



HAL
open science

Modelling the acceptability of BCIs for motor rehabilitation after stroke: a large scale study on the general public

Elise Grevet, Killiam Forge, Sébastien Tadiello, Margaux Izac, F. Amadiou, Lionel Brunel, Léa Pillette, Jacques Py, D. Gasq, Camille Jeunet

► To cite this version:

Elise Grevet, Killiam Forge, Sébastien Tadiello, Margaux Izac, F. Amadiou, et al.. Modelling the acceptability of BCIs for motor rehabilitation after stroke: a large scale study on the general public. 2022. hal-03893371v1

HAL Id: hal-03893371

<https://hal.science/hal-03893371v1>

Preprint submitted on 10 Dec 2022 (v1), last revised 2 Feb 2023 (v2)

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Modelling the acceptability of BCIs for motor rehabilitation after stroke: a large scale study on the general public

Elise Grevet^{1,*}, Killyam Forge², Sebastien Tadiello¹, Margaux Izac¹, Franck Amadiou², Lionel Brunel³, Léa Pillette¹, Jacques Py², David Gasq^{4,5} and Camille Jeunet¹

¹Univ. Bordeaux, CNRS, EPHE, INCIA, UMR5287 F-33000 Bordeaux, France

²CLLE, Université de Toulouse, CNRS, Toulouse, France

³Univ Paul Valéry Montpellier 3, EPSYLON EA 4556, F34000, Montpellier, France

⁴ToNIC, Université de Toulouse, INSERM, Toulouse, France

⁵Centre Hospitalier Universitaire Toulouse, Toulouse, France

Correspondence*:

Elise Grevet

elise.grevet@u-bordeaux.fr

2 ABSTRACT

3 Strokes leave around 40% of survivors dependent in their activities of daily living, notably due
4 to severe motor disabilities. Brain-computer interfaces (BCIs) have been shown to be efficient
5 for improving motor recovery after stroke, but this efficiency is still far from the level required to
6 achieve the clinical breakthrough expected by both clinicians and patients. While technical levers
7 of improvement have been identified (e.g. sensors and signal processing), fully optimised BCIs
8 are pointless if patients and clinicians cannot or do not want to use them. We hypothesise that
9 improving BCI acceptability will reduce patients' anxiety levels, while increasing their motivation
10 and engagement in the procedure, thereby favouring learning and, ultimately, motor recovery. In
11 other terms, acceptability could be used as a lever to improve BCI efficiency. Yet, studies on BCI
12 acceptability are missing in the BCI literature. Thus, our goal was to model this acceptability in
13 the context of motor rehabilitation after stroke, and to identify its determinants.

14 The main outcomes of this paper are the following: i) we designed the first model of acceptability
15 of BCIs for motor rehabilitation after stroke, ii) we created a questionnaire to assess acceptability
16 based on that model and distributed it on a sample representative of the general public in France
17 (N=753, this high response rate strengthens the reliability of our results), iii) we validated the
18 structure of this model and iv) quantified the impact of the different factors on this population.
19 Results show that BCIs are associated with high levels of acceptability in the context of motor
20 rehabilitation after stroke and that the intention to use them in that context is mainly driven by the
21 *perceived usefulness* of the system. In addition, providing people with clear information regarding
22 BCI functioning and scientific relevance had a positive influence on acceptability factors and
23 *behavioural intention*.

24 With this paper we propose a basis (model) and a methodology that could be adapted in the
25 future in order to study and compare the results obtained with: i) different stakeholders, i.e.,

26 patients and caregivers; ii) different populations of different cultures around the world; and iii)
27 different targets, i.e., other clinical and non-clinical BCI applications.

28 **Keywords:** Brain-Computer Interface, Neurofeedback, Acceptability, Acceptance, Stroke, Motor rehabilitation, Model, Questionnaire

INTRODUCTION

29 Brain-Computer Interfaces (BCIs) are technologies that enable users to control applications such as video
30 games (Kerous et al., 2018) or wheelchairs (Li et al., 2013), solely through their brain activity. Beyond
31 these control applications, BCIs can be used for neurofeedback (NF) training with the objective of learning
32 how to modulate our own cerebral activity, not in order to control something, but to improve or restore
33 cognitive or motor skills. BCI-based post-stroke motor rehabilitations are in this second category and
34 have demonstrated their efficacy to improve patients' motor and cognitive abilities (Cervera et al., 2018;
35 Bai et al., 2020; Nojima et al., 2022). In the coming years, they are expected to substantially improve
36 post-stroke subjects' quality of life (Nojima et al., 2022).

37 In classical motor rehabilitation, when subjects have no residual movement, i.e., when they cannot move
38 their affected limb at all, physical practice is impossible and both subjects and therapists must rely on
39 mental practice alone. Here, in mental practice, we include motor imagery (MI) as well as attempted
40 movements. In concrete terms, therapists usually ask the subjects to perform MI or to try to move their
41 arm (attempted movements), and simultaneously stimulate the limb by mobilising it or, for instance, by
42 using functional electrical stimulation (FES - which consists in stimulating peripheral motor nerves in
43 order to artificially generate movements). While associated to encouraging results (Sharma et al., 2006),
44 the difficulty encountered when trying to demonstrate the efficiency of this procedure might be related
45 to the impossibility to assess the patients' compliance when they are asked to perform MI tasks (Sharma
46 et al., 2006). In addition, we believe pure mental practice-based rehabilitation procedures present two main
47 limitations. The first one is due to the impossibility of the therapist to know when, exactly, the patient
48 imagines moving or tries to move. Therefore, the feedback patients are provided with will most likely not
49 be synchronised with their MI or movement attempts. A second limitation concerns the constant reminder
50 that the patient gets when the therapist asks them to move their arm and that they are unable to do so.
51 Post-stroke subjects experiencing high anxiety levels (Burton et al., 2013), this method might also have
52 detrimental psychological effects, potentially resulting in the patient disengaging from the rehabilitation
53 procedure, and in the therapy being less efficient.

54 In this context, BCIs are very relevant as they enable the detection of MI/attempted movements of the
55 impaired limb, which are underlain by modulations of the so-called sensori-motor rhythms (SMRs) - as
56 defined in the BCI field by a large band covering mu (μ) and beta (β) rhythms (8-30Hz) (Pfurtscheller
57 et al., 2000) -, and provide the patient with a synchronised NF, for instance using FES that triggers an arm
58 muscle contraction, or visual feedback (movement of a virtual hand on a screen (Pichiorri et al., 2015)).
59 Such a NF training enables the participants to train to voluntarily self-regulate their SMRs in a closed loop
60 process, which should favour synaptic plasticity and motor recovery (Jeunet et al., 2019).

61 While this is encouraging, BCI efficiency is still far from the level required to achieve the clinical
62 breakthrough expected by both clinicians and patients. Thus, BCIs remain barely used in clinical practice,
63 outside laboratories (Kübler et al., 2014). BCI efficiency is known to be modulated by several factors.
64 Many researchers are working on improving this efficiency either from a "technical" point of view (e.g.,
65 signal processing (Lotte et al., 2018)), or - less often - from the human learning standpoint (Roc et al., 2021;
66 Pillette et al., 2020). This is an important step forward: reaching high efficiency is a necessary condition
67 for BCI adoption. Nonetheless, it might not be sufficient for those technologies to be actually used in a

68 clinical setting: fully optimised BCIs (in terms of sensors, signal processing and training procedures) are
69 pointless if patients and clinicians are not able or do not want to use them, i.e., if BCIs are not accepted
70 (Blain-Moraes et al., 2012). For instance, misconceptions that patients and their entourage have regarding
71 BCIs may have a detrimental effect on the acceptance of these technologies. BCI acceptance could also
72 be altered by the fact that most stroke patients experience depression, and therefore high anxiety levels
73 (Burton et al., 2013) that have a detrimental effect on BCI acceptance and learning (Jeunet et al., 2016).
74 Thus, BCI acceptance is likely to have a major impact on the patients' learning processes and therefore on
75 the efficiency of BCI-based stroke rehabilitation procedures. We hypothesise that identifying acceptability
76 and acceptance factors will help us overcome these misconceptions and personalise the procedures, which
77 will in turn result in reduced anxiety, and increased motivation and engagement levels for the patients. This
78 should favour their learning and, ultimately, motor recovery. In other words, we expect that improving
79 the acceptance levels of BCIs will result in an increased efficiency of these technologies and therefore
80 contribute to their democratisation.

81 Thus, it is crucial, when designing stroke rehabilitation procedures, to consider technology acceptance as
82 a lever to optimise BCI efficiency –in terms of motor recovery. Yet, BCI acceptance remains an aspect
83 that has been little studied to date. To the best of our knowledge, only (Morone et al., 2015) assessed
84 the relevance of a BCI-based stroke rehabilitation procedure of the upper limb using acceptability and
85 usability measures as primary criteria (pilot study, N=8 patients). The acceptability and usability were
86 measured in terms of mood, motivation, satisfaction, and perceived workload. Indeed, in the BCI field,
87 acceptability is mostly assessed as an attribute of the user's satisfaction, itself being a dimension of user
88 experience (Kübler et al., 2014; Nijboer, 2015). (Morone et al., 2015) concludes that the BCI training was
89 "accepted with a good compliance/adherence". The same conclusion was drawn in the context of a BCI
90 dedicated to a gamified cognitive training for the elderly (Lee et al., 2013) as well as in different studies
91 dedicated to the acceptance of BCIs by Amyotrophic Lateral Sclerosis (ALS) patients (Huggins et al.,
92 2011; Blain-Moraes et al., 2012; Nijboer, 2015), which is the clinical condition for which acceptance has
93 been the most investigated (Nijboer, 2015). Using a focus group approach, (Blain-Moraes et al., 2012) have
94 shown that both personal and relational factors impacted BCI acceptance. The personal factors included
95 physical (pain, discomfort), physiological (fatigue, endurance) and psychological (anxiety, attitude towards
96 the technology) concerns, and the relational factors included corporeal (electrode type), technological
97 (relationship between BCI and other type of software and hardware) and social (appearance, training and
98 support personnel) factors. The relational factors had a stronger impact than the personal ones. In the same
99 line, Huggins and colleagues (Huggins et al., 2011, 2015) led qualitative studies to assess the influence
100 that different factors (physical interface, setup and training, acceptable performance, task and feature
101 priorities) had on BCI acceptance in ALS patients and patients who had undergone a spinal cord injury.
102 The functions provided by the BCI were rated as the most important feature, together with the ease of use
103 of the system and the availability of a stand-by mode. Finally, (Geronimo et al., 2015) have shown that
104 behavioural impairments such as apathy and mental rigidity had a negative impact on ALS patients' BCI
105 usage behaviour. Furthermore, the fact that they performed a pilot study during which patients appeared to
106 have a low perceived control over the system altered the perceived usefulness of the BCI. This latter study
107 is the only one in the field of BCIs that assessed acceptance in terms of usage behaviour and perceived
108 usefulness. These are concepts from the field of psychology and ergonomics, which we draw on in the next
109 paragraph (Kaleshtari et al., 2016). As claimed by (Kaleshtari et al., 2016), who designed the first Model
110 of Rehabilitation Technology Acceptance and Usability (RTAU), in order to be effective, rehabilitation
111 technologies have to be used and therefore accepted by the patients and their families. According to
112 (Kaleshtari et al., 2016), this acceptance depends both on personal features, technology features and social

113 influence. The domain-specific literature indeed suggests that BCI acceptability and acceptance seem to
114 rely on “subjective technical confidence and positive attitudes towards the use of technologies” (Morone
115 et al., 2015). The EEG cap characteristics (gel, montage, time to set up) seem important both for patients
116 and caregivers (Morone et al., 2015; Nijboer, 2015). Generally speaking, the simpler the better for them
117 (Huggins et al., 2011). Nonetheless, the EEG technology used and the reliability/discomfort trade-off,
118 together with all the BCI-related characteristics, need to be thought of in light of the characteristics and
119 requirements of the application (e.g., level of reliability required) as well as in light of the profile of the
120 patient. This is why BCI-based stroke rehabilitation procedures should be carefully adapted to the training
121 context of each patient. In this spirit, (Kübler et al., 2014) proposed an inspiring approach, suggesting to
122 “shift from focusing on single aspects, such as accuracy and information transfer rate, to a more holistic
123 user experience” using User-Centred Design. User-Centred Design has since then been shown to contribute
124 to the acceptability and usability of a BCI-based stroke rehabilitation procedure (Morone et al., 2015) and,
125 more broadly, improved user experience has been suggested to enhance user acceptance and increase the
126 performance of BCI systems (Gürkök et al., 2011).

127 The concepts of acceptability and acceptance were introduced in order to understand what led users
128 to adopt or not a new system (Alexandre et al., 2018). The adoption of a technology refers to a use
129 that is maintained over time, i.e., without abandonment. In concrete terms, acceptability measure is an
130 evaluation of the user’s behavioural intention (BI) i.e., their intention to use the studied technology. The
131 main determinants of BI are perceived usefulness (PU) and perceived ease of use (PEOU). PU is the
132 personal feeling about utility of the system, and PEOU the degree of belief to which using the system
133 will require little or no effort. Acceptability and acceptance differ by the moment they are measured at:
134 acceptability concerns the user’s standpoint before any interaction with the system, while acceptance comes
135 after at least one first use.

