Cognitive Computing Integrated Methodology For Smart Decision Making And Problem-Solving

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Research Article

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Cognitive computing integrated methodology for smart decision making and problem-solving

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Abstract:

Cognitive computing is the field of intelligent computational study that imitates the brain process for computational intelligence. Decision-making is part of the cognitive process in which opportunities based on certain criteria are selected for a course of action. The choice is generally made using the intelligent assistance system that can turn human decision-making into Artificial Intelligence, system engineering, machine learning approaches. Many complicated real-world problems have been solved by the desire to replicate human intelligence into robots and progress in artificial intelligent technologies. Autonomous systems with machine cognition continuously develop by using enormous data volume and processing power. The cognitive computing system uses skill and awareness derived from knowledge and intelligent decision-making. In this paper, the cognitive computing-based human speech recognition framework (CC-HSRF) takes advantage of next-generation technologies to assist smart decision-making effectively. The proposed methods overview cognitive calculation and its historical perspectives, followed by several strategies to implement algorithms for intelligent decision-making using machine learning. Methods for effective knowledge processing are explored based on cognitive computing models such as Object-Attribute-Relation (OAR). It offers visual and cognitive analytics information, highlighting the framework of conceptual vision and its difficulties. This framework aims to increase the quality of artificial intelligent decision-making based on human perceptions, comprehensions, and actions to reduce business mistakes in the real world and ensure right, accurate, informed, and timely human decisions.

Index: cognitive computing, decision-making, Object-Attribute-Relation (OAR), human speech recognition

1. Introduction of cognitive computing framework for smart decision:

The human brain has the multifaceted features to make choices and act based on the situation [1]. Imagine a system with the same functions as the human brain, called cognitive computing [2]. In this field, scientists and researchers strive to create a computer that can think, act and relate the situation emotionally [3]. However, they can achieve the feat in certain systems technically described as artificial intelligence, which can conduct activities such as the human brain [4]. Further computation of the cognitive system can be termed an interdisciplinary approach that has its artificial intelligence, psychology, philosophy, and language representation to imitate the human brain so computational intelligence can be implemented through cognitive inference and perception [5]. Cognitive computing develops by discovering knowledge that recognizes information that is possibly beneficial from different media based on application needs [6]. Then humans have the development of interdisciplinary named cognitive science on information production and the transcription into the brain of areas such as informatics, cognitive neuroscience, psychology, linguistics, etc. [7,8]. Big data is another leap in data processing, consideringdata properties such as speed, variety, and volume [9]. In cognitive computing, intelligence depends on the data and recognizes the potential for data to reach the computer's intelligence [10].

Decision-making is a fundamental human process at the basis of our global connection [11]. Users know that individuals make excellent decisions and poor decisions, and academics argue the most effective means of helping people make good decisions [12]. An approach to characterizing decisions that help them is to classify choices as organized, semi-structured, or unstructured [13]. Structured choice issues have an optimum solution and hence do not require help for decisions [14]. For example, an analytically accurate answer can solve a choice on the shortest route between two places [15]. No accepted criteria or solutions are found to the unstructured decision issues and rely on the decision-makers choices [16]. For example, it could be regarded as an unstructured decision to decide one's mate. In between these two difficulties, a large range of semi-structured issues typically have some accepted parameters and yet need human inspiration or preference for a decision with certain requirements [17]. For example, the corporation could decide half-structured whether to expand its operation into worldwide markets.

Cognition is the cognitive process of information receipt, storage, development, transformation, and recovery [18]. These are related to the functions of the human brain's perception, attention, and memory [19]. The need for avital architectures to handle such complex agent-based systems gives human mind-like talents with the continual growth of agent concepts in the contemporary era of smart systems [20]. In the field of cognitive artificial, starting with this current state of the artwork, it is important to focus on the fact that a single analysis must be done urgently to build a human-like feeling, understanding, and acting utilizing Cognitive Computing technology. Innovative design growth should be promoted, which leads to significant advancement of specific cognitive agents capable of serving in an unpredictable environment. This paper provides an architecture aimed at creating an artificial system based on cognitive computing systems and cognitive agent systems that can handle and link real-world facts and assimilate them with the know-how to address human difficulties.

The main contribution of the cognitive computing integrated framework is given below,

- To evaluate existing visual development works in the comparative state of the art, focusing on their benefits and constraints to enhance the proposed CC-HSRF design.
- They address human-like functions and their need for improved perception in a cognitive design, premeditated knowledge processing, and higher cognition and metacognition for better action and execution.
- The proposed CC-HSRF architecture removes the problems of existing architectural frameworks in a cognitive system.

In [21], Smart Personal Assistants allow people to engage more naturally and sophisticatedly with computers that were previously not feasible. Even while research in SPA technology (SPAT) in education was expanding, there is limited empirical proof for its capacity to give the ability to increase the ability of pupils to resolve problems dynamically. This article aims to determine if students can absorb and use self-contact problem solving processes through interactions with SPA technology in their 10th-grade secondary. The findings give first empirical proof of the usefulness of employing SPA technology to develop skills in general and for the development of problems in particular. In [22], The study priority was given to the essential factors of intelligent lockers with a simulated annealing-genetic algorithm through fractional factorial design (FFD-SAGA) and grey connection analysis. The major users of intelligent lockers were examined through a grey analysis of several attributes of decision. The results suggest that the concatenation and the money flow provider of the Web Application Programming Interface (API) is the major success element of intelligent lockers.

