Differentiated Measurements for Fatigue and Demotivation in Translation Process

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Abstract

Fatigue is physical and mental weariness caused by prolonged continuity of work and would undermine work performance. In translation studies, although fatigue is a confounding factor previous experiments all try to control, its detection and measurement are largely ignored. To bridge this lacuna, this article recommends some subjective and objective approaches to measuring translation fatigue based on prior fatigue research. Meanwhile, as demotivation is believed to be an emotion that confounds its accurate measurements, a discussion on how to distinguish those two states is further conducted from theoretical and methodological perspectives. In doing so, this paper not only illuminates on how to measure two essential influencers of translation performance, but also offers some insights into the distinction of affective and physical states during translation process.

1 Introduction

With the flourish of experimental studies on translation process, translators' cognitive and affective states at workplaces have gained increasing attention. However, compared with intense probes into the cognitive aspect of translation, how translators' emotional states influence their translation performance remains largely underexplored. And one of essential reasons is the shortage of reliable instruments to record interested variables accurately and concurrently, especially when the ecological validity is considered. Even though, recent decades have witnessed a growing number of endeavours on translators' emotion (Kitanovska-Kimovska & Cvetkoski, 2022; Lehr, 2014; Lehr & Hvelplund, 2020; Rojo & Caro, 2016), stress (details in Weng & Zheng, 2020) in particular, and motivation (Fan, 2012; Ghasem, 2019; Wu, 2019). Of note is that most experiments adopted subjective measurements (e.g., emotional or motivation scales) to investigate translators' affective states, which somehow ignores the inevitable discrepancy between self-evaluation and actual moods. In this regard, Weng and Zheng's (2020) combination of State-Trait Anxiety Inventory and biomarkers such as heart rate, blood pressure, skin conductance, and salivary cortisol is methodologically progressive. As there exist overlaps between biometrics used to measure different emotional and/or physical states, scholars have advocated the proper application of those techniques and meticulous interpretation of relevant data (Richter & Slade, 2017; Rojo & Korpal, 2020). In translation studies, Rojo and Korpal (2020) have elaborated on how to distinguish stress from other emotions when heart rate variability and skin conductance are employed as indicators. According to their review, no compelling evidence exists to support the assumption that discrete categories of emotions uniquely correspond to specific region(s) of brain, and the same applies to other biomarkers. Thus, the multiple explanations of same physiological indices are an obstacle to overcome before those cutting-edged devices are fully capitalised on. The story grows complexity when physical, cognitive, and emotional factors share one same indicator, of which pupil dilation is an example. Though researchers have designed experiments conscientiously to eliminate common confounding variables such as fatigue, to what extent such manipulations are successful remains unknown. As fatigue is a universally concerned influencer in translation experiments, this article proposes some measurements for translation fatigue with reference to previous literature on fatigue theories and measurements. Afterwards, a comparison between demotivation and fatigue is conducted from the perspective of conceptualisation and measurement. In doing so, it suggests on how to distinguish two phenomenologically similar states in translation scenarios and offers some methodological insights into differentiating physical states from affective states.