136 To the best of our knowledge, there is no model of BCI acceptability yet. Thus, our goals were to (i)
137 create a theoretical model of acceptability - based on the literature - including the factors influencing BI
138 towards BCIs, especially in the context of motor rehabilitation after stroke; (ii) implement a questionnaire
139 from this model to assess BCI acceptability in general public; (iii) validate the structure of our model and
140 questionnaire; and (iv) quantify the impact of the different factors included in the model on acceptability.

141 With this study we targeted the general public. This enabled us to collect the opinions and attitudes
142 of a large sample of persons, representative of the adult population in France, and thereby to capture an
143 estimation of BCI acceptability in the overall population that we will, in the future, compare with the one
144 of patients and clinicians. Targeting the general public seems particularly relevant in this case for two
145 reasons. First, due to the high prevalence of stroke that is one of the leading causes of disability in adults in
146 France (INSERM, 2019) and results in many of us being concerned, more or less directly, by this pathology
147 and associated rehabilitation techniques. Second, due to the fact that the opinion and attitude of their close
148 relatives will influence the patients’ acceptability levels (Venkatesh et al., 2003).

149 In this paper, we first explain our methodology to achieve these objectives in Section 1: (i) the design
150 of the model, (ii) the implementation of the associated questionnaire, (iii) the validation of these model
151 and questionnaire, and (iv) the quantification of the influence of the different factors included in the model
152 on BCI acceptability. Then, we present the results of this methodology in Section 2, which are based on
153 data collected on a sample representative of the population of France (N=753). We finish with a discussion
154 about limitations and benefits of our research.

1 MATERIAL AND METHODS

155 1.1 Design of the acceptability model

156 1.1.1 Review of the literature

157 To build our model, we reviewed the literature and selected the models that seemed the most relevant for
158 BCIs.

159 In the literature, several models dedicated to the acceptability and acceptance of technologies have been
160 depicted, most of them can be adapted depending on the focus (i.e., acceptability or acceptance). Their
161 objective is usually to explain, or even predict, the BI of the user. These models differ from each other in
162 the factors they include and that influence acceptance/acceptability. The most recent and main models are
163 the technology acceptance model (TAM) (Davis, 1989), of which there are a second (Venkatesh and Davis,
164 2000) and third (Venkatesh and Bala, 2008) versions, as well as the unified theory of acceptance and use of
165 technology (UTAUT) (Venkatesh et al., 2003), of which there is a second version (Venkatesh et al., 2012).
166 For more information about other existing acceptability models, their evolution is summarised in a recent
167 review (Pillette et al., in preparation).

168 1.1.2 Methodology to build our model

169 We have chosen to work with the most advanced versions of the evoked models: TAM3 (Venkatesh and
170 Bala, 2008) and UTAUT2 (Venkatesh et al., 2012), in addition to a less widespread model, the components
171 of user experience (CUE) model (Thüring and Mahlke, 2007), because we wanted up-to-date models that
172 were adapted to our context and as exhaustive as possible. We propose to present these latter and the details
173 of why we chose them in Table 1.

	Technology Acceptance Model 3 (TAM3) - (Venkatesh and Bala, 2008)
THEORY	<p>TAM3 is the third version of TAM (Davis, 1989). In TAM3, the main concepts are perceived usefulness (PU) and perceived ease of use (PEOU). PU is the degree to which a person believes that using a system will improve their performances; and PEOU, the degree to which using a system will be effortless. These factors are determined by the characteristics of the technology and influence the behavioural intention (BI). TAM3 also includes the <i>social influence</i> process which is constituted of subjective norm and image. Subjective norm is the subjective perception of individuals about what people who are important to them will think concerning the usage of a technology. According to the authors, the presence or absence of important effects of subjective norm on the BI is moderated by voluntariness, i.e. the voluntary or forced aspect of use, and by previous experience. The subjective norm can have a stronger impact when the use is constrained (Venkatesh and Davis, 2000). Concerning image, it can be defined as the degree of users' perception on whether or not the use of a technology will improve their status within the social group to which they belong (Moore and Benbasat, 1991).</p> <p>Another category is the <i>extrinsic motivational processes</i>, sometimes referred to the instrumental cognitive process (i.e. relevance of the technology, perceived quality, and result demonstrability). These factors allow users to form a judgement on what the use of technology can bring them given their needs to achieve their goals.</p> <p>In TAM3, the novelty in comparison to TAM2 (Davis et al., 1992) is the addition of determinants of PEOU. PEOU is determined by <i>intrinsic motivational processes</i> also called the anchored beliefs, i.e. playfulness of the interaction, perception of external control, self-efficacy and computer anxiety. Computer playfulness is the enjoyment when using the studied technology. Perception of external control are the "individuals' control beliefs regarding the availability of organisational resources and support structure to facilitate the use of a system" (Venkatesh and Bala, 2008). Self-efficacy can be defined as the "individuals' control beliefs regarding his or her personal ability to use a system" (Venkatesh and Bala, 2008). Finally, computer anxiety is an emotion that corresponds to the more or less conscious expectation of a danger or a problem to come associated with the use of the system. PEOU is in addition determined by adjustments factors that include enjoyment of use and objective usability. These adjustments are made by the user during the interaction, which appears only in the dimension of acceptance and no longer in acceptability like the other factors.</p>

JUSTIFICATIONS	A large majority of studies dedicated to the assessment of the acceptance of new technologies have used the first version of TAM (studies between 2001 and 2018 in the review of Altruas et al. (Alturas et al., 2021), and between 2006 and 2015 in Rad et al. (Rad et al., 2018)). This can be explained in part by the fact that this version is made up of fewer factors than TAM2 and TAM3, in consequence its implementation and test in a given research context can be easier. In our case, we preferred to use the most advanced version of TAM. We privileged the completeness of the model instead of the simplicity of implementation as we are in an exploratory stage of research on BCIs acceptability (the factors deletion will be addressed in a near future, in accordance with the results of our study and of other future papers).
Unified Theory of Acceptance and Use of technology 2 (UTAUT2) - (Venkatesh et al., 2012)	
THEORY	UTAUT2 is the second version of UTAUT (Venkatesh et al., 2003) which unifies the concepts of 8 models of acceptability. UTAUT is composed of four determinants - social influence, facilitating conditions, performance expectations and effort expectations - that influence the BI. It also includes four moderators: gender, age, experience and voluntary aspect of use. Performance expectation and effort expectation factors correspond to the PU and PEOU factors of TAM, respectively. Facilitating conditions are the material, organisational and/or human conditions facilitating the use of a technology (Février, 2011). In comparison to the first version, UTAUT2 adds three determinants of BI, namely hedonic motivation, price value and habit. Hedonic motivation is the pleasure provided by the use of a technology, this factor is close to computer playfulness factor of TAM3. Price value refers to the trade-off made by consumers between the perceived advantages of the technology and its cost. On the other hand, the authors have chosen to delete one of the moderators: the voluntariness no longer appears in UTAUT2.
JUSTIFICATIONS	UTAUT has the advantage of being created from previous reliable models, which makes it a robust reference. Moreover, in order to test the quality of UTAUT, its designers had created a questionnaire with items from the eight models. In their study, the questionnaire was circulated in four different organisations among employees being introduced to a new technology in their workplace. It appeared that UTAUT determinants achieved to predict 70% (adjusted R ²) of the BI. This score was the most accurate among the previous models (Venkatesh et al., 2003; Koul and Eydgahi, 2017). Its extension (UTAUT2) is of greater relevance to us since it was designed to be more suitable for consumer technologies rather than for an organisational setting (Rondan-Cataluña et al., 2015), which fits better with the use cases of BCIs.
Components of User Experience (CUE) - (Thüring and Mahlke, 2007)	
THEORY	In order to widen the field of research in human-computer interactions, authors (Dillon, 2001; Hassenzahl, 2001, 2003, 2004; Mahlke, 2008) have proposed an approach which considers a system not only with regard to its properties and its functional benefits, but also to the experience of use (emotional reaction, pleasure of use, etc.) (Février, 2011). CUE is in this line, it highlights the interaction of 3 components of user experience: (i) the perception of the instrumental qualities of the system (referring to the PU and PEOU), (ii) the perception of its non-instrumental qualities (aesthetics, motivational aspects and values conveyed), and (iii) the user's emotional reactions (subjective feelings, motor and behavioural expressions, physiological reactions, and cognitive evaluation) when interacting with the technology. These 3 dimensions lead to the formation of judgments and behaviours towards the use of a given technology.
JUSTIFICATIONS	What particularly interested us in CUE was the higher level of consideration - in comparison to TAM3 and UTAUT2 - of the attractiveness of the technology (aesthetics, motivational aspects and conveyed values) (Barcenilla and Bastien, 2009). This is indeed a point to be studied in the case of a technology such as an EEG-based BCI for which the visual aspect of the interface may seem cumbersome for users, especially novices.

174 Table 1: **Acceptability and acceptance models used to build our model for BCI-based post-stroke**
 175 **motor rehabilitation.**

176 Using the models presented in Table 1, our work was to identify their factors that seemed relevant in the
 177 context of BCI-based post-stroke motor rehabilitation, while reflecting on missing determinants that are
 178 however useful to assess with regard to the literature on BCIs.

179 1.2 Creation and distribution of the questionnaire

180 As we explained in introduction, from our acceptability model, we developed a questionnaire to identify
 181 and weight the factors influencing the acceptability of BCI-based post-stroke motor rehabilitation within the
 182 general population. The choice to rely on the questionnaire method to test our model is explained by several
 183 aspects: (i) It is the classic method used in acceptability or acceptance assessment (Davis, 1989; Venkatesh
 184 et al., 2003). (ii) It was necessary to be able to collect a large amount of data, on a sample representative of
 185 the adult population in France, and questionnaires are particularly adapted to these expectations (Vilatte,

186 2007). (iii) In addition, questionnaires offer good external validity (Ghiglione and Matalon, 1998), which
187 makes it possible to generalise the data, the information being more uniform than interviews results.

188 1.2.1 Creating the questions

189 To determine the wording of the questions, we adapted those of the questionnaires of the existing models
190 already translated into French. The questionnaire was created on the Qualtrics tool, it was fully anonymous,
191 and therefore not subject to the general data protection regulation (GDPR). It took approximately 15
192 minutes to be completed and consisted of four parts:

- 193 • (i) To start, participants were provided with all the information they should know about the research
194 project: objectives of the questionnaire, researchers involved, benefits and possible risks of filling the
195 questionnaire, rights (e.g., anonymity preserved), methodology used and estimated completion time.
196 Finally, the participants were asked if they consented to participate.
- 197 • (ii) Following these details, the experience of the participant with BCIs was assessed as it could have an
198 influence on some of the predictive factors of BI.
- 199 • (iii) The third part was devoted to the evaluation of the influence of the factors of our model. Each of
200 them was evaluated by up to three or five questions. The score of a factor was thus the average of the
201 scores of these different questions. The scale used to measure each of the quantitative factors was a
202 visual analogue scale (VAS) from 0 to 10 (“strongly disagree” to “strongly agree”). When a question
203 was negative (e.g., “*I think learning to use a brain-computer interface would be too time consuming*”),
204 we inverted its score. To measure the categorical factors (*computer self-efficacy* and *social support*),
205 we used checkbox questions.

206 In this part, we also introduced two explanatory videos edited by ourselves: one explaining the
207 operation of BCIs in general (video 1) and the second more specific to BCI-based stroke rehabilitation
208 procedures (video 2). The rationale of providing these explanatory videos is presented in the next
209 paragraph.

210 We provide in Figure 1 more details on the organisation of our questionnaire. The questions were
211 organised in blocks (a block is made up of 2 or more factors). To avoid any potential order effect,
212 i.e., that the previous questions would guide the following answers, the order of presentation of the
213 questions was randomised within each block.

- 214 • (iv) The last part concerned the socio-demographic characteristics of the respondents (age, gender, last
215 diploma obtained, socio-professional category, if they have had a stroke and are currently hospitalised
216 for it, or if they have people in their close circle who have experienced it and their involvement in the
217 rehabilitation of these relatives). Subjects were not obligated to position themselves, they had the
218 possibility to choose the option “I do not wish to answer”.

219 Concerning the factors, we evaluated different factors before and after the second video (Figure 1). PU
220 and BI were measured twice (before video 2: PU1/BI1; after video 2: PU2/BI2), the questions were the
221 same for the two moments. Our aim was to observe if the respondents’ scores for the two measures were
222 impacted by information given in the video. The factors before video 2 did not require to have plenty of
223 information on BCIs to answer, i.e., the respondents needed to understand what BCIs are but remained
224 novices on their use in post-stroke rehabilitation. On the other hand, for the factors following video 2, a
225 more detailed vision of these new rehabilitation procedures was needed (factors were *result demonstrability*,
226 *benefits/risk ratio* and *relevance*).

