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Machine learning in emotional intelligence studies: a survey

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ABSTRACT
Research has proven that having high level of emotional intelligence (EI) can reduce the chance of getting mental illness. EI, and its component, can be improved with training, but currently the process is less flexible and very time-consuming. Machine learning (ML), on the other hand, can analyse huge amount of data to discover useful trends and patterns in shortest time possible. Despite the benefits, ML usage in EI training is scarce. In this paper, we studied 92 journal articles to discover the trend of the ML utilisation in the study of EI and its components. This survey aims to pave way for future studies that could lead to implementation of ML in EI training, and to rope in researchers in psychology and computer science to find possibilities of having a generic ML algorithm for every EI's components. Our findings show an increasing trend to apply ML on EI components, and Support Vector Machine and Neural Network are the two most popular ML algorithms used in those researches. We also found that social skill and empathy are the least exposed EI components to ML. Finally, we provide recommendations for future research direction of ML in EI domain, and EI in ML.

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Machine learning; emotional intelligence; Support Vector Machine; Neural Network

1. Introduction

In 2001, WHO World Health reported that 450 million peoples are suffering from mental or behavioural disorder (WHO 2001). In their web article dated 22nd March 2018, they reported at least 300 million peoples are suffering from depression. Furthermore, they stated that every year, close to 800,000 peoples die from suicide, and this is the second highest death factor for 15–29-year-old. WHO estimated that in many countries, less than 10% of depressed individuals receive treatment (WHO 2018). Studies have shown that individuals with low emotional intelligence (EI) levels are more likely to feel depressed (Monteagudo et al. 2019), and depression leads to suicidal intention (Abdollahi et al. 2016). On the other hand, individuals with high EI are able to reduce problems related to depression (Marguerite et al. 2017). Additionally, quality life is often associated with high level of EI, and low level of EI is normally associated with undesirable behavioural outcome such as bullying, both in real life and online, substance abuse and suicidal intention (García-Sancho, Salguero, and Fernández-Berrocal 2015). These are among the reasons why research and development in EI should be given a serious consideration (García-Sancho, Salguero, and Fernández-Berrocal 2015).

According to Goleman (1995), EI consist of five components which are self-awareness, self-regulation, social skill, emotion and motivation. EI can be trained and improved (Herpertz, Schütz, and Nezlek 2016; Foster et al. 2017). There are various methods to measure EI such as Mayor-Salovey-Caruso Emotional Intelligence Test (MSCEIT), Bar-On Emotional Quotient Inventory (Bar-On EQ-i) (Mattingly and Kraiger 2018) and Trait Emotional Intelligence Questionnaire (TEIQue) (García-Sancho, Salguero, and Fernández-Berrocal 2015).

Mattingly and Kraiger (2018) have studied 58 researches that focus on EI training and their impact. They reported that there was a moderate positive impact on the participants after their EI training, regardless of their training design. The training is mainly aiming to create emotional awareness among participants. It normally consists face to face lecture, discussion and exercise (Herpertz, Schütz, and Nezlek 2016; Foster et al. 2017). The problem with this training method is it requires exclusive interaction with the trainer, thus the size of the training is small (Vesely, Saklofske, and NordStokke 2014). Furthermore, most of the training process is carried out manually with limited computer usage. As a result, expert analysis is required to continuously monitor and indicate any behavioural change, and this has raised many issues such as delay in getting

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expert's feedback on the training progress, and high dependency on the availability of the expert to guide participants (Herpertz, Schütz, and Nezlek 2016).

Machine learning (ML) has been studied and implemented in various fields, and its impact on unveiling patterns, and solving complex classification problems are huge (Alm, Roth, and Sproat 2005). It had been implemented in various fields such as finance (Barboza, Kimura, and Altman 2017) and education (Anaya and Boticario 2013). A possible inclusion of machine learning (ML) into the EI training session would allow a trainer to interact with more participants at a time (Molina et al. 2011). ML could also be used to provide either supervised or unsupervised emotional analysis that would take some of the training burden off the trainer (Gęsiarz and Crockett 2015). Additionally, the inclusion of ML in EI would make it possible for the training to cover participants in wider geographical area. With ML success in many fields, we believe that ML can be leveraged to assist EI training, and this belief is also shared by many researchers such as (Molina et al. 2011; Cardoso-Leite and Bavelier 2014; Gęsiarz and Crockett 2015). Unfortunately, a significant effort in using ML in the study of EI is not yet apparent, and this is evident from the lack of articles in the Web of Science and Scopus database.

Therefore, this article aims to survey the literatures related to the utilisation of ML in the EI studies in order to discover the current state and trend of ML in the EI study and vice versa, highlight the EI's components that could be further investigated by researchers, and provide some recommendations for future work. The contributions of this survey article are as follow. First is, we uncover the pattern of ML algorithm utilisation in the study of EI's components, and discover the top three most commonly used ML algorithms in the EI's studies. Secondly, we highlight the EI's components that need more studies by researchers in both computing and psychology fields. Finally, we pointed out the need for advance ML algorithm as one of the possible answers for creating a generic algorithm that can be used by all components of EI.

Section 2 presents the theoretical background of this study. Section 3 discusses the methodology of this study. Section 4 reports the survey's results. Section 5 reports the analysis followed by a discussion of the findings. Section 6 provides the future direction in this research. Finally, Section 7 concludes the findings of the study.

2. Theoretical background

This section describes the overview of ML followed by an overview on EI, its component, types of EI, and EI Training.

2.1. Machine learning (ML)

With the advancement of technology and the availability of massive online data, researchers in computer science are continuously attempted to understand the relationship between individuals and their online actions and interactions (Calvo et al. 2011; Anaya and Boticario 2013). To make sense of the available online data and user's response, ML is used to create models that are later implemented in various analytical studies such as learning analytics (Cen et al. 2016), video analytics (Portugal, Alencar, and Cowan 2018) and web analytics.

ML is basically giving a computer the ability to learn through experience (Negnevitsky 2005). Rather than hardcoding each response, the computer is given tasks, measures and conditions to enable it to make precise decisions. This model will then be used with new dataset to verify its accuracy. The methods used in the ML training process determine the types of ML as either supervised, unsupervised, or semi-supervised learning. Past studies have shown that the inclusion of ML can successfully produce desirable outcome on complex problem that was too tedious or impossible to be implemented by human. In ML, there are basic algorithms used by researchers, such as Support Vector Machine (SVM) (Li et al. 2017; Coutinho et al. 2018), k-Nearest Neighbour (k-NN) (López-gil et al. 2016; Polytak, Davier, and Peterschmidt 2017), neural network (NN) (Ali et al. 2018) and k-means (Molina et al. 2011; Troussas, Virvou, and Alepis 2013).

2.1.1 . Supervised learning

In supervised learning, the ML training set is normally supervised by an expert who provides the ML training data along with the desired outcome or the correct answer for a problem (Kotsiantis 2007). The computer would then use supervised learning algorithm to create a model that would be used to solve the problem in real world situation.

One of the major advantages of using supervised learning is the algorithm and its results are verified by human expert. Hence, studies utilising supervised learning normally report high percentage of accuracy for the algorithm.

One of the major disadvantages of supervised learning is the involvement of a human expert is a necessity. While this is beneficial to improve the accuracy of the data, there are situations where huge amount of data can make the involvement of human expert unfavourable (Li *et al.* 2018). First is, when the rate of new data availability is extremely fast, and secondly, when the data are huge and ambiguous. In these situations, high dependency on human expert could delay the ML process. These problems led to the utilisation of another type of ML known as unsupervised learning.

2.1.2. Unsupervised learning

In unsupervised learning the ML training set is either nonexistence or it may depend on online corpus (Celebi and Aydin 2016). This method eliminates the need for human expert involvement. The goal of this method is mainly to find hidden patterns that exist in a dataset. As the dataset becomes larger, the existing groups of data in this method may evolve from its first grouping to form a more refined grouping. Hence clustering algorithm plays such an important role in this type of ML. The more data involved in its training phase, the more accurate is its data clustering outcome. While it needs to process more data as compared to the supervised learning method, its accuracy is normally lower than the supervised learning method due to the absence of human expert.

2.2. Emotional intelligence

EI is actively discussed in the psychology field as reported in (Fabio and Saklofske 2014; Petrides 2016; Petrides et al. 2016; Cejudo 2017; Gribble, Ladyshewsky, and Parsons 2018). A person is considered as emotionally intelligent when they are aware of their own emotions, they could regulate their emotional responses, they are able to manage their social skills, they are being aware of others' emotions state, and they are driven by intrinsic motivation (Cliffe 2011). EI is said to be responsible to whether a person enjoy their work and life (Pocnet et al. 2017), has the ability to cope with stress (Beath, Jones, and Fitness 2015), can better manage their health (Bao, Xue, and Kong 2015) and can achieve better academic scores (Beath, Jones, and Fitness 2015).

EI is often used as an indicator to determine how well an individual understand their emotions, and how well they can control it (Mayer and Salovey 1997). This would later be translated to how well they react to another individual, based on the emotional information that they have. Many studies had shown how EI affects individuals' strategies in dealing with their problems (Beath, Jones, and Fitness 2015), individual happiness, healthy lifestyle (Bao, Xue, and Kong 2015), pro-social conduct (Bacon, Maughan, and May 2018) and patient care (Foster et al. 2017; Gribble, Ladyshewsky, and Parsons 2018).

In this survey, we follow the classification model of EI components stated in Goleman (1995). By using this model, it is easier to classify components that have been extensively researched in ML, and components that should be further explored. This model divides EI into five components. The first element is self-awareness. This element focuses on understanding individual emotions. The second element is self-regulation which focuses on controlling individual emotions. The third element is social-skill which focuses on prosocial interaction. The fourth element is empathy which focuses on individual's ability to sense others' emotions and react to it appropriately. The fifth element is motivation which dictates reason for individual reaction. A graphical representation of the Goleman model of EI element is shown in Figure 1.

2.2.1. Emotional intelligence types and measures

Generally, there are two types of EI, ability EI and trait EI. Ability EI mainly focus on emotions and how it affects an individual. It is mainly measured with MSCEIT (Mayer, Salovey, and Caruso 2002). The test measures individual ability to perceive and express emotions, how emotions influence their thinking, how well they understand emotions, and how they manage their emotions. Trait EI covers similar components with ability EI such as a person well-being, self-control, emotional state and sociability, but focus on self-reporting measurement. Trait EI normally affected by individual personality (Petrides and Furnham 2001). Trait EI is normally measured with self-reported questionnaire such as Bar-On EQ-i (Bar-On 2002), or TEIQue (Petrides and Furnham 2003). These two tests have different impacts on various things that affect an individual's life. Even though ability EI and trait EI components are similar, studies show that the results from both EI measurements are not the same, suggesting that both measures affect individual differently (Fabio and Saklofske 2014).

