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INTELLIGENTLY LEVERAGING MENTAL WELLNESS STATE IN COGNITIVE COLLABORATION WORKFLOWS

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ABSTRACT

A person's mental wellness plays a critical role in determining how efficiently a complex task that requires cognitive abilities is successfully completed. However, current solutions do not offer a mechanism for detecting an individual's mental wellness in a real-time and proactive manner. To address that lack, techniques are presented herein that leverage a range of information including electroencephalography (EEG) signals (e.g., as captured from an EEG headset); real-time health parameters such as heart rate, blood pressure, etc. (e.g., as captured from health monitoring devices such as wearable physical fitness monitors); etc. Such information may be processed by an online communication and collaboration facility at a network edge and may be shared to different trusted business applications. Further aspects of the presented techniques may encompass a model that comprises artificial intelligence (AI) and machine learning (ML). Such a model may incorporate different parameters, may include a training mode, and may be used to predict the mental state of an individual. By employing the presented techniques, proactive mental health insight data may be fed into a work routing system's mechanism so that the assignment of new or existing work that requires a higher level of focus (such as handling a Priority 1 or a Priority 2 technical support case, performing financial transactions, providing virtual medical consultation, etc.) may depend upon a person's mental readiness rather than just their physical availability.

DETAILED DESCRIPTION

A person's mental wellness plays a critical role in determining how efficiently a complex task that requires cognitive abilities is successfully completed. There is increased awareness across the globe about the fact that mental wellness is as important as physical wellness. Currently, people use applications or they consult with counselors to discuss their current mental state and obtain guidance on how to improve that state. Most of those engagements are initiated by a person after they become aware of their mental stress. None of the applications that are currently available provide a mechanism for detecting the mental condition, in a more real-time and proactive manner, before it becomes worse. The lack of such a mechanism has a serious impact on businesses, including a longer time for a person to complete a cognitive task; customers getting frustrated due to a lack of attention, care, and empathy from the person handling their request resulting in a lower customer satisfaction; etc.

The work assignment logic that exists today in the support services role is based primarily on a skill level, the availability of a human expert (such as a representative, an agent, or an engineer), the number of work items that are assigned to a human expert, and the number of peers and their position in a queue. If the person who is next in a queue is on a call, then that person is skipped and the case is assigned to the next person in the queue who is not on a call. Even if the person who is next in the queue is available, it could be possible that that person is mentally drained (e.g., due to the tasks that they have performed before they became available) or there may be other reasons why that person is not in a good mental state. Thus, it becomes important to understand the mental wellness of an individual before assigning work to that person. With a hybrid work environment being a reality now and for the foreseeable future, supervisors and managers no longer have visual clues as to their team members' mental wellness.

To address the type of challenge that was described above, techniques are presented herein that support using the current and the near-future mental state of an individual to provide a real-time, early warning regarding the mental state of that individual deteriorating within live virtual meetings. By applying aspects of the presented techniques, the assignment of more stressful work to a person may be avoided before the person goes into a mental breakdown or depression.

According to aspects of the techniques presented herein, proactive mental health insight data may be fed into a work routing system's mechanism so that the assignment of new or existing work that requires a higher level of focus (such as handling a Priority 1 (P1) or a Priority 2 (P2) technical support case, performing financial transactions, providing virtual medical consultation, etc.) may depend upon a person's mental readiness rather than just their physical availability. Such an approach does not apply just to work routing situations, but in general it may help with managing when a person should or should not take on work that may have negative consequences to their mental health. If it is necessary for someone to take on work in an urgent manner, the first thing that should be checked is mental availability after which physical availability may be confirmed. Currently, such an approach is almost never taken into consideration, and if it is it is subjective and likely not accurate (e.g., a team member who wishes to "prove themself" may push too hard and tell their manager that they are fine to take on more work, and vice versa).

Research has validated that human behavior may be accurately detected by processing electroencephalography (EEG) signals that are emitted by the neurons in the human brain. Elements of that research employ EEG signals to track the stress level of a person. EEG headsets, which are available in the market, may employ Bluetooth technology to transmit information to a local personal computer (PC) or mobile phone.

Aspects of the techniques presented herein leverage the information that is emitted from an EEG headset in determining the mental wellness of a human who is performing complex tasks. Such information may be processed by an online communication and collaboration facility (which for simplicity of exposition may be referred to herein as an online facility and which brings together capabilities such as video conferencing, online meetings, screen sharing, webinars, Web conferencing, and calling) at a network edge and may be shared to different trusted business applications while the engineers are on a call.