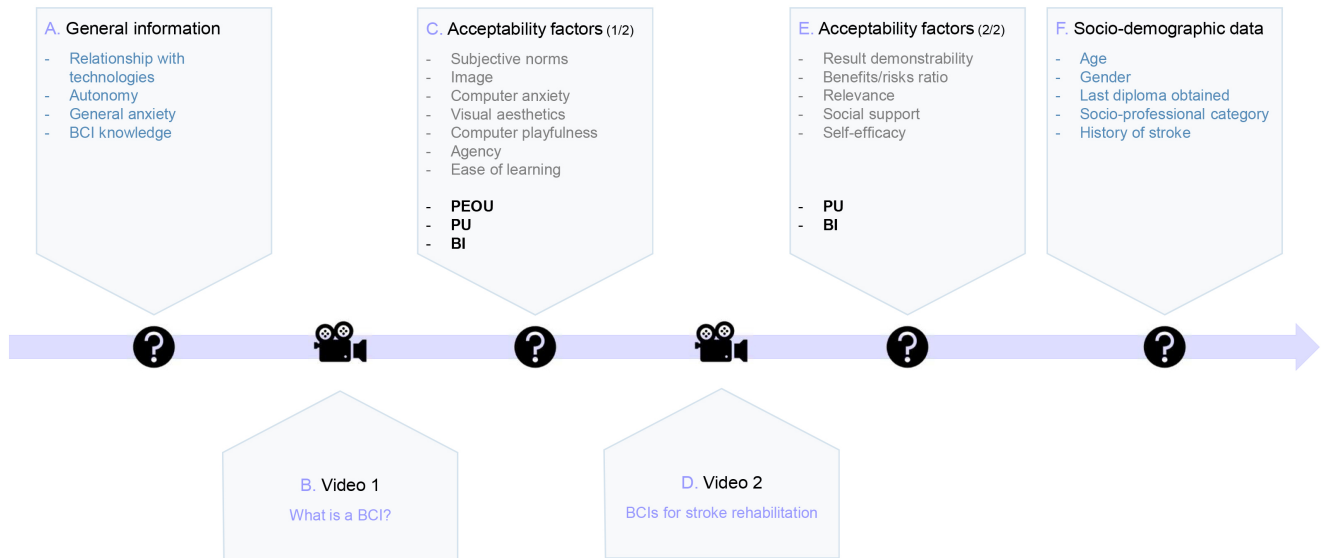


Figure 1.

Schematic representation of the structure of the questionnaire: (A) Assessment of the respondents' traits and general knowledge about BCIs; (B) Presentation of the first video that aimed at providing basic information regarding BCIs (functioning, installation, etc.); (C) Items related to a subset of acceptability factors (1/2); (D) Presentation of the second video during which the application of BCIs for post-stroke motor rehabilitation was introduced. (E) Items related to a subset of acceptability factors (2/2); (F) Collection of socio-demographic data. The two subsets of acceptability factors were divided depending on the need for respondents to have knowledge about how BCIs could be used for stroke rehabilitation.

227 1.2.2 Calculation of the statistical power

228 Our initial target was to have at least 10 respondents per item (i.e., question) on the factors influencing
 229 acceptability in order to be able to perform reliable analyses (Kline, 2015). As we had 62 items, this gave
 230 us a sample size of $N=620$ to respect this prerequisite.

231 1.2.3 Distribution of the questionnaire

232 The distribution of the questionnaire was done by the company Panelabs (<https://fr.panelabs.com/>)
 233 to ensure that the sample of respondents was representative of the adult population in France in terms
 234 of age, gender, place of residence and socio-professional category. We had a single exclusion criterion:
 235 minors could not participate. The experimental protocol was carried out in accordance with the Declaration
 236 of Helsinki and was approved by Institutional review board of Toulouse federal university (N°2019-140).
 237 We fixed with Panelabs a sample of $N = 665$ minimum in order to have a few more respondents than our
 238 aim (i.e., $N=620$), in case of invalid responses.

239 1.3 Validation of the structures of the model and questionnaire

240 The assessment of the validity of the structure of our model and questionnaire was performed following
 241 two steps. First, we measured the “within-factor” consistency, i.e., the internal coherence between the
 242 different items of the questionnaire that measured the same factor. Second, we assessed the “between-factor”
 243 consistency, i.e., the validity of the structure of our model.

244 1.3.1 Coherence of the factors: Cronbach's alpha

245 The Cronbach's alpha coefficient allowed us to calculate the internal consistency of each factor. Concretely,
246 this metric estimates the extent to which the items that are meant to measure one same factor are associated
247 with coherent scores. There is no fixed rule on the minimal value of the coefficient for the internal
248 consistency of the factor to be considered satisfactory. Nevertheless, the value 0.7 comes up very often in
249 the literature (Nunnally, 1994; Bland and Altman, 1997; DeVellis and Thorpe, 2021). It is also indicated
250 that a coefficient too close to 1 is to be taken with precaution, this high value may be due to redundancy in
251 the question statements (Tavakol and Dennick, 2011). In other words, the items would be too similar one
252 from the other, and do not bring additional information.

253 1.3.2 Structure of the model and questionnaire: Confirmatory factor analysis

254 Confirmatory factor analysis (CFA) is a validation test, which also aims to verify the internal consistency
255 of the questionnaire and check whether the model we propose fits correctly with the data collected. Several
256 indicators are used to interpret the CFA (Gallagher and Brown, 2013) : (i) The chi-square (X^2) test which
257 has the null hypothesis that the model fits perfectly. A good fit is shown by a p-value greater than 0.05 (i.e.,
258 not significant). This test is not always reliable on large samples because it is very sensitive to size. (ii)
259 The comparative fit index (CFI) estimates to what extent the tested model is better than the independence
260 model (i.e., the model where each of the factors are independent and uncorrelated). Ideally, this score
261 should be higher than 0.95 (perfect) or at least better than 0.90 (acceptable). (iii) The Tucker-Lewis index
262 (TLI) is very close to CFI, it evaluates the degree to which the model improves the fit with respect to the
263 independence model. For example, if the TLI is equal to 0.95, the studied model improves the fit by 95%
264 compared to the independence model. As CFI, this score should be higher than 0.95 or at least better than
265 0.90. (iv) The root mean square error of approximation (RMSEA) is the index of poor fit of the tested
266 model. The smaller the RMSEA, the better the goodness of fit. It is thus preferable to have the smallest
267 possible value of RMSEA (preferably less than 0.05). (v) Finally, we can also look at the standardised root
268 mean squared residual (SRMR), this latter must be less than 0.08. It measures the difference between the
269 correlation matrix of the observed sample and the matrix predicted by the model.

270 1.4 Quantification of the impact of the different factors on BCI acceptability

271 1.4.1 Important factors in each category of our model: Mediation analysis

272 As one of our main aims was to determine the most influential determinants of PU, PEOU and BI, we
273 chose to perform mediation analyses. This analysis is a rearranged linear regression, its objective being
274 to decompose and quantify the total effect of a cause X on a response variable Y into a direct effect
275 and an indirect effect through the mediator(s). This method was very relevant in our context: we had an
276 acceptability model with independent variables, moderators (PU and PEOU) and a target variable (BI).
277 We did one mediation analysis per category in our model (i.e., *social influence*, *individual differences*,
278 *facilitating condition and system characteristics* - these categories are depicted in Section 2.1), in order to
279 see which factors had the most impact in each of them. This analysis was also an interesting step to enable
280 us to propose a shorter and simplified version of our model and questionnaire in the future, one with only
281 the most relevant variables. The mediate library from R "psych" package was used (Revelle, 2021).

282 1.4.2 Important factors independently of structure of the model: Random forest algorithm

283 After mediation analyses, we wanted to do additional observations that do not depend on the architecture
284 of our proposed model. We thus opted for the random forest (RF) algorithm. The principle of this algorithm

285 is to randomly build multiple decision trees and train them on different subsets of our data. Thus, instead of
286 trying to obtain an optimised method at once, we generate several predictors before pooling their different
287 predictions. The final estimation is obtained, in the case of a regression as for this study, by taking the
288 average of the predicted values. RF algorithms have the advantage of being non-parametric tests allowing
289 the combination of quantitative and qualitative data, and making it possible to identify the factors associated
290 with the bigger weights.

291 1.4.3 Intensity of the connections between factors: Correlation analysis

292 After using the RF algorithm, we looked at the correlations between the most salient factors which stood
293 out. Our objective was to see if the correlations between these factors were rather positive or negative in
294 order to understand the meaning of their relationship (RF algorithm does not provide the strength of the
295 connection between factors and target variable). To build the correlation matrix, a non-parametric method
296 (Spearman's coefficient) was applied (Kowalski, 1972), and p-values were adjusted using the Bonferroni
297 method.

298 2 RESULTS

298 In this section, we present the acceptability model we built, the results of the questionnaire, our analyses to
299 validate these latter and finally those for quantifying the impact of the different factors on BCI acceptability.

300 We performed these analyses using data from Qualtrics, after measuring the average score of each factor
301 for every respondent (as explained in Section 1.2, a factor is measured by several questions which we
302 had to average). For the qualitative/categorical variables, we calculated the number of occurrences of the
303 sub-modalities.

304 2.1 Design of the acceptability model

305 We introduce here the theoretical model of acceptability dedicated to BCI-based post-stroke rehabilitation
306 procedures that we have created. To design this model, we selected factors from those of the existing
307 models presented in Table 1, using studies on BCIs to estimate their suitability in our context. To these
308 current factors, we have added new ones that seem particularly relevant to BCIs, still basing ourselves
309 on the BCIs literature. We present in this section the factors we included in our model (Table 2 contains
310 definition and justifications of our choices) and its structure (Figure 2).

311 Each factor is classified into a category: *social influence*, *individual differences*, *facilitating conditions*
312 and *system characteristics*. These categories are inspired by TAM3 (Venkatesh and Bala, 2008) and
313 UTAUT2 (Venkatesh et al., 2012). *Social influence*, as defined in the TAM2 and 3, is the influence of
314 an individual's relatives and social group on their choice of whether or not to adopt a system. It is a
315 determinant of PU and BI. Its effect on BI and PU decreases with experience (according to TAM3 and
316 UTAUT2, and only to TAM3, respectively). *Individual differences* is a category which groups the user
317 personal characteristics (socio-demographic information, cognitive traits and personality). Its factors are
318 determinants of PU and PEOU. We hypothesise that the weight of the factors of this category decrease
319 with experience as the effect of computer anxiety on PU and PEOU decreases with experience (TAM3).
320 *Facilitating conditions* brings together the factors related to the material, organisational and/or human
321 conditions that facilitate the use of a technology (Février, 2011). This category is a determinant of PEOU
322 (TAM3). Its impact is lessened while users acquire experience with the technology as their dependence
323 towards external support will be reduced (Alba and Hutchinson, 1987). Finally, *system characteristics*
324 is a category related to the instrumental cognitive process introduced by the TAM2. It is the mental

325 representation developed by the user to judge what the use of a technology can bring them in relation to
 326 their objective(s) (relevance of the system, perceived quality, etc.) (Terrade et al., 2009a). This category
 327 influences PU (TAM3) and in addition, among this category, *visual aesthetics* also influences PEOU
 328 because this factor comes from the CUE model which assumes that its effect is not limited to PU.

FACTORS	VALIDATED MODELS	EXPLANATIONS
Target factors		
Behavioural intention - BI	TAM3 - UTAUT2 - CUE	BI designates the prediction of an user's intention to use a technology. This is the key factor in acceptability models: a strong intention is the sign of a good acceptability of the system. BI is influenced by all other factors to greater or lesser degrees.
Perceived Usefulness - PU	TAM3 - UTAUT2 - CUE	DEFINITION: PU is equivalent to "performance expectancy" in UTAUT. It corresponds to the user's belief level of the fact that the use of the technology will improve them performance. PEOU is equivalent to "effort expectancy" in UTAUT. It consists in the degree of belief to which using the system will require little or no effort (Terrade et al., 2009b).
Perceived Ease of Use - PEOU	TAM3 - UTAUT2 - CUE	JUSTIFICATION: In the literature, these two factors and the way they interact with each other are essential in the prediction of BI. Moreover, they are present in all of the papers that assessed the acceptability of BCIs using validated questionnaires of acceptability (Pillette et al., in preparation)
Characteristics of the system		
Image	TAM3 - UTAUT2	DEFINITION: Image refers to the social image reflected when using a technology (social status, positive/negative perception by society). It is part of the process of social influence in TAM3 and UTAUT2, but we have chosen to introduce it within the characteristics of the system because BCIs can have different physical/material aspects, which probably influences the image. JUSTIFICATION: To our knowledge, the role of social norms on the intention to use BCIs has not really been studied. We nevertheless believe that there is an interest in verifying whether this factor plays or not a role on acceptability given the large number of categories of people who gravitate around post-stroke subjects - as we said for subjective norm.
Relevance	TAM3	DEFINITION: This is the relevance from a scientific standpoint (i.e., relevance according to experts, to the latest science advances). We hypothesise that the scientific relevance of the BCI can be called into question when the benefits on risk ratio is low. JUSTIFICATION: Due to the large number of false beliefs about BCIs (Bocquelet et al., 2016), there is a strong interest in taking this factor into account in the context of rehabilitation with these technologies.
Result demonstrability	TAM3	DEFINITION: This factor assesses the degree to which an individual believes that the results of using technology are tangible, observable and communicable (Moore and Benbasat, 1991). JUSTIFICATION: It is particularly interesting to evaluate it for BCIs in rehabilitation in order to understand how clear the information provided to the subject seems to them.
Visual aesthetics	CUE	DEFINITION: The factor is introduced by CUE among the non-instrumental qualities of a system which "concern the look and feel of the system [...] non-instrumental qualities result from its appeal and attractiveness" (Thüring and Mahlke, 2007). Visual aesthetics refers more particularly the physical appearance of the system. JUSTIFICATION: Given that BCIs do not have a very attractive or aesthetic appearance, it can be assumed that this will have a possible impact on their acceptability, both in the user's relationship to the system - in particular their anxiety - and in the reflected social image.
Benefits/risk ratio	-	DEFINITION: We decided to introduce this ratio as in medical context comparing a new therapy to conventional therapies is important; especially since learning how to use a BCI can be costly in time. In addition, the risk/benefit ratio is a common measure in the medical community (Edwards et al., 1996). JUSTIFICATION: Our choice is in accordance with the conclusion of (Wolbring et al., 2013) who notes that "the clinical viability of BMI [brain-machine interface] technology for disabled people is determined by a cost (surgical risks, financial accessibility, reliability) benefit (improvement of quality of life) analysis".
Social influence		

