A Comparison of Unimodal and Multimodal Measurements of Driver Stress in Real-World Driving Conditions

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ABSTRACT

Objectively measuring drivers' emotions in real-world conditions is a challenging endeavour. This study investigated whether drivers' emotional responses were captured more meaningfully by unimodal measurements or by a multimodal machine-learning approach. Ten participants drove a 23-mile route around Sunnyvale, California, while their heart rate, breathing rate and facial expressions were recorded. At regular intervals, participants indicated how they were feeling. After the study, independent observers reviewed a sample of the videotaped sessions, classifying the participants as experiencing high or low levels of stress according to their behaviour. The degree to which drivers' self-report scores, single physiological data streams and facial behaviour—as judged by a facial recognition machine classifier—reflected their actual stress levels was compared to the multimodal algorithmic estimates which combined physiological and facial data outputs. The results showed that, compared to the other single data modes, the multimodal approach captured how the participants were feeling in a way which most meaningfully corresponded with their observed behaviour. The findings re-affirm the need for multimodal emotion-recognition systems for capturing driver stress. The limitations of the study are also discussed.

CCS CONCEPTS

• **Applied computing** → **Psychology**; • **Human-centered computing** → **User studies**; • **Computing methodologies** → **Supervised learning by classification**.

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1 INTRODUCTION

The ability to meaningfully capture drivers' stress levels in real-world conditions has important applications for maintaining driver health, safety and performance, as well for the development of empathic vehicular feedback mechanisms for driver stress reduction—a thriving research area [1][2][3]. The experience of psychological stress—a state of emotional or mental tension that people experience in response to taxing or adverse environmental demands or events which threaten their well-being [4]—is not only harmful to health [5][6][7][8], but is also known to be a predictor of risky driving behaviour [9] and the incidence of traffic accidents [10]. Experiencing stress is thought to adversely impact an individual's cognitive flexibility [11], working memory [12][13] as well as navigation [14] and decision-making abilities [15]—critical factors for safe and careful driving performance. Evidence from several simulator driving studies has shown that people tend to demonstrate impaired performance when driving under stressful conditions [16][17][18], such as the experience of unpleasantly high levels of cognitive load [19].

Additionally, as higher numbers of users gradually avail of assisted and automated driving technologies, it is also becoming increasingly important to accurately monitor drivers' emotions as they engage in shared control with fully or partially automated driving systems. Drivers may experience stress during this interaction, as the human-machine interfaces that facilitate the exchange continue to change in appearance and interaction requirements [20].

People's trust in this type of technology may vary[21][22]—drivers with low levels of trust may remain in an unpleasant, tense state from the point of relinquishing control right up until the point of regaining control of their vehicle. This situation is not ideal as the experience of stress can impair drivers' ability to retrieve control from the automated system [23][24], may cause non-optimal manual driving performance, and may even result in a reduced tendency to engage with the assisted system in the future.

Driving performance is thought to deteriorate when drivers experience emotional extremes—becoming impaired at low, as well as high, levels of cognitive load [25][26]. Some drivers may, for example, *over* trust an assisted driving system and not pay attention to the road when the vehicle is in autonomous mode. They may even engage in irresponsible relaxation activities, such as napping, during this time. In situations where manual takeover is still necessary [27], such behaviours could have life-threatening consequences. The ideal driver should remain adequately engaged and calm, ready to resume control if required. It is critical to maintain appropriate levels of driver stress—whereby an individual's comfort is maximised yet they are still able to safely operate the takeover. Establishing an effective and reliable means of measuring drivers' emotions presents a complex methodological challenge, but is critical for enhancing driver safety and user experience.

2 PREVIOUS LITERATURE

2.0.1 Defining emotions. Emotions are not easily defined but are generally thought to be pleasant or unpleasant subjective experiences that people have in response to environmental stimuli, involving changes in physiology and behaviour [28]. Following Russell's Circumplex Model of Affect [29], it is possible to estimate a person's emotional state in terms of two dimensions—valence and arousal. Valence refers to the subjective quality of an emotional experience—whether a person feels positive or negative—while arousal refers to the degree to which an individual's physiological state is activated and ready to respond to cope with environmental demands. Stress is characterised by high levels of arousal and negative valence, and can be theoretically represented in Quadrant 1 of a two-dimensional valence-arousal space, as illustrated in Figure 1. Lower-arousal states are represented in the lower quadrants—for example, calmness would be represented in Quadrant 3 while less positive low-arousal states such as boredom, or fatigue, would be represented in Quadrant 4.