According to aspects of the techniques presented herein, a model that encompasses artificial intelligence (AI) and machine learning (ML) may be used to predict the mental state of an engineer. Such a facility may be referred to herein as a model or as an ML model. The following sections of the instant narrative describe the different model parameters and the process that may be used to train such a model.

Concerning ML model parameters, different EEG signals (which are assessed in different frequency bands such as Delta (between 1 and 4 hertz (Hz)), Theta (between 4 and 8 Hz), Alpha (between 8 and 12.5 Hz), and Beta (between 12.5 and 30 Hz)) may be examined to determine the current mental state of a human. The EEG signals may be captured from the frontal, parietal, and occipital lobes.

The Beta frequency is associated with alertness, concentration, and learning. An increase in Beta frequency results in anxiety, fear, and stress. The Alpha frequency is associated with relaxation, wellbeing, and superior learning. An increase in Alpha frequency results in superior confidence. The Theta frequency is associated with relaxation and daydreaming. An increase in Theta frequency typically means that a person is in a more relaxed state. The Delta frequency is associated with the deepest phase of sleep. An increase in this frequency means that a person is trying to get some rest.

An EEG headset may emit the above-described EEG signals (as captured from the brain) which may then be intercepted by an online facility client. Such a client may capture the raw signals and calculate different parameters (as depicted in Table 1, below) based on the value range of different frequency bands from the EEG signals.

Table 1: Exemplary Parameters

Parameter	Description
EL	Energy Level
FL	Focus Level
HF	Happiness Factor
SL	Stress Level

Aspects of the techniques presented herein may be further explicated with reference to an illustrative example encompassing engineers who are working in support services. Under the illustrative example the engineers wear EEG headsets to troubleshoot different issues while they are pursuing the work items (of different priorities such as P1 or P2) that are assigned to them.

Consider the case of an engineer who is involved in a high severity case in which they are highly stressed, their focus is moderate, and their energy level is low. Aspects of the techniques presented herein support the detection of such a state using the EEG raw input. In this case, the EEG data might show the Delta bands at a higher frequency since the individual has a low energy level. The Beta frequency would also be high since the individual is highly stressed and slightly focused. The Theta frequency would be low since the individual is not relaxed.

The local online facility client ML model may monitor the raw EEG data and derive mental insights in the form of parameters. The non-sensitive parameters of each team member may be sent to a server as part of telemetry data to help derive additional insights (e.g., the number of active individuals who are mentally able to take on new work). The sensitive parameters may just be processed locally and may be used to benefit the individual (e.g., to prompt the individual to request additional help).

Concerning the training of the above-described ML model, as an initial matter it is important to note that the techniques presented herein are applicable to support services in any industry including, for example, the financial sector, an Anything as a Service (XaaS) provider, the healthcare sector, the retail space, etc.

When training the model, it is necessary to measure actual end-users and real world experiences to collect the raw input data which may be used to train the ML model. The raw data from the EEG signals may include the health information of a user which might be sensitive, so the user would need to confirm their consent and opt-in to the sensitive monitoring while training the model. During the training process the system evaluates the raw data, attempts to derive certain parameters from it, and prompt the user for feedback regarding those parameters. While in the training mode, a user may be presented with parameters that are to be confirmed. Several possible parameters are described below.

The non-sensitive parameter NO_NEW_WORK may indicate that the user is not in a state to take on additional work. The non-sensitive parameter ASSISTANCE_REQUIRED may indicate that the user is struggling to solve an issue on their own, is "stuck," and could use assistance. The sensitive parameter ANGRY may indicate that the user is mad. This might be considered sensitive information about the user.

The sensitive parameters FL1, FL2, and FL3 may be derived from a user’s response to the prompt "provide your current focus level on a scale of low, medium, high.” For example, a selection of ‘high’ would yield the parameter FL3 which would associate a high focus level to the current value of the raw parameters. This may be compared to what the model currently believes the user’s focus level to be (based on the raw input) and if the user’s answer does not match then the user’s selection may help to adjust and re-train the ML model.

An online facility client may process the raw data from EEG signals and determine values for the different parameters (such as EL, FL, etc.) that were described previously. Different combinations of those monitoring parameters and time-of-day values may be assigned specific parameters to represent the corresponding mental states. Such data may be used as a training dataset for the ML model.