2 Fatigue

2.1 Theoretical Definition of Fatigue

State fatigue is defined as "weariness or exhaustion from labour, exertion, or stress" in Merriam Webster dictionary, which denotes its physical and mental aspects. Theoretically speaking, fatigue can also function as a trait since certain people have stronger propensity to feel exhausted under the same workload. Comparatively, physical fatigue gains less theoretical interest than mental fatigue, for which diverse frameworks have been proposed. At first, mental fatigue is depicted as a psychobiological state caused by lengthy and uninterrupted periods of attention-demanding tasks and features a feeling of energy-depletion (Boksem & Tops, 2008). And its adverse impacts on cognitive and motor performances are believed to originate from an impairment in attention maintenance (Boksem et al., 2005), self- regulation (Lorist et al., 2005), response promptness and accuracy (Boksem et al., 2006), as well as efficiency of information identification and utilisation (Lorist et al., 2000). As its conception evolves, more emphasis was placed on its indication of inefficient energy management. According to Thorndike (1900), fatigue is indexed by the inability to do the right thing, rather than continue to work over sustained time. Likewise, Bartley and Chute (1947) believe the conflict between competing behavioural dispositions as the essence of fatigue. By this logic, fatigue is an adaptive state serving to maintain effective and systematic management of goals and meanwhile signifying one's motivational control (details in Balkin & Wesensten, 2011). Also, theoretical attention has been paid to what determine the occurrence of mental fatigue. On a macro level, Grandjean (1968) posited that contextual elements, internal physical factors, and task features altogether accelerate the accumulation of fatigue, which can be alleviated by off-task or leisure activities. In comparison, microcosmic models explain cognitive fatigue through the lens of attention availability and utilisation. For instance, Kahneman's (1973) model on attention allocation delineates the prerequisites for a task to be fatiguing. It postulates that individuals' overall arousal during a task depends on the attentional resources available, whose distribution is a combined effect of one's long-term task interest, state motivation, and regular evaluations on the goal-performance discrepancy. To modify Kahneman's model, Hockey (1997) further included competence-related factors such as responses to challenges, capacity for sustained work, and tolerance of stress as well as perception-related element of task value (Hockey, 1997:80). In his viewpoint, when demands exceed efforts budgeted for the task, a downward revision of goals might be adopted to alleviate the discrepancy until a complete disengagement take places. Similarly, the integrated resource allocation model (Kanfer & Ackerman, 1989) surmised that the quantity of attention accessible for allocation is a joint function of one's ability and willingness. Attention can be diverted to task effort, off- task thoughts and distractions, and self-regulation. And it is the self-perception of effort-performance, performance-utility, and effort-utility functions that determines how much attention one would commit to the given task (details in Ackerman, 2011:21-23). Taken together, those theories not only explicate the role of personal characteristics, time on task, and task features in determining the fatigue effect (Kanfer, 2011:197-198), but also imply the interwoven relationship between motivation and fatigue in conditioning energy distribution and goal setting. It is such a functional overlap between demotivation and fatigue that legitimates the inclusion of motivational factors in some well-recognised fatigue scales (e.g.,Ahsberg's Occupational Fatigue Inventory).

In practice, apart from measurements of fatigue targeting clinic populations, various self-report and observational indicators for chronic and state fatigues have been developed and implemented in cognitive and physical tasks. The following part introduces typical measurements of fatigue for healthy people and examines their applicability in translation studies.

2.2 Measurement of Fatigue

Subjective Measurement of Fatigue

For nonclinical populations, subjective measurements of fatigue consist of task-specific scales, general scales, and measures of related constructions (details in Ackerman, 2011:24). The first type focuses on one single dimension of subjective fatigue (e.g., Stress-state measures in Matthews & Desmond, 2002). The second kind is more diversified with a distinction between short-term and long-term fatigue (e.g., Occupational Fatigue Inventory; Åhsberg, 2000) as well as trait (e.g., Modified Fatigue Impact Scale; Larson, 2013; Fatigue Severity Scale; Krupp, 1989) and state fatigue (e.g., Visual Analog Scale of Fatigue; Lee et al., 1991). Most of those inventories incorporate physical, psychosocial, and cognitive aspects of fatigue and measure the fatigue intensity on a Likert-based scale. In the last case, fatigue is assessed as a component of its highly relevant variables ranging from the activity level (Brooket et al., 1979), moods (Mcnair et al., 1971), activation–deactivation (Thayer, 1978), to tiredness (Montgomery, 1983). When implemented, different scales are often combined, and a comparison of pre-task and post-task data reveals the fatigue caused by a lengthy and attention-demanding task. For instance, when Trejo et al. (2005) examined cognitive fatigue in a continuous mental arithmetic task, both Activation Deactivation Adjective Checklist and Visual Analogue Mood Scale were administered. As evidence on individualised influences (e.g., personality) over self-rated fatigue accrues, meticulous scholars began to enclose personality tests into their instruments. A case in point is Ackerman and Kanfer's (2009) investigation on how the temporal length of SAT test impacts self-rated cognitive fatigue, which shows that differences in neuroticism accounted for the variance in pre-test and post-test cognitive fatigue. However inclusive current fatigue scales are, subjective data is criticised for being unidentical to real-time states, not to mention the concurrent influence of individual differences. In this sense, objective measurements serve as a healthy supplement.