In [23], It examines the problem of rapid automatic decision-making, including human-robot collaboration, mass customization, and the requirement to modify operations quickly to new conditions in changing manufacturing setting surroundings. The strategy is to adapt the Monte Carlo Tree Search (MCTS) algorithm to give the machinery and workers online dynamically intertwined choices in response to changing production conditions. In [24], Cognitive methods divide complex problems into separate parts that can gradually handle lower data interfaces, all the way to sensors and actuators. Although autonomous decision-making has improved, certain important problems remain unresolved. One of the problems is identifying, coordinating, and deciding on the various specialist activities needed to achieve the mission goals. This paper deals with the decision-making of the cognitive aircraft architecture, which was termed Aerial Robotics Cognitive Architecture (ARCog). The system is designed for decision-making at a high level.

In [25], People decide and take everyday measures to better their livelihoods and turn more to the Artificial intelligence Approach (AIA) to help them decide. Such developments indicate how AI and other cognitive technologies impact the co-creation of value. An integrated paradigm, founded upon the logic of service and theory of nudge, conceptualizes smart leaping as the application of cognitive technology to predictably impact human behavior without restricting their decisions or changing their incentives.

The remainder of the CC-HSRF study can be organized accordingly. In section 2 summarize the proposed work that has been utilized in this paper. The numerical outcomes and discussion are described in section 3. Finally, section 4 concludes CC-HSRF with a detailed discussion of the observation and results.

2. Proposed cognitive computing-based human speech recognition framework for smart decision-making:

Cognitive computing captures human thoughts. It increases the technologies used by the users themselves. Cognitive technologies can actively interpret such language and react to data gathered from the exchanges in natural languages. They can detect objects, such as human faces. Enhance organizational agility by using extremely complicated and massive amounts of unstructured data—improved quality of service by decreasing human mistakes, intelligent insights, and fewer downtimes. Effective monitoring, fraud detection, and predictive analytics ensure increased data security and compliance.

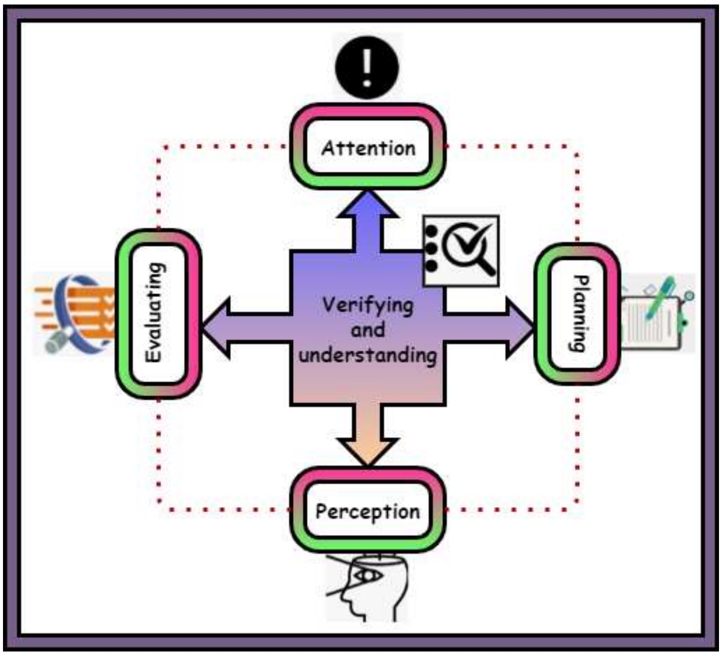

Fig 1:Fundamental of cognitive computing (CC)

Fig 1 shows the fundamentals of cognitive computing (CC).It consists of six cognitive elements connected to understanding, verifying, planning, evaluating, paying attention, and perceiving. Anyone can serve in a certain cognitive task as a starting point or an aim. The system selects a simple or complicated interaction path, depending on the information necessary to engage with the outside environment to achieve the objective of cognition. Usually, the selective attention from the down-top is focused on the plan, whereas attention from the top to bottom mostly depends on perception. Evaluation based on planning or understanding is the previous chance, whereas perception-based evaluation is the subsequent possibility. In general, the CC process always involves an external environment based on the information necessary for objective tasks to be carried out. Cognitive activities start gradually instead of focusing on knowledge processing. An intelligent system is conceived to execute the cycle in the face of problems, including lack of preparation and without a probability of attaining the proposed goal. Instead, the CC process should incorporate verifications with what to do next? Has the desired result been achieved? Or do I try other techniques or do more? In this process, environmental awareness and leadership are increased based on reasoning and experience, enhancing veracity.

The above CC includes the creation of a causal model for explaining and understanding reality. The combined analysis is based on an assessment of probabilities of the data and the imagination or prediction based on time and space, provides an understanding, supplementation, and evaluation of environments or situations by using the causal model to update the previous probability to a prior possibility (the observation). Planning action sequences improve future incentives, and advanced knowledge is used to increase reasoning of little facts for outstanding generalization and rapid learning capacity.

A statistical approach to the patterns classification problem is Bayesian theory. The statistical systems utilize this method to measure the processes in decision-making using their probabilities and costs. The choice function S_t is termed the decision rule in this theory. A loss function $Loss_f$ is utilized to analyze the consequences of actions in equation (1),

$$Loss_f = \alpha \times G \rightarrow (M + S_t) \qquad (1)$$

As shown in equation (1), α is the set of potential natural states, G is the set of behaviors, the M is the Cartesian method of choice.The choice of decision making can be determined by utilizing the loss function,

$$\begin{aligned} R &= \{h|K[z(\mu,\beta)]\} \\ &= MIN\ a \in H[K(\mu,a)] \qquad (2) \end{aligned}$$

As shown in equation (2),Where $H[K(\mu,a)]$ is the anticipated risk for loss of action a on $z(\mu,\beta)$. Despite the difference in the performance of the Bayesian theory, the loss in Bayes' theory corresponds to the negative utility of cognitive psychology. It is utilized to optimize the decision-making process. The decision-makers who expect an optimal decision can utilize the theory of utility. In contrast, the decision-makers who desire conservative decision-making can use the theory of loss or risk for decision-making.

