Else, the model assigns 0 (the smoker will not reduce smoking.).

5. Materials and Methods

In the context of advancing technology and health, innovative solutions like smart connected e-cigarettes offer promise for addressing critical issues such as smoking cessation. This study aims to explore smokers' perceptions, attitudes, and expectations regarding the use of smart connected e-cigarette through a qualitative data analysis. Additionally, a quantitative experiment tests the effectiveness of a prediction approach based on the health belief model (HBM). Integrating qualitative perspectives and quantitative analyses aims to provide a comprehensive understanding of factors influencing smoking behavior and inform future developments in the field of smoking cessation interventions. To assess the adoption of intelligent connected e-cigarettes, a detailed survey was developed, covering demographic information, smoking habits, awareness and familiarity with e-cigarettes and wearable devices, acceptance of technology, and potential adoption of smart e-cigarettes.

5.1 Data Collection

The survey was conducted using Google Forms, and data collection took place from August 1, 2023 to September 1, 2023. The survey link was distributed through different social networks. This allowed us to gather responses from a wide range of smokers, thus enhancing the representativeness of the collected data. Table 2 presents a selection of gathered responses from participants, providing a snapshot of their insights and perspectives.

Table 2. Participants' answers

Questions	**Answers**			
	Male : 97	*Female* :14		
Age	*18-25*	*25-35*	*35-50*	*>50*
	42	41	27	1
Main reasons why you might choose to use e-cigarettes?	*Quit smoking:* 55	*Curiosity:* *33*	*Prefer flavour:* *53*	*Social influence: 14*
How many times do you use e-cigarettes per week?	*Daily*	*A few times a week*	*From time to time*	*Rarely*
	50	30	22	09
Do you use a smartwatch?	Yes	No		
	64	47		
How do you find the idea of monitoring your health using a smartphone?	*Very Helpful*	*Fairly useful*	*Not useful*	*Not useful at all*
	45	60	4	2
Do you monitor any of the following vital signs regularly?	*Heart rate*	*Blood pressure*	*Respiratory rate*	*Oxygen saturation*
	55	54	25	56
How do you find the idea of making your e-cigarette a smart cigarette connected to your phone?	*Very Innovative Idea*	*Good Idea*	*Ordinary Idea*	*Useless*
	55	41	9	6
What features do you think a smart e-cigarette should have to help you reduce smoking consumption?	*Link consumption to vital signs*	*Health guidelines based on vital signs*	*Notifications to reduce smoking*	*Check statistics on mobile*
	67	84	55	81
If your e-cigarette recorded unusual vital signs and suggested to stop smoking immediately, how would you react?	*I stop immediately*	*I stop and call the doctor immediately*	*Continue smoking then call doctor*	*Ignore warning & keep smoking*
	30	58	17	6
Suppose you entered a hall and you received a notification on your phone stating, "*You cannot use the cigarette,*	*I accept it and feel satisfied with the smart e-cigarette*	*I accept it, but I keep thinking about smoking*	*I don't accept it and stay in the hall*	*I quickly leave the hall and turn on the*

you are in a no-smoking zone." What would you do?				*cigarette to smoke*
	75	23	4	9
Which of the following vital signs influences your decision to immediately cease smoking?	Increase in heart rate	Decreased oxygen saturation	Elevated blood pressure	
	28	53	30	
If you are interested in reducing or regulating consumption, what factors motivate you most?	*Improved my vital signs and overall health*	*Concern about potential long-term health risks*	*Save money by reducing the use of e-cigarettes*	*Professional help such as cessation programs*
	37	92	57	39

5.2 Methods

5.2.1 The qualitative study

In this study we aimed to investigate the potential relationships between smokers' familiarity with measuring vital signs, ownership of smartwatches, and their potential acceptance of smart e-cigarette recommendations. Accepting the recommendations could engage smokers to accept the smoking cessation program and could increase the chances of successfully reducing and eventually quitting tobacco use. To achieve this, we formulated two hypotheses and employed the chi-squared test to determine whether the collected data supports rejecting the null hypothesis in favour of the alternative hypothesis.