2.1 Measurement approaches

Estimating drivers' valence and arousal levels to place them within these theoretical zones presents a complex challenge.

2.1.1 Drivers' self-report. The most commonly-used approach seems to be the use of self-report, where drivers are asked to report how they are feeling, either during, or after, the drive. A disadvantage of this approach is that it may be difficult for people to objectively gauge their own feelings or to judge their physiological activation levels. Standardisation can be an issue, as people may not necessarily understand and conceptualise emotions in the same way [30]. Additionally, people may vary in their scoring tendencies, with some individuals scoring themselves more liberally compared to others [31]. Self-report measures can be affected by

Figure 1: Theoretical valence-arousal space

social desirability bias [32][33]—participants in a user study may feel obliged to report favourable feelings towards a driving system to not appear critical or rude, for example. Additionally, the act of reporting during the study disrupts the flow of the participant's driving experience, and can even have an immediate impact on a person's physiological state [34]. Perhaps most pressingly, emotions are dynamic phenomena—an individual's arousal and valence levels can change quickly and dynamically [35][36]. The use of self-report scoring does not allow for continuous measurement and so may not adequately capture how an individual's emotional experience evolves over time.

2.1.2 Drivers' physiological signals. The practice of analysing changes in drivers' physiological signals may offer a more objective means of estimating how they are feeling. The experience of stress is thought to be characterised by elevation in heart rate [37][38][39], breathing rate [40][41][42] and skin conductance response [43][44][31][45][46]. This approach has been employed in both real [47][43][48] and simulated [44][49] driving studies. However, the quality of cardiac data can be affected by movement artefacts [50] while skin conductance signals can be sensitive to temperature, humidity or participant age [51]. Additionally, it has been questioned whether physiological changes are always experienced as specific emotions, or whether such changes necessarily impact behaviour [52][53]. The effect of stressful events on a person's physiology can be long-lasting, while the anticipation of stressful events which are yet to happen can also heighten a person's level of arousal in advance—making interpretation of physiological changes complex [54]. Additionally, some wearable physiological sensors may not be well-suited for real-driving situations, such as the placement of electrodes on participants' fingertips to measure skin conductance activity.

2.1.3 Drivers' facial expressions. Facial cues offer a non-invasive method of estimating drivers' emotions [55][56]. However, the notion that facial expressions dependably convey specific emotions is controversial [57][58][59]. Nonverbal signals can have different meanings across contexts [60][61]. For example, smiling behaviour can indicate amusement, but can also indicate derision [62], social discomfort [63] or embarrassment [28]. There are other factors to consider—perhaps as a result of societal expectations

[64][65], it has been suggested that men do not always express their emotions as openly as women [66], although this is contentious [67] and likely depends on context [68]. Additionally, facial expressions are thought to be tools that people utilise to let others know how they are feeling [69]—in situations when drivers are alone, they may display fewer facial expressions as there is no one present with whom they can communicate how they are feeling.

2.1.4 Multimodal approach. As each of the mentioned approaches to analysing drivers' emotions—the analysis of self-report, physiological signals or facial expressions—is associated with certain caveats, it is preferable to estimate drivers' valence and arousal levels by using a multimodal approach. There is an increasing movement towards the use of multimodal emotion-prediction systems [70][71][72], with a meta-analysis reporting that unimodal systems are outperformed 85% of the time by multimodal systems for both natural versus acted emotions [73]. Such approaches allow for the inherent multidimensional nature of emotions and the context-dependent nature of their expression—that in some situations, a person may not reveal their emotional state outwardly, in which case their physiological responses might offer the best insight into how they are feeling. In more social settings, where facial expressions come to the fore as tools for social communication [74], a person's heart and breathing rate might indicate a high level of physiological activation, while facial cues may provide the strongest indication of valence. By combining physiological signals with facial behaviour using a data-fusion approach, it is theoretically possible to build a richer and more meaningful picture of how a person is feeling.