According to aspects of the techniques presented herein, a training dataset may be built using inputs that are collected from users (such as agents, customer service representatives, and support engineers) for a specific period of time (e.g., 14 days, one month etc.) that is sufficient to capture the different mental states. A dataset may also be continuously refreshed on a periodic basis to ensure that the current training dataset is reflective of the user's mental behaviors. Such a continuous training process is important because a user might get frequently irritated during midday in Month 1 but they could have modified their lifestyle in Month 2 to take a walk which could make the user less irritable during midday in Month 3. Such a change should be reflected in the training dataset.

Further, the working environment plays an important factor in the training dataset. A person who is working at a workplace for a defined duration of hours could be less stressed than a person who is working at home for long hours and without technical or moral support from their team members. The geographic location may be made part of the training dataset and may be provided as an input parameter to the prediction model.

Additionally, in addition to a role-specific training model aspects of the techniques presented herein may also include company-specific or customer segment-specific models.

While the above narrative considered EEG signals, it is important to note that the techniques presented herein may employ any type of raw input (including, for example, screen sharing, audio, etc.) to derive the above-described sensitive and non-sensitive parameters.

Since people are not the same, either mentally or physically, aspects of the techniques presented herein support a distinction between user-specific and role-specific ML models.

Accordingly, the training process that was described above may first be performed on an example group of people after which the realized ML model may be applied to the general populous. However, it will be necessary to test how well the ML model that was built from one person or from one group of people applies to other people to ensure that it detects the same scenarios given the same data input and scenario for different users. There are many considerations (i.e., variables) that may be made here, such as genetics, age, gender, etc.

Most likely, each user will need to have a somewhat custom ML model built for them. Accordingly, a general role-specific model may be used as a starting point and then trained to yield a custom model for each user. For example, a user may opt-in to train their model, which would monitor the user for known scenarios using the general specific model and prompt the user to confirm or dispute those states (i.e., parameters). Any deviations may be incorporated into the custom model that is being built and that custom model may then be used for the individual user (instead of the general role-specific model) for real world use. Such an approach may provide more accurate results for the individual user. In addition to a role-specific training model, aspects of the techniques presented herein may also include company-specific or customer segment-specific ML models.

Figure 1, below, presents elements of the above-described ML model according to aspects of the techniques presented herein and reflective of the above discussion.

