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Clinical Implication of Maumgyeol Basic Service-the 2 Channel Electroencephalography and a Photoplethysmogram-based Mental **Health Evaluation Software**

Seung-Hwan Lee^{1,2,3}, Hyeon-Ho Hwang^{3,4}, Sungkean Kim⁴, Junseok Hwang¹, Jaehyun Park¹, Sangshin Park¹

Objective: Maumgyeol Basic service is a mental health evaluation and grade scoring software using the 2 channels EEG and photoplethysmogram (PPG). This service is supposed to assess potential at-risk groups with mental illness more easily, rapidly, and reliably. This study aimed to evaluate the clinical implication of the Maumgyeol Basic service. Methods: One hundred one healthy controls and 103 patients with a psychiatric disorder were recruited. Psychological evaluation (Mental Health Screening for Depressive Disorders [MHS-D], Mental Health Screening for Anxiety Disorders [MHS-A], cognitive stress response scale [CSRS], 12-item General Health Questionnaire [GHQ-12], Clinical Global Impression [CGI]) and digit symbol substitution test (DSST) were applied to all participants. Maumgyeol brain health score and Maumgyeol mind health score were calculated from 2 channel frontal EEG and PPG, respectively.

Results: Participants were divided into three groups: Maumgyeol Risky, Maumgyeol Good, and Maumgyeol Usual. The Maumgyeol mind health scores, but not brain health scores, were significantly lower in the patients group compared to healthy controls. Maumgyeol Risky group showed significantly lower psychological and cognitive ability evaluation scores than Maumgyeol Usual and Good groups. Maumgyel brain health score showed significant correlations with CSRS and DSST. Maumgyeol mind health score showed significant correlations with CGI and DSST. About 20.6% of individuals were classified as the No Insight group, who had mental health problems but were unaware of their illnesses. Conclusion: This study suggests that the Maumgyeol Basic service can provide important clinical information about mental health and be used as a meaningful digital mental healthcare monitoring solution to prevent symptom aggravation.

KEY WORDS: Digital healthcare; Mental health; EEG; PPG; Maumgyeol.

INTRODUCTION

The face-to-face interview and psychological scales have measured the clinical symptom severity and diagnosis of mental health problems. The interview-based assessment and diagnosis depend on participants' frankness and insight or self-awareness of their mental symptoms.

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Address for correspondence: Seung-Hwan Lee

Bwave Inc., 1547 Jungang-ro, Ilsanseo-gu, Goyang 10380, Korea Department of Psychiatry, Ilsan Paik Hospital, Inje University College of Medicine, 170 Juhwa-ro, Ilsanseo-gu, Goyang 10380,

E-mail: seunghwan.lee@bwaveeeg.com; lshpss@paik.ac.kr ORCID: https://orcid.org/0000-0003-0305-3709

Mental health professionals have recognized the discrepancy between overt and covert symptoms expressed by interviewees intentionally or unintentionally [1,2]. There have been several trials to solve this discrepancy. The most promising solution is the biosignal-based mental health evaluation under the mount of rapidly developing digital healthcare.

Digital healthcare is one of the most promising candidates to solve this discrepancy because digital healthcare gathers healthcare data and information unintentionally by smartphone and various forms of sensors, which means no needs to intentionally produce their healthcare information [3,4]. Digital health is a broad, multidisciplinary concept that includes both hardware and software solutions. It comprises telemedicine, wearable de-

¹Bwave Inc., Goyang, Korea

²Department of Psychiatry, Ilsan Paik Hospital, Inje University College of Medicine, Goyang, Korea

³Clinical Emotion and Cognition Research Laboratory, Department of Psychiatry, Inje University, Goyang, Korea

⁴Department of Human-Computer Interaction, Hanyang University, Ansan, Korea

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vices, augmented or virtual reality, mobile health (mHealth) apps, electronic health records (EHRs), electronic medical records (EMRs), etc. [5]. It can make medicine more preventive, personalized, and precise [6].