2.2 Study overview

The present study compared how meaningfully drivers' emotional responses were captured by single data streams compared to a multimodal approach. The comparison analysis was performed using sample data from a driving study where participants drove for 45 minutes on actual highways and industrial roads in Sunnyvale, California. Participants' physiology and facial behaviour were captured as they completed periods of manual driving as well as periods where they interacted with an assisted driving system. The degree to which drivers' self-report scores, single physiological data streams and facial behaviour reflected their actual stress levels—as classified by observer judgments of their behaviour—was compared to multimodal algorithmic estimates which fused physiological and facial data outputs.

3 METHOD

3.1 Participants

In the original study, 36 employees within a leading international automotive brand were recruited for an internal study to test user reactions to an assisted driving system. As the footage from each participant's session had to be reviewed in-depth by two research assistants, this was a highly time-consuming process and it was therefore only possible to analyse 30% of the sample here. Data-recording difficulties meant that data for 3 participants was not usable. From the remaining sample of 33, session data was extracted for 10 randomly-selected individuals (3 females and 7 males, mean

age = 38.8 years). Participants were all at least 18 years old, possessed a full driving licence, drove a minimum of three to five days a week on average and had moderate experience of using the brand's assisted driving functionality.

3.2 Materials and measures

3.2.1 Questionnaires. Participants completed two questionnaires—one before and one after their drive—answering questions about their personality traits, driving tendencies, as well as their attitude towards the assisted driving system that they tested and towards new technology in general. These responses are not analysed here.

3.2.2 Self-report scores. At various checkpoints during the drive, the experimenter asked the participant to verbally state how positive they were feeling on a scale of 1 to 10, with 1 being “not at all positive” to 10 being “highly positive”. The experimenter recorded their response on a mobile device. The scores were averaged to obtain a mean self-report positivity score for each participant's session—a low score representing higher levels of stress.

3.2.3 Physiological signals. Each participant wore an Equival EQ02+ LifeMonitor. This high-quality [75][76][77] sensor belt is made of a breathable, light-weight fabric that makes direct contact with the upper body. It has in-built sensors for measuring heart and breathing rate, and a skin conductance response attachment—a pair of electrodes which are placed on the underside of two fingers to record changes in sweat gland activity. Data is stored in the Electronics Module (SEM) unit—docked inside the vest. The placement of these sensors is illustrated in Figure 2.

Figure 2: Placement of wearable sensors

3.2.4 Facial behaviour. Participants' facial expressions were recorded with a dash-mounted ELP Webcam USB 1080P Camera. The camera was placed in the left-bottom corner of the windscreen, angled upwards to capture the participant's facial movements

as directly as possible. This camera, which works during both daytime and night-time conditions, allowed high-quality recording to continue regardless of any disruptions in lighting during the drive—for example, in shaded areas. The recorded facial expression footage was analysed in real-time using the SHORE [78] facial classification library. For each frame of footage, a participant's emotional expression was classified according to several discrete emotion categories, applying a confidence score for each category. In the current case, only SHORE's scores for "Positive Valence" were used—this score was presumed to reflect the degree to which the person was demonstrating positive facial behaviours, such as smiling and laughter.

3.2.5 Context data. Context information—the driver's view of the road—was recorded with a Logitech RGB webcam camera which was mounted mid-way on the dash, pointing outwards. This captured any emotionally-salient events encountered during the drive which may have had an impact on the driver's stress levels, such as the behaviour of other drivers or traffic congestion. Anything the participants said, or any nonverbal vocalisations they produced, were recorded with a RØDE lapel microphone. The placement of these devices is illustrated in Figure 3.

Figure 3: Placement of data-capture devices within cabin

3.2.6 Multimodal predictions. Data from the cameras, EQ02 vest and the experimenter's mobile were transmitted via Bluetooth to a Synsis™Empathic AI Developer Kit developed by Sensum [79]. Data capture was initiated when the experimenter hit the "Start Session" button on the Synsis user interface, allowing all data streams to be time-synchronised, regardless of format and sampling frequency. Participants' emotions were then predicted by the kit's multimodal arousal and valence algorithms. These were developed using a decision-tree machine learning approach—using data collected in previous studies where people were required to complete stressful and calming activities in a simulated driving context. This data was labelled by multiple annotators using a continuous scoring method. The models were then trained to recognise changes in physiological activation and "positivity" or "negativity" based on these annotated labels. Approximately one valence and one arousal

prediction score were produced per second for each participant's session.