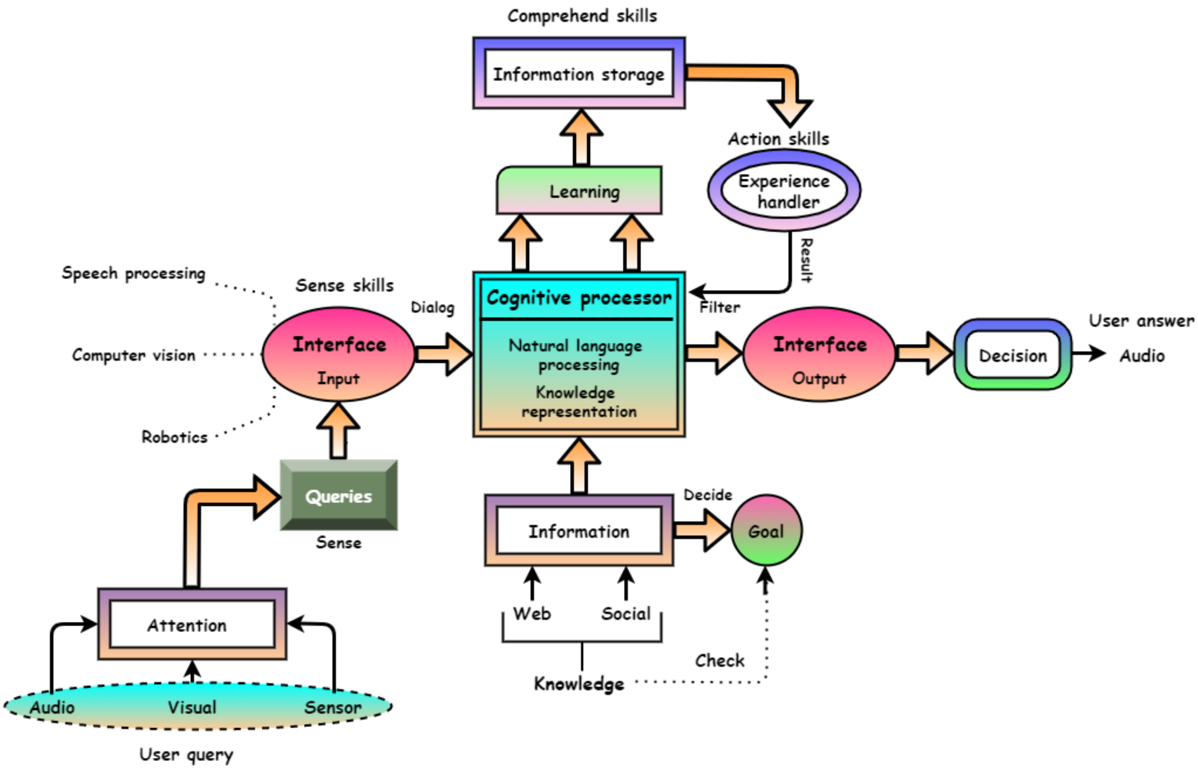

Fig 2: Proposed cognitive computing-based human speech recognition framework for smart decision-making

Fig 2 shows the proposed cognitive computing-based human speech recognition framework for smart decision-making. Cognitive data management in the architecture, executing three skills, sensors, understanders, actions. The perception of the audio, visual, sensor and textual information depends on attention. The abilities of understanding enhance teacher, web, and social information. The abilities of action provide plans and models for information. The optimal plan/model is picked to achieve the aim. Cognitive information technology (CIT) handles question data instructions, statements, pictures, and sensor details.

The input interface is a dialogue information system are computer vision, audio processing, sensor processing. In the information storage system, the cognitive processor uses natural language and images. Experience Handler collects information from experience and produces results. Cognitive processors deliver the best information and filtered results to accomplish the goal. CIT refreshes the stored experience to enhance its future performance via Feedback Information. To create and store information on the semantic web and networks and reason with particular rules or models using the inference engine. In this way, it will be better to combine cognitive computing with agent technology in one system than prior humanoid systems to resolving real-world problems. The cognitive agents' main objective is to develop and detect experience-based knowledge in a certain state framework and help with experts' decision-making in their respective fields. The next step is to take environmental action.

Decision-making is a cognitive activity of a high level, depending on cognitive processes such as perception, learning, and memory. In real-life circumstances, several decisions need to be taken, and each decision is based on prior feedback from an environment that could be changing. The decision-making process is a cognitive process leading to a choice of path or faith from several possibilities. It can be viewed as a specific form of problem-solving; it is considered solved if an acceptable solution is found. Many researchers have thought that cognitive agents and specialized systems are similar because these two things comprise the essential component. The main difference is how the database is generated and used. Expert systems utilize pre-programmed rule logic in all circumstances, whereas cognitive agents are more like humans who have previous experiences. According to human research goals, it is vital to obtain accurate outcomes and get particular perspectives.

A General $B_{n(anm)}$ model for a cognitive agent specifies that it is the dynamic series of models (K_0) developed by using various prototypes of cognitive computing ω_m.

$$B_{n(anm)} = \sum_{m=1}^{N} \omega_m \,(K_0), \forall \doteq E_n \tag{3}$$

As shown in equation (3),$B_{n(anm)}$ the basic concept for cognitive agents E_n.An experience R_q is a decision of a human expert for the instant n of a model W_n the idea that is an instance of a real-world circumstance in which

Entity S_i has G_{il}related facts with Associations l. Therefore, equation (4) gives the pattern of immediate experience

$$R_q = [E_n \times \sum_{i=1}^{n} S_i \cup (\sum_{l=1}^{m} G_{il})] \in W_n \quad (4)$$

The concept of cognitive computing is generally used to describe AI systems designed to imitate people's thinking. There are various AI technologies necessary to develop computer systems that imitate human thinking processes, including machine learning, deep learning, neural networks, NLP, and sentiment analysis.