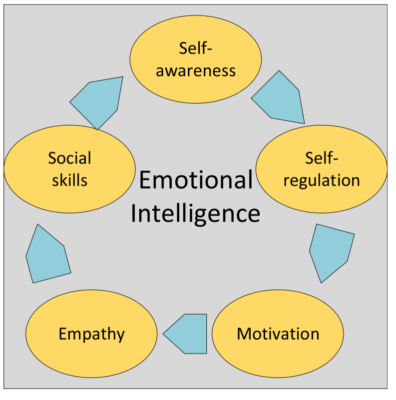

Figure 1. Daniel Goleman Emotional Intelligence components (Goleman 1995).

The main principal of ability EI are as follows: emotional perception and expression, using emotions to influence thinking, understanding emotions and managing individual emotions. Nonetheless, a person may understand their emotions but could not properly manage their action when they undergo certain situation such as a stressful environment. This individual normally scores high in their ability EI but low in their trait EI (Fabio and Saklofske 2014). Trait EI investigates wider perspective of EI. While ability EI mainly focus on emotional understanding of an individual, trait EI considers individual differences such as personality, emotion expression, self-esteem and stress management.

2.2.2. Emotional intelligence training

There were various studies to improve EI. These studies vary in duration, with some took a very long time, while others are relatively short. Since EI is reported to have significant impact on individual wellbeing, researchers have conducted studies to train EI (Herpertz, Schütz, and Nezlek 2016). There are studies that show the sustainable effect of EI training on a person even after a year he/she completed the training (Petrides et al. 2016). Both trait and ability EI are normally trained using the same procedure, and there is no report of exclusive training for either types of EI.

Trait EI model (TEI) is used as a framework to train EI (Petrides and Furnham 2001; Petrides et al. 2016). This model introduces four objectives in EI training. First is to enhance the perception and identification of emotions in a person and in others. Secondly, to promote self-esteem and self-motivation. Thirdly, to improve interpersonal relationship skills and assertiveness. Finally, to regulate one's own emotions and moods. Majority of these studies relied on face-to-face sessions where a trainer facilitates or guides participants to focus on learning how to improve their EI (Cejudo 2017). It is also possible to include EI training in formal curriculum, as demonstrated in a nursing course by (Foster et al. 2017).

Besides face-to-face sessions, EI training can also be carried out with a mixture of face-to-face and online sessions (Herpertz, Schütz, and Nezlek 2016; Gribble, Ladyshewsky, and Parsons 2018). A review by Mattingly and Kraiger (2018) shows that EI training had moderate positive impact in 58 studies that they had reviewed, regardless of ability, trait or mixed model EI training measures. However, many of these training suffers from small sample size (Petrides et al. 2016), and long training duration (Gribble, Ladyshewsky, and Parsons 2018). Recently, several researchers have shown interest to consider the potential of applying ML to address the problems associated with EI training process (Molina et al. 2011; Cardoso-Leite and Bavelier 2014; Gęsiarz and Crockett 2015; Jang et al. 2015)

3. Methodology

This survey aims to study the application of ML in the field of EI. In order to create our procedure, we initially execute 'Emotional Intelligence' and 'Machine Learning*' queries in four databases; Web of Science, Scopus, Emerald Insight and PubMed. The search is limited to articles published from year 2009 to 2018 in all databases. With this query, we found three articles in Web of Science, nine in Scopus, one from Emerald Insight and two from PubMed.

From these results, none were related to studies about EI with ML. Nonetheless, two results that we obtained from PubMed were related to emotion, a component of EI. The small number of related articles obtained from the earlier search had triggered the need to re-define our search procedure. We then redesigned our procedure following a similar study by (Portugal, Alencar, and Cowan 2018). In reference to their systematic review, we created the following three objectives:

(1) To identify the trend of using ML in the study of EI and its components.
(2) To identify the preferred ML algorithm in the study of EI and its components.
(3) To recommend future research direction for ML and EI.

We then proceed with the following three research questions (RQ):

- RQ1. What is the trend of using ML in the study of EI and its component?
- RQ2. In a specific year, what are the commonly selected ML algorithm for the study?
- RQ3. What are the future research directions for ML and EL?

The first step in this survey is to gather as many publications as possible from the aforementioned databases. The Emerald Insight databases are included in this search because it has many publications on EI studies on people in the business field, and in the managerial position. The search results to these databases are then filtered based on exclusion criteria as follows: peer-reviewed journal articles, study must be original article and the article must be published within the last 10 years. The keyword is searched in the title, provided list of keywords, and the abstract section. If the search term exists in either of these sections, the article will go through the second step. The second step is to read the whole article, and analyse the relevancy of the studies according to the purpose of this survey. The last step is to compile and answer all the research questions.

3.1. Search criteria

We first run multiple queries in four databases, stating with 'Emotional Intelligence' followed by 'self-awareness', 'self-regulation', 'social skill', 'collaborative learning', 'empathy', 'emotions' and 'motivation'. The next step is to filter out the results by using the fourth and fifth exclusion criteria. This is to ensure that studies that involved all components of EI are covered during the search.

Subsequently, we refine the query by entering 'machine learning*', 'supervise*learning*', 'un*supervise* learning*' or 'semi*supervise*learning*', or concatenate our queries for the first research question with queries for second research question with an 'AND' in between the two queries. The search includes wild card '*' to capture all spelling differences. The overall search results are shown in Table 1.

Note that in computer-based research, the study that could be related to social skill are normally found in collaborative learning. This can be seen in Table 1. in which results from 'social skill' query is significantly lower than 'collaborative' query. Realising this, we expanded our search terms to include collaborative learning as our search term. Similar situation occurs for empathy where our search term only managed to find low numbers of studies on empathy. Our final list for empathy consists of only five articles but one needs to be removed after full article review as it does not fulfil the objectives of this survey. Therefore, we have to expand our search term for 'empathy' to include term 'emotion' as these terms are inter-related according to (Bedi et al. 2014; Pläschke et al. 2017; Inkster, Sarda, and Subramanian 2018). The difference between emotion and empathy is their measurement technique in which emotions can be evaluated by using multi-mode while empathy mostly depends on self-report or partner-report.

3.2. Exclusion and inclusion criteria

Even though some articles are published in indexed journal in PubMed, some of these journals are not indexed in databases that are normally used in the computing field. For this, we created our first exclusion criteria (EC), which stated that the studies surveyed in this article must go through peer-review process and must be published in either ISI or Scopus indexed journal.

EC1. Studies must be published in ISI or Scopus ranked journal and have been through peer-review process.

Only the original research articles are included in this study in order to ensure that the ML algorithm had been used and evaluated in those studies(which involve EI and/or its components).

EC2. Other than original articles are not included in this survey.

Table 1. Results of search queries.

	Results			
Search Criteria	Web of Science	Scopus	Emerald Insight	PubMed
'Emotional Intelligence' AND 'Machine learning*'	3	9	9	2
'self-awareness' AND 'Machine learning*'	3	3	14	3
'self-regulation' AND 'Machine learning*'	14	16	14	7
'social skill' AND 'Machine learning*'	1	7	1	2
'collaborative' AND 'Machine learning*'	269	390	281	168
'empathy' AND 'Machine learning*'	9	13	29	12
'emotion' OR 'Emotions' AND 'Machine learning*'	46,109	459	9549	153
'Emotions' AND 'Machine learning*'	184	459	101	106
'emotion' AND 'Machine learning*'	261	459	93	112
'motivation' AND 'Machine learning*'	465	592	240	463

Notes: These search queries return no value in all databases. Exception to collaborative and motivation which return 1 and 2 results respectively from Emerald Insight. The search queries are: self-awareness AND 'supervise*learning*', 'self-awareness' AND 'un*supervise*learning*', 'self-awareness' AND 'semi*supervise*learning*', 'self-regulation' AND 'supervise*learning*', 'self-regulation' AND 'un*supervise*learning*', 'self-regulation' AND 'semi*supervise*learning*', 'social skill' AND 'supervise*learning*', 'social skill' AND 'un*supervise*learning*', 'social skill' AND 'semi*supervise*learning*', 'collaborative' AND 'supervise*learning*', 'collaborative' AND 'un*supervise*learning*', 'collaborative' AND 'semi*supervise*learning*', 'empathy' AND 'supervise*learning*', 'empathy' AND 'un*supervise*learning*', 'empathy' AND 'semi*supervise*learning*', 'Emotions' AND 'supervise*learning*', 'Emotions' AND 'un*supervise*learning*', 'Emotions' AND 'semi*supervise*learning*', 'emotion' AND 'supervise*learning*', 'emotion' AND 'un*supervise*learning*', 'emotion' AND 'semi*supervise*learning*', 'motivation' AND 'supervise*learning*', 'motivation' AND 'un*supervise*learning*', 'motivation' AND 'semi*supervise*learning*'. 'collaborative' AND 'supervise*learning*' returns 1 result, and 'motivation' AND 'supervise*learning*' returns 2 results in Emerald Insight database but all were discarded as they did not fulfil the intention of this survey.

The third EC was created to ensure that only studies published in the last 10 years are considered in this survey.

EC3. Only articles published from year 2009–2018 are considered in this survey.

The fourth EC is to ensure the survey of the ML utilisation is carried out within the EI studies only.

EC4. Only studies relate to emotional intelligence, ability emotional intelligence, or trait emotional intelligence are included in this survey.

As the aim of this survey is also to provide suggestions for future research direction in ML and EI, we include the following EC.

EC5. Emotional intelligence studies that do not clearly define their limitation and future works are excluded from this survey.

The sixth EC is included to ensure that the related work on ML in EI is thoroughly covered by also considering different types of ML approach.

EC6. The studies must implement ML therefore the term 'machine learning' or 'supervised learning', or 'unsupervised learning' must exist in those studies.

For emotion, in the current studies, most of the studies does not focus on improving individual emotions state. However, to pave way for future research, these papers are valuable and are the crucial building blocks that would allow researchers to focus on emotion improvement. Realising this, we decided to create an exemption for emotion as Inclusion Criteria (IC) 1.

IC1. Any studies that implement ML in detecting and recognising emotion are included in this survey.

By introducing these 6 ECs and 1 IC, 92 articles are retained for further analysis, as described in the following section. Table A1 in the appendix provides the final list of articles surveyed for each EI's components.

3.3. Advance and state-of-the-art algorithm

In most of the papers that we have reviewed, the researchers would normally propose an algorithm that could be considered as advance algorithm or state-of-the-art algorithm. A good fundamental idea on how the advance and the state-of-the-art ML algorithms would be better than the basic ML algorithms can be found in (Dehghan et al. 2017; Buolamwini and Gebru 2018). Unfortunately, these publications were excluded in our study as they are not indexed in ISI or Scopus databases, which is one of our publications selection criteria.

As our study also attempts to identify the possibility of having a generic algorithm that could be implemented across all EI's components, utilisation trends of both advance and basic ML algorithms in the study of EI's components are analysed and discussed accordingly. In doing so, we studied the basic algorithms that are used as benchmark in most ML applications and the related advanced ML algorithms as this would be the initial step in finding the generic ML algorithm.