Recently, digital therapeutics (DTS) has been drawing the attention of many business companies and clinical research groups in mental health. In contrast, digital diagnostics (DDS) is less attentive than DTS [7,8]. However, the DDS is a clinically and basically meaningful area of healthcare because the diagnosis, not treatment, should be the first step to approaching people with health problems. Thus, DDS is a gateway to true digitalization if they want the DTS to be successful in the digitalized healthcare ecosystem.

Among the various forms of intelligent wearable devices, the small channels electroencephalography (EEG) and photoplethysmogram (PPG) hardware have been applied to evaluate multiple mental health problems. Primarily the frontal EEGs have been utilized to assess emotional regulation [9], suicidal behavior [10,11], behavioral attitude [12], several psychiatric disorders [13-15], massive disaster victims [16,17], seizure detection [18], and childhood developmental problems [19,20]. Prefrontal EEG has the advantage of easy accessibility due to its direct attachment to the skin without hairs. PPG is an optically obtained plethysmogram that can detect blood volume changes in the microvascular bed of tissue [21]. A PPG is often obtained using a pulse oximeter which illuminates the skin and measures changes in light absorption [22]. Heart rate variability (HRV) can be calculated from PPG because PPG could provide heartbeat cycles. Clinically, HRV has been used as a stress measurement in the mental health area [23]. The device comprised of frontal 2 channels EEG and PPG was successfully applied to the massive disaster victims to evaluate their mental health problems [16,17]. Recently, there has been a growing need to develop an easily measurable, rapidly accessible, and reliable solution for digital mental healthcare.

This study aimed to test the validity and usefulness of Maumgyeol Basic (brain health and mental health), an evaluation and grade scoring software for mental health from the bio-signals originated from 2 channel frontal EEG and an ear ball PPG, which Bwave Inc. developed Korea Republic. We hypothesized that Maungyeol Basic would reflect the mental health symptom and severity well. Specifically, we expected the Maumgyeol Basic brain health score (EEG-based scoring) to reflect cognitive ability rather than the affective symptom. Also, the Maumgyeol Basic - mind health score (PPG-based scoring) would reflect stress and affective symptoms rather than cognitive ones.

METHODS

Participants

A total of 204 participants (101 healthy control and 103 patients with psychiatric disorders) between the ages of 19 and 75 (mean age = 45.90 ± 13.78) were recruited in this study (Table 1). Healthy controls were recruited from the local community through flyers and website advertise-

Table 1. Demographic data and	l clinical in	formation of a	ll participants
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Variable	Healthy controls (n = 100)	Patients (n = 99)	t	p value
Age	47.68 ± 13.30	44.15 ± 14.09	1.83	0.068
Sex (M/F)	33/68	36/67		0.769
MHS-D	6.18 ± 6.86	18.68 ± 14.58	-7.95	< 0.001
MHS-A	7.05 ± 7.92	18.39 ± 12.37	-7.80	< 0.001
CSRS	10.21 ± 9.50	27.62 ± 19.94	-7.97	< 0.001
GHQ-12	2.45 ± 2.35	6.22 ± 3.54	-8.92	< 0.001
CGI	1.35 ± 0.65	3.97 ± 0.84	-24.62	< 0.001
DSST	67.98 ± 18.57	53.79 ± 24.07	4.71	< 0.001
Maumgyeol Brain	77.11 ± 9.12	76.13 ± 9.75	0.73	0.46
Maumgyeol Mind incl.	76.22 ± 10.77	63.12 ± 16.16	6.7	< 0.001
Maumgyeol Mind excl.	68.59 ± 12.71	63.89 ± 16.09	2.2	0.034

Values are presented as mean ± standard deviation or number.

M, male; F, female; MHS-D, Mental Health Screening for Depressive Disorders; MHS-A, Mental Health Screening for Anxiety Disorders; CSRS, cognitive stress response scale; GHQ-12, 12-item General Health Questionnaire; CGI, Clinical Global Impression; DSST, digit symbol substitution test; incl., including psychological scale score; excl., excluding psychological scale score.

ments. All participants in the healthy control group reported no history of or current psychiatric medical treatment or need for clinical mental health services. Participants were excluded when they couldn't read and sign the consent form voluntarily, were under an education level of 12 years, and had any history of organic brain problems or consciousness loss.