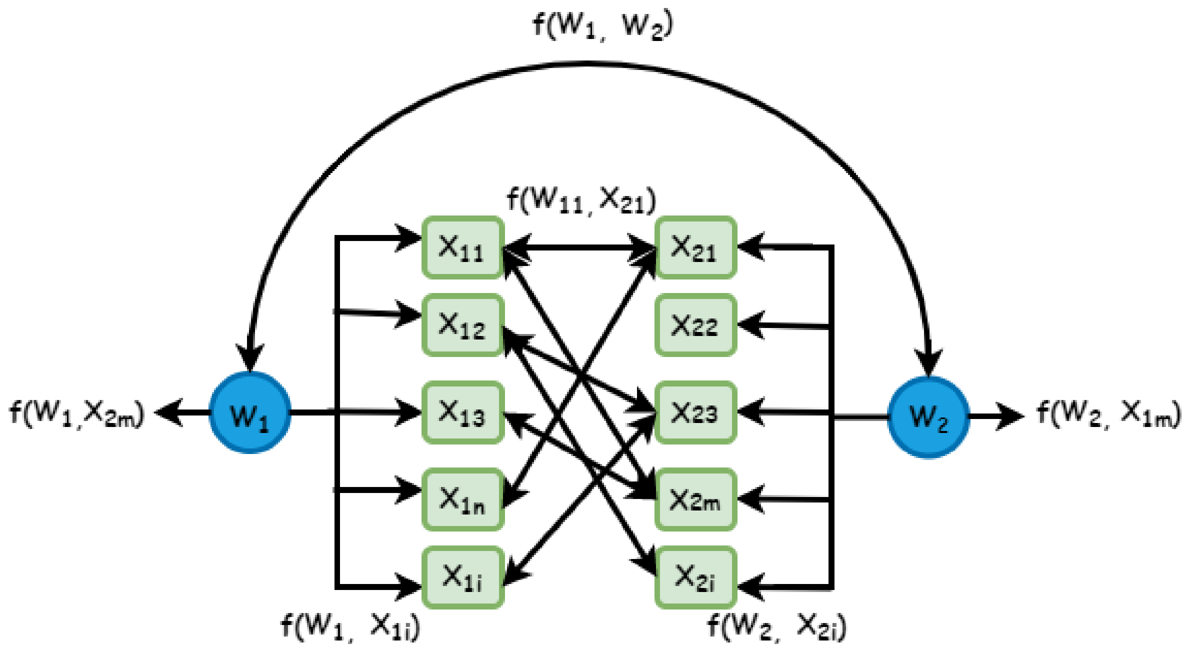

Fig 3: Design of Object-Attribute-Relation (OAR)

Fig 3 shows the design of Object-Attribute-Relation (OAR). Cognitive information technology is the complex undertaking of knowledge and information science. The processing of human information based on business applications and computer technology comprises other areas, such as software engineering, artificial intelligence, and information processing brain psychology. These models have seven levels: sensational processes, memory processes, perception processes, action processes, meta-cognitive processes, and meta-inference processes. In layer 1 of the Layered referenced model brain (LRMB) model, the sensational processes deal with fundamental human attributes such as vision, speech, smell, tactility, and taste, which obtain the input signal from the brain. Layer 1 transfers the data into the layer of memory processing and consists of Sensory Buffer Memory (SBM), Short Term Memory, Long Term Memory (LTM). All memories are received and stored as information.

The data obtained in layer 2 will be applied in layer 3 for concepts such as self-confidence, attention, motivation, goal-setting, emotions, attitudes, spatiality, and movement. These qualities provide the basis for actions in layer 4 with several abilities and temporary behaviors. These activities lead to a cognitive process with sophisticated features such as comparison, choice, creativity, identification of objects, classification, search. The information collected in the previous layer is metaphorically induced, analyzed, synthesized, and further transferred into higher cognitive processes. The conclusion is achieved using qualities such as understanding, problem-solving, and, above all, by taking decisions and effectively implementing the results. The OAR model explains how information and knowledge pass through the brain structure is based on the link between the characteristics and objects. The OAR model consists of $W_1$and W_2 objects that link an object, an attribute to attribute, and an intricate connection.