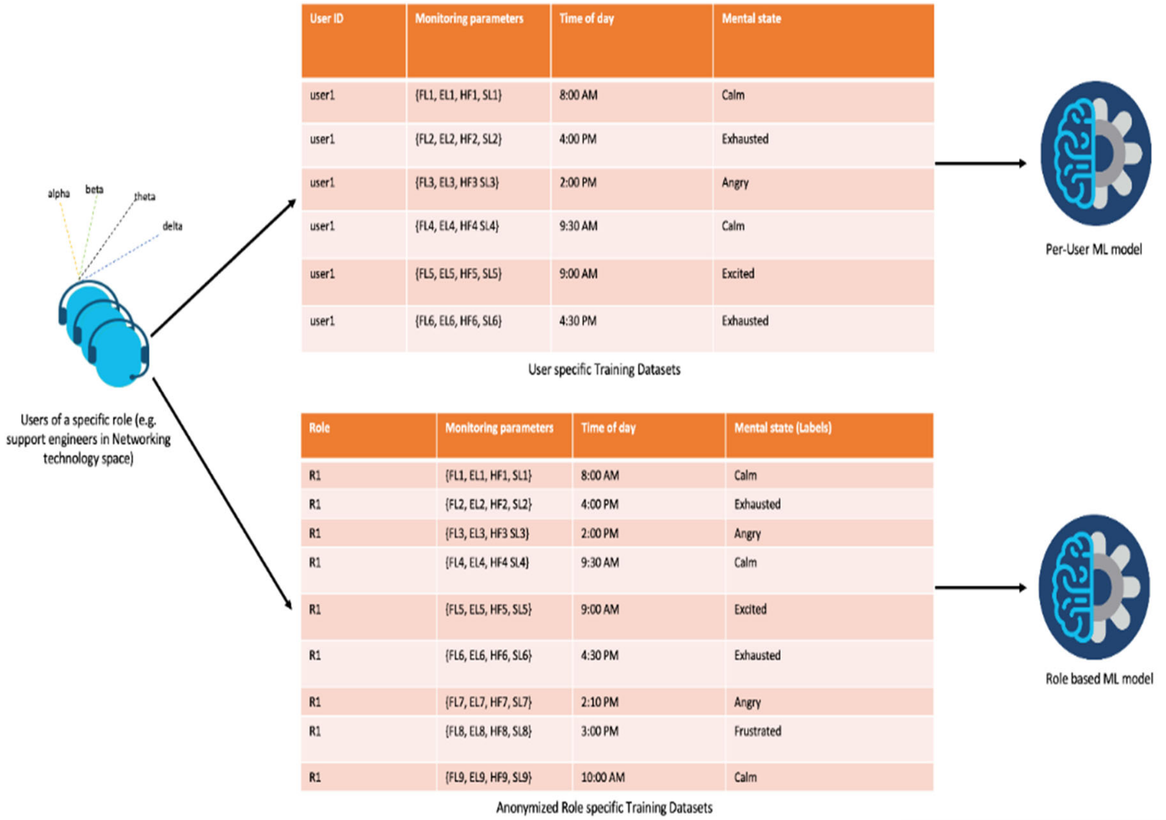

Figure 1: User- and Role-Specific ML Models

It is important to note that the parameters that are presented in Figure 1, above, are exemplary only and an implementation may employ several other real-time health parameters, in addition to EEG, such as heart rate, blood pressure, etc. for training and prediction purposes. Such real-time health parameters may be derived from health monitoring devices such as wearable physical fitness monitors.

Aspects of the techniques presented herein may be employed to predict the future mental state of an individual based on trends that may be found in raw data.

Accordingly, the above-described model may be used to predict where a user's mental state is headed. This may be accomplished by measuring within a range for each parameter and when the values are trending towards a certain known state it may be predicted that the user will soon be in that state. For example, for a "calm" parameter to be determined it may require a Theta value of 7 Hz and a Beta of value of 20 Hz. If a user is currently measured at a Theta value of 6.5 Hz and a Beta value of 20 Hz, the user is close to a "calm" state (i.e., if the Theta frequency increases by .5 Hz the ML model would output the "calm" parameter). If the Theta frequency from the raw input has been trending in an upward direction for the past ten minutes, it is possible to predict that the user will soon reach the "calm" state.

The next portion of the instant narrative discusses how the techniques presented herein work. That discussion incorporates two illustrative use cases.

A first use case encompasses the assignment of work based on mental wellness. Figure 2, below, depicts elements of an exemplary case routing system, according to aspects of the techniques presented herein and reflective of the above discussion, that may leverage mental insights when assigning work to engineers.

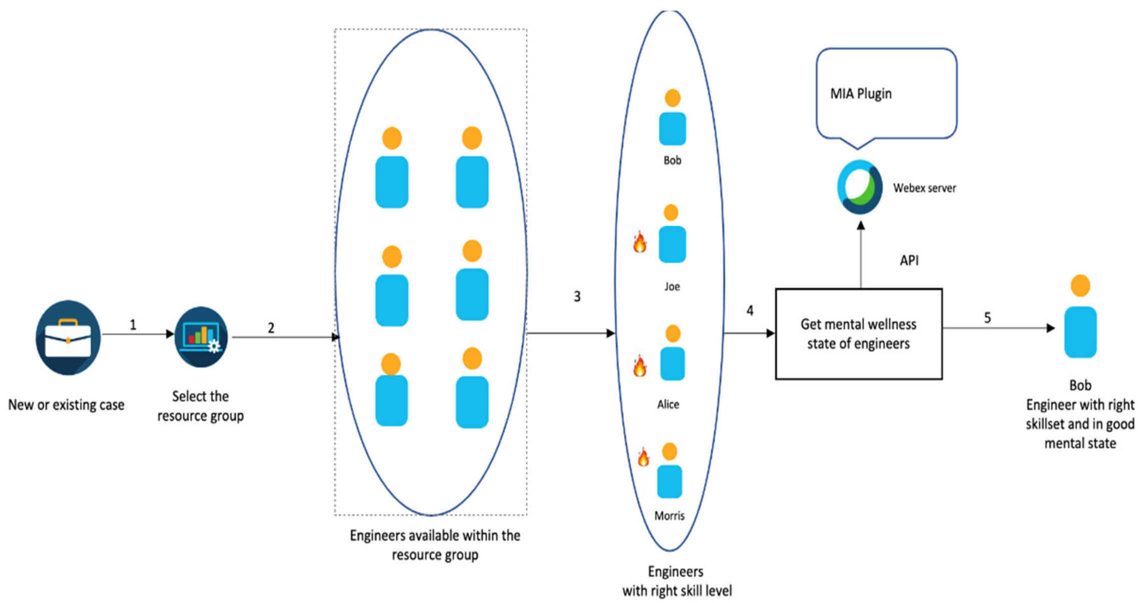

Figure 2: Illustrative Case Routing Application

As illustrated in Figure 2, above, a case assignment and reassignment process may be enhanced, according to aspects of the techniques presented herein, through a series of steps.