3.3 Procedure

3.3.1 Driving task. Participants were fitted with the wearable sensors, before receiving a brief explanation of the study. They then drove a 23-mile route around Sunnyvale, California, which took approximately 40-45 minutes on average. The driving task began on a brief section of industrial road. Participants then entered a long section of highway driving which involved a roundabout and periods of using the assisted driving system. This was followed by a brief section of industrial roads again and a few minutes in a more pedestrianised downtown area. Participants then returned to the testing area. The route is summarised in Figure 4.

Figure 4: Route driven by participants

3.3.2 Behavioural stress classification. After the study, two undergraduate research assistants, who were blind to the study aims and protocol, were asked to review the videotaped footage of each participant as well as the corresponding context footage of the road and behaviour of other drivers. The assistants were independently asked to classify which individuals seemed to be experiencing higher levels of stress based on their behaviour during the drive. The assistants' classifications were in agreement in each instance—both perceived five of the drivers to be demonstrating stressed behaviour. These individuals were allocated to the "High Stress Behaviour" group. The remaining five drivers were perceived to be calmer, and were allocated to the "Low Stress Behaviour" group.

3.4 Results

3.4.1 Self-report scores. Participants' verbally self-reported positivity scores were compared. Each group's mean score is shown in Table 1. This result indicated that participants in both groups reported feeling generally positive—there was very little difference between them.

Table 1: Mean Verbally Self-reported Positivity Scores

Group	Mean	SD
"High Stress Behaviour"	6.91	2.64
"Low Stress Behaviour"	6.80	2.09

3.4.2 Generalised additive models. The changes in participants' facial behaviour, physiological signals and multimodal arousal and valence predictions were examined over time using generalised additive models (GAMs) with restricted maximum

likelihood estimation. This method is preferred over standard regression for analysing non-linear trends[80]. The GAMs were created in R [81] using the mgcv package [82] and took the generalised form:

$$y = \alpha + f(\text{time}) + \epsilon \sim N(0, \sigma^2)$$

where y represents either breathing rate, heart rate, facial positivity, arousal or valence, α represents the intercept, $f(\text{time})$ represents the smoothing function, and ϵ represents normally distributed errors. The best way to interpret GAMs is through graphical presentation of the smooths [83]. Visualisations were performed in R using ggplot2 [84] and tidymv [85]. The grey variability bands surrounding each smooth represent pointwise 95% confidence intervals. Where they overlap there is no significant difference between the groups. Due to the scaling of each graph, these bands are only wide enough to be visibly observable in Figure 9.

3.4.3 Non-linear data preparation. GAMs were created for breathing rate, heart rate and facial positivity, as well as for the multimodal valence and arousal predictions. Before GAMs could be created, it was necessary to prepare the data and check its suitability for this form of modelling. GPS location tags were used to trim the different sessions to the same length so that the journeys were as comparable as possible. The gam.check function in the mgcv package was used to check for independence of model residuals for each data type. Only data for skin conductance did not pass this check and is therefore not analysed here. Autocorrelation may have been a problem, or it is also possible that, as this is a highly sensitive signal [86], there may have been a higher degree of inter-individual variation which prevented GAMs from being produced—a larger participant sample might have resolved this issue.

3.4.4 Breathing rate. Separate GAMs were created to model changes in each group's breathing rate over time. The smooths for both the "High" ($edf = 5.96$, $F = 7.70$, $p < .001$) and the "Low" ($edf = 2.80$, $F = 9.09$, $p < .001$) stress groups were significant. As shown in Figure 5, the "High" stress group's breathing rate tended to be consistently higher than the "Low" group's across the session. The confidence intervals do not overlap—indicating that these two groups' breathing rates were significantly different across the session.

Figure 5: Changes in each group's breathing rate

3.4.5 Heart rate. Separate GAMs modelled changes in each group's heart rate over time. The GAM smooths for both the "High" ($edf = 2.80$, $F = 18.48$, $p < .001$) and "Low" ($edf = 3.80$, $F = 12.53$, $p < .001$) stress groups were significant. As shown in Figure 6, both groups' heart rates were relatively high at the beginning of the session, gradually decreasing as time went on. However, participants who displayed more stressful behaviour showed a lesser rate of deceleration compared to the "Low" stress group. For the majority of the session, the confidence intervals do not overlap, indicating that the two group's heart rates were significantly different. However, at around 750-1500 seconds, when the participants were using the assisted driving system, the two groups' heart rates were almost equivalent.