Objective Measurement of Fatigue

Performance as a Fatigue Indicator: Although a decrement in performance after a long-period task execution is accepted as one objective marker of fatigue (Hockey, 2011:171), the validity of such a proposition depends on the satisfaction of following requirements: 1). for a between-group comparison, participants' task specific competency and differences in fatigue proneness and regulation should be considered as confounding factors; for a within-subject comparison, task difficulty should be controlled at a comparable level. 2). time-on-task is key to distinguishing fatigue effects from those of others (e.g., unfamiliarity with experimental setting-up) when task difficulty is within one's competency. Fatigue normally occurs at the later stage of a lengthy and continuous task, which means underperformance at the onset is nonattributable to fatigue unless a taxing task is deliberately assigned beforehand. 3). the task must be intrinsically enjoyable and attention-demanding so that confounders of amotivation or boredom can be eliminated. Even though, extensive evidence has shown that direct effects of fatigue on task performance can be unnoticeable (Ackerman, 2011:14-15), which according to Compensatory Control Model (Hockey, 1997), may result from self-regulation and cognitive control. From this perspective, performance may not be an effective and reliable index of translation fatigue as self-reports and physiological markers do.

Physiological Markers as Fatigue Indicators: Prior experiments resorting to biomarkers cover varied cognitive and physical tasks, among which literature on drivers' fatigue has established a systematic measurement mechanism. In Ani et al.'s (2020) review of detecting systems for driving fatigue, extant approaches were summarised as behavioural, physiological, psychophysical, and biomechanical based. As to behaviours observable by naked eyes, yawning, eye closure or blinking, and changed head or sitting positions can manifest the appearance of fatigue. To capture more subtle changes of physiological signals precisely, electrocardiogram (ECG), electromyogram (EMG), electrooculogram (EOG), electroencephalogram (EEG) and eye trackers have been applied. As far as ecological validity and operational simplicity is concerned, eye trackers seemingly outperform neuro-imaging detectors. And eye-related indicators in service range from eye closure, blink, saccades, fixation, to pupil dilation. Of note is that most research co-used different indices to represent the multi-facets of fatigue. Considering translators' normal work environments, indices of practical value are enumerated in Table1 along with cautions on their application.

Fatigue type	Author & task situation	Tools	Variables and signs of fatigue	Measurement and data analysis, findings	Applicability in translation
Muscular fatigue	Rahayu *et al*, 2016 Driving test	Grip pressure measurement System	Decrease in hand grip pressure force	Compare the force of hands during the first and the last 15-min sessions	Applicable
		EMG	Higher average EMG responses indicates higher level of fatigue	Electrodes were put on the skin surface of interested muscles, and compare data from the first and the last 15-min sessions	Applicable
	Zhang *et al*, 2014 2-hour driving simulation	EMG	Lower tonus of EMG signals increased fatigue	Electrodes were put on the subjects' neck and occiput	Applicable
Muscular visual fatigue		EOG	Decreased eye movement and increased blink rate signal fatigue	Electrodes were placed on the upper eyelid	Applicable
Cognitive/ mental fatigue	Jing *et al*., 2020 Field driving	portable EEG cap	increase in α & β frequency band and a decrease in β frequency band	$(\alpha+\theta)/\beta$ positively relates to self-rated fatigue; $(\alpha+\theta)/\beta$ negatively relates to self-rated fatigue	Applicable
	Zhang *et al*., 2014	EEG	Self-developed algorithm	Electrodes were placed on O1 and O2	Data analysis is too complicated
	Punsawad *et al*., 2015 Simulated driving	electrode cap with Ag/AgCl electrodes & EEG amplifier	three different weighting factors applied to the index $(\theta+\alpha)/\beta$	Electrodes placed in opposition to dominant hand on Temporal, Central, and Parietal areas.	
	Antons *et al*., 2012 Listen to 40-min audios of different qualities for comprehensi-on tasks	EEG (Ag/AgCl electrodes)	An increase in Theta and Alpha frequencies	Electrodes were placed on 7 standard locations with a reference electrode on the tip of the nose. filter data with the threshold of 40 Hz and used data from electrodes with the highest band in the first and last 10-min	Applicable
	Peng *et al*., 2022 vigilance test, cognitive task (foreign language reading and math), or simulated driving	Wearable functional near infrared spectroscopy (fMRI)	functional connectivity strength, characteristics of brain functional network, and time-domain characteristics of blood oxygen	From no to moderate fatigue, the network connectivity overall decreased, especially between regions of PFC and FEF, PFC and PMC. From moderate to severe fatigue, the network connectivity overall increased, and a relatively compact connectivity remained between left PFC and other regions, especially between PFC and FEF.	Applicable but lack compelling evidence
	Shin *et al*., 2019 50-min driving simulation	Smart phone system	The concentration of salivary cortisol: low level indicates fatigue	saliva was collected at the end of each test (5-min practice and three 15-min driving tests)	Applicable but requires the control of confounding factors (stress)
	cognitive tasks (a review in Lee *et al*., 2021)	Smart watch /Electrocardiograph	Heart rate variability	increased high-frequency power and decreased low-frequency power	Applicable
	Qiao *et al*., 2016 Driving test	Eye tracker	Increased blink duration & frequency, delay of lid reopening	Standardised	Applicable when stress-related factors are controlled
	Zhu *et al* Ji, 2004 Driving test		Increased ratio of eye closure and average eye closure speed		Applicable for extremely lengthy or taxing tasks