Under a first step, a new or existing case that requires assignment to an engineer may arrive at the case routing application. The case routing system determines the correct queue or resource group to which the case needs to be routed.

During a second step, the case routing system identifies the list of available engineers in the selected queue or resource group. Then, under a third step, the case routing system determines the skill set level that is required for handling the instant case and it selects a subset of the available engineers with the correct skill levels.

As described previously, the non-sensitive parameters may be sent to a server. As a result, during a fourth step the case routing system may use those parameters to determine the current and near-future (e.g., one to two hours) mental state of an engineer before assigning the case to the engineer.

Finally, under a fifth step, the case routing system may select the correctly-skilled engineer who also has a good current and near-future mental state. The system may also use other factors such as case severity, a recent customer satisfaction score, etc. to determine what possible mental states would be suitable to provide the best customer experience.

A second use case encompasses proactive notifications during live meetings. Aspects of the techniques presented herein include new ways of detecting an engineer's focus level by analyzing their activities within a real-time virtual meeting. Such activity may include, for example, processing a content sharing video stream to determine the level of interaction with network devices, the type of commands that are being entered or not entered, and the type of menu items that are selected or not selected while troubleshooting a problem in a specific domain. A user may be alerted based on their focus level within a live troubleshooting session. The system may also suggest actions such as a proactive notification regarding lack of focus, an appreciation to a team member, the engagement of another team member to assist the current team member, and the reassignment of work.

The suggested actions may be shared by a plugin running on the online facility server which may, in turn, send same on to the online facility client. Such a local plugin may be able to use both the sensitive and non-sensitive parameters (as described above) to derive the insights and actions.

Figure 3, below, depicts elements of an active troubleshooting scenario according to aspects of the techniques presented herein and reflective of the above discussion.

Figure 3: Active Troubleshooting Scenario

Figure 3, above, depicts an engineer interacting with a device using a Secure Shell Protocol (SSH)-based session during a live virtual troubleshooting session. By observing the actions of the engineer, the online facility platform may dispatch an appreciation notification to the engineer.

Figure 4, below, presents elements of an inactive troubleshooting scenario according to aspects of the techniques presented herein and reflective of the above discussion.