4. Results

This section reports the results of our survey. To recall, in this survey, we mainly aim to discover the trend of ML implementation in each component of EI studies, and preferences for a particular ML algorithm over the last 10 years. In addition to that, the survey aims to discover the use of the basic ML algorithms in several studies of EI's components, in the attempt to establish a possibility for the need of a generic ML algorithm for EI analysis. Table 2 provides the implementation of ML algorithms for each component of EI studies.

To facilitate the analysis of the survey result, Naïve Bayesian and Bayesian network are grouped under Bayes category, and all basic Neural Network (NN) algorithms are grouped under NN category. Likewise, multiple type of Decision Tree (DT) are grouped under DT category (Bang et al. 2018). However, logistic regression and regression analysis remained separated as regression analysis studies may employ other than logistic regression technique as demonstrated in (Qin et al. 2014; Kessler et al. 2016; Feng et al. 2018). The number of implementations of these ML algorithms in EI studies for the past 10 years, i.e. from year 2009 to 2018, are shown in Table 3.

Table 4 presents the number of studies of each EI component that utilise ML over the last 10 years. It shows that the EI components studies that employ ML have started since 2010 (Khashman 2010; Lin et al. 2010; Merrick 2010) for the study of emotion, sentiment and motivation. Some of the studies had implemented more than one ML algorithms in their study, for example, in Lin and Kao (2018), and one study covers multiple components of EI (López-gil et al. 2016)

In 2013, studies that utilise ML for social skill was published. The focus of this study is mainly about participants' collaborative manner (Anaya and Boticario 2013; Troussas, Virvou, and Alepis 2013), followed by a study about empathy in 2014 (Bedi et al. 2014). 2016 shows that two studies about self-regulation was published (López-gil et al. 2016; Zhu et al. 2016) and in

Table 2. Implementation of ML in the components of EI studies.

	Self-awareness	Self-regulation	Social skills	Empathy	Emotion	Motivation
Bayes		1	2		14	1
DT	1	1	1		6	1
k-means	1		3			
k-NN		1	1		9	1
Logistic regression		1	1	1	4	
NN	1				12	2
regression analysis		1	1		3	2
RF		1	5		5	2
SVM	2	3		2	26	2

Table 3. ML implementation in the components of EI studies according to year.

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Bayes					2	1	4	5	4	2
Deep learning									1	2
DT					1	1	2	3		3
ELM							2			
k-means			1		1				2	
k-NN						2	3	3	3	1
Logistic regression			1				1	3		2
MLP		1						2	1	
NN		2					4	1	4	5
Radial basis function								2		
regression analysis						1		3	1	2
RF					1		2	2	4	4
SVM		1	1		1	3	8	7	6	8

Table 4. Components of EI studies that uses ML according to year.

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Self-awareness									1	2
Self-regulation								2	3	2
Social skills			2		2		1	1	3	1
Emotions, and sentiment		2	2		2	5	13	10	11	16
Motivation		1					1		2	4
Empathy						1			1	2

2017, studies about self-awareness that utilised ML was first published (Luo et al. 2017).

From the same table, the results show that most of the EI related study that had implemented ML gave focus on emotions. Nonetheless, other components are gaining more attention in recent years.

5. Analysis and discussion

This section discusses the research trends of the ML algorithms in EI studies, and the research trends of each EI component in using ML, for the last 10 year.

5.1. Research trend of machine learning in emotional intelligence studies

Figure 2 shows an increasing number of ML algorithm being used in the study of EI components for the past 10 years with the exception in the year 2012. This graph includes both basic and advance ML algorithms in the selected studies. The following sub sections provide detail information on the usage of both basic and advanced ML in the EI component's studies.

5.1.1. Utilisation of machine learning algorithm

The utilisation of basic ML algorithms in EI studies according to year is presented in Figure 2. However, we remove 2009 and 2012 from the graph as we could not find any related articles. We consider AdaBoost, Bayes, decision tree (DT), gradient boosting (Bass et al. 2018), k-means, k-NN (Shon et al. 2018), linear regression, logistic regression, neural network, regression analysis, random forest (RF) and support vector machine (SVM) as basic ML algorithm.

Figure 3 shows that SVM had been constantly used throughout the decade, in which itappears in 34 studies out of 92 of the total studies. For the past 5 years, SVM has become the most commonly used algorithm in the study of EI's components with 3 studies in 2014, 8 in 2015, 6 in 2016, 6 and 8 in 2017 (see table A2 in

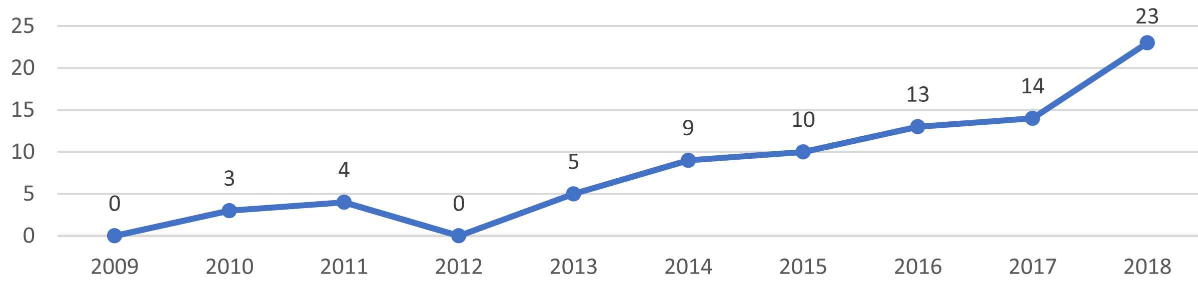

Figure 2. The Trends of ML utilization in EI Studies.

appendix for detail). The trend of SVM utilisation in components of EI studies shows an increment throughout the years. The preference for SVM is because it produces one of the best accuracy rates for supervised learning (Ali et al. 2018). Our study found that SVM appears in many EI's components studies. It is mainly used (26 studies) for emotions and sentiments studies (Kim et al. 2015). It appears twice in the studies for self-awareness, empathy and motivation (Bedi et al. 2014; Pläschke et al. 2017; Coutinho et al. 2018; Lin and Kao 2018; Mokhtari et al. 2018; Soleymani, Riegler, and Halvorsen 2018). In self-regulation, SVM appears in three studies (López-gil et al. 2016; Li et al. 2017; Mermarian et al. 2017).

Interestingly, while SVM appears in the studies of many components of EI, it has never been used in collaborative studies or social skill studies, as shown in Table 2. Or at least there is yet any direct reporting on the use of SVM algorithm in studies related to social skills. Even though there are studies that mentioned the inclusion of SVM but upon further investigation, the detail results of SVM's implementation are not shown (Birnbaum et al. 2017). Apart from that, some studies have claimed that their algorithms are better than SVM with no empirical evidence (Cen et al. 2016). Other ML algorithms were frequently used in the study of social skill, such as random forest (Baggott et al. 2015; Birnbaum et al. 2017; Viswanathan and VanLehn 2018), k-means (Molina et al. 2011; Troussas, Virvou, and Alepis 2013; Polytak, Davier, and Peterschmidt 2017) and Bayes based algorithm (Anaya and Boticario 2013; Deetjen and Powell 2016; Polytak, Davier, and Peterschmidt 2017).

The second most commonly used algorithm in the study of EI is neural network, which mainly consists of the basic feed forward NN. Its derivations, in the form of advance ML (Tang et al. 2015) used in the last 5 years are, for example, weightless NN (Simões et al. 2018) and cellular-NN (Ali et al. 2018). The overall trend of NN utilisation shows an increasing pattern along the year. It appears twice in 2010, 4 studies in 2015 and 2017, and 5 studies in 2018. Similar to SVM and Bayes based algorithms, NN is normally used in emotions and sentiments studies (Vempala and Russo 2018) as shown in Table 2, with 12 studies applied NN. Apart from that, other studies that have applied NN are two studies in motivation, and one study each in self-awareness and social skill. The flexibility of NN provides a good foundation for building advance ML that produces better accuracy rate as compared to basic ML algorithm implementation (Özerdem and Polat 2017; Al Zoubi, Awad, and Kasabov 2018; Al-Saffar et al. 2018; Ali et al. 2018; Simões et al. 2018). This can be seen in the work by López-gil et al. (2016) where their advance ML algorithm outperforms other basic algorithms in various EI's components such as emotions and sentiment, self-regulation and motivation. More studies are needed to test the accuracy of the advanced ML algorithms for other EI components.

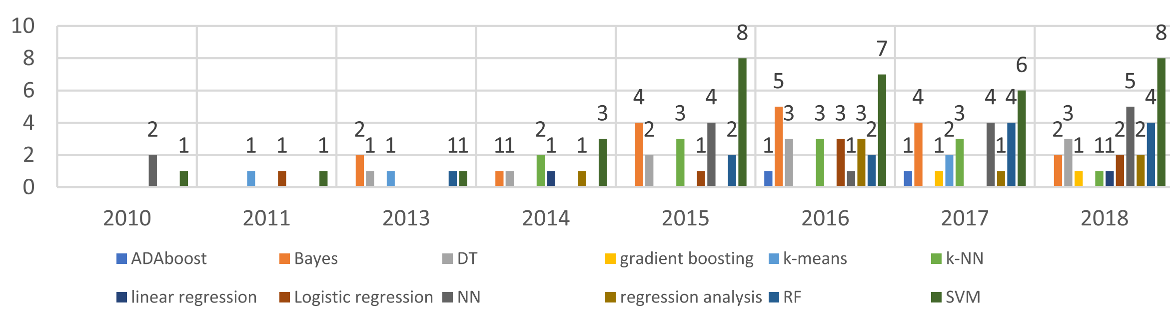

Figure 3. The trend of basic ML algorithms utilisation in EI studies.

The third most commonly used ML algorithm in the study of EI is Bayes based algorithm. While some studies used naïve Bayes, others used Bayesian network (Urizar et al. 2016). These algorithms have also been used as the foundation to develop advance ML algorithm. Generally, the use of Bayes based algorithms in EI's components has demonstrated a constant presence since it was first reported in 2013. Bayes based algorithm appears once in 2014, twice in 2013 and 2018, four times in 2015 and 2017, and five times in 2016 (see table A3 in appendix). Similar to SVM, Table 2 shows that Bayes based algorithm was mainly used in emotions and sentiment studies, where it appears in 14 studies. Two studies in social skill (Anaya and Boticario 2013; Polytak, Davier, and Peterschmidt 2017) and one study in self-regulation (López-gil et al. 2016) and motivation (Hussain et al. 2018).

Besides utilisation of basic ML algorithms, some studies choose to improvise the ML algorithm to provide a better solution to a problem in hand. Some of these algorithms were derived from basic ML algorithm, while others derived from natural language processing (NLP) and statistical methods. Figure 4. shows deep learning (Fayek, Lech, and Cavedon 2017), extreme learning machine (ELM), multilayer perceptron (MLP) and radial basis function. These algorithms are grouped as advance ML algorithms.

5.2. Research trends of EI's components in relation to ML

This section aims to discover the trend of EI components studies in using and applying ML for the past 10 years and discuss their research directions.