Patients with a psychiatric disorders were recruited from the local community through flyers posted in local psychiatric clinics of Goyang areas and website advertisements (https://bwaveeeg.com/). Patients with a psychiatric disease voluntarily participated and were confirmed as patients with proof of at least one medication prescription, doctor-certified diagnosis, and opinion in this study. The diagnosis of patients was including major depressive disorder (n = 71), panic disorder (n = 14), post-traumatic stress disorder (n = 5), bipolar disorder (n = 2), schizophrenia (n = 6), and unknown diagnosis (n = 5). Participants were excluded when they couldn't read and sign the consent form voluntarily, were under an education level of 12 years, and had any aggressive and uncooperative tendencies.

After a thorough explanation of the procedure and protocol of the experiment, written informed consent was obtained from all participants according to the procedures of the public Institutional Review Board (IRB no. 2022-0326-002).

Mental Symptom Evaluation

Psychological evaluation

Mental Health Screening Tool for Depressive Disorders (MHS-D)

The MHS-D is a 12-item depression screening tool encompassing all nine diagnostic criteria of Diagnostic and Statistical Manual of Mental Disorders 5th edition (DSM-5) for Major Depressive Disorder (MDD) [24]. A total of 10 items were constructed based on DSM-5 diagnostic criteria. The preliminary examination identifies two questionnaires measuring helplessness and hopelessness to diagnose depression among the Korean population effectively. Therefore, these two items were added to the test, and a total of 12 items were constructed. On a 5-point Likert scale each item is evaluated using a 5-point Likert scale ranging from 0 (not at all) to 4 (always).

Mental Health Screening Tool for Anxiety Disorders (MHS-A)

The MHS-A is an 11-item self-report screening tool for Generalized anxiety disorder (GAD) [25]. Each item of the MHS-A reflects all diagnostic criteria for GAD from the DSM-5. Each item is evaluated using a 5-point Likert scale ranging from 0 (not at all) to 4 (always). These scores indicate how respondents felt about each symptom over the previous two weeks.

Cognitive Stress Response Scale (CSRS)

The CSRS consists of a total of 21 items on a 5-point Likert scale ranging from 0 (not at all) to 4 (always) [26]. The range of scores is obtained by summing each item from 0 to 84 points. The 21 items consist of three subscales: 'extreme-negative thoughts' with nine items; 'aggressive-hostile thoughts' with four items; and 'self-depreciative thoughts' with eight items.

Korean Version of the General Health Questionnaire (GHO-12)

The GHQ-12 is a self-report tool designed to detect mental disorders in non-clinical settings [27]. The questionnaire consisted of 12 items; the rating method for the GHQ-12 items was 0-0-1-1, and the reverse-scored items (items 1, 3, 4, 7, and 12) were 1-1-0-0. The items were summed to produce a global score (range 0-12); higher scores indicate higher psychiatric morbidity. In this study, the Korean GHQ-12 was used [28].

Clinical Global Impression (CGI)

The severity and improvement of psychiatric symptoms were evaluated using CGI [29]. In this study, the CGI-Severity scale (CGI-S) was used. The severity of psychiatric symptoms ranges from 1 (normal and not ill) to 7 (among the most severely ill).

Cognitive ability evaluation

Digit Symbol Substitution Test (DSST)

This test provides a list of digits and digit-symbol pairs [30]. Participants were instructed to draw as many paired symbols for each assigned digit as possible within two minutes. The score was determined by the total number of correctly drawn symbols within the given time, with a higher score indicating a higher level of performance.

EEG & PPG Bio-signal Acquisition

Resting-state EEG and PPG data were collected concurrently while participants sat in a comfortable chair in a sound-attenuated room and closed their eyes for five minutes. EEG and PPG were recorded using a two-channel EEG device (Model: Amp AD8220) (SOSO H&C, Kyungpook National University).