Cognitive/ mental fatigue	Munoz-de-Escalona et al., 2020 aircraft tasks	Eye tracker	Reduced pupil size	baseline correction of pupil-size	Applicable if confounding factors (*e.g.*, task difficulty, emotionality of source texts) are controlled
	Rasyad *et al.*, 2020 1-hour computer-based work	Eye link II	Saccades, eye blink frequency and duration	fatigue occurs from 30-40 min, microsleep from 40-50 min; eye blink variables are more sensitive than saccades	
General fatigue	Zhu & Ji, 2004 Test of Attention	Facial expression detector	lagging facial muscles, expressionless, and frequent yawning	multi-scale and multi-orientation Gabor wavelets are used to represent and detect facial features	Only applicable in extremely lengthy or taxing tasks
	Zhang *et al.*, 2014 2h simulated driving	Human observation	Signs of boredom, anxiety, agitation, restlessness, or grimace; yawn and doze		

Table 1: Physiological Indicators of Fatigue in Previous Literature.

Translation can induce both muscular and cognitive fatigues. For the former, thin, and high-resolution sensors or EMG electrodes can be placed on the skin surfaces where translators exercise continuous forces such as thenar to detect physical fatigue caused by typing. Meanwhile, cameras and EOG can be combined to document changes in translators' facial expressions (e.g., face lagging) and eye movements (increased eye blink frequency and duration, and decreased eyelid muscle activities indicate visual fatigue), which serve as indicators of facial muscular fatigue. As to cognitive fatigue, attention decrement and drowsiness can be monitored by portable EEG cap (fatigue is indexed by an increase in theta and alpha frequency band and a decrease in beta frequency band), fMRI (indicated by changes in network connectivity between different brain regions), or eye trackers (a decrease in pupil size, eye closure speed, or an increase in the percentage of eye closure and saccades). However, it merits notice that when applying aforesaid biomarkers, confounding factors must be considered in the experimental design. For instance, when using pupil size as an indicator of fatigue, environmental (e.g., light, noise), task (e.g., time pressure), textual (e.g., difficulty and emotionality of source texts) and personal (e.g., health condition, medication and coffee consumption) factors should be controlled for a between-period comparison as evidence shows that pupil dilation is sensitive to those elements (Hvelplund & Lehr, 2021). Moreover, to ensure those physiological changes result from fatigue, time on task is essential. The duration of previous experiments ranged from 30 minutes to 8 hours depending on the task workload. And one study conducted in the similar scenario to translation (Rasyad et al., 2020) indicated fatigue due to computer-based work normally occurs after 30-40 minutes. In this sense, translators' fatigue may appear after a similar length of screen-based translation. Researchers interested in this topic should set their studies at a reasonably long time to detect its effect and meanwhile consider individualised factors such as fatigue proneness.