5.2.1. Self-awareness

Figure 5 shows that the first self-awareness research that implements ML was published in 2017. In 2018, two more articles were published under this category. Study by Luo et al. (2017) relates self-awareness to emotional awareness, and they have conducted an experiment to measure the effect of dynamic change in the blood flow on individual emotional awareness by using ML algorithm. As most experiments for self-awareness study were conducted in a short period of time, problem of fatigue data bias may occur (Coutinho et al. 2018), a problem akin to subject's comfort in Luo et al. (2017) study. Additionally, a study by Lin and Kao (2018) shows that there is a need for a generic classifier to reduce the burden of the ML algorithms. Currently, basic algorithms such as SVM, k-means, DT and NN were mainly used in the study of EI's components.

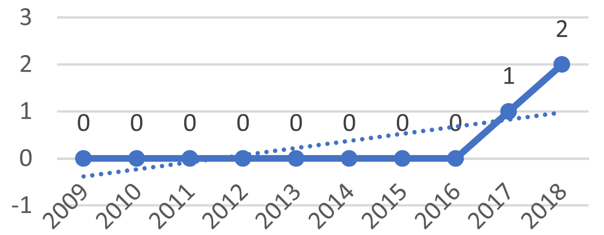

Figure 5. Self-awareness study vs year.

Our suggestion to researchers in the psychology field is to come out with a set of assessments to determine the most significant features that contribute to someone's self-awareness The availability of the assessment is hoped can simplify and enhance the process of feature selection and classification. A clear demarcation in the assessment would therefore assist in higher number of adoptions of ML in the self-awareness studies.

5.2.2. Self-regulation

Similar to self-awareness, study for self-regulation that implement ML algorithms have only gained popularity in recent years. As shown in Figure 6, the first two self-regulation studies that implement ML are published in 2016. In most study that we surveyed, self-regulation was not the main focus, but rather as one of the moderating factors (Zhu et al. 2016; Li et al. 2017; Mermarian et al. 2017), or the genetic cause that determines the differences in individual self-regulation (Zwir et al. 2018). On the other study done by Rosales et al. (2017), they did focus on self-regulation but via the

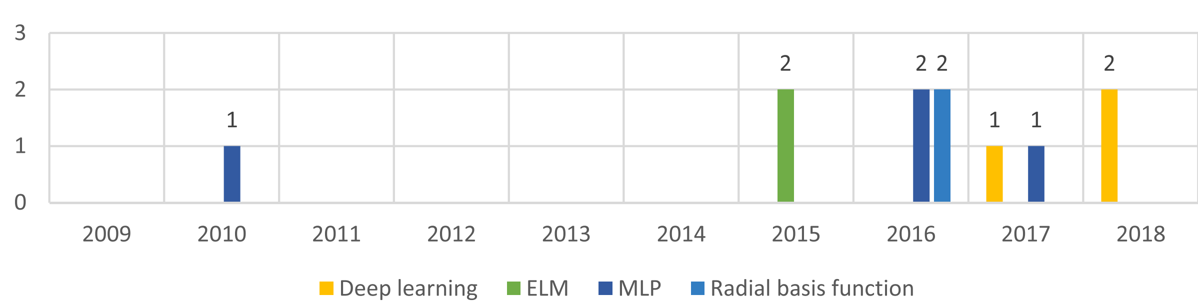

Figure 4. A growing trend of utilizing advance ML in EI studies.

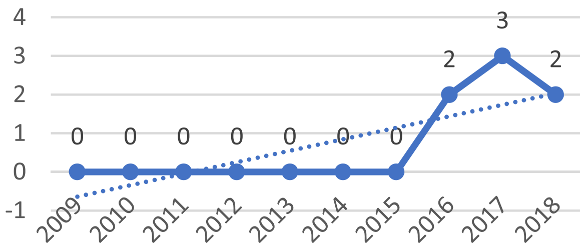

Figure 6. Self-reg. studies vs. year.

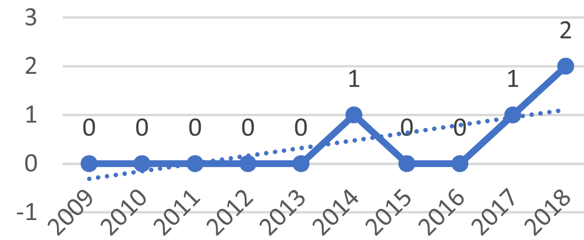

Figure 8. Empathy study vs. year.

use of software agents. A possible reason for limited ML study in self-regulation is due to unclear understanding on how to measure self-regulation (Eisenberg et al. 2018). Hence, there is a necessity for psychologist to devise a standardise method for measuring and evaluating self-regulation, to enable computer scientist to generate a self-regulated software agent. ML algorithms used in these studies are mainly basic algorithms. Nevertheless, three studies, one in 2017 and two in 2018 have used advance ML algorithms.

5.2.3. Social skill

Studies in social skill show a different trend from both self-awareness and self-regulation. Seven out of 10 studies surveyed focus on detecting students' collaboration in e-learning environment (Calvo et al. 2011; Molina et al. 2011; Anaya and Boticario 2013; Troussas, Virvou, and Alepis 2013; Cen et al. 2016; Polytak, Davier, and Peterschmidt 2017; Viswanathan and VanLehn 2018). There is one study on empathic response (Vaughn et al. 2018), and two studies focus on health-related issue in which one of them focus on collaboration between patients (Fernandez et al. 2017), and the other focus on collaboration between doctors and software agent (Birnbaum et al. 2017). One study in this category focuses on drug impact on openness to talk about emotional topics (Baggott et al. 2015). The overall trend of studies shows a slight increase throughout the years even though the usage pattern is a bit inconsistence, as shown in Figures 7–8.

Behavioural change may occur in these studies, but there is no clear indication on the type of the behavioural change, the magnitude of the change, and the polarity of it being reported in any of these studies. Since the behavioural change is one of the outcomes that signify the success of an EI training, an evaluation method to measure the change should be developed and adopted as a criteria for measuring the effectiveness of ML application for social skills.

5.2.4. Empathy

The first study that used ML in the studies of empathy was published in 2014, followed by another in 2017 and two studies in 2018. The increasing popularity of chat agent, and application of smart assistance such as Siri, Google now and Alexa could be benefitted from a greater understanding about empathy. Hence, there is a need to quantify empathic responses, and this can be accomplished through collaboration between psychologist and computer scientist. A possible suggestion would be the demarcation between genuine empathic response and Machiavellian type of response. We believe that, with enough dataset and input mode, ML algorithms would be able to tell the difference between the two types of responses.

5.2.5. Emotion

Among the EI components studies, emotion gets the most attention, and it has been well studied in the computer science field. Figure 9 shows the trend of emotion studies that utilises ML in the last 10 years. Note that our survey also includes sentiment analysis studies that are directly related to emotion and contain emotion(s) keyword. Lin et al. (2010) have utilised

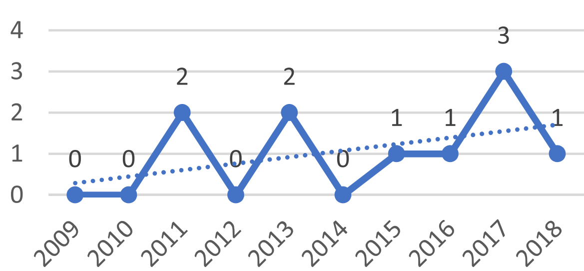

Figure 7. Social skill studies vs. year.

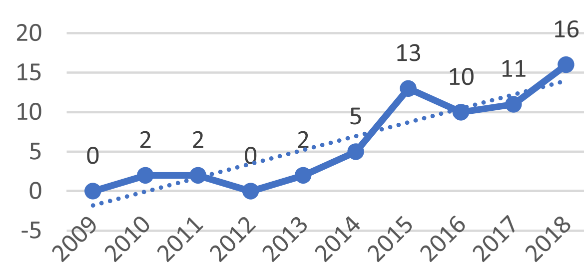

Figure 9. Emotions study vs. year.

multilayer perceptron (MLP) to map emotional state with brain activities. Khashman (2010) also used NN based algorithm in their attempt to create emotionally sensitive agent. The trend of applying ML in the study of emotion continues in 2013, when Li et al. (2013) include dynamic Bayesian network for facial feature tracking when various emotional expression occurs.

Besides MLP (López-gil et al. 2016; Özerdem and Polat 2017), and Bayesian network, there are many advance ML that are used in emotion studies (Nicholson et al. 2018) such as Repeated Incremental Pruning to Produce Error Reduction (RIPPER) (Álvarez et al. 2015), linear discriminant analysis (Jang et al. 2015; Jeong et al. 2017), genetic algorithm (Arruti et al. 2014; Mistry et al. 2017) and deep learning (Wen et al. 2017; Al-Saffar et al. 2018; Choi and Kim 2018).

Finding from our survey also shows that the focus of research related to emotion is to detect users' emotions (Daly et al. 2015). There are studies to detect users' emotions online by utilising NLP, as demonstrated in the work by (Amini, Sabourin, and Koninck 2011; Choi et al. 2017; Fernández-Gavilanes et al. 2018). Noteworthy that data collection for detecting users' emotions is mainly done in real time via sensors such as electroencephalogram(EEG) sensors (Lin et al. 2010; Modinos et al. 2013; Ahn et al. 2014; Yuvaraj et al. 2014; Lin and Kao 2018), or/and optical devices such as camera with built-in facial recognition capability (Chen and Lee 2011; Li et al. 2013; Shojaeilangari et al. 2015; Li et al. 2016; Zanette et al. 2016; Moghadam and Seyyedsalehi 2018) and eye tracker (Babiker et al. 2015; Tavakoli et al. 2015).

5.2.6. Motivation

Figure 10 shows that for the past 10 years, only 8 studies have applied ML in studies about motivation. We were surprised by this finding as our primary search in Table 1 shows an average of 440 search results from 4 databases. When we did our survey, we came to a conclusion that most of these results stated motivation as motivation of their studies or research motivation, and not about the studies on user's motivation. However, as motivation is one of the important factors in e-learning, it raised another curiosity, which has prompted us to execute a query for 'motivation' and 'e-learning'. Upon completing our survey for the query's results, we only found two studies that utilise ML in e-learning domain (Klebanov et al. 2017; and Hussain et al. 2018). This small number of available studies on the application of ML in e-learning leads us to a conclusion that many motivation studies in e-learning did not utilise ML, or did not specifically mentioned about ML in their studies.

Nonetheless, Figure 10 does show that the trend of applying ML in the studies on motivation is increasing in recent years. These studies focus on learning motivation for robots (Merrick 2010; Gatsoulis and McGinnity 2015), users' intention during online interaction (Dalins, Wilson, and Carman 2018; Soleymani, Riegler, and Halvorsen 2018), and users' motivation for healthy lifestyle (Webster et al. 2017; Mokhtari et al. 2018).