EEG was recorded at Fp1 and Fp2 according to the 10-20 system. The reference electrode was located on the right ear lobe. The sampling rate was 256 Hz. Online notch filtering (60 Hz) was applied to remove powerline noise. EEG signals were acquired using a bandpass filter with cutoff frequencies between 4 and 41 Hz. Maumgyeol Basic Solution (software version 2.0) was used for the automatic visual inspection for artifact rejection. Artifacts with a maximum absolute value exceeding 100 μV were rejected at all electrode sites. The eye movement-related artifacts were removed using the mathematical procedure of standard deviation for each epoch [31]. After that, it was divided into 2s epochs without any overlap. Participants with less than 30 epochs after pre-processing were excluded from the analysis. After that processing, one participants from healthy controls and 4 participants from patients with psychiatric disorder were excluded for further analysis. The final participants were 100 healthy controls and 99 patients with psychiatric disorder.

The PPG signals were recorded from the right ear lobe. The recorded signal was bandpass filtered at 0.5 – 5 Hz using a Butterworth filter. When the signal amplitude was outside the measurable range, the clipping detection function reconstructed the waveform using spline interpolation [32]. In addition, all peaks of the filtered signal were detected using the peak detection function, and beat-by-beat RR intervals with a Beats Per Minute (BPM) of less than 40 and greater than 180 were excluded [32]. To address the amplitude issue, clean RR intervals were used in the analysis by applying Z-score normalization [33].

All EEG and PPG data pre-processing and analysis were conducted in Maumgyeol Basic solution based on Python.

Maumgyeol Brain Score and Mind Score Calculation

There were three kinds of Maumgyeol scoring solutions; Maungyeol Brain score, Maumgyeol Mind score incl., and Maumgyeol Mind score excl. The Maumgyeol Mind incl. refers to the mind health score, including scores of the self-rating psychological scales. Maumgyeol Mind score excl. refers to the mind health score without scores of the self-rating psychological scales. Each scoring solution has a scoring algorithm, meaning that above 80 is considered Good, 70–79 Moderate, 60–69 Warning, and below 60 Risky.