Null Hypothesis (H0): *There is no significant relationship between smokers' familiarity with measuring vital signs, ownership of smartwatch, and acceptance of smart e-cigarette recommendations*.

Alternative Hypothesis (H1): *There is a significant relationship between smokers' familiarity with measuring vital signs, ownership of smartwatch, and acceptance of smart e-cigarette recommendations*.

Due to the nature of the research and data, we have chosen the Chi-Square test for the analysis. It has been specifically designed to analyze the relationships between categorical variables. Variables we are working with are categorical in nature: Familiarity with measuring vital signs, ownership of smartwatches, and acceptance of smart e-cigarette recommendations are all discrete categories that can't be meaningfully quantified on a numerical scale. Measuring vital signs can encompass the use of personal wearable devices, medical tools, or any equipment commonly found in healthcare field. Variable 1: Smokers' familiarity with measuring vital signs (Yes/No) and Variable 2: Ownership of a smartwatch (Yes/No). The Outcome: Acceptance of smart e-cigarette recommendations (Yes/No).

We then defined four groups based on the combinations of the two variables:

(1) Smokers familiar with measuring vital signs and familiar with smartwatches; (2) Smokers familiar with measuring vital signs but not familiar with smartwatches; (3) Smokers not familiar with measuring vital signs but familiar with smartwatches and (4) Smokers not familiar with measuring vital signs and not familiar with smartwatches

In this experiment, we seek to gauge the likelihood of acceptance of the smart e-cigarette recommendations. To address this inquiry effectively, we posed to participants the following question: "*Imagine your e-cigarette detected a notably low oxygen saturation (SpO2), and advised you to immediately stop smoking. How would you respond to such a situation*?". The acceptance and rejection rate are presented in table 3.

Table 3. Acceptance and rejection rate of Recommendations

Smokers' state	**Accept Recommendation**	**Reject Recommendation**	**Total**
Familiar with smartwatches (FS)	52	12	64
Not familiar with smartwatches (NFS)	25	22	47
Familiar with measuring vital signs (FVS)	57	16	73
Not familiar with measuring vital signs (NFVS)	21	17	38

5.2.2 The quantitative study

In this quantitative study, our primary objective is to validate the efficacy of the predictive model previously introduced (Please see section 4.6) and to quantify the likelihood of smokers' cessation based on their vital signs' measurements, leveraging the HBM framework. For this end, we developed a dedicated web page where participants are invited to make a definitive decision on smoking cessation or continuation, according to their vital signs—O_2, BP, and HR. Each participant received three randomly assigned values for these vital signs and was prompted to make a decision accordingly. Subsequently, participants provided their chosen decision along with the corresponding vital sign values. Following data cleaning and the exclusion of incomplete entries, a total of 32 participants took part.

Concurrently, we sought expert input by inviting a doctor to evaluate the same set of vital sign values for the 32 participants and render decisions on smoking cessation. We applied then the predictive model to calculate cessation predictions for each participant. Our analysis involves comparing the outcomes derived from the participants and the doctor's assessments with those predicted by the model. In order to make the comparison, we have employed the Confusion Matrix and the Receiver Operating Characteristic (ROC) curve. Table 4 presents a comprehensive summary of responses from 32 participants, juxtaposed with evaluations from both the doctor and predictions derived from our model. Where in Smokers' decisions a value of 1 indicates "Yes, I will reduce smoking," while a value of 0 indicating "No, I will not." Similarly, within the doctor's decision framework, a value of 1 signifies "Immediate Cessation Urged,", whereas a value of 0 signifies "Moderate Advice to Quit,".

Table 4. Participant Responses and Doctor Evaluations VS. Model Predictions for Smoking Cessation Likelihood.