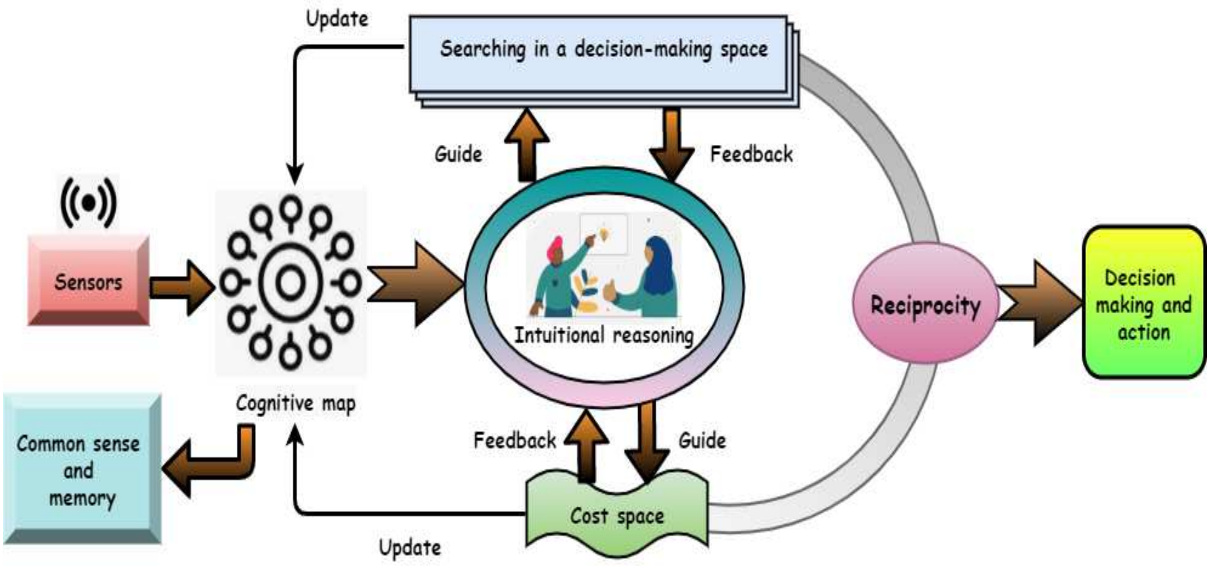

Fig 4: Intuitive thinking and the cognitive mapping relationship

Fig 4 shows the intuitive thinking and the cognitive mapping relationship.Intuition is a sequence of activities in the human brain that includes analyses, feedback, discriminating, and human decisions. Studies showed that the average accuracy is greater than the accuracy of non-intuitive decisions for human intuition. Humans take numerous judgments by intuitively evaluating the closeness of two things, the unfriendliness of the tone of another and picking one's partner and a book. It's not simply common sense which is intuitive decision-making. It includes other sensors to detect the information from outside and to become aware of it.

Intuition can be split into two procedures, selective encryption and selective combination. Selective encryption requires screening the important data from irrelevant data. However, for a person to achieve exact comprehension, selective coding is still insufficient. In addition to combining the information encrypted and forming appropriate internal connections with other data as a whole, a selective combination is needed. Thus selected combination entails merging, in a unified whole and that it would not resemble its components, anything that could originally appear to be independent pieces of information. The selective comparison includes connecting information newly received to old information already available. If people are aware of the similarity to a certain degree between old and new knowledge, they can use this resemblance to understand new information better. Intuition, therefore, enables humans in complicated and dynamic settings to make rapid decisions. In addition, the search area is much reduced in the resolution of issues, and the cognitive process of the human being is more effective.

Intelligence has a more comprehensive classification approach. A cognitive pattern of the mind can be considered a world model built on past information. This concept has three aspects of communication: interaction, causality, and control. As an environment image, a cognitive map of a human brain can be regarded as the world model. It represents the immediate environment exhaustively, encompassing a basic series of occurrences and directions, distances, and even time. This concept has been proposed on a semantic web through the use of the cognitive map. It is a dynamic process based on management, data collection, encoding, storage, processing, decoding, and external information.

The human population can influence its environment status and relation and provide an interpretable model to provide the basis for risk and value assessment and measurements. Human cognitive acts are integrated into a sequence of map-based decision-making, a model-like process. The creation of a true cognitive map is connected to brain perception and external information processing. As seen above, a person builds a field for decisions making. The brain searches the decision-making choices randomly, and humans can react intuitively when selected decisions represent the new cognitive map. A minimum cost can describe a match. The intuition process function can be regarded as a reference for searching for decisions and creating cost spaces in the computing process. The intuitive thought of humans is related directly to the cognitive reaction of the brain to understanding knowledge.

A measurement to identify the total percentage of accurate word match is given in equation (5),

$$TR_{phr} = \frac{J_m(Q_r + H_n)}{BM}.(T + V_b) \tag{5}$$

As shown in equation (5), TR_{phr} is the true recognized phrases. The precision of the performance is a measurement BM and increasing the high accuracy, improving the system's performance. Only the text that replicates the user questioned and certain numerical characteristics vectors for the $J_m$object's visual appearance is displayed after $(Q_r + H_n)$the cognitive agent has moved out through the pictorial and V_b speech detecting procedure. The next level is the use as a cognitive computing approach of natural language processing (NLP). The humanoid recognizes in this context T, the object in plain text format with language processing after transforming user inquiries.