Maumgyeol Brain score

```
Maumgyeol_{Brain\ score}
= W_1Brain_{activity} + W_2Brain_{flexibility} + W_3Brain_{brighteness-power}
+ W_4Brain_{brighteness-peak} + W_5Brain_{balance}
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Fast Fourier Transform with a 4-41 Hz bandpass filter was applied to calculate brain activity. First, the frequency power was calculated as the square of amplitudes: relative theta (4-8 Hz), low alpha (8-10 Hz), high alpha (10-12 Hz), low beta (12-15 Hz), middle beta (15-20 Hz), high beta (20-30 Hz) and gamma (30-40 Hz) signals [34]. Next, the relative frequency power was calculated.

Kolmogorov complexity (KC) has been utilized to predict the irregularity or degree of randomness of symbolic sequences [35]. In order to calculate KC, Signal S(n) must be converted into a binary sequence as follows [36]:

$$S = s(1), s(2), \dots, s(n)$$

where

$$s(i) = \begin{cases} (0, s(i) < T_m \\ 1, otherwise \end{cases}$$

where s(n) was the original time series and T_m was the threshold that was determined to be the mean value of signal S [37]. Then, signal S was scanned from left to right to determine the number of distinct patterns, and the complexity value c(n) was increased whenever a new pattern appeared. The KC depends on the number of disparate subsequences in signal S. To acquire KC independent of sequencing length, c(n) needs to be normalized as follows [38]:

$$KC = \frac{C(n)}{\frac{n}{\log_2(n)}}$$

The normalized KC indicates the sequence's temporal structure by reflecting the increasing rate of new patterns over time series. More complexity corresponds to higher KC values.

To calculate brain brightness, alpha peak frequency and power were analyzed. First, individual Alpha Peak Frequency (IAPF) was evaluated by submitting the relative power spectrum of each participant [39], averaged across epochs, to the Python "PeakUtils" algorithm [40], which identifies local maxima, for the frequency range 8 – 12 Hz.

To calculate hemispheric brain balance, Frontal alpha (8-12 Hz) asymmetry was analyzed [11]. Then, the difference between the two hemispheres was divided by their total.

Alpha asymmetry = $(P_{left} - P_{right})/(P_{left} + P_{right}) \times 100$,

where P_{left} (left hemisphere) and P_{right} (right hemisphere) represent the relative powers. A score of zero represents that alpha power and brain activity are equivalent in both hemispheres; a positive score represents increased alpha power and hypoactivation of the left hemisphere; and a negative score represents increased alpha power and hypoactivation of the right hemisphere.

Maumgyeol Mind score

Maumgyeol_{Mind score} incl.

= W₁ANS_{activity} + W₂ANS_{balance} + W₃ANS_{stress}

+ W₄ANS_{resistance} + W₅Scale_{score}

Maumgyeol_{Mind score} excl.

= W₁ANS_{activity} + W₂ANS_{balance} + W₃ANS_{stress}

+ W₄ANS_{resistance}

To calculate autonomic nerve system (ANS) activity, the Welch method was used to calculate the power spectral density (PSD) from the HRV signals [41]. The power spectrum was divided into four bands: very low frequency (VLF: 0-0.04 Hz), low frequency (LF: 0.04-0.15 Hz), high frequency (HF: 0.15-0.4 Hz), and total power (VLF + LF + HF). In addition, the log transformation was applied to the frequency power.

ANS balance was calculated by dividing LF and HF by LF + HF, respectively [42]. That produced normalized LF (nLF) and normalized HF (nHF).

To calculate stress and resistance, the standard deviation of the NN interval (SDNN) was computed [41]. SDNN refers to a resistance index that indicates whether

the human body can maintain a stable state by responding appropriately to environmental changes or stress. nLF/SDNN refers to a stress index.

To calculate self-rating scores of depression and anxiety, which were used in the Maumgyeol Mind score incl., MHS-D and MHS-A were used [24,25].

Classification based on Maumgyeol Brain & Mind Health Scores

Classification by symptom severity

Participants were divided into three groups Risky, Good, and Usual, according to Maumgyeol Brain & Mind incl. scores. The Risky group was defined as both scores lower than 70, and the Good group was both scores over than 80, and Usual was included as the Others.

Classification by insight level