Compared with scales, physiological data collected by those devices have the merits of reflecting the unconscious aspect of fatigue and accurately recording online states. Nevertheless, its flaws are also obvious. Multiple sources of one physiological signal means that it can be hard to make a confident interpretation of changes in interested variables. As fatigue shares some cognitive, physiological and behavioural indicators with demotivation, the following section will discuss how to differentiate fatigue from demotivation based on their conceptual and measurement differences.

3 Definition of (De)motivation and its Measurement

Motivation is a topic of interdisciplinary discussion for which multitudes of theories and models (e.g., self-determination theory, motivational intensity theory) have been established to explicate its operating mechanism. Some treat motivation as a trait which exercises long-term effects on work and learning performance (Deci & Ryan, 1985), while others regarded it as a state that have direct influences over task effort and outcomes (Brehm & Self, 1989). To illustrate how motivation as a trait and a state play their role in cognitive and physical activities, emphasis have been placed on its measurement.

Theoretically speaking, trait motivation composes of intrinsic and extrinsic motivations, which stem from the satisfaction of competence, relatedness, autonomy, and external rewards or regulations (Deci & Ryan, 1985). Contrarily, a failure to meet those requirements entails amotivation/demotivation. Though relatively steady, trait motivation can be domain specific as one's motivation to work is no equivalence of that to learning or entertainments. Moreover, trait motivation is so implicit that its measurement largely relies on established scales. In translation studies, a typical example is interpreter trainers' learning (de)motivation scale (Wu, 2016). In comparison, state motivation is temporary and task-specific, whose intensity is believed to have detectable cognitive, behavioural and physiological outcomes (Blaise et al., 2021; Derbali & Frasson, 2010; Neigel et al., 2019). Defined strictly, state motivation is regulated by the biological structure of Basal Ganglia and its intensity can shift even within one single task (Wasserman & Wasserman, 2020). In practice, state motivation is always interchangeably used with task motivation and operates as a multi-component structure (de Brabander & Martens, 2014). As such, the more prudent measurement is a combination of self-report and biometric data. Regarding self-report data, factors such as self-efficacy, autonomy, task meaning, utility, enjoyment, and difficulty, as well as output satisfaction are theoretically presumed as reflections of task motivation (Kormos & Wilby, 2019). As to biomarkers, motivational intensity theory (Brehm & Self, 1989) proposes task effort as an indicator of task motivation which can be measured by sympathetic system responses in systolic blood pressure and pre-ejection period. Ideally, task motivation would increase as tasks get more complicated if task accomplishment is possible and justified. And enhanced motivation is indicated by a higher level of systolic blood pressure and shorter pre-ejection period. By contrast, when task difficulty exceeds one's competence, a sense of demotivation would entail a sharp decline in task effort, thus lowering systolic blood pressure and lengthening pre-ejection period. Empirical evidence from varied cognitive and physical tasks have lent adequate validity to those assumptions (Guido et al., 2012). Although SBP and PEP are most suitable measures of motivational intensity from a biological angle, alternative indices such as diastolic blood pressure, heart rate, pupil size and skin conductance are also utilised in many experiments in case one indicator may be insensitive to certain stimuli. Of note is that current practice measures task motivation holistically and focuses on differences in selected parameters between pre-task and during-task conditions rather than subperiods in one lengthy task. Specifically, task motivation is calculated as the mean level of biological data over the whole task deducted by baseline data collected at the resting condition.

More recently, EEG has also been applied to record motivational states (Gergelyfi et al., 2015) since changes of band power in the prefrontal cortex proved to be modulated by emotion and motivation (Spielberg et al., 2008). Specifically, approach motivation leads to more activations in the left hemisphere whereas withdrawal motivation activates the right hemisphere more (Gollan et al., 2014, Horan et al., 2014). And more motivating tasks produce greater magnitude EEG alpha and beta band power in the left prefrontal cortex (Sammler et al., 2007). With the growing application of EEG, channels corresponding to attention, emotion, motivation, and fatigue were further identified. Moreover, using residual-to-residual CNN algorithm, beta waves proved to outperform alpha waves in the accurate predication of motivation for game-playing (Chattopadhyayet al., 2021).