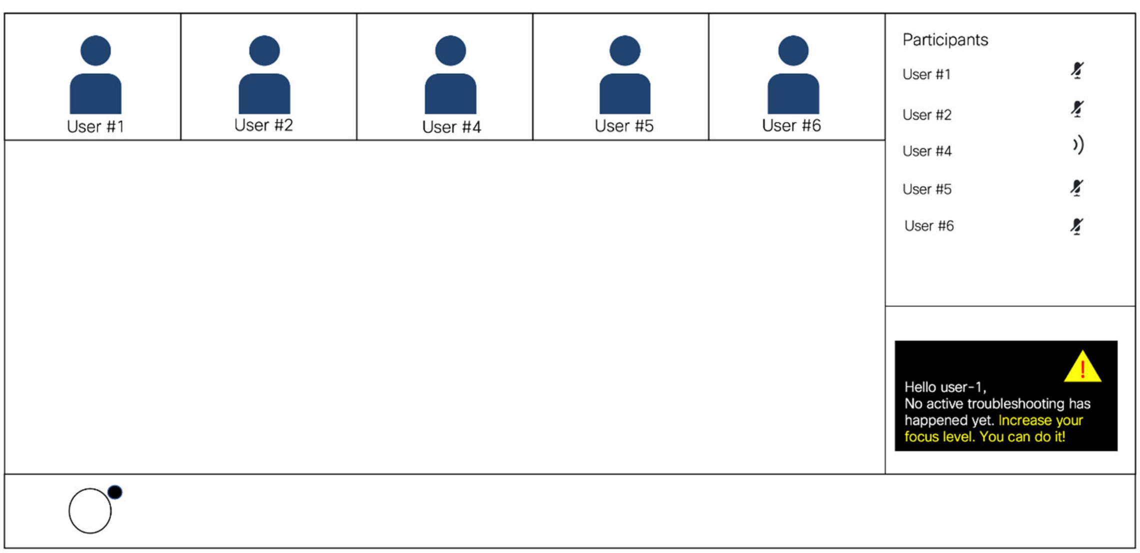

Figure 4: Inactive Troubleshooting Scenario

Figure 4, above, illustrates a scenario in which an engineer has not yet performed any active troubleshooting and the online facility platform alerts the engineer accordingly.

Figure 5, below, depicts elements of a long troubleshooting scenario according to aspects of the techniques presented herein and reflective of the above discussion.

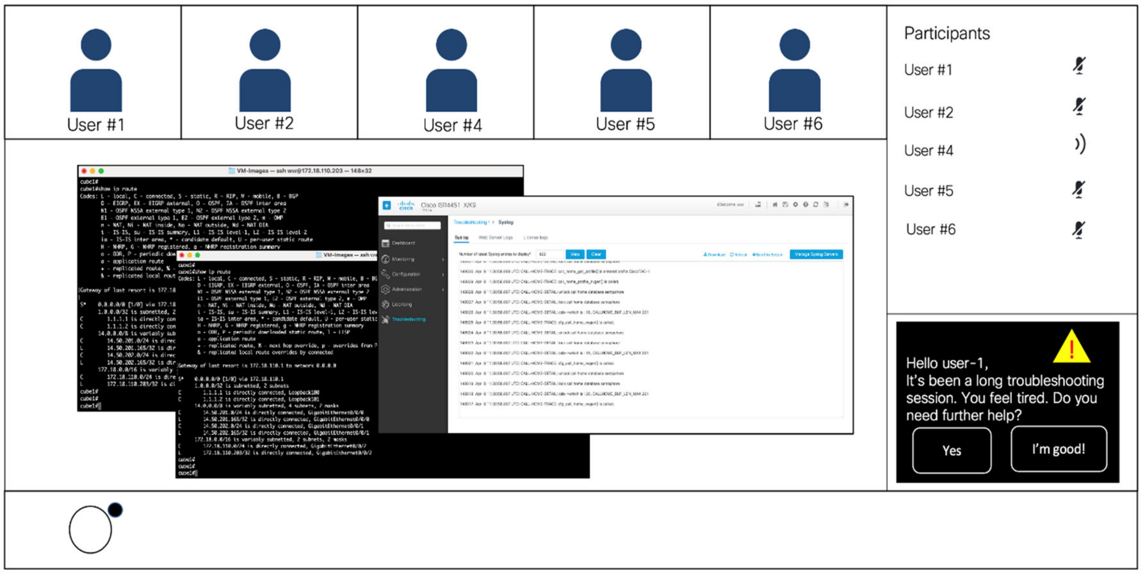

Figure 5: Long Troubleshooting Scenario

Figure 5, above, illustrates a scenario in which an engineer has been involved in a lengthy troubleshooting session and the online facility platform alerts accordingly by asking the engineer if they need any help.

As described and illustrated in the above narrative, the techniques presented herein offer a number of important capabilities. A first capability encompasses using raw input data from EEG signals, other health monitoring devices, and live content sharing video streams to derive the context of the cognitive task that is being performed. A second capability encompasses the proactive, real-time, early warning of a focus level and the suggestion of actions to the individual. A third capability encompasses leveraging the developed mental wellness insights to assign or reassign work items.

In summary, techniques have been presented herein that leverage a range of information including EEG signals (e.g., as captured from an EEG headset); real-time health parameters such as heart rate, blood pressure, etc. (e.g., as captured from health monitoring devices such as wearable physical fitness monitors); etc. Such information may be processed by an online communication and collaboration facility at a network edge and may be shared to different trusted business applications. Further aspects of the presented techniques may encompass a model that comprises AI and ML. Such a model may incorporate different parameters, may include a training mode, and may be used to predict the mental state of an individual. By employing the presented techniques, proactive mental health insight data may be fed into a work routing system's mechanism so that the assignment of new or existing work that requires a higher level of focus (such as handling a P1 or a P2 technical support case, performing financial transactions, providing virtual medical consultation, etc.) may depend upon a person's mental readiness rather than just their physical availability.