Subjective norm	TAM3 - UTAUT2	<p>DEFINITION: “The degree to which an individual perceives that most people who are important to him think he should or should not use the system” (Fishbein and Ajzen, 1977; Venkatesh and Davis, 2000).</p> <p>Subjective norm is supposed to influence <i>image</i> (TAM3). This link would reflect the effect of the so-called identification process, i.e. when the subjects accept the use of a technology in order to maintain a positive relationship with the social group to which they belong (Kelman, 1958)</p> <p>JUSTIFICATION: Subjective norm is relevant for BCIs in clinical settings because patients are often assisted/supported by many people (close relations, nursing staff, other patients, etc.) who can influence their choices.</p>
Individual differences		
Age and Gender	UTAUT2	<p>JUSTIFICATION: The user’s personal characteristics were introduced as moderator variables in UTAUT (Venkatesh et al., 2003). We have chosen to keep them as classic factors (i.e., not just moderators), in order to see whether or not, in our context, they directly influence PU, PEOU or BI. In UTAUT2, age and gender influence also the <i>Facilitating conditions</i> category.</p>
Computer anxiety	TAM3	<p>DEFINITION: “The degree of an individual’s apprehension, or even fear, when she/he is faced with the possibility of using computers” (Venkatesh, 2000; Venkatesh and Bala, 2008).</p> <p>JUSTIFICATION: Computer anxiety (here anxiety regarding BCIs) is a relevant factor as it has been shown that fear of BCIs affects user performance (Burde and Blankertz, 2006; Nijboer et al., 2010; Witte et al., 2013). This apprehension towards the use of BCIs can be compared to a feeling of computer anxiety (Jeunet et al., 2016).</p>
Computer self-efficacy	TAM3	<p>DEFINITION: “The degree to which an individual believes that he or she has the ability to perform a specific task/job using the computer” (Venkatesh and Bala, 2008; Compeau and Higgins, 1995).</p> <p>JUSTIFICATION: The study (Nijboer et al., 2008) shows that participant’s high confidence in their training success leads to a better control over the BCI. Conversely, this same study found that a high level of fear of incompetence is associated with much lower control capacities.</p>
General anxiety	–	<p>DEFINITION: Anxiety corresponds to waiting more or less consciously for future dangers or problems. In post-stroke subjects, the overall pooled estimate of anxiety disorders assessed by rating scale is 25% (Campbell Burton et al., 2013).</p> <p>JUSTIFICATION: This factor was chosen because the measure of general anxiety enables to differentiate anxiety generated by BCIs from anxiety disorder; the former can be softened by the context of use whereas the second is less controllable.</p>
Autonomy	–	<p>DEFINITION: Autonomy is defined as people’s concern “for their individuality, their independence, their efforts to achieve a goal, as well as a low concern for others” (Husky et al., 2004).</p> <p>JUSTIFICATION: A BCI study showed a strong correlation between self-reliance and mental imagery (MI) BCI performance (Jeunet et al., 2015). Self-reliance is an item of the 16PF5 questionnaire (Cattell and P. Cattell, 1995) which is an equivalent to autonomy as it measures the capacity to act in an autonomous way. We therefore believe that autonomy is a factor to include in order to better understand the attitude towards BCIs.</p>
Facilitating conditions		
Agency	–	<p>DEFINITION: “The sense that I am the one who is causing or generating an action” (Gallagher, 2000).</p> <p>JUSTIFICATION: We introduce this factor in our model in light of BCIs studies. Indeed (Jeunet et al., 2016) showed that a low feeling of control and agency leads to poor performance with BCIs and (Dussard et al., 2022) had preliminary results implying that a greater agency can improve BCI performances.</p>
Computer playfulness	TAM3 - UTAUT2 - CUE	<p>DEFINITION: Introduced in TAM3, this factor is inspired by the concept of microcomputer playfulness presented by Martocchio et al., it “represents a type of intellectual or cognitive playfulness [...] an individual’s tendency to interact spontaneously, inventively, and imaginatively with microcomputers”. (Martocchio and Webster, 1992)</p> <p>JUSTIFICATION: We think that in BCI context, a pleasant and playful interface can reduce the apprehension and the fear felt towards the system. The consideration of playfulness is common in motor rehabilitation (Korn and Tietz, 2017), but also in the field of BCIs, in particular in a logic of gamification and of combination of virtual reality and BCI (Ron-Angevin and Díaz-Estrella, 2009; Wang et al., 2022).</p>

Ease of learning	–	<p>DEFINITION: This factor is inspired from the System Usability Scale (SUS) (Brooke, 1986) - the questionnaire measures ease of use, but some questions are in link with the learning. We define it as the degree to which a person believes that learning how to use a system will be effortless.</p> <p>JUSTIFICATION: This is particularly interesting for BCIs as learning to use them is not easy (Benaroch et al., 2021), regardless of the level of expertise in the use of others technologies. For example, (Pasqualotto et al., 2011) found that computer skills did not influence BCI - type P300 Speller - performance.</p>
Social support	–	<p>DEFINITION: Social support is a new item which we believe may help to adapt BCIs for rehabilitation protocols. It is the degree to which an individual feels they need a human presence for BCI use and the context in which they would need it.</p> <p>JUSTIFICATION: The study of Pillette et al. shows that the presence of a tangible companion, who provides social and emotional support, has positive effects for certain participant profiles (Pillette et al., 2020). For rehabilitation, we find it especially relevant to measure social support since research on BCIs in clinical situation is conducted both in hospital and at home (Leeb et al., 2013; Zulauf-Czaja et al., 2021).</p>
Moderators		
Previous experience	TAM3 - UTAUT2	<p>DEFINITION: This moderator concerns both taking into account the user’s experience with BCIs and with new technologies in general. It moderates the effects that <i>social influence</i>, <i>individual differences</i> and <i>facilitating conditions</i> have on the target factors as well as the influence that PEOU has on PU and BI.</p> <p>The effect of PEOU on BI is lessened (TAM3 and UTAUT2) while the one of PU is strengthened (TAM3) with experience. In UTAUT2, it is also suggested that this <i>previous experience</i> factor moderates the effect of BI on the final use of the technology: the more experienced the user, the less influence BI has on actual use of the technology.</p> <p>JUSTIFICATION: It is not new to take experience into consideration in BCIs studies, it is for example the case in (Pasqualotto et al., 2011) and (Randolph, 2012).</p>
Voluntary	TAM3 - UTAUT2	<p>DEFINITION: This factor expresses if the use is mandatory or voluntary, this can potentially affect acceptability factors. It has been suggested to influence directly BI (TAM3).</p> <p>In our questionnaire, we could not really measure this factor since it was not followed by an actual use of a BCI. We have therefore adapted the wording of the questions so that they correspond to a supposedly voluntary use. (e.g., “If I had the possibility...”).</p> <p>JUSTIFICATION: Some researchers have found, for example, that the role of <i>social influence</i> is significant when use is constrained, and not when it is voluntary (Wills et al., 2008). These results are not always found (Schaupp et al., 2010; Wang et al., 2009), so it is relevant to observe the role of this moderator for BCIs.</p>

329 Table 2: Factors included in our acceptability model for BCIs in post-stroke motor rehabilitation

330 **2.2 Results of the questionnaire**

331 2.2.1 Participants

332 We managed to obtain a set of N = 753 respondents to our questionnaire based on the model. This sample
 333 was representative of the composition of the adult population in France. We provide the socio-demographic
 334 details in Table 3.

335 95.8% of our sample had never used BCIs - including 68.7% that didn’t hear about BCIs before this
 336 questionnaire. This lack of knowledge was consistent with our objectives because it is more relevant to
 337 have novice users when measuring acceptability - as it should be before any interaction with the technology.
 338 In consequence, we didn’t discuss in detail the *previous experience* moderator of our model in this paper,
 339 as we do not had enough expert respondents to differentiate inexperienced/experimented users.

Source: INSEE (National Institute of Statistics and Economic Studies) – 2016 to 2019

	Objective %	Objective N	Obtained %	Obtained N
--	-------------	-------------	------------	------------

Sex				
Male / Female	47.4% / 52.6%	315 / 350	48.7% / 51.3%	367 / 368
Age (years)				
20-24	7.7%	51	10.2%	77
25-34	16.2%	108	17.4%	131
35-44	16.9%	112	18.2%	137
45-54	17.7%	118	16.3%	123
55-64	16.4%	109	14.9%	112
65 and more	25.1%	167	23.0%	173
Socio-professional categories				
Own account workers (agriculture, craftsperson, shopkeeper, company head)	4.6%	31	5.2%	39
Higher managerial, administrative and professional occupation	10.9%	72	11.2%	84
Intermediate managerial, administrative, professional occupations	15.2%	101	15.1%	114
Lower supervisory and technical occupations	29.4%	196	27.2%	205
Retired	28.9%	192	28.6%	215
Others unemployed	11.0%	73	12.7%	96
Region				
Ile-de-France	20.8%	138	19.3%	145
North-west	21.7%	144	23.5%	177
North-east	21.0%	140	22.2%	167
South-west	10.7%	71	10.2%	77
South-east	25.8%	172	24.8%	187
TOTAL	100.0%	665	100.0%	753

Table 3 : Socio-demographic information of the respondents of the questionnaire.

340 2.2.2 Descriptive analysis

341 In Table 4, we present the mean scores of each quantitative factor, and the percentages for categorical
 342 factors. None of the factors was associated with a score below 5/10, which reflects globally positive feelings
 343 and well-perceived BCIs among the respondents. Indeed, regarding the target factors, BI2 had a mean of
 344 8.23 (SD=1.69), for PU2 it was 8.28 (SD=1.57) and for PEOU the mean was 7.17 (SD=1.57).

345 As explained in Section 1.2, our questionnaire contained two videos. We wanted to verify if, depending
 346 on the richness of information provided to people about BCIs in rehabilitation (possibilities of use, expected
 347 results, etc.), the factors that most impact BI and PU are or not the same. In this aim, we compared the
 348 means of the two paired samples (before/after the video explaining how BCIs could be integrated in stroke
 349 rehabilitation, i.e., video 2) for BI and PU. Wilcoxon test with Bonferroni correction was used, it evaluated
 350 if there was a significant difference between the values of PU1/PU2 and BI1/BI2. We didn't measure PEOU

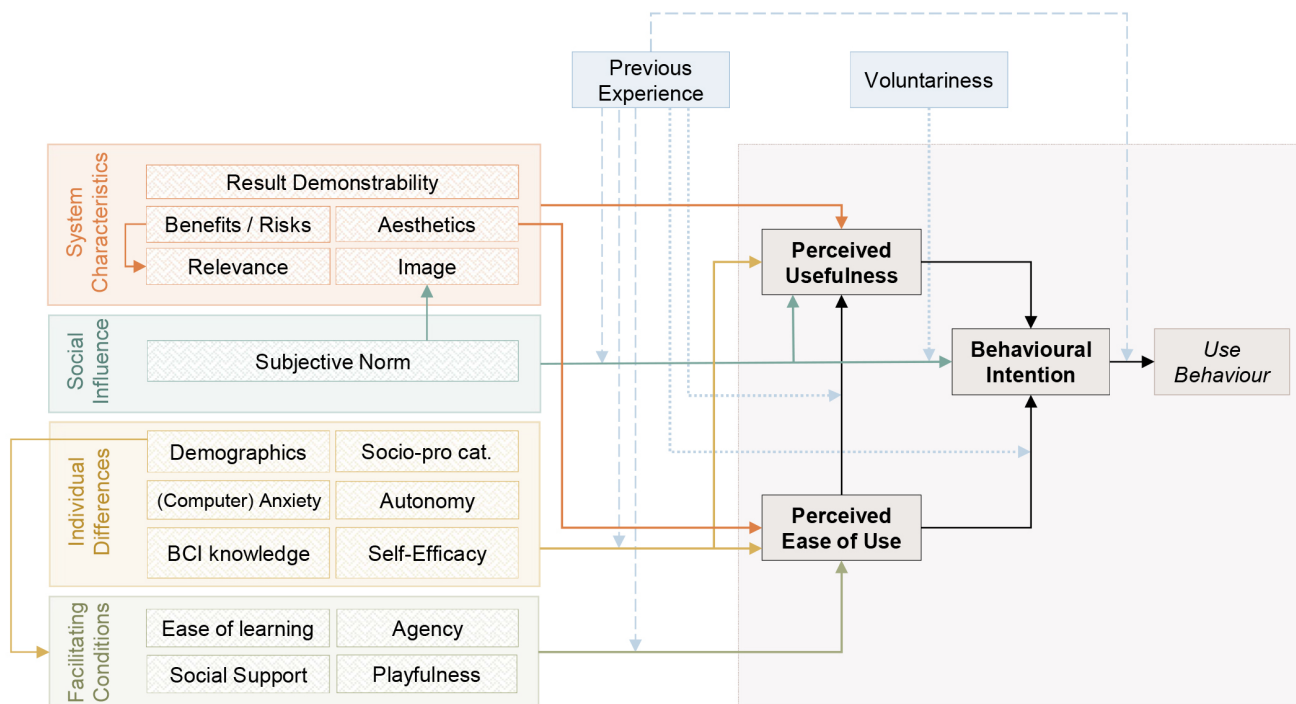


Figure 2. Representation of the tentative model of acceptability of BCIs for motor rehabilitation after stroke. On the right (in grey) are the target factors from TAM3 namely, PU, PEOU and BI. On the left are the four categories of factors that may influence the target factors: *system characteristics* (orange), *social influence* (turquoise), *individual characteristics* (yellow) and *facilitating conditions* (green). Each category includes one or more factors, themselves assessed in the questionnaire by 3 to 5 items. Solid arrows represent the potential influence of those categories on the target factors. Finally, on top, two moderators are represented in blue. Those factors moderate the effect of the different categories on the target factors. Dotted lines represent moderation effects presented in TAM3 while broken lines represent effects depicted in UTAUT2 (or in both).