In addition, participants were classified according to insight levels, comparing their subjective symptoms (selfawareness of mental symptoms) and objective symptom (biosignal-based Maumgyeol scores). By this logic, participants were classified into five groups such as No Insight, Hypochondriac, Healthy Insight, Risky Insight, and Others. To avoid the influence of the self-reporting score, the Maumgyeol Mind score (Maumgyeol Mind excl.) was used in this classification. No insight group was defined as self-awareness of mental symptoms (no to mild: MHS-D score < 13, MHS-A score < 15), and both Maumgyeol scores below 70 or at least one Maumgyeol score below 60. The hypochondriac group referred to individuals with self-awareness of mental symptoms (moderate to severe: MHS-D score \geq 17, or MHS-A score \geq 20) and both Maumgyeol scores ≥ 70. The healthy insight group referred to individuals with self-awareness of their mental symptoms (no to mild: MHS-D score < 13, MHS-A score < 15), and both Maumgyeol scores \geq 70. Finally, the risky insight group referred to individuals with selfawareness of mental symptoms (moderate to severe: MHS-D score \geq 17, or MHS-A score \geq 20), and both Maumgyeol scores below 70 or at least one Maumgyeol score below 60.

Statistical Analysis

For comparison of group differences in age, psychological evaluation scale, and cognitive ability evaluation

scale, a two-tailed *t* test was used. For the comparison of the sex ratio, the chi-square test was used. Analysis of variance (ANOVA) was performed for three group comparisons. The associations among Maumgyeol Brain, Maumgyeol Mind incl., Maumgyeol Mind excl., psychological evaluation scale, and cognitive ability evaluation scale were calculated by Pearson correlation analysis. All statistical analyses were carried out using SPSS software (version 21.0; IBM Co.).

RESULTS

Comparison between Healthy Control and Patients

There were no differences in demographic data between healthy controls (n = 100) and patient groups (n = 99). There were significant differences in psychological evaluation scales (MHS-D, MHS-A, CSRS, GHQ-12, CGI), DSST scales, Maumgyeol Mind incl., and Maumgyeol excl. (Table 1). However, Maumgyeol Brain showed no significant difference between healthy controls and patient groups (ρ = 0.46).

Comparison among Maumgyeol Risky, Maumgyeol Usual, and Maugyeol Good

There were no differences in demographic data among Maumgyeol Risky, Usual, and Good groups. There were significant differences in psychological evaluation scales (MHS-D, MHS-A, CSRS, GHQ-12, CGI), DSST scales, Maumgyeol Brain, Maumgyeol Mind incl., and Maumgyeol

Mind excl. (Table 2, Fig. 1). Maumgyeol Risky group showed significantly worse scores in all psychological and cognitive ability evaluation scores.

Correlation Analysis between the Maumgyeol Score System and Psychological and Cognitive Function

Maumgyeol Brain score showed a significant correlation (r = 0.23, p < 0.001) with cognitive ability (DSST). In a subscale analysis, brain activity significantly correlated with cognitive ability (DSST; r = 0.14, p = 0.046). Brightness power showed significant correlations with cognitive stress (CSRS; r = -0.18, p = 0.011), health quality (GHQ-12; r = -0.14, p = 0.044), and cognitive ability (DSST; r = 0.16, p = 0.019) (Fig. 2).

Maumgyeol Mind score significantly correlated with severity impression (CGI; r = -0.14, p = 0.035) and cognitive ability (DSST; r = 0.16, p = 0.024). In a subscale analysis, mind activity showed significant correlations with health quality (GHQ-12; r = -0.17, p = 0.012) and severity impression (CGI; r = -0.22, p < 0.001). The stress index significantly correlated with cognitive ability (DSST; r = 0.22, p = 0.002). Stress resistance correlated considerably with cognitive ability (DSST; r = 0.24, p < 0.001) (Fig. 2).

Classification by Insight Level

There were five classifications according to insight levels. Of all participants, the no insight group was 20.6%, hypochondriac group 16.8%, healthy insight 25.1%, ris-

Table 2. Three groups categorization according to Maumgyeol Brain and Mind scores

Variable	Maumgyeol Risky ^a (n = 21)	Maumgyeol Usual ^b (n = 152)	Maumgyeol Good ^c (n = 26)	df	F	p value	Post-hoc
Age	49.00 ± 12.31	44.91 ± 14.30	48.69 ± 11.48	2	1.452	0.237	
Sex (M/F)	33/68	36/67	36/67			0.917	
MHS-D	24.73 ± 15.34	12.10 ± 12.71	4.86 ± 3.55	2	15.594	< 0.001	a > b > c