6. Future research direction

Studies of EI and its components can be found across various domains, but they are mostly studied in the nursing domain (Gribble, Ladyshewsky, and Parsons 2018). Regardless of any domain, they shared the same problems when it comes to EI training i.e. highly dependence on a trainer (Cejudo 2017), interaction with the trainer is normally exclusive (Vesely, Saklofske, and NordStokke 2014), the size of the EI training class is small (Petrides et al. 2016) and normally with long training duration (Gribble, Ladyshewsky, and Parsons 2018) which can span across several sessions.

In order to address the problems associated with EI training process, many researchers have considered or attempted to apply ML in the study of EI and its component (Molina et al. 2011; Cardoso-Leite and Bavelier 2014; Gęsiarz and Crockett 2015; Jang et al. 2015). According to (Li et al. 2018), it is possible to use ML to support trainer, or use intelligent agents to act as their peers. Some studies have implemented ML for specific components of EI in the attempt to push an individual to learn and improve the degree of their EI's components, and those in the computer science discipline have attempted to implement them on robots (Merrick 2010; Gatsoulis and McGinnity 2015) and software agents (Rosales et al. 2017). However, there are lack of evaluation standards to measure the effectiveness of each EI's component in both human and artificial agent. Moreover, there is yet no empirical data to determine the effect of using ML in improving someone's EI (i.e. not just some of its components).

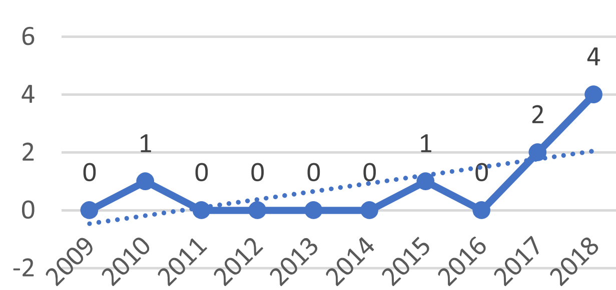

Figure 10. Motivation studies vs. year.

Therefore, suggestions for future directions of researches are as follows. First is for each EI's, unambiguous measures that could be used to evaluate the effectiveness of the ML algorithm in satisfying the EI's requirements should be established. Additionally, features required for the ML implementation must be clearly defined and tested by psychologist. Also, in order for an ML algorithm to be able to supplement EI training, it is essential to have a standard measure to evaluate EI and perform benchmarking evaluation. Secondly, there should be an effort to create an advance ML algorithm can that be made generic for implementing ML for all EI's components. The availability of this generic algorithm could be the first step to automatically measure someone's EI and provide the necessary intervention for those with critically low EI. As EI training requires extensive interaction between a trainer and participants, the use of intelligent software agent would reduce the load of the trainer, and most importantly it can reach a larger number of participants in a single session. Thirdly, the literature has reported that there are many research for detecting emotions. While it is important to discover a new way to detect emotions, or improve the current detection methods, applying innovative ML algorithm into the study of emotion and empathy would allow the creation of a humanoid software agent that can interact more like human with favourable respond. Finally, our study found that most of the research in EI and ML came from the study of emotion, particularly in emotion detection. Hence, more study on how ML can benefit the rest of the EI's components needs to be conducted.

During our survey, we encountered many studies that utilise multi-mode detection method in their study, especially emotion identification and recognition. While this survey does not specifically differentiate single and multi-mode detection methods, the multi-mode could be considered for future research to improve the identification and recognition accuracy of each EI component. Furthermore, by considering multi-mode method in tracing the improvement and the effectiveness of each EI components, the possibility of false negative and false positive can be minimised, hence the accuracy of the algorithm can be improved, as demonstrated in later researches such as the study by Erol, Majumdar, Benavidez, Rad, Choo, and Jamshidi(2020).

7. Conclusion

Research efforts in applying and implementing ML in EI are still in their infancy. Nonetheless, it is extremely important to investigate how ML can be used to train someone's EI due to the rising concern on mental health worldwide. Our survey aims to provide a clear understanding of the current state and trend in using ML in the EI studies. Our findings confirm that existing researches only addressed the application of ML on individual components of EI, and the trend of applying ML in those components is increasing over the years. This survey also found that the most preferred ML algorithms used in the current studies of EI's components is Support Vector Machine (SVM) followed by Neural Network (NN) algorithms. The SVM algorithm has been applied in the studies of EI' components except for social skills. On the other hand, random forest and k-means are the mostly preferred ML algorithms for social skill. Details on how SVM is implemented in each study need to be explored further to infer the possibility of its extension in order to serve as a generic algorithm for measuring EI. Another interesting finding is that among the six components of EI, social skill and empathy has limited exposure to ML, and more effort is needed to address this lacking. Finally, as there is an urgent need to use ML to train EI, and as EI comprises of the six components, it is crucial to develop the generic algorithm that can serve all the six components successfully. The availability of this algorithm would enable the development of an intelligent software agent to facilitate the EI training.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

Abdollahi, A., P. Carlbring, M. Khanbani, and S. A. Ghahfarokhi. 2016. "Emotional Intelligence Moderates Perceived Stress and Suicidal Ideation among Depressed Adolescent Inpatients." *Personality and Individual Differences* 102: 223–228.

Ahn, W. Y., K. T. Kishida, X. Gu, T. Lohrenz, A. Harvey, J. R. Alford, K. B. Smith, et al. 2014. "Nonpolitical Images Evoke Neural Predictors of Political Ideology." *Current Biology* 24: 2693–2699.

Al-Saffar, A., S. Awang, H. Tao, N. Omar, W. Al-Saiagh, and M. Al-Bared. 2018. "Malay Sentiment Analysis Based on Combined Classification Approaches and Senti-Lexicon Algorithm." *PLoS ONE* 13 (4): e0194852. doi:10.1371/journal.pone.0194852.

Ali, M., F. A. Machot, A. H. Mosa, M. Jdeed, E. A. Machot, and K. Kyamakya. 2018. "A Globally Generalized

Emotion Recognition System Involving Different Physiological Signals." *Sensors* 18 (6), doi:10.3390/s18061905.
Alm, C. O., D. Roth, and R. Sproat. 2005. "*Emotions from Text: Machine Learning for Text-Based Emotion Prediction*." Proceedings of the Human Language Technology Conference and the 2005 Conference on Empirical Methods in Natural Language Processing, Vancouver, Canada, 6-8 October 2005, 579–586.
Álvarez, A., B. Sierra, A. Arruti, J. M. L. Gil, and N. G. Vitoria. 2015. "Classifier Subset Selection for the Stacked Generalization Method Applied to Emotion Recognition in Speech." *Sensors* 16 (21), doi:10.3390/s16010021.
Al Zoubi, O., M. Awad, and N. K. Kasabov. 2018. "Anytime Multipurpose Emotion Recognition Form EEG Data Using a Liquid State Machine Based Framework." *Artificial Intelligence in Medicine* 86: 1–8.
Amini, R., C. Sabourin, and J. D. Koninck. 2011. "Word Associations Contribute to Machine Learning in Automatic Scoring of Degree of Emotional Tones in Dream Reports." *Consciousness and Cognition* 20: 1570–1576.
Anaya, A. R., and J. G. Boticario. 2013. "A Domain-Independent, Transferable and Timely Analysis Approach to Assess Student Collaboration." *International Journal on Artificial Intelligence Tools* 22 (4), doi:10.1142/S0218213013500206.
Arruti, A., I. Cearreta, A. Álvarez, E. Lazkano, and B. Sierra. 2014. "Feature Selection for Speech Emotion Recognition in Spanish and Basque: On the Use of Machine Learning to Improve Human-Computer Interaction." *PLoS ONE* 9 (10): e108975. doi:10.1371/journal.pone.0108975.
Babiker, A., I. Faye, K. Prehn, and A. Malik. 2015. "Machine Learning to Differentiate Between Positive and Negative Emotions Using Pupil Diameter." *Frontiers in Psychology*, doi:10.3389/fpsyg.2015.01921.
Bacon, A. M., L. L. Maughan, and J. May. 2018. "Trait Emotional Intelligence and Social Deviance in Males and Females." *Personality and Individual Differences* 122: 79–86.
Baggott, M. J., M. G. Kirkpatrick, G. Bedi, and H. D. Wit. 2015. "Intimate Insight: MDMA Changes How People Talk About Significant Others." *Journal of Psychopharmacology* 29 (6): 669–677.
Bang, J., T. Hur, D. Kim, T. H. The, J. Lee, Y. Han, O. Banos, J. I. Kim, and S. Lee. 2018. "Adaptive Data Boosting Technique for Robust Personalized Speech Emotion in Emotionally-Imbalanced Small-Sample Environment." *Sensors* 18: 3744. doi:10.3390/s18113744.
Banos, O., C. Villalonga, J. Bang, T. Hur, D. Kang, S. Park, T. Huynh-The, et.al,. 2016. "Human Behavior Analysis by Means of Multimodal Context Mining." *Sensors* 16 (8): 1264.
Bao, X., S. Xue, and F. Kong. 2015. "Dispositional Mindfulness and Perceived Stress: The Role of Emotional Intelligence." *Personality and Individual Differences* 78: 48–52.
Bar-On, R. 2002. *EQ-i: Baron Emotional Quotient Inventory: A Measure of Emotional Intelligence. Technical Manual.* North Tonawanda, NY: Multi-Health System.
Barboza, F., H. Kimura, and E. Altman. 2017. "Machine Learning Models and Bankruptcy Prediction." *Expert System with Application* 83: 405–417.
Bass, C. W., R. Suchting, R. L. Olvera, and D. E. Williamson. 2018. "Inflammatory Markers as Predictors of Depression and Anxiety in Adolescents: Statistical Model Building with Component-Wise Gradient Boosting." *Journal of Affective Disorder* 234: 276–281.
Beath, A. P., M. P. Jones, and J. Fitness. 2015. "Predicting Distress via Emotion Regulation and Coping: Measurement Variance in Trait EI Scales." *Personality and Individual Differences* 84: 45–51.
Bedi, G., G. A. Cecchi, D. F. Slezak, F. Carrillo, M. Sigman, and H. D. Wit. 2014. "A Window Into the Intoxicated Mind? Speech as an Index of Psychoactive Drug Effects." *Neuropsychopharmacology* 39: 2340–2348.
Birnbaum, M. L., S. K. Ernala, A. F. Rizvi, M. D. Choudhury, and J. M. Kane. 2017. "A Collaborative Approach to Identifying Social Media Markers of Schizophrenia by Employing Machine Learning and Clinical Appraisals." *Journal of Medical Internet Research* 19 (8): e289.
Buolamwini, J., and T. Gebru. 2018. "Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification." *Conference on Fairness, Accountability and Transparency* 81: 77–91.
Calvo, R. A., S. T. O'Rourke, J. Jones, K. Yacef, and P. Reimann. 2011. "Collaborative Writing Support Tools on the Cloud." *IEEE Transaction on Learning Technologies* 4 (1): 88–97.
Cardoso-Leite, P., and D. Bavelier. 2014. "video Game Play, Attention, and Learning: how to Shape the Development of Attention and Influence Learning?" *Current Opinion in Neurology* 27 (2): 185–191.
Cejudo, J. 2017. "Effects of a Programme to Improve Emotional Intelligence on Psychosocial Adjustment and Academic Performance in Primary Education/Efectos de un programa de mejora de la inteligencia emocional sobre el ajuste psicosocial yel rendimiento académico en educación primaria." *Infancia y Aprendizaje / Journal for the Study of Education and Development* 40 (3): 503–530.
Celebi, M., and K. Aydin. 2016. *Unsupervised Learning Algorithms*. doi:10.1007/978-3-319-24211-8.
Cen, L., D. Ruta, L. Powell, B. Hirsch, and J. Ng. 2016. "Quantitative Approach to Collaborative Learning: Performance Prediction, Individual Assessment, and Group Composition." *International Journal of Computer-Supported Collaborative Learning* 11 (2): 187–225.
Chen, C. M., and T. H. Lee. 2011. "Emotion Recognition and Communication for Reducing Second-Language Speaking Anxiety in a Web-Based one-to-one Synchronous Learning Environment." *British Journal of Educational Technology* 42 (3): 417–440.
Chimeno, Y., G. Zapirain, B. G. Beldarrain, M. G. Ruanova, B. F. & Monco, and J. C. G. 2017. "Automatic Migraine Classification via Feature Selection Committee and Machine Learning Techniques Over Imaging and Questionnaire Data." *BMC Medical Informatics and Decision Making* 17: 38. doi:10.1186/s12911-017-0434-4.
Choi, E. J., and D. K. Kim. 2018. "Arousal and Valance Classification Model Based on Long Short-Term Memory and DEAP Data for Mental Healthcare Management." *Healthcare Informatics Research* 24 (4): 309–316.
Choi, S., J. Lee, M. G. Kang, H. Min, Y. S. Chang, and S. Yoon. 2017. "Large-scale Machine Learning of Media Outlets for Understanding Public Reaction to Nation-Wide Viral Infection Outbreaks." *Methods* 129: 50–59.