Motivation type	Author, date & instruments	Application scenarios	Dimensions & indications	Measurement features & cautions when applied
Trait motivation	Wu 2016 Interpretation learning motivation scale	Motivation for learning interpretation	Motivation and demotivation	Theory-based and data-driven scale. Require administration immediately before or after the investigated period as participants' responses can vary noticeably across time
	Cai & Dong 2017 Interpretation learning motivation scale		Intrinsic motive, instrumental motive, achievement goal, intended effort	
	Wu 2019 Translation learning motivation scale	Motivation for learning translation	Attitudes to learning environment, teachers and translation, interest in translation, willingness to translate	Modified motivation scale with no distinction between intrinsic and extrinsic motivations
	Amabile *et al*.1994 Work preference inventory	Professionals' work motivation or students' learning motivation	Intrinsic (challenge & enjoyment) and extrinsic (outward & compensation) motivations	Widely applied; requiremodifications to make the scale more relevant to translation work, scale validation in different cultures has generated different subdimensions (Ocal *et al*., 2019)
State motivation	Carver & White 1994 BIS/BAS scale	Simple cognitive tasks	Approach (reward responsiveness, drive, and fun seeking) & Avoidance motivations: lower score indicates low motivation	Have been validated and applied in different cultures; validation of this scale in different contexts has led to different subdimensions (Maack & Ebesutani, 2018)
	Task-specific motivation scale *e.g.*, Martin (2012)'s English Writing Motivation and Engagement Scale	(L2) writing task	Self-belief, anxiety, task value, learning focus, persistence, uncertain control, task management, disengagement, planning, failure avoidance and self-sabotage	Situational but subjective, for whose implementation individual differences should be considered
	Heart rate-related variables (*e.g.*, pre-ejection period)	Simple cognitive and physical tasks	difference in indicators between the resting and the operating states: a reduced difference indicates declined motivation	Spontaneous and simultaneous. Hard to interpret if confounding factors (*e.g.*, emotional source texts) were not strictly controlled; may not be so sensitive in certain conditions and better used combinedly
	Blood pressure	Cognitive tasks		
	Skin conductance	Cognitive tasks		
	EEG	Cognitive tasks		Sophisticated operation and calculation

Table 2: Applied/applicable motivation measurements for translation activities

As shown in Table2, in translation studies, previous investigators have adopted theories and models in the learning domain to develop their scales and confined their targets on language learners. However, as professional translators' motivation has been found to shape their performance (Lehr, 2014), trait and state motivation measurements dedicated to translation are in urgent demand if further exploration of the underlying mechanism were conducted. In this sense, pre-existing generic scales (e.g., work preference inventory, BAS/BIS scale), though not directly applicable, lay the foundation for translation scholars to build their measurement toolkits. Take WPI as an example, the general expression that "I love tackling problems completely new to me" can be situationalised by adding "translation" before "problems". Moreover, as exploratory factor analysis in previous studies on employers' motivation has generated structures different from the original ones, it is essential to validate the modified scales with adequate sample size before their implementation. Regarding state motivation, psychological metrics (e.g., blood pressure, heart rate variables, skin conductance) widely applied in other cognitive tasks are worthy of consideration if confounding factors (e.g., emotional valence of source texts) were meticulously controlled. Another two cautions are: 1). when the attentional and emotional aspects of translation are concurrently examined, eye-movement indicators such as pupil size may not be a rigorous biomarker; 2). in practice, some biomarkers may not be so sensitive to motivational alteration, for which a combined use of indexes are recommended.