Figure 6: Changes in each group's heart rate

3.4.6 Facial behaviour. The same approach was used to model changes in participants' facial positivity levels over time. The smooths were significant for both the "High" ($edf = 8.90$, $F = 147.90$, $p < .001$) and "Low" ($edf = 8.93$, $F = 113.80$, $p < .001$) stress groups. As shown in Figure 7, participants' facial behaviours were generally negatively-valenced for both groups across the session. However, the "High" stress participants were consistently more positive by around ten points across the session. As demonstrated by a lack of overlap between each smooth's confidence intervals, the differences between the groups were significant.

Figure 7: Changes in each group's facial positivity levels

3.4.7 Multimodal arousal predictions. Separate GAMs were created to model changes in each group's arousal levels over time. The smooths were significant for both the "High" ($edf = 8.65$, $F = 27.04$, $p < .001$) and "Low" ($edf = 8.85$, $F = 54.18$, $p < .001$) stress groups. As shown in Figure 8, participants who behaved in a more stressed way had consistently higher levels of arousal across the session compared to the "Low" stress group. As shown by the separation of confidence intervals, this difference was significant.

Figure 8: Changes in each group's arousal levels

3.4.8 Multimodal valence predictions. Separate GAMs were created to model changes in each group's valence levels over the session. The smooths were significant for both the "High" ($edf = 8.79$, $F = 65.64$, $p < .001$) and "Low" ($edf = 8.88$, $F = 74.48$, $p < .001$) stress groups. As shown in Figure 9, participants who demonstrated more stressful behaviour experienced greater levels of negative valence across the session compared to the "Low" stress group. While the "Low" stress participants became gradually more positive, this pattern did not occur for the "High" stress individuals. For the majority of the session, this difference was significant—indicated by the non-overlapping confidence intervals which are wider and more clearly visible in this case, compared to the other data streams. However, when participants were using the assisted driving system—approximately between 600 and 1000 seconds into the session—the two groups' valence levels became more aligned, and were practically equivalent at the points where the confidence intervals overlap.

3.4.9 Combined valence-arousal predictions. Figure 10 is a visualisation of all the arousal and valence predictions produced for each group across all sessions. The predictions for the "High" stress group were most densely populated in Quadrant 1—a zone in the VA space associated with stress. Conversely, the predictions for participants who behaved in a less stressed way were more heavily concentrated in Quadrant 3—an area theoretically associated with relaxation and calm.

4 DISCUSSION

The current study compared different methods of measuring driver stress levels—assessing whether participants' emotional responses were reflected more meaningfully by their verbal self-report scores,

Figure 9: Changes in each group's valence levels

The white contour lines demarcate zones in the VA space where the valence-arousal predictions are populated to the same degree. The innermost "peak" represents the emotional zone most experienced by participants in each group.

Figure 10: Valence-arousal space predictions for each group

by their raw physiological signals, their facial expressions or by a multimodal algorithmic prediction of their arousal and valence levels. The results showed that the multimodal arousal and valence predictions corresponded correctly with the observers' judgments of the participants' stress levels. The multimodal approach particularly outperformed the self-report approach, as the drivers' self-report scores were not associated particularly meaningfully with their behaviour. Although the independent observers judged one group of participants to be demonstrating greater levels of stress compared with the other group, there was relatively little difference between the groups' mean positivity scores. Therefore, the "High" stress participants reported themselves to be just as positive as the participants who seemed to be visibly calmer. Additionally, although the two groups reported feeling relatively similar levels of stress, there were clear differences between their physiological signals. The participants who showed more stressful behaviours had a consistently higher breathing rate across the session. They also did not experience the same level of heart rate deceleration as participants in the "Low" stress group.