351 twice, even if it is one of the main determinant of BI in literature, because the users' viewpoint about the
 352 functioning of BCI remains the same as long as they had never have the opportunity to actually test the
 353 interface before.

354 Wilcoxon test showed that the scores of BI1 and PU1 were significantly different from BI2 and PU2
 355 respectively (see Figure 3). As pointed out in Table 4, the means were higher after the video, which seemed
 356 to have a positive impact on the respondents' standpoint about BCI (*Before video 2*: PU1 mean=7.87,
 357 SD=1.63 / BI1 mean=7.88, SD=1.73. *After video 2*: PU2 mean=8.28, SD=1.57 / BI2 mean = 8.23,
 358 SD=1.69). The score of PEOU was also high (mean=7.17, SD=1.57).

359 2.3 Validation of the structures of the model and questionnaire

360 2.3.1 Coherence of the factors: Cronbach's alpha

361 Cronbach's alpha analyses (Table 5) show that 13/17 factors had a satisfactory internal consistency, with
 362 scores comprised between 0.72 and 0.97. Among the four other factors, the scores were the following: 0.5
 363 (*agency*), 0.52 (*autonomy*), 0.57 (*ease of learning*) and 0.62 (*benefits/risk ratio*).

Categories	Factors	Alpha coefficient
------------	---------	-------------------

System characteristics	Benefits/Risk ratio	0.62
	Result demonstrability	0.72
	Image	0.80
	Visual aesthetics	0.83
	Relevance	0.91
Social influence	Subjective norm	0.83
Individual differences	Agency	0.50
	Autonomy	0.52
	General anxiety	0.77
	Computer anxiety	0.91
Facilitating conditions	Ease of learning	0.57
	Playfulness	0.83
Target factors	PEOU	0.83
	PU 1	0.91
	BI 1	0.95
	PU 2	0.95
	BI 2	0.97

Table 5 Cronbach's alpha reliability values for the questionnaire based on our acceptability model.
The closer the value is to 1, the better the internal consistency of the factor. It is estimated that below 0.7, consistency is weak.

364 2.3.2 Structure of the model: Confirmatory factor analysis

365 Regarding the CFA results, we obtained a p-value of 0.0 for the chi-square test. This means that the
366 hypothesis of the perfect fit of the model to our data is rejected. Nevertheless, this can be explained by the
367 large size of our sample. The comparative fit index (CFI) value was 0.913 and the Tucker–Lewis index
368 (TLI) value 0.897, which indicates a good fit between the model and the data. Indeed, these scores mean
369 that our model is better than the independence model. The RMSEA, which is the index of poor adjustment
370 of the model, should ideally be below than 0.05. Results indicated a value of 0.059, with a confidence
371 interval ranging from 0.056 to 0.062. It was thus close to the expected value. Finally, our SRMR was
372 0.076 (i.e., less than 0.08, as expected as this test assesses the divergence between observed and expected
373 correlations).

374 2.4 Quantification of the impact of the different factors on BCI acceptability

375 2.4.1 Important factors in each category of our model: Mediation analysis

376 Table 6 presents the different results we obtained following the mediation analyses. It should be noted
377 that the categorical factors are not presented here (demographics, self-efficacy, BCI knowledge and social
378 support), we studied only the quantitative variables because our categorical variables were not binary, so it
379 was not adapted to this method. Nevertheless, they are not left out, we present an analysis included them
380 with RF algorithm in Section 2.4.2.

381 Figure 4 shows that the BI was mainly influenced by PU2 (effect: 0.94, p-value < .001), the weight of the
382 PEOU being much lower (direct effect: .08, standard error SE= .02, p-value < .001 ; indirect effect: 0.65,
383 SE = .03, CI = [0.59,0.71]), i.e., PEOU had a low effect on BI2 but a significant effect on PU2.

384 Concerning the other categories of our model, our results revealed that for the *individual differences*,

FACTOR	TYPE	MEAN	SD
System characteristics			
		<i>Mean</i>	<i>SD</i>
Result demonstrability	Quantitative	6.84	1.68
Benefits/risk ratio	Quantitative	7.27	1.51
Relevance	Quantitative	8.03	1.48
Image	Quantitative	6.10	2.17
Visual aesthetics	Quantitative	6.62	1.89
Social influence			
		<i>Mean</i>	<i>SD</i>
Subjective norm	Quantitative	7.38	1.71
Individual differences			
		<i>Mean</i>	<i>SD</i>
Autonomy	Quantitative	7.40	1.46
General anxiety	Quantitative	5.49	1.87
Computer anxiety	Quantitative	6.34	2.50
		<i>Condition</i>	<i>%</i>
Computer self-efficacy	Qualitative	Alone. independently	23.10%
<i>Usage conditions if BCI installed and explained</i>		Alone. if has experience with a similar technology	12.00%
		Alone. with support from a virtual companion	36.70%
		Only with human guidance and presence	28.30%
Social support	Qualitative	Independently. alone at home	32.80%
		In the presence of a health professional	47.70%
		Alone. but in a health facility	19.50%
BCI Knowledge	Qualitative	Yes - has already used a BCI	4.00%
		Yes - but has never used a BCI	27.10%
		No	68.70%
Facilitating conditions			
		<i>Mean</i>	<i>SD</i>
Agency	Quantitative	6.29	1.65
Playfulness	Quantitative	6.90	1.79
Ease of learning	Quantitative	5.96	1.62
Target factors			
		<i>Mean</i>	<i>SD</i>
PEOU	Quantitative	7.17	1.57
PU	Quantitative	7.87	1.63
BI	Quantitative	7.87	1.72
PU 2	Quantitative	8.28	1.57
BI 2	Quantitative	8.23	1.68

Table 4. : Results from general public questionnaire.

On the left column are presented the quantitative variables, the scores were continuous from 0 to 10 (*strongly disagree* to *strongly agree*). On the middle and right are the qualitative/categorical variables.

385 *autonomy* was the most influential factor on BI, but this effect was moderate ($c = 0.34$, p -value $< .001$), it
 386 equally impacted PU2 and PEOU (respectively, 0.36 and 0.33, with p -value $< .001$) (quality of the model:
 387 $R^2 = 0.87$, p -value = .0).

388 For *social influence*, *subjective norm* had a similar and moderate impact on both PU2 and PEOU

Distribution of the scores as a function of the different target factors

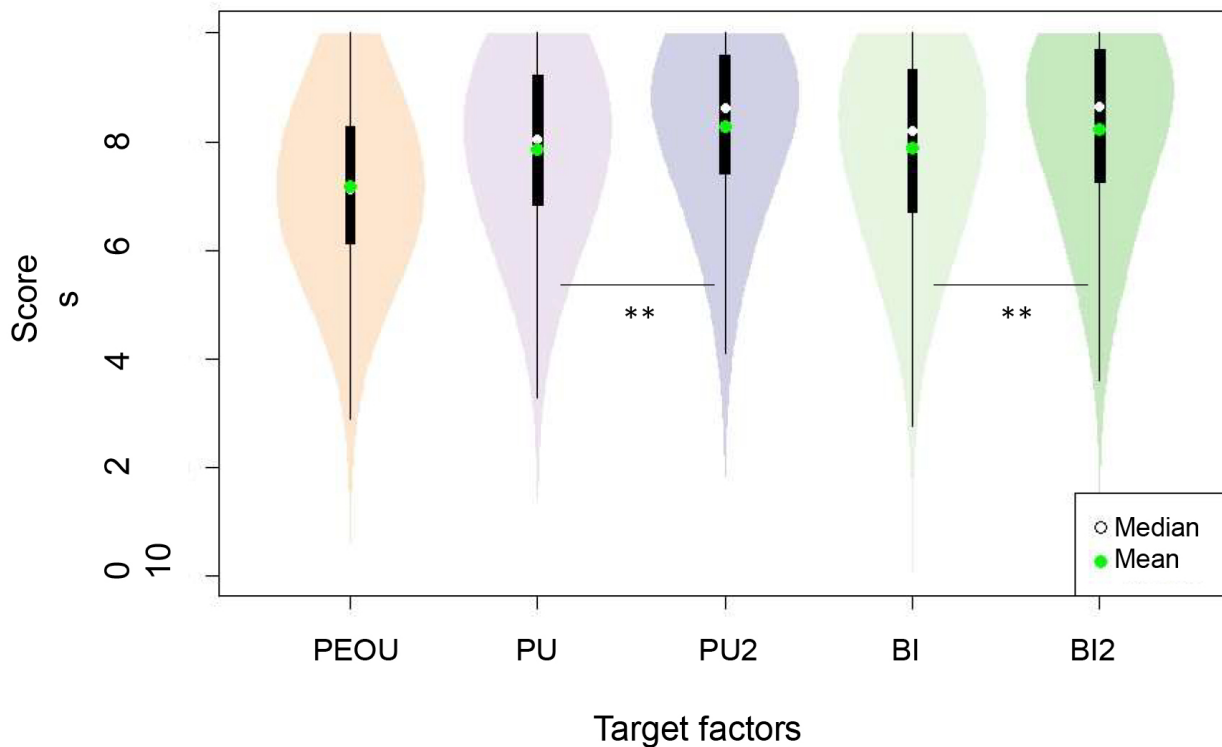


Figure 3. Violin plots of main acceptability factors scores for general population.

PAIRED WILCOXON TEST: for the [PU1-PU2] and [BI1-BI2] pairs, we obtained a p-value < .001 (with Bonferroni correction), each factor was therefore significantly different.

389 (respectively, 0.58 and 0.57, with p-value < .001). The influence on BI2 was rather high ($c = 0.63$,
390 p-value < .001) (quality of the model: $R^2 = 0.86$, p-value < .001).

391 For **characteristics of the system**, we did two analyses: (i) one with only PEOU as mediator, and factors
392 present before video 2 (PU1 was not included since we chose to focus on PU2); (ii) the second only with
393 PU2 as mediator, and factors present before and after video 2 (PEOU was among these factors since, as
394 shown in Figure 2, it influences PU). (i) shows that *visual aesthetics* was the most - but weak - influential
395 factor on PEOU (0.38, with p-value < .001). The total effect of *visual aesthetics* on BI2 was low: $c=0.32$
396 (p-value < .001) (quality of the model: $R^2 = 0.47$, p-value < .001). On the other hand (ii) revealed that
397 *relevance* was the most influential factor on PU2 (0.65, with p-value < .001). Its total effect on BI2 was
398 $c=0.56$ (p-value < .001) (quality of the model: $R^2 = 0.87$, p-value = 0.0).

399 Finally, for **facilitating conditions**, the variable with most impact was *computer playfulness*, it equally
400 impacted PU2 and PEOU (respectively, 0.36 and 0.39, with p-value < .001). The influence of *computer*
401 *playfulness* on BI2 was moderate ($c=0.41$, p-value < .001) (quality of the model: $R^2 = 0.86$, p-value <
402 .001).

403 2.4.2 Important factors independently from the structure of the model: Random forest algorithm

404 We ran the RF algorithm in order to explain the values of our 3 target factors: BI, PU and PEOU. RF
405 algorithms have the advantage of enabling analyses with qualitative and quantitative variables at the same
406 time so we used it on all our factors. Table 7 presents the important variables of BI2, PU2 and PEOU. The

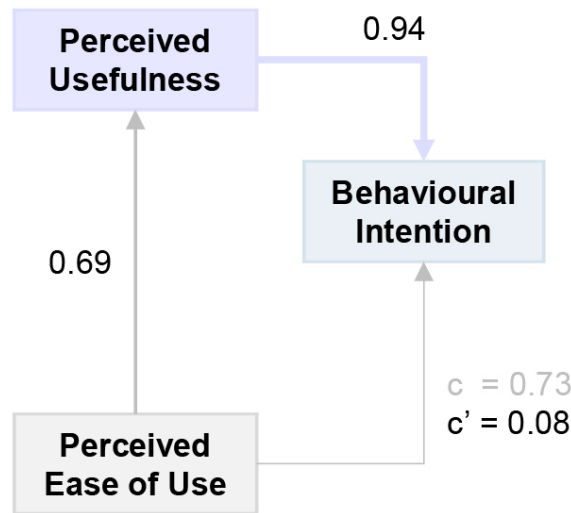


Figure 4. Mediation analysis for the target factors: **Behavioural intention (BI2)**, **Perceived usefulness (PU2)** and **Perceived ease of use (PEOU)**. $R^2 = 0.86$ (p -value < .001).

c : total effect of PEOU on BI2; c' : direct effect of PEOU on BI2; $c-c'$: indirect effect of PEOU on BI2 through PU2.