					Prediction of the model		
O2 %	**BP**	**HR**	**Smokers' Decisions**	**Doctor's Decision**	**Z**	**P(S|R)**	**Model decision**
97	135	145	1	0	0.11247449	0.754867785	1
92	120	60	1	1	0.142222222	0.805686554	1
94	135	155	0	1	0.190841837	0.870841355	1
94	135	160	1	1	0.200790816	0.881624887	1
98	130	70	0	0	0.01824263	0.545480516	0
100	120	60	0	0	0	0.5	0
93	140	140	1	1	0.207528345	0.888477548	1
99	120	70	1	0	0.00324263	0.508105866	0
94	160	115	1	1	0.24420068	0.919974955	1
92	150	115	0	1	0.248089569	0.922791638	1
95	165	125	1	1	0.2674178	0.935485643	1
95	148	110	1	0	0.146399093	0.812142318	1
99	120	65	0	0	0.002477324	0.506192994	0
96	155	175	1	1	0.272587868	0.938536525	1
90	145	90	1	1	0.283489229	0.944532472	1
93	150	160	0	1	0.285929705	0.945797274	1
90	155	85	1	1	0.330683107	0.964662414	1
88	145	90	0	1	0.381267007	0.978388264	1
91	160	150	1	1	0.395986395	0.981290992	1
99	125	95	0	0	0.016805556	0.541915285	0
88	135	145	0	1	0.41247449	0.984089615	1
88	145	140	1	1	0.437389456	0.98755477	1
100	120	60	0	0	0	0.5	0
85	120	60	1	1	0.5	0.993307149	1
85	140	135	1	1	0.590731293	0.997287891	1
99	125	95	1	1	0.016805556	0.541915285	0
85	125	175	0	1	0.637032313	0.998291319	1
86	160	170	1	1	0.692358277	0.999016671	1
99	123	60	0	0	0.002972222	0.507430009	0
85	170	200	1	1	0.908333333	0.99988647	1
85	180	200	0	1	1	0.999954602	1
100	120	100	0	0	0.016326531	0.540725902	0

5.3 Results and Interpretation

After constructing a contingency table that cross-tabulated the variables, we applied the Chi-Square test to calculate the expected frequencies for each cell, assuming that there is no relationship between the variables. The test then calculated the Chi-squared statistics on the basis of the frequencies observed and expected. By comparing the value of the calculated Chi-square with the critical value of the distribution of the Chi-square, we have determined whether the relationship between the variables was statistically significant. We got these results:

The *p-value* equals 0.003306, ($p(x \leq \chi^2) = 0.9967$). The test statistic χ^2 equals 13.7242, which is not in the 95% region of acceptance: [$-\infty$: 7.8147]. The observed effect size *phi* is medium, 0.35. *Cramer's V* effect size is 0.35. Since p-value < α, it is then concluded that the null hypothesis is rejected in favour of the alternative hypothesis (H_1) and a significant association was found between variables. Consequently, our analysis provides solid evidence of a significant relationship between the examined variables. The assertion implies that smokers who monitor their vital signs and familiar with using wearable devices are inclined to be more receptive to the smart connected e-cigarette recommendations, unlike smokers without these options. This increased receptivity could potentially pave the way for a greater probability of adopting smart e-cigarettes as a means of restricting and possibly reducing smoking habits.

The Confusion Matrix serves as an essential tool for assessing predictive model effectiveness, capturing essential elements like True Positives, False Positives, False Negatives, and True Negatives. Key performance indicators including Precision, Sensitivity, Specificity, and Accuracy are commonly derived from the Confusion Matrix, offering a comprehensive evaluation of the model's predictive capabilities across positive and negative outcomes. These metrics, along with others, are detailed in table 5.

Table 5. Metrics of the Confusion Matrix

Analysis results	**Model vs. Smokers**	**Model vs. Doctor**
Metrics	TP =16; FP = 07; FN = 02; TN = 07	TP =21; FP = 02; FN = 01; TN = 08
Accuracy	0.7188	0.9063
Precision	0.6957	0.913
Recall	0.8889	0.9545
F1 score	0.7805	0.9333
True positive rate (sensitivity)	0.8889	0.9545
False negative rate	0.1111	0.04545
False positive rate	0.5	0.2
True negative rate (specificity)	0.5	0.8

Drawing insights from the comprehensive analysis presented in table 5, where we juxtaposed the predictive model's decisions on smoking cessation against both the decisions of smokers and those of the doctor, notable conclusions emerge:

- Accuracy: indicates that roughly 71.88% of the model's predictions aligned with the actual decisions made by the smokers and 90.63% made by the doctor.
- Precision: Both models have high precision (0.6957 for smokers, 0.913 for doctor), indicating the model tends to correctly identify individuals who will actually quit smoking when it predicts them to quit.
- Recall: The high recall scores for both doctor (0.9545) and smokers (0.8889) imply that the model accurately predicted smoking cessation compared to instances where smokers actually quit. This suggests a robust capability of the model to correctly identify and classify instances of smoking cessation, whether it involves doctor or smokers themselves.
- Specificity: The model exhibits higher specificity for doctors (0.8) compared to smokers (0.5). This suggests the model's proficiency in accurately identifying instances where doctors correctly predicted smokers would not quit. However, its performance is fair robust in recognizing situations where smokers appropriately chose not to quit, even if the model incorrectly suggested otherwise, highlighting accurate predictive accuracy.
- Sensitivity: The model's sensitivity is similar for both smokers (0.8889) and doctor (0.9545). This means the model has a similar ability to identify individuals who will actually quit when predicted to do so for both groups.
- F1 Score: achieving a high F1 score of 0.9333 for doctor and 0.7805 for smokers. These scores indicate a

strong balance between precision and recall for both groups.

The model's predictions, based on vital signs, show higher accuracy in predicting smokers' cessation. The model exhibits precision and balance in identifying positive and negative predictions. Doctors may have access to more comprehensive information, leading to more accurate predictions, while smokers' decisions to quit may be influenced by various external factors. Figure 6, presents visualisation of Confusion Matrix Metrics.

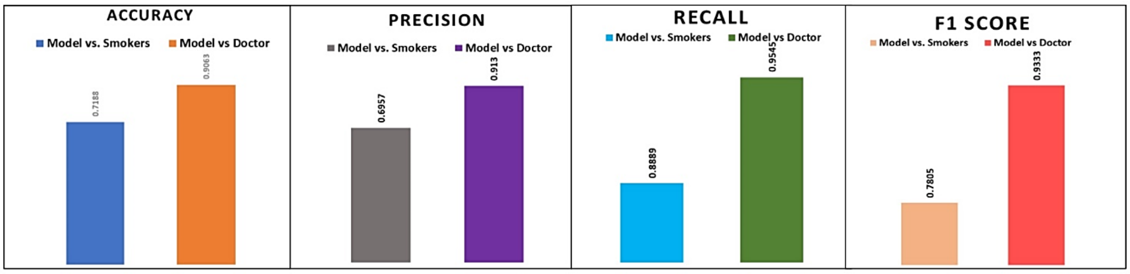

Fig. 6. Confusion Matrix Metrics.

The AUC (Area Under the Curve) is a metric commonly used to evaluate the performance of a binary classification model, such as one predicting smoking cessation decisions. An AUC score ranges from 0 to 1, with a higher score indicating better discrimination between positive and negative cases. A score of 0.737 for smokers and a score of 0.901 of doctor suggests that the model's ability to distinguish between positive and negative smoking cessation decisions among smokers is high. The AUC values provide insights into the model's effectiveness in correctly ranking individuals in terms of their likelihood to quit smoking based on vital signs. Figure 7, presents the ROC Curve Analysis for both cases.