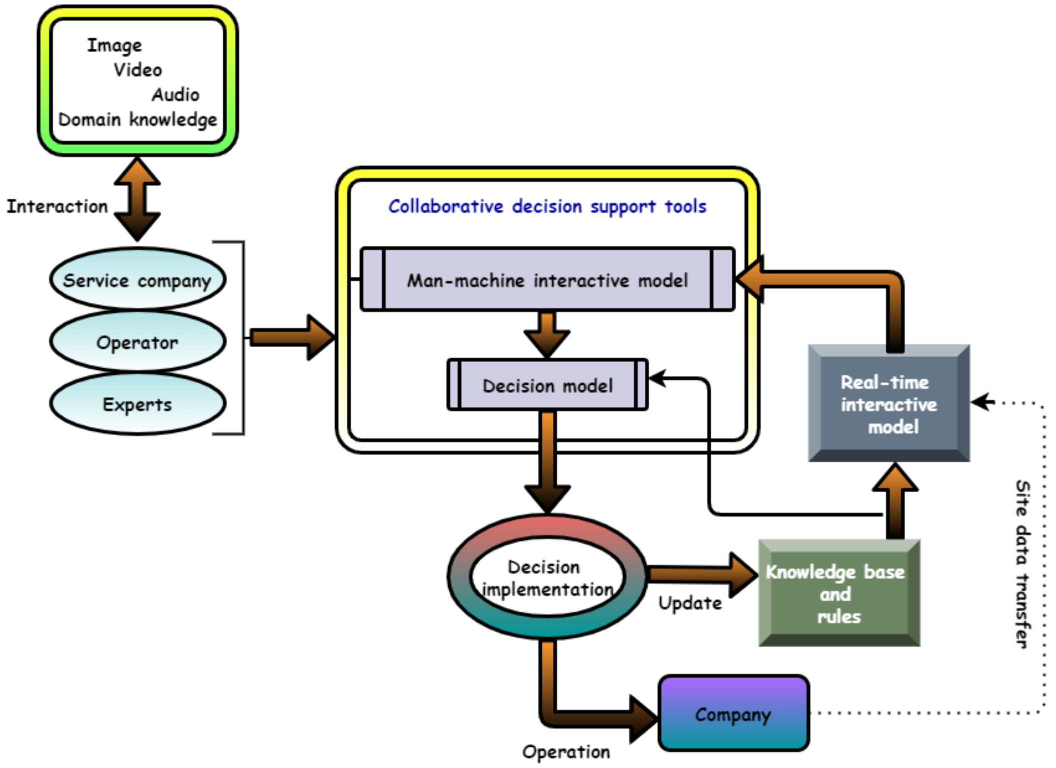

Fig 5: Basic hybrid intelligence framework for collaborative decision-making in enterprises

Fig 5 shows the basic hybrid intelligence framework for collaborative decision-making in enterprises. In virtually all companies, collaborative decision-making is important. The open exchange of ideas can develop more innovative goods, strategic solutions, and attractive business decisions in a company. Collaboration on human computers can give applied solutions for broad-based coordination of processes with a high-value generation potential. Enterprise-based collaborative decisions that promote coordination and communication amongst the process participants are hybrid-enhanced intelligence. To give transparency and make processes easier to follow, the hybrid increasing intelligence systems of decision-making on business cooperation must be open to all CEO partners. In hybrid-enabled intelligence systems, integrating different machine-learning algorithms, decision models, and field knowledge are important.

Computer vision, machine learning, reasoning, natural language processing (NLP), speech recognition, and robot technology are the most important cognitive technologies. Users of these technologies can create solutions for their companies and users to generate immersive experiences. Cognitive computing is generally used to help people make their decisions. Some examples of cognitive computing applications include assisting physicians in their ill-treatment. In other words, it is not very easy to integrate. In addition, a collaborative application includes an expert system that recommends an ideal solution by combining the explicit knowledge of the basic knowledge and implicit knowledge of the experts. Simple interfaces between different modules are required for such a joint application. For example, users can investigate and solve problems in a program through exchanges and the communication and sharing of photos, videos, sound, and other linguistic contexts. Several solutions will be added to the decision-making model to obtain the best potential response during the problem's solution.

This hybrid intelligence integrates organizational events, technical components, and society to provide an environment for interaction between human beings that promotes learning, understanding, reasoning, and decision-making and supports fundamental technologies. The application of hybrid intelligence can considerably enhance modern companies' ability to handle risks, raise their value and promote competitiveness.

An assessment of ASR performance taking into account a minimum number of word changes associated with replacement H, insertions $(U_i + y)$, deletions E of the reference transcription to a hypothesis sentence.

$$VG = \frac{H + (U_i + y) + E}{BM}$$

$$Word\ E_r = VG \times 100\% \quad (6)$$

As shown in equation (6), VG is speech recognition quality and $WordE_r$ indicates word error rate. All parameters are weighted for ASR performance, although they can have different weights

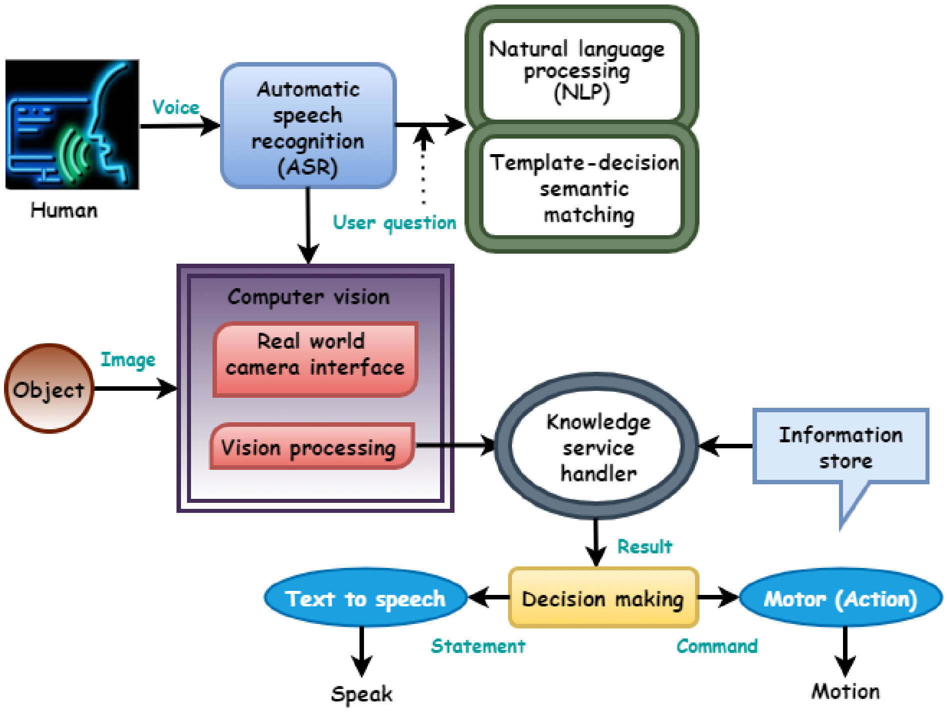

Fig 6: Voice recognition technique

Fig 6 shows the voice recognition technique. Cognitive computing emulates the human-like cognitive ability to detect, understand and decide on questions. The above figure shows the interface model artificially introducing these talents using the newest technology such as Computer Vision to detect items under vision and audio processing to receive users' inquiries about the object the humanoid is observing. The cognitive humanoid uses Natural Language Processing to interpret language inquiries to carry out comprehension skills and the semanticized knowledge model in XML for answering object problems. The humanoid utilizes the object's inference inquiry motor, finally. The voice model is transformed to the automatic voice recognition model as "Speech to Text" or "Text to Speech." Spoken language recognition and response primarily aim to have natural questioning among human beings and cognitive agents systems through spoken dialogue. ASR offers CC-based artificial systems to enhance the comprehension of communication between users and agents.