MHS-A	23.36 ± 12.52	12.59 ± 11.61	5.17 ± 5.48	2	15.605	< 0.001	a > b > c
CSRS	32.04 ± 22.31	18.81 ± 17.49	8.34 ± 7.46	2	11.107	< 0.001	a > b > c
GHQ-12	6.61 ± 3.44	4.37 ± 3.60	2.26 ± 2.06	2	9.391	< 0.001	a > b > c
CGI	3.90 ± 1.26	2.55 ± 1.48	2.23 ± 1.42	2	9.204	< 0.001	a > b, a > c
DSST	40.52 ± 25.46	63.28 ± 21.69	62.88 ± 18.49	2	10.249	< 0.001	a < b, $a < c$
Maumgyeol Brain	61.96 ± 7.61	77.27 ± 8.13	84.58 ± 3.71	2	53.043	< 0.001	a > b > c
Maumgyeol Mind incl.	52.68 ± 10.78	69.38 ± 14.23	85.35 ± 3.24	2	36.829	< 0.001	a > b > c
Maumgyeol Mind excl.	54.94 ± 12.88	65.63 ± 14.40	79.00 ± 5.86	2	19.247	< 0.001	a > b > c

Values are presented as mean \pm standard deviation or number.

M, male; F, female; MHS-D, Mental Health Screening for Depressive Disorders; MHS-A, Mental Health Screening for Anxiety Disorders; CSRS, cognitive stress response scale; GHQ-12, 12-item General Health Questionnaire; CGI, Clinical Global Impression; DSST, digit symbol substitution test; incl., including psychological scale score; excl., excluding psychological scale score.

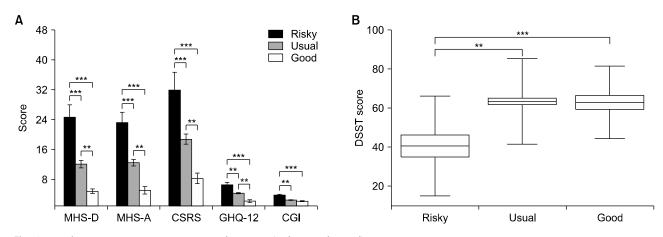
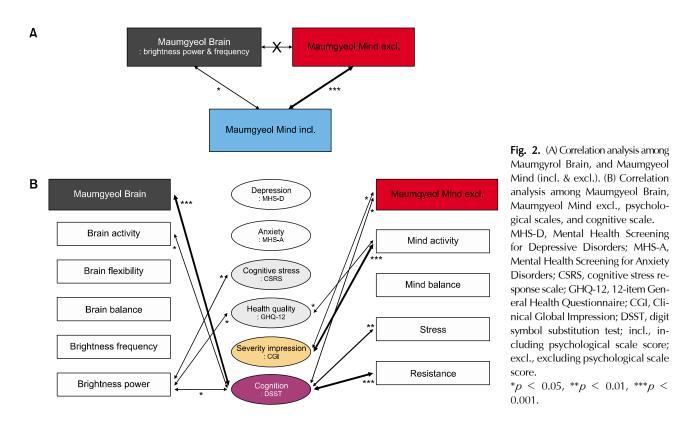


Fig. 1. Graphic comparison among Maumgyeol 3 groups (Risky, Usual, Good). MHS-D, Mental Health Screening for Depressive Disorders; MHS-A, Mental Health Screening for Anxiety Disorders; CSRS, cognitive stress response scale; GHQ-12, 12-item General Health Questionnaire; CGI, Clinical Global Impression; DSST, digit symbol substitution test. **p < 0.01, ***p < 0.001.



ky insight 15.1%, and others 31.2%. In healthy controls, healthy insight was 38.8%, and risky insight was 5%. In the patient group, healthy insight was 12.1%, and risky insight was 25.3% (Fig. 3).

DISCUSSION

This study evaluated the clinical implication of Maumgyeol Basic service, an evaluation and grade scoring software for mental health based on user's bio-signals. First, we present this service as an easily measurable, rapidly accessible, and reliable digital solution for mental health-

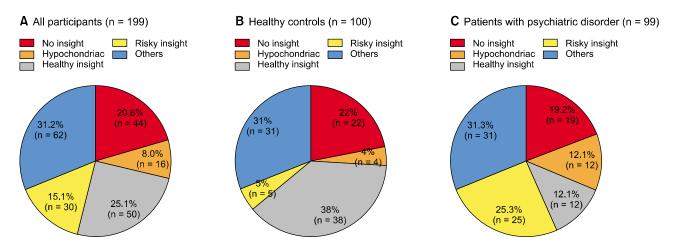


Fig. 3. Five group classification according to insight levels comparing their subjective symptom (self- awareness of mental symptom) and objective symptom (biosignal based Maumgyeol scores). (A) All Participants, (B) healthy controls, and (C) patients with psychiatric disorder were as 5 group such as no insight, hypochondriac, healthy insight, risky insight, and others. In this classification, scores form Maumgyeol Brain and Maumgyeol Mind excl. were used.

excl., excluding psychological scale score.

care. Second, we found that Maumgyeol Basic well reflected the mental health symptom and severity. Third, as expected, the Maumgyeol Brain score (EEG-based scoring) mainly represented cognitive stress, cognitive ability, and health quality. In contrast, the Maumgyeol Mind score (PPG-based scoring) reflected symptom severity, cognitive symptom, and health quality. Fourth, 20.6% of individuals who were unaware of their mental illnesses were no insight group.

First, we proved that this service could easily be applied to participants without any significant side effects or complaints rapidly and reliably. The participants were well adapted to the new high-tech service with a measurement time of 10-15 minutes. In this experiment, research assistants helped the participants to wear the wearable device in the investigation. However, in the future, participants can conduct the test by themselves.

Second, we found that Maumgyeol Basic reflected the mental health symptom and severity. The Maumgyeol mind health scores were significantly lower in the patients group compared to healthy controls. However, brain health scores did not show any significant difference between the two groups. Maybe, this is because the participants in our experiment consisted mainly of neurotic patients with no organic brain abnormalities. Most patients showed mild symptoms rather than severe mental illness (CGI mild to moderate).

Among the three Maumgyeol groups, Maumgyeol Risky