Cliffe, J. 2011. “Emotional Intelligence: A Study of Female Secondary School Head-Teachers.” *Educational Management Administration & Leadership* 39 (2): 205–218.
Coutinho, E., K. Gentsch, J. V. Peer, K. R. Scherer, and B. W. Schuller. 2018. “Evidence of Emotion-Antecedent Appraisal Checks in Elecroencephalography and Facial Electromyography.” *PLoS ONE* 13 (1): e0189367.
Dalins, J., C. Wilson, and M. Carman. 2018. “Criminal Motivation on the Dark web: A Categorisation Model for Law Enforcement.” *Digital Investigation* 24: 62–71.
Daly, I., D. Williams, J. Hallowell, F. Hwang, A. Kirke, A. Malik, J. Weaver, E. Miranda, and S. J. Nasuto. 2015. “Music-induced Emotions can be Predicted from a Combination of Brain Activity and Acoustic Features.” *Brain and Cognition* 101, doi:10.1016/j.bandc.2015.08.003.
Deetjen, U., and J. A. Powell. 2016. “Informational and Emotional Elements in Online Support Groups: A Bayesian Approach to Large-Scale Content Analysis.” *Journal of the American Medical Informatics Association* 23: 508–513.
Dehghan, A., E. G. Ortiz, G. Shu, and S. Z. Masood. 2017. “Dager: Deep Age, Gender and Emotion Recognition Using Convolutional Neural Network.” *arXiv Preprint ArXiv*. CoRR abs/1702.04280
Eisenberg, I. W., P. G. Bissett, J. R. Canning, J. Dallery, A. Z. Enkavi, S. W. Gabrieli, O. Gonzalez, et al. 2018. “Applying Novel Technologies and Methods to Inform the Ontology of Self-Regulation.” *Behaviour Research and Therapy* 101: 46–57.
Erol, B. A., A. Majumdar, P. Benavidez, P. Rad, K. K. R. Choo, and M. Jamshidi. 2020. “Toward Artificial Emotional Intelligence for Cooperative Social Human–Machine Interaction.” *IEEE Transactions On Computational Social SystemS* 7 (1): 234–246.
Fabio, A. D., and D. H. Saklofske. 2014. “Comparing Ability and Self-Report Trait Emotional Intelligence, Fluid Intelligence, and Personality Traits in Career Decision.” *Personality and Individual Differences* 64: 174–178.
Fayek, H. M., M. Lech, and L. Cavedon. 2017. “Evaluating Deep Learning Architectures for Speech Emotion Recognition.” *Neural Networks* 92: 60–68.
Feng, C., Z. Cui, D. Cheng, R. Xu, and R. Gu. 2018. “Individualized Prediction of Dispositional Worry Using White Matter Connectivity.” *Psychological Medicine*, doi:10.1017/S0033291718002763.
Fernández-Gavilanes, M., J. Juncal-Martínez, S. García-Méndez, E. Costa-Montenegro, and F. J. González-Castaño. 2018. “Creating Emoji Lexica from Unsupervised Sentiment Analysis of Their Description.” *Expert Systems with Application* 103: 74–91.
Fernandez, S. A., H. R. Brown, Y. Zhao, J. A. Raithel, S. L. Bishop, S. B. Kern, C. Lord, and A. D. Martino. 2017. “Perceived Social Support in Adults with Autism Spectrum Disorder and Attention-Deficit/Hyperactivity Disorder.” *International Society for Autism Research* 10: 866–877.
Foland-Ross, L. C., M. D. Sacchet, G. Prasad, B. Gilbert, P. M. Thompson, and I. H. Gotlib. 2015. “Cortical Thickness Predicts the First Onset of Major Depression in Adolescene.” *International Journal of Developmental Neuroscience* 46: 125–131.
Foster, K., J. Fethney, H. McKenzie, M. Fisher, E. Harkness, and D. Kozlowski. 2017. “Emotional Intelligence Increases Over Time: A Longitudinal Study of Australian pre-Registration Nursing Students.” *Nurse Education Today* 55: 65–70.
García-Sancho, E., J. M. Salguero, and P. Fernández-Berrocal. 2015. “Angry Rumination as a Mediator of the Relationship Between Ability Emotional Intelligence and Various Types of Aggression.” *Personality and Individual Differences* 89: 143–147.
Gatsoulis, Y., and T. M. McGinnity. 2015. “Intrinsically Motivated Learning Systems Based on Biologically-Inspired Novelty Detection.” *Robotic and Autonomous Systems* 68: 12–20.
Gęsiarz, F., and M. J. Crockett. 2015. “Goal-directed, Habitual and Pavlovian Prosocial Behavior.” *Frontiers in Behavioral Neuroscience* 9, doi:10.3389/fnbeh.2015.00135.
Goleman, D. 1995. *Emotional Intelligence: Why It Can Matter More Than IQ*. New York: Bantam.
Gribble, N., R. K. Ladyshewsky, and R. Parsons. 2018. “Changes in the Emotional Intelligence of Occupational Therapy Students During Practice Education: A Longitudinal Study.” *British Journal of Occupational Therapy* 81 (7): 413–422.
Herpertz, S., A. Schütz, and J. Nezlek. 2016. “Enhancing Emotion Perception, a Fundamental Component of Emotional Intelligence: Using Multiple-Group SEM to Evaluate a Training Program.” *Personality and Individual Differences* 95: 11–19.
Hettich, D. T., E. Bolinger, T. Matuz, N. Birbaumer, W. Rosenstiel, and M. Spüler. 2016. “EEG Responses to Auditory Stimuli for Automatic Affect Recognition.” *Frontiers in Neuroscience* 10: 244. doi:10.3389/fnins.2016.00244.
Hussain, M., W. Zhu, W. Zhang, and S. M. R. Abidi. 2018. “Student Engagement Prediction in an e-Learning System and Their Impact on Student Course Assessment Scores.” *Computational Intelligence and Neuroscience*, doi:10.1155/2018/6347186.
Inkster, B., S. Sarda, and V. Subramanian. 2018. “An Empathy-Drive, Conversational Artificial Intelligence Agent (Wysa) for Digital Mental Well-Being: Real-World Data Evaluation Mixed-Methods Study.” *JMIR Mhealth and Uhealth* 6 (11), doi:10.2196/12106-.
Jang, E. H., B. J. Park, S. H. Park, and J. H. Sohn. 2015. “Analysis of Physiological Signal for Recognition of Boredom, Pain, and Surprise Emotions.” *Journal of Physiological Anthropology* 34: 25. doi:10.1186/s40101-015-0063-5.
Jeong, J. W., T. W. Wendimagegn, E. Chang, Y. Chun, J. H. Park, H. J. Kim, and H. T. Kim. 2017. “Classifying Schizotypy Using an Audiovisual Emotion Perception Test and Scalp Electroencephalography.” *Frontiers in Human Neuroscience* 11: 450. doi:10.3389/fnhum.2017.00450.
Just, M. A., L. Pan, V. L. Cherkassky, D. McMakin, C. Cha, M. K. Nock, and D. Brent. 2017. “Machine Learning of Neural Representations of Suicide and Emotion Concepts Identifies Suicidal Youth.” *Nature Human Behaviour* 1: 911–919.
Karstoft, K. I., A. Statnikov, S. B. Andersen, T. Madsen, and I. R. G. Levy. 2015. “Early Identification of Posttraumatic

Stress Following Military Deployment: Application of Machine Learning Methods to a Prospective Study of Danish Soldiers." *Journal of Affective Disorder* 184: 170–175.

Kessler, R., C. Loo, H. M. V. Wardenaar, K. J. Bossarte, R. M. Brenner, L. A. Cai, T. Ebert, et al. 2016. "Testing a Machine-Learning Algorithm to Predict the Persistence and Severity of Major Depressive Disorder from Baseline Self-Report." *Molecular Psychiatry* 21 (10): 1366–1371.

Khashman, A. 2010. "Modelling Cognitive and Emotional Process: A Novel Neural Network Architecture." *Neural Networks* 23: 1155–1163.

Kim, Y. B., S. H. Lee, S. J. Kang, M. J. Choi, J. Lee, and C. H. Kim. 2015. "Virtual World Currency Value Fluctuation Prediction System Based on User Sentiment Analysis." *PLoS ONE* 10: 8. doi:10.1371/journal.pone.0132944.

Klebanov, B. B., J. Burstein, J. M. Harackiewicz, S. J. Priniski, and M. Mulholland. 2017. "Reflective Writing About the Utility Value of Science as a Tool for Increasing STEM Motivation and Retention – Can AI Help Scale Up?" *International Journal of Artificial Intelligence in Education* 27 (4): 791–818.

Kotsiantis, S. 2007. "Supervised Machine Learning: A Review of Classification Techniques." *Informatica (Ljubljana)* 31 (3): 249–268.

Lacoviello, D., A. Petracca, M. Spezialetti, and G. Placidi. 2015. "A Real-Time Classification Algorithm for EEG-Based BCI Driven by Self-Induced Emotions." *Computer Methods and Programs in Biomedicine* 122: 293–303.