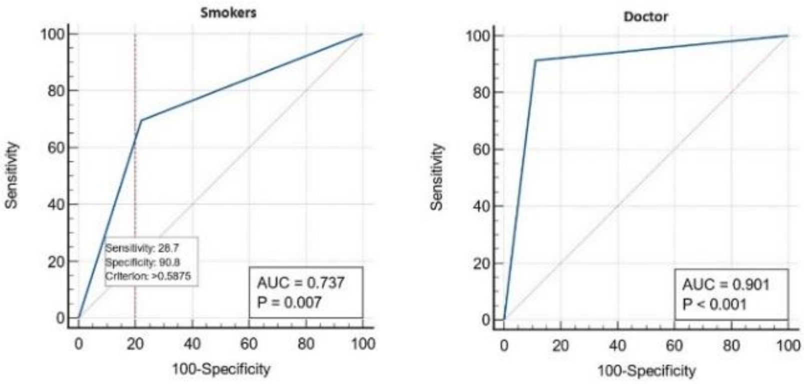

Fig. 7. ROC Curve Analysis: Sensitivity vs. Specificity

5.4 Discussion

The findings confirm a convincing connection, clarify the relation between individuals' awareness of physiological indicators and the distinctive consequences of smoking. This good understanding contributes valuable insights into the intricate dynamics that shape smokers' health perceptions and behaviours, emphasizing the pivotal role played by self-awareness and technological interventions in the context of smoking-related health outcomes. Furthermore, our predictive model, designed around vital signs, exhibits superior accuracy in predicting smoking cessation compared to doctor’s opinion, indicating the potential effectiveness of our approach. Aligned with the foundational principles of the Health Belief Model, the approach holds promise as an innovative and personalized strategy for smoking cessation interventions. Based on results and the survey findings, we have been able to draw the following conclusions:

Smokers are enthusiastic about integrating IoT technologies into e-cigarettes, viewing it as a potential game-changer in smoking cessation methods. This excitement reflects a desire to utilize technology to enhance the vaping experience and promote better health outcomes. Those already familiar with monitoring vital signs show a strong inclination towards accepting smart e-cigarette recommendations, suggesting a synergy between health-conscious behavior and technology. Even smokers who monitor their health at medical centres are receptive to smart e-cigarette recommendations due to their proactive approach to health preservation. Smokers tend to respond to abnormal vital signs as a natural self-preservation instinct, indicating a strong link between health awareness and quitting behavior. However, young smokers with a tech-oriented mindset may resist recommendations due to various factors such as perceived invincibility and societal influences. Overall, there is a substantial desire among smokers for personalized health advice based on their vital signs and smoking habits, highlighting the potential for technology-driven cessation strategies to promote healthier behaviours. This insight highlights the potential of smart e-cigarettes and data-driven interventions to encourage positive health decisions among smokers.

5.5. Addressing threats to validity

Addressing threats to validity is paramount in the successful implementation of the smart connected e-cigarette system. Here are some possible threats to consider: Internal validity is crucial to ensure the accuracy of data collected from IoT devices and vital signs sensors, while external validity requires careful consideration to generalize recommendations across diverse user populations. Construct validity involves defining system constructs accurately, while selection bias must be minimized to ensure the system's applicability to the target user population. Ethical considerations regarding data privacy, and user autonomy must be addressed, along with ensuring user engagement and compliance for the system's effectiveness. Over-reliance on technology and the potential for system downtime also present challenges, along with the need to assess the long-term effectiveness of the system in reducing tobacco consumption. The implementation of data quality control, taking into account the involvement of various user during the development and test phases can improve the generalization of the system. In addition, collaboration with health and industry can help guarantee the validity of the system and promote responsible tobacco cessation strategies.

6. Conclusion and Future Work

In conclusion, this paper presents an innovative approach that integrates Semantic IoT technologies and vital signs monitoring to develop a smart connected e-cigarette tailored for reducing tobacco consumption. Emphasizing the significance of vital signs in monitoring health during smoking, the paper discusses the IoT architectural framework of the proposed system, highlighting its efficiency and scalability. It outlines the design of the smart connected e-cigarette, incorporating a variety of sensors and wearable devices to enhance data sharing and user engagement. A semantic modelling framework, including an ontology SWRL rules, and a semantic representation of smokers' model contributes to intelligent data analysis and personalized intervention. Additionally, a predictive model aligned with the Health Belief Model is presented to theorize the impact of the system on users' beliefs and behaviours related to smoking cessation. The paper concludes with an experimental study validating the technical feasibility of the e-cigarette and exploring its acceptance among smokers. Furthermore, it demonstrated notable success in anticipating smoking cessation when smokers were informed of a deviation in their vital signs' indicators. Future research includes conducting real-world validation studies, refining triggers for smoking behavior, monitoring long-term effects on users' habits and health, and developing AI-based algorithms for personalized interventions. Ensuring data privacy, and incorporating gamification design are also important.

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