group showed significantly lower psychological and cognitive ability evaluation scores than Maumgyeol Usual and Good groups. These results demonstrate that the Maungyeol Basic could be an excellent evaluation method for the general population's psychological and cognitive ability evaluation. Paper and pencil-type psychological tests usually take longer to complete, depending on participants' frankness, insight (self-awareness), and the experimenter's proficiency. However, Maumgyeol Basic takes 10—15 minutes without the need for participants' frankness and insight (self-awareness). It is a measurement with ease, speed, and reliability. Our results demonstrate that Maumgyeol Basic could be an excellent DDS with a good fit for digital mental healthcare.

Third, as expected, the Maumgyeol Brain score (EEG-based scoring) mainly reflected cognitive stress, cognitive ability, and health quality. In contrast, the Maumgyeol Mind score (PPG-based scoring) reflected symptom severity, cognitive symptom, and health quality. EEG originally have been used as a useful evaluation tool for cognitive [43,44] and affective disorders [45,46]. However, the Maumgyeol service comprised five sub-components of brain activity, brain flexibility, brain brightness frequency, brightness power, and brain hemispheric balance. They are focusing more on the cognitive domain rather than the affective domain.

On the other hand, PPG has originally been used as a useful evaluation tool for stress-related states and affective

disorders. HRV indices calculated from PPG are well known to reflect stress [47], severity of psychiatric illness [48], mental health resilience [49], and affective dysregulation [50].

Fourth, 20.6% of individuals were the no insight group who lacked self-awareness of their mental health issues. There are two aspects of no awareness of mental problems. From the service provider's viewpoint, general clinical practitioners don't have the proficiency to diagnose mental illness correctly. One study found that in a general internal medicine practice treating a diverse population, 10% of the patients had diagnosable depressive disorders, and 11% had a disorder with depressive symptoms that did not fit into any standard diagnostic categories [51]. Due to the fear of stigmatization, many psychiatric patients are reluctant to acknowledge to themselves or others that they are experiencing emotional problems. Similarly, patients may be unwilling to disclose information to the insurance company or employment records. People may fear potential discrimination against their history of psychiatric diagnosis and consequently avoid seeking professional help [52]. Through monitoring, clinicians and patients can take preventative and therapeutic measures before symptoms exacerbate. It can facilitate the application of therapeutic interventions such as Digital Therapeutics to avoid the aggravation of the disease and effectively treat overt symptoms.

This study has several limitations. First, an accurate diagnosis of psychiatric illness could not be obtained because the presence of psychiatric illness was confirmed by proof of at least one medication prescription, doctor-certified diagnosis, and opinion. A majority of patients presented the medication prescriptions as the proof of their diagnosis and the direct diagnosis was not possible. Second, the medication effects on EEG and PPG were not controlled.

Despite these limitations, our study demonstrated an informative clinical implication of Maumgyeol Basic service, a mental health evaluation, and grade scoring software. This service can monitor and assess participants easily, rapidly and reliably. The Maungyeol Basic primarily reflected the mental health symptom and severity. Specially, the Maumgyeol Brain score (EEG-based scoring) mainly reflected cognitive domain of mental function while Maumgyeol Mind score (PPG-based scoring) reflected symptom severity, and affective domain. About

20% of participants were classified as No Insight group which implies the need of careful medical attention.

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■ Conflicts of Interest—

Maumgyeol is commercial software of Bwave Inc.

■ Author Contributions-

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ORCID-

Seung-Hwan Lee https://orcid.org/0000-0003-0305-3709 Hyeon-Ho Hwang https://orcid.org/0009-0006-3563-3782 Sungkean Kim https://orcid.org/0000-0003-4649-6112 https://orcid.org/0009-0005-3106-7149 Junseok Hwang Jaehyun Park https://orcid.org/0009-0004-9028-8980 https://orcid.org/0000-0002-4985-7473 Sangshin Park

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