Automatic speech recognition systems and TTS are quite excellent at imitating human voice processes because of their speech comprehension algorithm. The system employs cutting-edge technology based on a less than 10% mistake based on a hybrid model of a profoundly learning model based on personal grammar. Several previous studies of companies and university institutions using model compatibility and probabilistic models based on the extraction of functions have been boosted by demand for ASR-based artificial systems. Neither, however, has managed to provide improved outcomes. It isn't easy to distinguish which ones humans need to develop the CC system of language recognition. The study effectively established a new hybrid language and deep learning models template to recognize speech.

First, an MFCC (Mel Frequency Cepstral Coefficient) speech template is developed to produce a feature vector. Then each feature vector in the step RNN recognizes (recurring neural network). Therefore, this CC technology is based on an acoustic model quality component, the depths of the language model to understand the human voice, and the number of language dictionaries occurring. The Cognitive Information Technology (CIT) Design thus includes both Automated Speech Recognition (ASS) technology and speech text (TTS) conversion technology.

An agent $CIT_{(anm)}$ is clearly described as the cognitive data technology structure in which information technology uses cognitive computing to build human intelligence and resolve actual-world problems. Equation (7) illustrates the $CIT_{(anm)}$cognitive IT framework for an (anm) agent.

$$CIT_{(anm)} = [C_{G(anm)} + H_{G(anm)} - L_{G(anm)} + K_{G(anm)}] \qquad (7)$$

As shown in equation (7), C_G denotes concept pattern, H_G is the method of experience, L_G is a mode of knowledge and K_G indicates the model of the interface. Therefore demonstrates that a $CIT_{(anm)}$of Cognitive CIT of an agent (anm) is the union of its concept, expertise, and interface information.

3. Numerical outcomes:

Numerical results of the proposed CC-HSRFwere analyzed by selecting the humans. Hence,smart decision-making procedures were assessed using performance metrics like accuracy ratio, time management ratio, development ratio, intellectual function, and evaluation of cognitive functionality. The cognitive computing approaches are discussed in this section on methods such as visual and cognitive analyses.

Table 1: Accuracy ratio

Algorithm	Word error rate	True recognized phrases
RNN	27.5	95.7
HMM	83.2	38.5
MFCC	89.9	23.6

Table 1 shows the accuracy ratio in speech recognition. The existing methods outcome does not improve or equal the company with the deep learning model, announced word error rate$Word\ E_r$ 10 %. However, the results are still inspirational by applying the test data on the recommended technique. As indicated in Table 1, the RNN method achieved $Word\ E_r$ is 27.5% and TR_{phr} is 85.7%. The conventional probabilistic models are the Hidden Markov Model (HMM) and the Mel Frequency Cepstral Coefficient (MFCC) template have the lowest $Word\ E_r$ of 83.2% and 89.9%.Thetrue recognized phrasesTR_{phr}outcomes are 38.5% and 23.6% respectively.

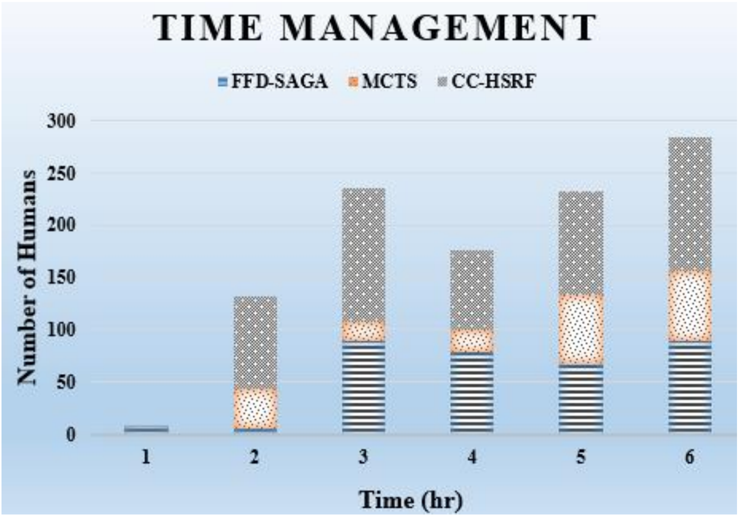

Fig 7: Time management

Fig 7 shows the time management ratio. Time for decision-making is an essential factor for good decision-making. The timing of choice is significant because it enables decision-makers to see different components necessary for decision-making. It helps decisions to be better coordinated with vital points taken throughout decision-making. A range of options contributes to reducing urgent stress, deadlines, and high time requirements. Bad time allocation is the outcome of poor decisions and will lead to errors. Failures require time to rectify and can lead to more stress, urgency, and errors in the ongoing cycle. For time management, decision-making is essential. Decision-making will be the essential component in the operations of a manager. In the planning phase, it plays the most significant part. When demand arises, they decide on numerous questions about their company's objectives, resources, and the human to carry out each task.