Category	Independent variable (IV)	Total effect	Effect IV-MV		Effect MV-DV		Direct effect	Indirect effect	BC 95% CI of indirect effect (bootstrap : nb iterations = 500)
			PU2	PEOU	PU2	PEOU			
System Characteristics - PEOU	Visual aesthetic	0.32** $p = 3.19e-22$	-	0.38** $p = 2.48e-43$	-	0.73** $p = 1.04e-75$	0.04 $p = 2.17e-01$	0.28	[0.09 ; 0.16]
	Image	0.09 $p = 1.61e-03$	-	0.17** $p = 8.81e-14$	-	-	-0.04 $p = 6.63e-02$	0.13	[0.22 ; 0.5]
System Characteristics - PU2	Relevance	0.56** $p = 1.48e-51$	0.65** $p = 6.24e-83$	-	-	-	0.05 $p = 1.10e-01$	0.51	[0.42 ; 0.6]
	PEOU	0.2** $p = 4.89e-11$	0.2** $p = 2.77e-14$	-	-	-	0.04 $p = 6.18e-02$	0.15	[0.09 ; 0.22]
	Benefits/risk ratio	0.23** $p = 1.73e-13$	0.15** $p = 1.51e-08$	-	0.78** $p = 2.31e-100$	-	0.11** $p = 1.65e-06$	0.12	[0.05 ; 0.18]
	Result demonstrability	0.12** $p = 3.51e-06$	0.04 $p = 5.15e-02$	-	-	-	0.08** $p = 6.73e-06$	0.03	[0.0 ; 0.07]
	Visual aesthetics	0 $p = 9.99e-01$	-0.02 $p = 3.06e-02$	-	-	-	0.01 $p = 3.49e-01$	-0.01	[-0.04 ; 0.01]
	Image	-0.02 $p = 1.69e-01$	-0.01 $p = 5.26e-01$	-	-	-	-0.01 $p = 1.99e-01$	-0.01	[-0.03 ; 0.01]
Social influence	Subjective norm	0.63** $p = 2.49e-87$	0.58** $p = 5.68e-86$	0.57** $p = 1.88e-80$	0.91** $p = 1.52e-196$	0.06 $p = 8.40e-03$	0.07** $p = 1.59e-04$	0.56	[0.46 ; 0.59]
Individual differences	Autonomy	0.34** $p = 1.32e-19$	0.36** $p = 1.24e-23$	0.33** $p = 8.39e-19$	-	-	-0.01 $p = 6.03e-01$	0.35	[0.26 ; 0.39]
	Computer anxiety	0.27** $p = 4.42e-33$	0.22** $p = 4.94e-26$	0.15** $p = 1.68e-12$	0.9** $p = 4.49e-200$	0.08** $p = 4.62e-08$	0.06** $p = 1.03e-08$	0.21	[0.16 ; 0.25]
	General anxiety	-0.05 $p = 9.88e-02$	-0.04 $p = 1.43e-01$	-0.04 $p = 1.34e-01$	-	-	-0.01 $p = 5.12e-01$	-0.04	[-0.09 ; 0.02]
Facilitating conditions	Playfulness	0.41** $p = 1.69e-25$	0.36** $p = 3.25e-21$	0.39** $p = 1.38e-30$	-	-	0.08** $p = 3.86e-05$	0.33	[0.26 ; 0.4]
	Agency	0.28** $p = 3.76e-13$	0.25** $p = 8.75e-12$	0.06 $p = 5.87e-02$	0.9** $p = 5.07e-203$	0.01 $p = 5.39e-01$	0.05 $p = 7.57e-03$	0.23	[0.16 ; 0.3]
	Ease of learning	0 $p = 9.93e-01$	-0.01 $p = 6.90e-01$	0.29 $p = 6.19e-01$	-	-	0.01 $p = 6.65e-01$	-0.01	[-0.08 ; 0.05]
Main target factors	PEOU	0.73** $p = 9.94e-105$	0.69** $p = 4.25e-110$	-	0.94** $p = 1.51e-218$	-	0.08** $p = 6.32e-05$	0.65	[0.6 ; 0.71]

Table 6. Table of scores for mediation analysis (only with quantitative factors). The mediators variable were PU2 and PEOU, the dependant variable was BI2.

** $p < .001$

BC, bias corrected; DV, dependent variable; MV, mediator variable; PU, perceived usefulness; PEOU, perceived ease of use.

ordering of these variables enabled us to determine which of our factors explained the best the scores of these target factors. The three most important variables for each of them were:

- **For BI2:** PU2 followed by *relevance* and *benefits/risk ratio*. PU2 was in large predominance (value = 100) in comparison to the other (37.4 and 30.3, respectively). The quality of the prediction was high: 86.09% of the variance is explained.

Perceived ease of use (PEOU)		Perceived usefulness (PU) 2		Behavioural intention (BI) 2	
Ease of learning	100.00	Relevance	100.00	PU2	100.00
Playfulness	83.21	PEOU	33.54	Relevance	37.44
Subjective norm	80.86	Benefits/risk ratio	33.42	Benefits/risk ratio	30.25
Visual aesthetics	66.46	Subjective norm	31.96	Subjective norm	29.56
Image	41.11	Result demonstrability	19.11	Result demonstrability	28.02
Agency	32.73	Playfulness	17.11	Playfulness	27.67
Age	24.75	Computer anxiety	14.43	PEOU	24.94
Computer anxiety	22.98	Autonomy	12.59	Computer anxiety	22.83
General anxiety	19.28	Visual aesthetics	12.34	Autonomy	17.37
Autonomy	17.19	Ease of learning	12.02	Agency	17.29
Experience - pleasure	12.27	Experience - confidence	10.60	Visual aesthetics	16.86
Gender - Women	11.78	Experience - pleasure	10.51	Ease of learning	16.05
Self-efficacy - 3	11.77	Agency	10.03	Image	15.17
Self-efficacy - 2	8.80	Image	8.01	Experience - pleasure	12.88
Employees	8.49	Gender - Women	6.27	Experience - confidence	12.16
Intermediate occupations	7.58	General anxiety	5.78	Self-efficacy - 2	10.60
Experience - confidence	7.28	Lower occupations	5.20	Self-efficacy - 1	10.30
Higher occupation	6.89	Higher occupation	5.19	Without activity	9.68
Without activity	6.24	Intermediate occupations	4.73	Employees	8.70
Social support - 1	6.11	Self-efficacy - 3	4.56	Intermediate occupations	8.41

Table 7. The 20 most influential factors for each target factor (BI, PU, PEOU) based on the RF algorithm. The factors *Experience - pleasure* and *Experience - confidence* were about the pleasure and confidence of respondents towards the use of technologies in general.

% Variance explained: **BI2** = 86.09; **PU2** = 79.64; **PEOU** = 57.76 (RF with 500 trees and cross-validation (5-fold)).

The importance values correspond to the mean decrease accuracy (%IncMSE). We scaled the values from 0 to 100 and ranked them in decreasing order to facilitate comparisons. Therefore, the most influential ones appear on top of the table.

- 412 • **For PU2:** *Relevance*, *PEOU* and *benefits/risk ratio*. *Relevance* was much more influential than the
 413 others (value = 100, versus 33.5 and 33.4, respectively). The quality of the prediction was still quite
 414 high with 79.64% of the variance is explained.
- 415 • **For PEOU:** *Ease of learning*, *computer playfulness* and *subjective norm*. The values were less
 416 disparate: 100, 83.2, 80.9, respectively. But the prediction had a lower quality with 57.76% of the
 417 variance is explained.

418 Categorical factors appeared to have only moderate, if not low impact on BCI acceptability. The age was
 419 the only one in the top 10 of most influential factors, for PEOU only.

420 To provide a visual overview of our analyses results, we propose a simplified version of our initial model
 421 in Figure 5, keeping only the most significant factors.

422 2.4.3 Intensity of the connections between factors: Correlation analysis

423 We ran correlation analyses between all our quantitative factors (with Bonferroni correction). For seeks
 424 of readability, we show in 8 only the factors that had been identified as the most influential ones based on
 425 RF analyses. Results reveal that all the correlation coefficients were positive. The strongest correlations
 426 were between BI2 and PU2 (0.92 - Bonferroni-corrected p-value < .001), PU2 and relevance (0.89 -

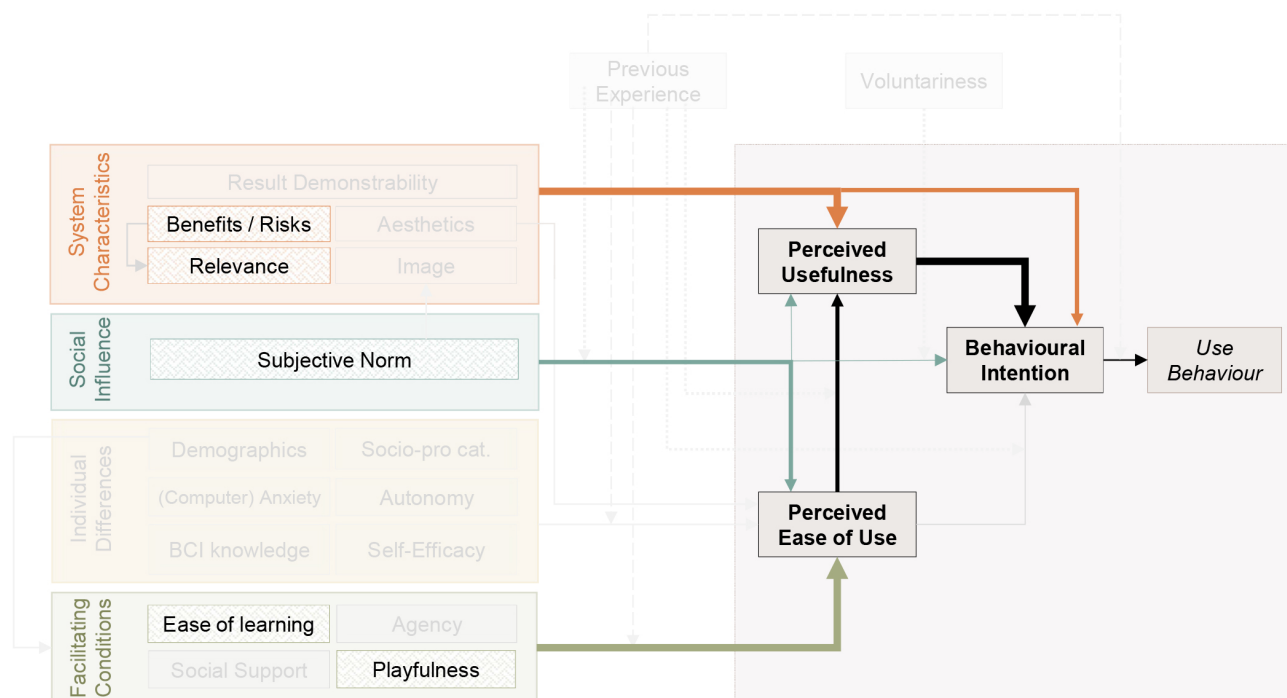


Figure 5. Representation of the factors of the tentative model of acceptability that influence the most the target factors. Boldest arrows link factors to the target factor they influence the most: *relevance* is the factor that has the highest impact on PU, *ease of learning* is the most influential factor for PU, itself being the most influential factor for BI. In addition, *relevance* also has a strong influence on BI. *Benefits on risk ratio* strongly influences both PU and BI. *Subjective norm* has a strong impact on PEOU (which was not expected based on the TAM3 and UTAUT2) and a medium impact on PU and BI. Finally, *computer playfulness* has a strong impact on PEOU.

427 Bonferroni-corrected p-value < .001), BI2 and relevance (0.86 - Bonferroni-corrected p-value < .001), but
 428 all the factors were significantly and strongly correlated with the target factors.

	Subjective norm	Visual aesthetics	Playfulness	Ease of learning	PEOU	Result demonstrability	Benefits/risk ratio	Relevance	PU2
PEOU	0.59 p<.001	0.54 p<.001	0.63 p<.001	0.6 p<.001					
PU2	0.63 p<.001	0.39 p<.001	0.55 p<.001	0.37 p<.001	0.66 p<.001	0.69 p<.001	0.74 p<.001	0.89 p<.001	
BI2	0.63 p<.001	0.41 p<.001	0.59 p<.001	0.39 p<.001	0.64 p<.001	0.71 p<.001	0.74 p<.001	0.86 p<.001	0.92 p<.001

Table 8. Spearman correlation analyses for the most significant factors
 p-values adjusted with Bonferroni correction

DISCUSSION

429 This paper provides the following contributions. First, we designed a first-of-its-kind model of acceptability
 430 of BCIs for motor rehabilitation after stroke. This model is based on the literature, and notably on three
 431 validated models: TAM3 (Venkatesh and Bala, 2008), UTAUT2 (Venkatesh et al., 2012) and CUE (Thüring
 432 and Mahlke, 2007). Second, we created, based on this model, a questionnaire to assess acceptability. This

433 questionnaire follows the structure of the model and includes 3 to 5 items to measure each of the factors.
434 The quantitative items are represented as analog visual scales for which participants move a cursor from
435 “do not agree at all” to “perfectly agree”. The position of the cursor is then translated into a score (from 0 to
436 10). The scores of the items measuring the same factor are averaged in order to obtain a robust estimation
437 of this factor that is not (or at least as little as possible) dependent on the (mis)understanding of the item or
438 on the state of the person when they answered the question. We distributed this questionnaire to a sample
439 representative of the adult population in France (N=753). This large and representative sample theoretically
440 ensures the reliability of our results. Third, we performed analyses on the data obtained to validate the
441 structure of the model. More specifically, we assessed on the one hand the internal consistency of the
442 factors using Cronbach’s alpha analyses. This enabled us to verify the relevance and complementarity of
443 the items used to assess each factor.