However, these results highlight the nuances involved in interpreting how a person is feeling from a single data stream. While there was a clear distinction between the groups' breathing rate

patterns in Figure 5, the distinction is less clear in Figure 6 where, at one stage, the groups' heart rates were roughly equivalent. In the case of facial behaviour, although there was a clear difference between the two groups, it was not a simple case of the stressed participants displaying greater negativity. Participants who were perceived to be more stressed consistently displayed greater levels of "positive" facial behaviours compared to those who were perceived to be calmer. It is possible that these participants may have laughed and smiled as a means of coping with the stressful situation or to appear calm to the experimenter. It is possible that participants in the "Low" stress group may have demonstrated a combination of occasional frowning in the absence of intense smiling—resulting in a more "negative" score. This finding illustrates why it is important to interpret the output of facial expression classifiers carefully, in the context of other sources of evidence about an individual's state, where possible.

Here, only participants' facial "positivity" scores were analysed as they fluctuated over time. However, information about the timing of each positive behaviour was not taken into account. Nonverbal expressions work together in subtle ways to convey complex social messages [87]—it may have been more useful to explore the frequency with which these positive behaviours occurred. It is possible that it was the volatility of the SHORE Positive Valence signal which was more important—perhaps negative valence is not characterised by the absence of smiling and laughter, but is rather signalled by frequent, yet erratic and brief bursts of these signals. A future investigation could explore whether including the volatility of participants' facial positivity scores as a data input improves the performance of the multimodal predictions.

There are some limitations to the current approach that must be considered. Comparisons were performed for a relatively small number of individuals—only 30% of the original participant sample were analysed due to resource-constraints. The in-depth post-study review of each participant's videotaped face camera and context footage, performed by two assistants, took at least 2 hours for each participant. There was therefore insufficient time to classify the entire sample in the same way. However, although only ten individuals were examined here, each session produced—on average—536.9 heart rate, 179 breathing rate and 18430.6 facial positivity values, as well as 2571.5 multimodal valence and 2569.9 arousal predictions. Therefore, the results should be considered in light of the large volume of data points recorded as well as the length of each session—rich, complex, multimodal real-world driving data was captured for at least 40 minutes for every participant. It should also be acknowledged that the current analyses focused on three specific data inputs. Alongside skin conductance, which was captured but not analysed here, there are many other important data inputs that can be used to provide an even richer picture of a person's stress level, such as heart rate variability [88] or changes in skin temperature [89]. Gesture and body movements [90][91], as well as acoustic and speech signals [92][93][94], can also provide meaningful insights about how an individual is feeling.

Participants' stress levels were classified as high or low by human judges—a future study could also incorporate metrics of driver performance such as drivers' speed [95] or braking tendencies [96][97]. The current approach would also have been stronger with the addition of context data inputs. The behaviour of other drivers

and the navigation of heavy traffic are known to trigger stressful events [98], and capturing these, along with information about a drivers' acceleration, speed, braking and gas usage [99][1] would add additional information by which algorithms can make meaningful predictions about how a person is likely to be feeling in that context. It is also appreciated that the current procedure required participants to wear a vest that made direct contact with their skin, as well as electrodes on their fingers—this may not always be possible in normal driving conditions. However, increasingly reliable non-invasive methods of capturing physiological changes continue to be developed, such as the presence of skin conductance electrodes on the steering wheel [1], heart rate detection by ultra-wideband impulse radar technology [100], the use of cameras to capture pulse rate [101][102], heart rate variability [103][104] as well as head motion [102]. Machine vision systems are being developed to track cardio-respiratory changes from video for more than one person at a time with sophisticated noise removal [105]. As individuals tend to exert greater hand pressure under stressful conditions [106], it may also be possible to detect driver stress by monitoring changes in hand grip pressure on the steering wheel and in the use of in-vehicle interfaces [1].

In conclusion, the current findings reaffirm the importance of measuring driver stress levels using multiple data modes. By using machine learning models which are sensitive to subtle changes in physiological signals in conjunction with patterns of facial behaviour, the multimodal approach produced emotion predictions which corresponded with the drivers' observed behaviour in a way that was more meaningful than simply assessing their physiological signals and facial behaviour in isolation, or by asking them to judge how they were feeling. As we move towards progressively non-invasive in-cabin physiological sensing techniques, as well as towards increasingly automated context event labelling technology, data obtained from further studies with more participants will help to train increasingly sophisticated, context-aware, multimodal valence-arousal prediction algorithms.

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