4 How to Differentiate Fatigue and Demotivation in Translation

In theory, demotivation and fatigue is easily distinguishable. The former is a physical and mental state out of personal control, while the latter is more related to one's willingness and are thus largely self-determined. However, concerning their measurements, the boundary becomes less clear-cut. Not only fatigue can be a source of demotivation, but also demotivation and fatigue share some cognitive (less focused) and behavioural (underperformance) signals. The theoretical premise that the amount of deliberate effort, efficiency of attention allocation and information processing can index one's motivation fails to discriminate demotivation from fatigue which could lead to same outcomes, albeit at an unconscious level. In this regard, the employment of traditional scales, though at the risk of inaccuracy and latency, seems more helpful in differentiating physical states from emotional states than biomarkers of attention and effort.

However, a perusal of theoretical and biological underpinnings for their measurements sheds more lights. First, fatigue is an exhausting state due to protracted work, which means long time-on-task is a requisite to its occurrence. Differently, lack of motivation can happen at any stage of task performance, either because of one's unwilling to take the task (in the very beginning), a growing understanding of task difficulty (in the middle of task) or gradually getting bored. Second, as one subdimension of fatigue, muscle fatigue has physical features undetectable in the case of demotivation. Biologically speaking, human beings are unlikely to control their muscles in a conscious way, especially in cognitive tasks where skeletal muscle does not play a noted role. In this sense, biometers for measuring muscle fatigue such as EMG and EOG are effective in distinguishing fatigue from demotivation. Third, as far as the mental aspect of both states is concerned, bio-signals of drowsiness (e.g., increased activities in Alpha band power) are peculiar to fatigue as motivation is more self-controlled and operates consciously in most of time. Meanwhile, neuroscience scholars have mapped out some brain regions correspond to motivation and fatigue respectively (Chattopadhyay et al., 2021), which paves the way for applying EEG to tell fatigue from demotivation that may occur at the similar stage. Finally, physiological indices of parasympathetic and sympathetic activities are also useful. Based on motivational intensity theory, demotivation is associated with decreased arousal in sympathetic activities (indicated by lower SBP and longer PEP), which has gained ample empirical supports. Contrarily, fatigue was discovered to be linked to increased sympathetic arousal (Tran et al., 2009) and decreased parasympathetic nervous activities (Lee et al., 2021). Hence, the opposite reflections of those two states in the autonomic nervous system speaks to the applicability of heart rate and blood pressure related parameters for their distinction. Actually, Gergelyfi et al. (2015) have employed a series of neural, autonomic, psychometric, and behavioural signatures to dissociate effects on working memory performance of mental fatigue (measured by ECG, eye blink, and Multidimensional Fatigue Inventory) from that of motivation (measured by EEG, pupil diameter, skin conductance response, and self-rated task interest, efficacy, effort, and value). And their results showed participants' subjective feeling of fatigue is positively related to their eye blink rate and heart rate variability. While reward-induced EEG, pupillometric and skin conductance signal changes (indexes of motivation) did not correlate with subjective and objective indices of mental fatigue. Tentative as their findings are, this research nevertheless indicates the differentiable manifestations of amotivation and fatigue.

5 Conclusion

In summary, although fatigue is a confounding factor that previous translation experiments all try to control, no objective or subjective approaches have been adopted to detect its occurrence. To bridge this gap, this article, based on the fatigue literature, proposed some methods for monitoring and measuring translators' fatigue, which cover self-report scales and various physiological biomarkers. To avoid the impacts of emotional states that share similar cognitive and behavioural consequences with fatigue on its accurate measurement, demotivation was taken as an example to illustrate how to distinguish affective and physical states in translation activities. In doing so, this paper not only illuminates on the measurement of two essential influencers of translation performance, but also cautions on the meticulous employment of biomarkers in translation studies. For future experimenters with an eye on translation (de)motivation and fatigue, it is advised to incorporate objective and subjective measures for the sake of data triangulation. Specifically, PEP and S/DBP, heart rate and skin conductance can be useful indicators of (de)motivation. While muscular activities (in face or body) recorded by EMG, EOG or cameras can help detect translation fatigue. Meanwhile, a combination of biomarkers serves as a safeguard to potential "insensitivity" issue. On the other hand, when scales or self-reports are employed, their relevance to translation tasks, translation (if not phrased in participants' mother tongue) and validation (for both newly developed and established scales) are things to consider.

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