Li, S., L. Cui, C. Zhu, B. Li, N. Zhao, and T. Zhu. 2018. "Emotion Recognition Using Kinect Motion Capture Data of Human Gaits." *PeerJ*, doi:10.7717/peerj.2364.

Li, Y., X. Hou, D. Wei, X. Du, Q. Zhang, G. Liu, and J. Qiu. 2017. "Long-Term Effects of Acute Stress on the Prefrontal-Limbic System in the Healthy Adult." *PLoS ONE* 12 (1): e0168315.

Li, Y., S. Wang, Y. Zhao, and Q. Ji. 2013. "Simultaneous Facial Feature Tracking and Facial Expression Recognition." *IEEE Transactions on Image Processing* 22 (7): 2559–2573.

Li, L., Q. Xu, T. Gan, C. Tan, and J. H. Lim. 2018. "A Probabilistic Model of Social Working Memory for Information Retrieval in Social Interaction." *IEEE Transactions on Cybernetics* 48 (5): 1540–1552.

Lin, Y. P., P. K. Jao, and Y. H. Yang. 2017. "Improving Cross-Day EEG-Based Emotion Classification Using Robust Principal Component Analysis." *Frontiers in Computational Neuroscience* 11 (64), doi:10.3389/fncom.2017.00064.

Lin, F. R., and C. M. Kao. 2018. "Mental Effort Detection Using EEG Data in e-Learning Contexts." *Computers & Education* 122: 63–79.

Lin, Y. P., C. H. Wang, T. P. Jung, T. L. Wu, S. K. Jeng, J. R. Duann, and J. H. Chen. 2010. "EEG-Based Emotion Recognition in Music Listening." *IEEE Transactions on Biomedical Engineering* 57 (7): 1789–1806.

Lin, Y. P., Y. H. Yang, and T. P. Jung. 2014. "Fusion of Electroencephalographic Dynamics and Musical Contents for Estimating Emotional Responses in Music Listening." *Frontiers in Neuroscience* 8 (94), doi:10.3389/fnins.2014.00094.

López-gil, J. M., J. Virgili-Gomá, R. Gil, T. Guilera, I. Batalla, J. Soler-González, and R. García. 2016. "Method for Improving EEG Based Emotion Recognition by Combining It with Synchronized Biometric and Eye Tracking Technologies in a Non-Invasive and Low Cost Way." *Frontiers in Computational Neuroscience* 10), doi:10.3389/fncom.2016.00085.

Luo, Q., Y. Ma, M. A. Bhatt, P. R. Montague, and J. Feng. 2017. "The Functional Architecture of the Brain Underlies Strategic Deception in Impression Management." *Frontiers in Human Neuroscience* 11: 513. doi:10.3389/fnhum.2017.00513.

Marguerite, S., B. Laurent, A. Marine, L. Tanguy, B. Karine, A. Pascal, and Z. Xavier. 2017. "Actor-partner Interdependence Analysis in Depressed Patient-Caregiver Dyads: Influence of Emotional Intelligence and Coping Strategies on Anxiety and Depression." *Psychiatry Research* 258: 396–401.

Mattingly, V., and K. Kraiger. 2018. "Can Emotional Intelligence be Trained?" *A Meta-Analytical Investigation. Human Resource Management Review*, doi:10.1016/j.hrmr.2018.03.002.

Mayer, J. D., and P. Salovey. 1997. "What is Emotional Intelligence?" In *Emotional Development and Emotional Intelligence: Implications for Educators*, edited by P. Salovey and D. Sluyter, 3–31. New York, NY: Basic Books.

Mayer, J. D., P. Salovey, and D. Caruso. 2002. *Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT) User's Manual*. Toronto, ON: MHS.

Mermarian, N., J. B. Torre, K. E. Haltom, A. L. Stanton, and M. D. Lieberman. 2017. "Neural Activity During Affect Labelling Predicts Expressive Writing Effects on Well-Being: GLM and SVM Approach." *Social Cognitive and Affective Neuroscience* 12 (9): 1437–1447.

Merrick, K. E. 2010. "A Comparative Study of Value System for Self-Motivated Exploration and Learning by Robots." *IEEE Transaction on Autonomous Mental Development* 2 (2): 119–131.

Mistry, K., L. Zhang, S. C. Neoh, C. P. Lim, and B. Fielding. 2017. "A Micro-GA Embedded PSO Feature Selection Approach to Intelligent Facial Emotion Recognition." *IEEE Transaction on Cybernetics* 47 (6): 1496–1509.

Modinos, G., A. Mechelli, W. Petterson-Yeo, P. Allen, P. McGuire, and A. Aleman. 2013. "Pattern Classification of Brain Activation During Emotional Processing in Subclinical Depression: Psychosis Proneness as Potential Confounding Factor." *PeerJ*, doi:10.7717/peerj.42.

Moghadam, S. M., and S. A. Seyyedsalehi. 2018. "Nonlinear Analysis and Synthesis of Video Images Using Deep Dynamic Bottleneck Neural Networks for Face Recognition." *Neural Networks* 105: 304–315.

Mohan, D. M., P. Kumar, F. Mahmood, K. F. Wong, A. Agrawal, M. Elgendi, R. Shukla, et al. 2016. "Effect of Subliminal Lexical Priming on the Subjective Perception of Images: A Machine Learning Approach." *PLoS ONE* 11: 2. doi:10.1371/journal.pone.0148332.

Mokhtari, F., W. J. Rajeski, Y. Zhu, G. Wu, S. L. Simpson, J. H. Burdette, and P. J. Laurienty. 2018. "Dynamic fMRI Networks Predict Success in a Behavioral Weight Loss Program among Older Adults." *NeuroImage* 173: 421–433.

Molina, A. I., F. Jurado, R. Doque, M. A. Redondo, C. Bravo, and M. Ortega. 2011. "Applying Genetic Classifier Systems for the Analysis of Activities in Collaborative Learning

Environments." *Computer Applications in Engineering Education* 21 (4): 704–716.

Monteagudo, M. C. M., C. J. Inglés, L. Granados, D. Aparisi, and J. M. G. Fernández. 2019. "Trait Emotional Intelligence Profiles, Burnout, Anxiety, Depression, and Stress in Secondary Education Teachers." *Personality and Individual Differences* 142: 53–61.

Negnevitsky, M. 2005. *Artificial Intelligence: A Guide to Intelligent System Second Edition*. England: Pearson.

Nicholson, A. A., M. Densmore, M. C. McKinnon, R. W. J. Neufeld, P. A. Frewen, J. Théberge, R. Jetly, J. D. Richardson, and R. A. Lanius. 2018. "Machine Learning Multivariate Pattern Analysis Predicts Classification of Posttraumatic Stress Disorder and its Dissociative Subtype: A Multimodal Neuroimaging Approach." *Psychological Medicine* 1 (11), doi:10.1017/S0033291718002866.

Özerdem, M. S., and H. Polat. 2017. "Emotion Recognition Based on EEG Features in Movie Clips with Channel Selection." *Brain Informatics* 4: 241–252.

Petrides, K. V. 2016. "Four Thought on Trait Emotional Intelligence." *Emotion Review* 8 (4): 345.

Petrides, K. V., and A. Furnham. 2001. "Trait Emotional Intelligence: Psychometric Investigation with Reference to Established Trait Taxonomies." *European Journal of Personality* 15: 425–448.

Petrides, K. V., and A. Furnham. 2003. "Trait Emotional Intelligence: Behavioural Validation in Two Studies of Emotion Recognition and Reactivity to Mood Induction." *European Journal of Personality* 17: 39–57.

Petrides, K. V., M. Mikolajczak, S. Mavroveli, M. J. Sanchez-Ruiz, A. Furnham, and J. C. Pérez-González. 2016. "Developments in Trait Emotional Intelligence Research." *Emotion Review* 8 (4): 335–341.

Pläschke, R. N., E. C. Cieslik, V. I. Müller, F. Hoffstaedter, A. Plachti, D. P. Varikuti, M. Goosses, et al. 2017. "On the Integrity of Functional Brain Networks in Schizophrenia, Parkinson's Disease, and Advanced Age: Evidence from Connectivity-Based Single-Subject Classification." *Human Brain Mapping* 38 (12): 5845–5858.

Pocnet, C., M. Dupuis, A. Congrad, and D. Jopp. 2017. "Personality and its Links to Quality of Life: Mediating Effects of Emotion Regulation and Self-Efficacy Beliefs." *Motivation and Emotion* 41 (2): 196–208.

Polytak, S. T., A. A. V. Davier, and K. Peterschmidt. 2017. "Computational Psychometrics for the Measurement of Collaborative Problem Solving Skills." *Frontiers in Psychology*, doi:10.3389/fpsyg.2017.02029.

Poria, S., E. Cambria, N. Howard, G. B. Huang, and A. Hussain. 2015. "Fusing Audio, Visual and Textual Clues for Sentiment Analysis from Multimodal Content." *Neurocomputing* 174: 50–59.

Portugal, I., P. Alencar, and D. Cowan. 2018. "The use of Machine Learning Algorithm in Recommender System: A Systematic Review." *Expert System with Application* 97: 205–227.

Qin, S., C. B. Young, X. Duan, T. Chen, K. Supekar, and V. Menon. 2014. "Amygdala Subregional Structure and Intrinsic Functional Connectivity Predicts Individual Differences in Anxiety During Early Childhood." *Biological Psychiatry* 75 (11): 892–900.

Ramirez, R., J. Planas, N. Escude, J. Mercade, and C. Farriols. 2018. "EEG-Based Analysis of the Emotional Effect of Music Therapy on Palliative Care Cancer Patients." *Frontiers in Psychology* 9: 254. doi:10.3389/fpsyg.2018.00254.

Rosales, J. H., F. Ramos, M. Ramos, and J. A. Cervantes. 2017. "Search for an Appropriate Behavior Within the Emotional Regulation in Virtual Creatures Using a Learning Classifier System." *Computational Intelligence and Neuroscience*, doi:10.1155/2017/5204083.

Sevel, L. S., J. Boissoneault, J. E. Letzen, M. E. Robinson, and R. Staud. 2018. "Structural Brain Changes Versus Self-Report: Machine-Learning Classification of Chronic Fatigue Syndrome Patients." *Experimental Brain Research* 36: 2245–2253.

Shojaeilangari, S., W. Y. Yau, J. Li, and W. K. Teoh. 2015. "Robust Representation and Recognition of Facial Emotions Using Extreme Sparse Engineering." *IEEE Transactions on Image Processing* 24 (7): 2140–2152.

Shon, D., K. Im, J. H. Park, D. S. Lim, B. Jang, and J. M. Kim. 2018. "Emotional Stress State Detection Using Genetic Algorithm-Based Feature Selection on EEG Signals." *International Journal of Environmental Research and Public Health* 15: 2461. doi:10.3390/ijerph15112461.