444 On the other hand, we performed a confirmatory factor analysis to evaluate the internal consistency of
445 the questionnaire, or in other words the relevance of the structure of the model. Finally, this is the fourth
446 contribution, we quantified the impact that the different factors had on our target factors (PEOU, PU and
447 BI) in order to identify the factors that influence the most BCI acceptability in the general public. To do
448 so, we used two complementary methods: mediation analyses and regressions based on random forest
449 algorithms. The first one assessed this influence by taking into account the structure of the model while the
450 second was independent from that structure. Our results show that BCIs are associated with high levels
451 of acceptability for motor rehabilitation after stroke in the general public, and that the intention to use
452 these technologies in that context is mainly driven by the perceived usefulness of the system, itself being
453 mostly influenced by some characteristics of the system, and notably the benefits on risk ratio and scientific
454 relevance. Facilitating conditions, and notably ease of learning and playfulness are the main determinants of
455 the perceived ease of use. Finally, the subjective norm significantly influences the three target factors. With
456 this methodology and results, our study is a first step towards an in-depth consideration of acceptability of
457 BCIs for motor rehabilitation procedures after stroke.

458 For now, the model and questionnaire, while (we hope) insightful, are not really usable in practice due to
459 their length and complexity. We voluntarily used an exploratory approach by including all the potential
460 influential factors in our model, considering that the literature in the field did not enable us to have strong a
461 priori. The extensive dataset collected enabled us to obtain first indications of the most influential, and
462 therefore most relevant-to-assess factors. More data should now be collected to (un)validate those first
463 results and refine the estimation of the impact that each factor has on BCI acceptability. Our objective
464 is, ultimately, to design a shorter and more usable questionnaire that will enable the prediction of BCI
465 acceptability based on a few factors (and so few items). This prediction could provide scientists/clinicians
466 some indications on how to adapt the procedure, including the instructions, tasks, feedback and training
467 environment, to favour BCI acceptability. As mentioned in the introduction, high acceptability levels could
468 serve as levers to improve BCI efficiency. A main result of this study is that, globally, acceptability levels in
469 terms of behavioural intention seem to be very high in the general public (with an average score of 8.23/10).
470 This is consistent with other BCI acceptability studies (Al-Taleb et al., 2019; Voinea et al., 2019; Benaroch
471 et al., 2021) who reported average scores of 8.0/10 (Al-Taleb et al., 2019) and 6.0/7 (Voinea et al., 2019)
472 for perceived usefulness.

473 The analysis of Cronbach’s alpha revealed that all the factors from the TAM3, UTAUT2 and CUE
474 questionnaire were associated with high-quality internal consistency, i.e., scores were between 0.70 and
475 0.95 (Cortina, 1993; Tavakol and Dennick, 2011). It was not the case for some of the factors we added (in
476 complement of those from TAM3, UTAUT2 and CUE) to fit with specificities of BCIs, namely, *agency*
477 (0.50), *autonomy* (0.52), *ease of learning* (0.57) and *benefits/risk ratio* (0.62). This might be due to

478 inadequate wording of the items. It should be noted though that the items used to assess *autonomy* were
479 directly extracted, word-by-word, from the “Sociotropy-autonomy scale” (SAS, (Husky et al., 2004)), while
480 those used to measure *agency* and *ease of learning* are reformulations (adapted to the context of BCIs) of
481 items from the French adaptations of the Sense of Agency Scale (F-SoAS, (Hurault et al., 2020)) and of the
482 System Usability Scale (SUS, (Gronier and Baudet, 2021)), respectively. In the future, it would be relevant
483 to i) collect more data to assess the significance of this result, and ii) lead investigations regarding the
484 comprehension of those items by potential BCI users, and maybe to reword them to increase the internal
485 consistency to the associated factors.

486 Regarding the extreme score of internal consistency obtained for BI2 (0.97), we hypothesise that it might
487 be due to the repetition of the items. Indeed, when participants saw the same items a second time, it might
488 have happened that they automatically put some scores without really thinking about it, due to perceived
489 redundancy. This hypothesis is supported by the fact that PU2 was also associated with very high, internal
490 consistency scores (0.95) –while still in the “acceptable range”. This high score might also be due to a
491 ceiling effect on those dimensions. Indeed, PU1 and BI1 were already rated with high scores (7.87+/1.63
492 and 7.88+/-1.73, respectively). After the second video, participants globally increased their rating and gave
493 PU2 scores of 8.28+/1.57, and BI2 scores of 8.23+/-1.69. Thus, the range of values attributed to the items
494 of PU2 and BI2 was narrow, resulting in low variability and thereby very high consistency within those
495 dimensions.

496 To conclude on the validity of the questionnaire, while it is certainly not perfect yet –we hope that the
497 community will help us improving it by collecting data and suggesting modifications- analyses have
498 globally revealed i) good internal consistency (as measured by Cronbach’s alpha scores) for a large majority
499 of the factors, and ii) a relevant structure of the model (as measured by the confirmatory factorial analysis).
500

501 If we have a closer look at the factors influencing the intention to use BCIs, thanks to the random
502 forest-based regression analyses, we notice that our different analyses are consistent, notably in showing
503 no significant impact of individual differences, including demographics (age, gender, socio-professional
504 category) or cognitive/psychological profile (autonomy, anxiety, self-efficacy). Yet, BCI studies have
505 suggested an influence of those variables on BCI performance and learning (Burde and Blankertz, 2006;
506 Nijboer et al., 2008, 2010; Witte et al., 2013; Jeunet et al., 2015). It might be possible that the weight of
507 psychological variables such as anxiety or autonomy are stronger in persons with clinical conditions. It
508 might also be the case that this influence is directly on efficiency as high levels of anxiety and low levels of
509 autonomy and self-efficacy are detrimental for learning but does not alter acceptability. This reinforces the
510 relevance of our approach consisting in optimising acceptability in order to put the users/patients in the
511 best conditions to favour learning despite their clinical condition, and thereby use acceptability as a lever to
512 favour efficiency.

513 Behavioural intention is mainly influenced by the perceived usefulness of BCIs, itself being mainly
514 determined by the perceived scientific relevance of the technology. This result highlights the importance of
515 informing the population about BCIs, the way they function, and the level of scientific evidence regarding
516 their clinical efficacy. This idea is strengthened by the significant increase of BI and PU scores following
517 the second video in which the benefits of BCIs for motor rehabilitation after stroke are presented. In the
518 same category of “system characteristics”, the benefits on risk ratio of the technology also seems to have
519 a strong impact of acceptability. We hypothesise that this balance, as perceived by the user/patient, may
520 have a moderator effect on the emphasis on scientific relevance that is objectively depicted by scientists
521 and clinicians. Indeed, (irrational) fears or over-expectations may bias the balance making inaudible the
522 scientific discourses.

523 Another main finding of this study is the influence that subjective norm has on the three target factors.
524 This was expected for PU and BI. Nonetheless, if we refer to TAM3 and UTAUT2, this factor is not
525 supposed to influence PEOU. In our results yet, this is on the latter that the subjective norm has the
526 strongest impact. We hypothesise that the opinions of the patients' close ones, their technophilia and trust
527 in science will, in the case of BCIs, not only play a role on the perceived usefulness, but will also contribute
528 to emphasise or reduce apprehension towards the technology. This in turn may alter the perceived ease of
529 use of the technology. In any case, the fact that social influence contributes in determining acceptability
530 levels by acting on the three target factors reinforces the relevance of informing the general public, in
531 which patients' relatives are included, to favour the acceptability and adoption of BCIs.

532 Finally, facilitating conditions, and especially ease of learning and playfulness, are the main determinants
533 of PEOU that, while not influencing BI directly, significantly impacts PU. We believe that this result should
534 encourage us to keep in mind that instructions should be clear and training motivating when we design
535 BCI procedures. This will enable patients to feel confident in their ability to use a BCI. Providing an
536 engaging environment can also be a way to make training more accessible. These results are consistent
537 with the guidelines for successful MI-BCI training (Roc et al., 2021). The question of the transferability
538 of this result to populations of patients could be raised. Indeed, the general population, while they do not
539 need to use BCIs for rehabilitation, may perceive BCIs as a "toy", which could explain this result. In fact,
540 playfulness has also been shown to increase the compliance of patients in the rehabilitation process in other
541 fields (Burke et al., 2009; Korn and Tietz, 2017; Lopes et al., 2018).

542 This question of differences between populations is definitely relevant. While we can assume some
543 similarities and differences based on the literature, it will be necessary to lead the same approach with
544 patients and clinicians in order to confront the results, deepen our knowledge and increase our ability to
545 adapt BCIs accordingly. Once more, this will be a lever to improve BCI efficiency. Beyond the differences
546 depending on the status of the respondents (patients, clinicians, general public), there might also be
547 differences related to their culture (Straub et al., 1997). Therefore, it also seems necessary to apply this
548 approach on different populations around the world.

549 Collecting more data on diverse populations will enable us to refine our model. It is classic for acceptability
550 models to evolve and to be adjusted to the time and context. The two versions of the UTAUT give us
551 a perfect illustration of the necessity of adaptations. Indeed, whereas the first one was rather adapted
552 to technologies for organisations (Venkatesh et al., 2003), the second one gravitates towards individual
553 consumers/users (Venkatesh et al., 2012). For appropriate adaptations to be made, an open science approach
554 will be necessary. Indeed we think that it will be possible only if people collect data, share their findings
555 and work together on improving the soundness and reliability of the model.

556 Recommendations

557 These results offer first trails to make BCI-based stroke rehabilitation procedures more acceptable. On
558 the one hand, we have seen that the video which explains the use of BCIs in post-stroke rehabilitation had
559 an influence on BI and PU scores and on the predictors of these scores. Thus, informing (future) users is
560 a key step: it is necessary to be as clear as possible on the objectives of using a BCI, on its functioning,
561 on the expected results, but also on the constraints related to the use (learning time, cognitive cost, etc.).
562 These recommendations are important to consider to improve the perception of the *benefits/risk ratio* and
563 *relevance* factors. We think that one of the most interesting formats of information can be the production
564 of educational videos that help demystify BCIs, as we did in the questionnaire. This is in line with what
565 could be done to take *social influence* into account. Indeed, one of the best ways to play on *subjective*

566 *norm*, and use the influence of this factor to improve acceptability, is to lead pedagogical actions on the
567 general population. If people surrounding post-stroke subjects have an enlightened point of view on BCI,
568 this could positively influence the acceptability of the therapy of this population. We want to underline that,
569 to our viewpoint, these recommendations can be replicated in others BCIs settings, not only in post-stroke
570 rehabilitation context.

571 Our most important recommendation, in any context of use of BCIs, remains to ensure that acceptability
572 is assessed in order to adapt the protocol accordingly. It is an easy way to improve patients' well-being
573 during rehabilitation phases and thereby, most certainly, to increase their engagement and thereby leverage
574 the efficiency of BCI-based rehabilitation procedures.

575 **Conclusion**

576 This paper is dedicated to the general public acceptability of BCI-based post-stroke rehabilitation
577 procedures. We are conscious that that collecting the opinions of post-stroke subjects and caregivers is also
578 essential. We are currently working on this, conducting questionnaires and semi-structured interviews with
579 post-stroke subjects and caregivers. This will allow us to investigate whether the acceptability factors that
580 stand out the most are similar to those of the general public, and if not, to try to understand what could be
581 the cause of these differences and how to move towards more personalised acceptability models, adapted to
582 the targeted users.

ETHIC

583 The questionnaire was distributed with the agreement of the Institutional Review Board of Toulouse federal
584 university (N°2019-140).

DATA AVAILABILITY

585 Data will be shared on demand, together with the code used to analyse them.

AUTHOR CONTRIBUTIONS

586 Conceived and designed the experiments: CJ, EG, KF, LB, ST, DG, FA and JP. Performed the survey: EG,
587 KF, ST and CJ. Analysed the data: EG and CJ. Wrote the manuscript: EG. Corrected the manuscript: LP,
588 FA, DG, MI, CJ and JP.