Table 2: Intellectual function

Effect size	Intellectual Functions				
	Language	Working memory	Cognitive control	memory	Visual cognition
0.2	0.6	0.3	0.1	0.8	0.21
0.4	0.3	0.52	0.05	0.4	0.2

0.6	0.7	0.24	0.15	0.3	0.3
0.8	0.6	0.34	0.18	0.5	0.5
1.0	0.8	0.5	0.25	0.7	0.6

Table 2 shows the intellectual function. It includes the intellectual processes of the brain that lead to information and knowledge. These mental functions provide care, learning skills, remembering, processing of information, and solving problems. The first department is applied in balanced behavioral for the use of the linguistic ability, visual and spatial skills, memory. The socioeconomic status is reflected by more than 45% percent of the variation in the left language system and much less, and considerably, in most other systems. The extended maturity time in the perisylvian brain area involved in language creation explains the strong link between financial status and language. When compared with other cognitive functions, language has 0.8 high impact sizes. Cognitive control has a 0.25-dimensional influence compared to other cognitive functions.

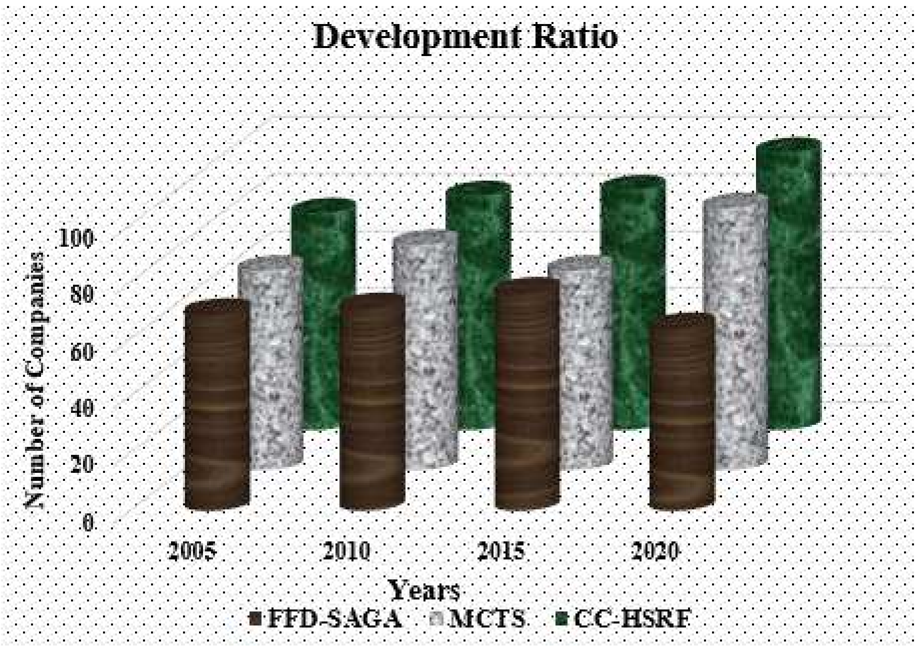

Fig 8: Development ratio

Fig 8 shows the development ratio. The time involved in developing strategy applications using cognitive computing is one of the major obstacles.

Cognitive computing is a generalized solution — that is not to say, without powerful development teams, the resolution cannot be applied across multiple companies and a very long time for developing a solution. The conceptual knowledge and ability of a human to think and understand demonstrate cognitive growth. While language improves cognitive growth, linguistic sophistication affects cognitive ability. Humans gain cognitive skills through having the ability to communicate in the language. Decision-making for humans on several tasks and contributes to higher cognitive performance. Much time a week, concentration helps humans practice awareness. Cognitive talents underpin the desire to function effectively to comprehend, think, prioritize, understand, plan, remember and solve problems. Cognitive development offers humans the opportunity to reflect on their reality. Cognitive comprises a human's memory, attention, and ability to handle and respond to knowledge and experiences.

Table 3: Evaluation of cognitive functionality

Function	Case	Correct	Wrong	H1	H2	H3	Reward
Object recognition	**60**	**32**	**5**	**2**	**1**	**2**	**9.5**
Question-answer	**60**	**29**	**3**	**2**	**2**	**1**	**7.9**

The evaluation parameters are mistakes and rewards for assessing the performance of a CC-based object recognition system. As seen in Table 3, these factors indicate that cognitive computing is better equipped to improve decision-making. The $CIT_{(anm)}$cognitive agent presents the results on a test occasion. Once the problem is found in the cognitive agent, the items are identified, and questions are answered based upon their best outcomes. The task assesses the right responses and error kind. The three errors H1 is the agent doesn't comprehend the query. H2 is the agent gives the answers, but the user is not happy. H3 is the cognitive agent that does not respond properly.

This unique approach is implemented by analyzing the distinctions between cognitive computing systems and existing Web-based decision-making systems depending on deterministic search engines for answers. The user types terms and gains result using a search engine based on an appropriate ranking. It can ask for a careful analysis and obtain findings in certain decision-making systems, and it will never establish a dialogue that will be enduring to enhance results.

4. **Conclusion:**

The cognitive computing-based human speech recognition framework (CC-HSRF) examines the decision-making methods in Bayesian theory. It predicts decision-making with certain possibilities and methodologies, such as cognitive information technology, including OAR models. It addresses the relationship between attributes and objects. A general decision-making system incorporating cognitive computing and agent technology is developed using the proposed technique. This design enables the agent to question various judgments that combine cognitive ability with cognitive humanoid. The whole strategy avoids problem-solving methodology improvements to existing agents and employs a cognitive calculation agent approach based on responding to the artificial agent's questions. The humanoid eventually concludes by addressing the existing inquiry problem skills by skill. CC-HSRF will undertake the required steps to achieve the goal by assuming an objective and several cognitive technologies. The simulation analysis of CC-HSRF improves the accuracy ratio (95.7%), time management ratio, development ratio (98.6%), intellectual function, and evaluation of cognitive functionality (96.9%).

Ethics Declarations

Conflict of interest

The authors declare that they have no conflict of interest.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Author Statement

Conception and design of study : **Arun M**

Acquisition of data : **Arun M**

Analysis and/or interpretation of data : **Arun M**

Reference:

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