Silva, N. F. F., L. F. S. Coletta, E. R. Hruschka, and E. R. Jr. Hruschka. 2016. "A Survey and Comparative Study of Tweet Sentiment Analysis via Semi-Supervised Learning." *ACM Computing Surveys* 49 (1), doi:10.1145/2932708.

Simões, M., R. Monteiro, J. Andrade, S. Mouga, F. França, G. Oliveira, P. Carvalho, and M. C. Branco. 2018. "A Novel Biomarker of Compensatory Recruitment of Face Emotions Imagery Networks in Autism Spectrum Disorder." *Frontiers in Neuroscience* 12 (791), doi:10.3389/fnins.2018.00791.

Soleymani, M., M. Riegler, and P. Halvorsen. 2018. "Multimodal Analysis of User Behavior and Browsed Content Under Different Image Search Intents." *International Journal of Multimedia Information Retrieval* 7 (1): 29–41.

Soroush, M. Z., K. Maghooli, S. K. Setarehdan, and S. M. Nasrabadi, 2018. "Emotion recognition through EEG phase space dynamics and Dempster-Shafer theory." *Medical Hypotheses*,127, 34–45.

Tang, D., B. Yusuf, J. Botzheim, N. Kubota, and C. S. Chan. 2015. "A Novel Multimodal Communication Framework Using Robot Partner for Aging Population." *Expert Systems with Application* 42: 4540–4555.

Tavakoli, H. R., A. Atyabi, A. Rantanen, S. J. Laukka, S. N. Meziani, and J. Heikkilä. 2015. "Predicting the Valence of a Scene from Observers' Eye Movement." *PLoS ONE* 10: 9. doi:10.1371/journal.pone.0138198.

Troussas, C., M. Virvou, and E. Alepis. 2013. "Comulang: Towards a Collaborative e-Learning System That Supports Student Group Modelling." *SpringerPlus*, doi:10.1186/2193-1801-2-387.

Urizar, O. J., M. S. Baig, E. I. Barakova, C. S. Regazzoni, L. Marcenaro, and M. Rauterberg. 2016. "A Hierarchical Bayesian Model for Crowd Emotions." *Frontiers in Computational Neuroscience* 10, doi:10.3389/fncom.2016.00063.

Vaughn, D. A., R. R. Savjani, M. S. Cohen, and D. M. Eagleman. 2018. "Empathic Neural Responses Predict

Group Allegiance." *Frontiers in Human Neuroscience* 12 (302), doi:10.3389/fnhum.2018.00302.

Vempala, N. N., and F. A. Russo. 2018. "Modelling Music Emotion Judgements Using Machine Learning Methods." *Frontiers in Psychology* 8: 2239. doi:10.3389/fpsyg.2017.02239.

Vesely, A. K., D. H. Saklofske, and D. W. NordStokke. 2014. "EI Training and pre-Service Teacher Wellbeing." *Personality and Individual Differences* 65: 81–85.

Viswanathan, S. A., and K. VanLehn. 2018. "Using the Tablet Gestures and Speech of Pairs of Students to Classify Their Collaboration." *IEEE Transaction on Learning Technologies* 11 (2): 230–242.

Webster, E., N. Sekaviriya, H. Y. Chang, and J. Kozloski. 2017. "Predicting Cognitive States from Wearable Recordings of Autonomic Function." *IBM Journal of Research and Development* 61 (2/3): 2:1–2:11.

Wen, G., H. Li, J. Huang, D. Li, and E. Xun. 2017. "Random Deep Belief Networks for Recognizing Emotions from Speech Signals." *Computational Intelligence and Neuroscience*, doi:10.1155/2017/1945630.

WHO. 2001. *The World Health Report* 2001. Retrieved from https://www.who.int/whr/2001/en/.

WHO. 2018. *Depression*. Retrieved from http://www.who.int/en/news-room/fact-sheets/detail/depression.

Yin, Z., Y. Wang, W. Zhang, and J. Zhang. 2017. "Cross-Subject EEG Feature Selection for Emotion Recognition Using Transfer Recursive Feature Elimination." *Frontiers in Neurorobotics* 11: 19. doi:10.3389/fnbot.2017.00019.

Yuvaraj, R., M. Murugappan, N. M. Ibrahim, K. Sundaraj, M. I. Omar, K. Mohama, and R. Palaniappan. 2014. "Optimal Set of EEG Features for Emotional State Classification and Trajectory Visualisation in Parkinson's Disease." *International Journal of Psychophysiology* 94: 482–495.

Zanette, S., X. Gao, M. Brunet, M. S. Bartlett, and K. Lee. 2016. "Automated Decoding of Facial Expressions Reveals Marked Differences in Children When Telling Antisocial Versus Prosocial Lies." *Journal of Experimental Child Psychology* 150: 165–179.

Zhang, Q., and B. Li. 2015. "Relative Hidden Markov Models for Video-Base Evaluation of Motion Skills in Surgical Training." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 37 (6): 1206–1218.

Zhu, Y., D. Ghosh, D. L. Coffman, and J. S. Savage. 2016. "Estimating Controlled Direct Effects on Restrictive Feeding Practices in the 'Early Dieting in Girls' Study." *Journal of The Royal Statistical Society Series C-Applied Statistics* 65 (1): 115–130.

Zwir, I., J. Arnedo, C. D. Val, L. P. Råback, B. Konte, S. S. Yang, R. R. Zaliz, et al. 2018. "Uncovering the Complex Genetics of Human Character." *Molecular Psychiatry*, doi:10.1038/s41380-018-0264-5.

Appendix

Table A1. ML studies according to EI Component

Self-awareness	Coutinho et al. (2018); Lin and Kao (2018); Luo et al. (2017).
Self-regulation	López-gil et al. (2016); Zhu et al. (2016); Li et al. (2017); Mermarian et al. (2017); Rosales et al. (2017); Li et al. (2018); Zwir et al. (2018).
Social skill	Calvo et al. (2011); Molina et al. (2011); Anaya and Boticario (2013); Troussas, Virvou, and Alepis (2013); Baggott, M. J., Kirkpatrick, M. G., Bedi, G., & Wit, H. D.(2015); Cen et al. (2016); Birnbaum, M. L., Ernala, S. K., Rizvi, A. F., Choudhury, M. D., & Kane, J. M.(2017); Fernandez et al. (2017); Polytak, Davier, and Peterschmidt (2017); Viswanathan and VanLehn (2018).
Empathy	Bedi et al. (2014); Pläschke et al. (2017); Inkster, B., Sarda, S., & Subramanian, V.(2018); Vaughn et al. (2018).
Emotions	Khashman, A.(2010); Lin et al. (2010); Amini, Sabourin, and Koninck (2011); Chen and Lee (2011); Li et al. (2013); Modinos et al. (2013); Ahn et al. (2014); Arruti et al. (2014); Lin, Y. P., Yang, Y. H., & Jung T. P.(2014); Qin et al. (2014); Yuvaraj et al. (2014); Álvarez et al. (2015); Babiker et al. (2015); Daly et al. (2015); Foland-Ross et al. (2015); Jang et al. (2015); Karstoft et al. (2015); Kim et al. (2015); Lacoviello et al. (2015); Poria et al. (2015); Shojaeilangari et al. (2015); Tang et al. (2015); Tavakoli et al. (2015); Zhang and Li (2015); Banos, O., Villalonga, C., Bang, J., Hur, T., Kang, D., Park, S., The, T. H., Ba, V. L., Amin, M. B., Razzaq, M. A., Khan, W. A., Hong, C. S., & Lee, S. (2016); Deetjen and Powell (2016); Hettich et al. (2016); Kessler et al. (2016); Li et al. (2018); López-gil et al. (2016); Mohan et al. (2016); Silva et al. (2016); Urizar et al. (2016); Zanette et al. (2016); Chimeno et al. (2017); Choi, S., Lee, J., Kang, M. G., Min, H., Chang, Y. S., & Yoon, S.(2017); Coutinho et al. (2018); Fayek, Lech, and Cavedon (2017); Jeong et al. (2017); Just et al. (2017); Lin, Jao, and Yang (2017); Mistry et al. (2017); Özerdem and Polat (2017); Wen et al. (2017); Yin et al. (2017); Al Zoubi, Awad, and Kasabov (2018); Ali et al. (2018); Al-Saffar et al. (2018); Bang et al. (2018); Bass et al. (2018); Choi and Kim (2018); Feng et al. (2018); Fernández-Gavilanes et al. (2018); Moghadam, S. M., & Seyyedsalehi, S. A.(2018); Nicholson et al. (2018); Ramirez, R., Planas, J., Escude, N., Mercade, J., & Farriols, C.(2018); Sevel et al. (2018); Shon et al. (2018); Simões et al. (2018); Soroush, M. Z., Maghooli, K., Setarehdan, S. K., & Nasrabadi, A. M. (2018); Vempala and Russo (2018).
Motivation	Merrick (2010); Gatsoulis and McGinnity (2015); Klebanov et al. (2017); Webster et al. (2017); Dalins, Wilson, and Carman (2018); Hussain et al. (2018); Mokhtari et al. (2018); Soleymani, Riegler, and Halvorsen (2018).

Table A2. Utilisation of SVM according to year.

2010	Lin et al. (2010).
2011	Chen and Lee (2011).
2012	
2013	Modinos et al. (2013).
2014	Bedi et al. (2014); Lin, Y. P., Yang, Y. H., & Jung T. P.(2014); Yuvaraj et al. (2014).
2015	Álvarez et al. (2015); Foland-Ross et al. (2015); Jang et al. (2015); Karstoft et al. (2015); Lacoviello et al. (2015); Poria et al. (2015); Tavakoli et al. (2015); Zhang and Li (2015).
2016	López-gil et al. (2016); Hettich et al. (2016); Li et al. (2018); López-gil et al. (2016); Mohan et al. (2016); Silva et al. (2016); Zanette et al. (2016).
2017	Li et al. (2017); Mermarian et al. (2017); Pläschke et al. (2017); Chimeno et al. (2017); Wen et al. (2017); Yin et al. (2017).
2018	Coutinho et al. (2018); Lin and Kao (2018); Al-Saffar et al. (2018);Ramirez, R., Planas, J., Escude, N., Mercade, J., & Farriols, C.(2018); Sevel et al. (2018); Mokhtari et al. (2018); Soleymani, Riegler, and Halvorsen (2018).

Table A3. Utilisation of Bayes based algorithm according to year

2010	
2011	
2012	
2013	Anaya and Boticario (2013); Li et al. (2013).
2014	Arruti et al. (2014).
2015	Álvarez et al. (2015); Jang et al. (2015); Poria et al. (2015); Zhang and Li (2015).
2016	López-gil et al. (2016); Deetjen and Powell (2016); Li, S., Cui, L., Zhu, C., Li, B., Zhao, N., & Zhu, T. (2016); Urizar et al. (2016).
2017	Polytak, Davier, and Peterschmidt (2017); Chimeno et al. (2017); Just et al. (2017); Lin, Jao, and Yang (2017).
2018	Al-Saffar et al. (2018); Hussain et al. (2018).