FUNDING

589 This research was funded by the French National Research Agency (project ABCIS, grant ANR-20-CE38-
590 0008-01).

DISCLOSURE STATEMENT

591 The authors report there are no competing interests to declare.

REFERENCES

- 592 Al-Taleb, M., Purcell, M., Fraser, M., Petric-Gray, N., and Vuckovic, A. (2019). Home used, patient
593 self-managed, brain-computer interface for the management of central neuropathic pain post spinal cord
594 injury: usability study. *Journal of neuroengineering and rehabilitation* 16, 1–24
- 595 Alba, J. W. and Hutchinson, J. W. (1987). Dimensions of consumer expertise. *Journal of consumer*
596 *research* 13, 411–454
- 597 Alexandre, B., Reynaud, E., Osiurak, F., and Navarro, J. (2018). Acceptance and acceptability criteria: a
598 literature review. *Cognition, Technology and Work* doi:10.1007/s10111-018-0459-1. Cited By 29
- 599 Alturas, B. et al. (2021). Models of acceptance and use of technology research trends: Literature review
600 and exploratory bibliometric study. *Recent Advances in Technology Acceptance Models and Theories* ,
601 13–28
- 602 Bai, Z., Fong, K. N., Zhang, J. J., Chan, J., and Ting, K. (2020). Immediate and long-term effects of
603 BCI-based rehabilitation of the upper extremity after stroke: a systematic review and meta-analysis.
604 *Journal of NeuroEngineering and Rehabilitation* 17, 1–20
- 605 Barcenilla, J. and Bastien, J. M. C. (2009). L'acceptabilité des nouvelles technologies: quelles relations
606 avec l'ergonomie, l'utilisabilité et l'expérience utilisateur? *Le travail humain* 72, 311–331
- 607 Benaroch, C., Sadatnejad, K., Roc, A., Appriou, A., Monseigne, T., Pramij, S., et al. (2021). Long-term
608 bci training of a tetraplegic user: Adaptive riemannian classifiers and user training. *Frontiers in Human*
609 *Neuroscience* 15, 118
- 610 Blain-Moraes, S., Schaff, R., Gruis, K. L., Huggins, J. E., and Wren, P. A. (2012). Barriers to and mediators
611 of brain-computer interface user acceptance: focus group findings. *Ergonomics* 55, 516–525
- 612 Bland, J. and Altman, D. (1997). Statistics notes: Marketing. uk. *McGraw-Hill International. Cronbach's*
613 *alpha. BMJ* 314, 572
- 614 Bocquelet, F., Piret, G., Aumonier, N., and Yvert, B. (2016). *Ethical reflections on brain-computer*
615 *interfaces* (Wiley Online Library). doi:10.1002/9781119332428.ch15. Cited By 1
- 616 Brooke, J. (1986). System usability scale (sus): a quick-and-dirty method of system evaluation user
617 information. *Reading, UK: Digital equipment co ltd* 43, 1–7
- 618 Burde, W. and Blankertz, B. (2006). Is the locus of control of reinforcement a predictor of brain-computer
619 interface performance? In *Proceedings of the 3rd International Brain-Computer Interface Workshop*
620 *and Training Course*
- 621 Burke, J. W., McNeill, M., Charles, D. K., Morrow, P. J., Crosbie, J. H., and McDonough, S. M.
622 (2009). Optimising engagement for stroke rehabilitation using serious games. *The Visual Computer* 25,
623 1085–1099
- 624 Burton, C. A. C., Murray, J., Holmes, J., Astin, F., Greenwood, D., and Knapp, P. (2013). Frequency
625 of anxiety after stroke: a systematic review and meta-analysis of observational studies. *International*
626 *Journal of Stroke* 8, 545–559
- 627 Campbell Burton, C., Murray, J., Holmes, J., Astin, F., Greenwood, D., and Knapp, P. (2013). Frequency
628 of anxiety after stroke: A systematic review and meta-analysis of observational studies. *International*
629 *Journal of Stroke* doi:10.1111/j.1747-4949.2012.00906.x. Cited By 209
- 630 Cattell, R. B. and P. Cattell, H. E. (1995). Personality structure and the new fifth edition of the 16pf.
631 *Educational and Psychological Measurement* 55, 926–937
- 632 Cervera, M. A., Soekadar, S. R., Ushiba, J., Millán, J. d. R., Liu, M., Birbaumer, N., et al. (2018).
633 Brain-computer interfaces for post-stroke motor rehabilitation: a meta-analysis. *Annals of clinical and*
634 *translational neurology* 5, 651–663

- 635 Compeau, D. R. and Higgins, C. A. (1995). Application of social cognitive theory to training for computer
636 skills. *Information systems research* 6, 118–143
- 637 Cortina, J. M. (1993). What is coefficient alpha? an examination of theory and applications. *Journal of*
638 *applied psychology* 78, 98
- 639 Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information
640 technology. *MIS quarterly* , 319–340
- 641 Davis, F. D., Bagozzi, R. P., and Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers
642 in the workplace 1. *Journal of applied social psychology* 22, 1111–1132
- 643 DeVellis, R. F. and Thorpe, C. T. (2021). *Scale development: Theory and applications* (Sage publications)
- 644 Dillon, A. (2001). User acceptance of information technology. *Encyclopedia of human factors and*
645 *ergonomics* 1, 1105–1109
- 646 Dussard, C., Pillette, L., Jeunet, C., and George, N. (2022). Can feedback transparency improve motor-
647 imagery bci performance? In *Cortico 2022*
- 648 Edwards, I., Wiholm, B.-E., and Martinez, C. (1996). Concepts in risk-benefit assessment. a simple merit
649 analysis of a medicine? *Drug Safety* doi:10.2165/00002018-199615010-00001. Cited By 54
- 650 Février, F. (2011). *Vers un modèle intégrateur” expérience-acceptation” : rôle des affects et de*
651 *caractéristiques personnelles et contextuelles dans la détermination des intentions d’usage d’un*
652 *environnement numérique de travail*. Ph.D. thesis, Université Rennes 2; Université Européenne de
653 Bretagne
- 654 Fishbein, M. and Ajzen, I. (1977). Belief, attitude, intention, and behavior: An introduction to theory and
655 research. *Philosophy and Rhetoric* 10
- 656 Gallagher, M. W. and Brown, T. A. (2013). Introduction to confirmatory factor analysis and structural
657 equation modeling. In *Handbook of quantitative methods for educational research* (Brill). 287–314
- 658 Gallagher, S. (2000). Philosophical conceptions of the self: implications for cognitive science. *Trends in*
659 *cognitive sciences* 4, 14–21
- 660 Geronimo, A., Stephens, H. E., Schiff, S. J., and Simmons, Z. (2015). Acceptance of brain-computer
661 interfaces in amyotrophic lateral sclerosis. *Amyotrophic Lateral Sclerosis and Frontotemporal*
662 *Degeneration* 16, 258–264
- 663 [Dataset] Ghiglione, R. and Matalon, B. (1998). Les enquêtes sociologiques, théories et pratique.
- 664 Gronier, G. and Baudet, A. (2021). Psychometric evaluation of the f-sus: creation and validation of the
665 french version of the system usability scale. *International Journal of Human–Computer Interaction* 37,
666 1571–1582
- 667 Gürkök, H., Hakvoort, G., and Poel, M. (2011). Evaluating user experience in a selection based brain-
668 computer interface game a comparative study. In *International Conference on Entertainment Computing*
669 (Springer), 77–88
- 670 Hassenzahl, M. (2001). The effect of perceived hedonic quality on product appealingness. *International*
671 *Journal of Human-Computer Interaction* 13, 481–499
- 672 Hassenzahl, M. (2003). The thing and i: understanding the relationship between user and product. In
673 *Funology* (Springer). 31–42
- 674 Hassenzahl, M. (2004). The interplay of beauty, goodness, and usability in interactive products. *Human–*
675 *Computer Interaction* 19, 319–349
- 676 Huggins, J. E., Moinuddin, A. A., Chiodo, A. E., and Wren, P. A. (2015). What would brain-computer
677 interface users want: opinions and priorities of potential users with spinal cord injury. *Archives of*
678 *physical medicine and rehabilitation* 96, S38–S45

- 679 Huggins, J. E., Wren, P. A., and Gruis, K. L. (2011). What would brain-computer interface users want?
680 opinions and priorities of potential users with amyotrophic lateral sclerosis. *Amyotrophic Lateral*
681 *Sclerosis* 12, 318–324
- 682 Hurault, J.-C., Broc, G., Crône, L., Tedesco, A., and Brunel, L. (2020). Measuring the sense of agency: A
683 french adaptation and validation of the sense of agency scale (f-soas). *Frontiers in Psychology* 11, 2650
- 684 Husky, M. M., Grondin, O. S., and Compagnone, P. D. (2004). frValidation de la version française du
685 questionnaire de Sociotropie-Autonomie de beck et collègues. *Can. J. Psychiatry* 49, 851–858
- 686 Jeunet, C., Glize, B., McGonigal, A., Batail, J.-M., and Micoulaud-Franchi, J.-A. (2019). Using eeg-based
687 brain computer interface and neurofeedback targeting sensorimotor rhythms to improve motor skills:
688 Theoretical background, applications and prospects. *Neurophysiologie Clinique* 49, 125–136
- 689 Jeunet, C., N’Kaoua, B., and Lotte, F. (2016). enAdvances in user-training for mental-imagery-based BCI
690 control: Psychological and cognitive factors and their neural correlates. *Prog. Brain Res.* 228, 3–35
- 691 Jeunet, C., N’Kaoua, B., Subramanian, S., Hachet, M., and Lotte, F. (2015). Predicting mental imagery-
692 based bci performance from personality, cognitive profile and neurophysiological patterns. *PloS one* 10,
693 e0143962
- 694 Kaleshtari, M. H., Ciobanu, I., Seiciu, P. L., Marin, A. G., and Berteanu, M. (2016). Towards a model
695 of rehabilitation technology acceptance and usability. *International Journal of Social Science and*
696 *Humanity* 6, 612
- 697 Kelman, H. C. (1958). Compliance, identification, and internalization three processes of attitude change.
698 *Journal of conflict resolution* 2, 51–60
- 699 Kerous, B., Skola, F., and Liarokapis, F. (2018). Eeg-based bci and video games: a progress report. *Virtual*
700 *Reality* 22, 119–135
- 701 Kline, P. (2015). *A handbook of test construction (psychology revivals): introduction to psychometric*
702 *design* (Routledge)
- 703 Korn, O. and Tietz, S. (2017). Strategies for playful design when gamifying rehabilitation: a study on user
704 experience. In *Proceedings of the 10th international conference on pervasive technologies related to*
705 *assistive environments*. 209–214
- 706 Koul, S. and Eydgahi, A. (2017). A systematic review of technology adoption frameworks and their
707 applications. *Journal of technology management & innovation* 12, 106–113
- 708 Kowalski, C. J. (1972). On the effects of non-normality on the distribution of the sample product-moment
709 correlation coefficient. *Journal of the Royal Statistical Society: Series C (Applied Statistics)* 21, 1–12
- 710 Kübler, A., Holz, E. M., Riccio, A., Zickler, C., Kaufmann, T., Kleih, S. C., et al. (2014). The user-centered
711 design as novel perspective for evaluating the usability of bci-controlled applications. *PloS one* 9,
712 e112392
- 713 Lee, T.-S., Goh, S. J. A., Quek, S. Y., Phillips, R., Guan, C., Cheung, Y. B., et al. (2013). A brain-computer
714 interface based cognitive training system for healthy elderly: a randomized control pilot study for
715 usability and preliminary efficacy. *PloS one* 8, e79419
- 716 Leeb, R., Perdikis, S., Tonin, L., Biasiucci, A., Tavella, M., Creatura, M., et al. (2013). Transferring
717 brain-computer interfaces beyond the laboratory: successful application control for motor-disabled users.
718 *Artificial intelligence in medicine* 59, 121–132
- 719 Li, Y., Pan, J., Wang, F., and Yu, Z. (2013). A hybrid bci system combining p300 and ssvep and its
720 application to wheelchair control. *IEEE Transactions on Biomedical Engineering* 60, 3156–3166
- 721 Lopes, S., Magalhaes, P., Pereira, A., Martins, J., Magalhaes, C., Chaleta, E., et al. (2018). Games used
722 with serious purposes: a systematic review of interventions in patients with cerebral palsy. *Frontiers in*
723 *psychology* 9, 1712

- 724 Lotte, F., Bougrain, L., Cichocki, A., Clerc, M., Congedo, M., Rakotomamonjy, A., et al. (2018). A review
725 of classification algorithms for eeg-based brain–computer interfaces: a 10 year update. *Journal of neural*
726 *engineering* 15, 031005
- 727 Mahlke, S. (2008). *User experience of interaction with technical systems*. Ph.D. thesis, Technische
728 Universität Berlin
- 729 Martocchio, J. J. and Webster, J. (1992). Effects of feedback and cognitive playfulness on performance in
730 microcomputer software training. *Personnel Psychology* 45, 553–578
- 731 Moore, G. and Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting
732 an information technology innovation. *Information Systems Research* doi:10.1287/isre.2.3.192. Cited
733 By 5167
- 734 Morone, G., Pisotta, I., Pichiorri, F., Kleih, S., Paolucci, S., Molinari, M., et al. (2015). Proof of principle
735 of a brain-computer interface approach to support poststroke arm rehabilitation in hospitalized patients:
736 design, acceptability, and usability. *Archives of physical medicine and rehabilitation* 96, S71–S78
- 737 Nijboer, F. (2015). Technology transfer of brain-computer interfaces as assistive technology: barriers and
738 opportunities. *Annals of physical and rehabilitation medicine* 58, 35–38
- 739 Nijboer, F., Birbaumer, N., and Kübler, A. (2010). The influence of psychological state and motivation
740 on brain-computer interface performance in patients with amyotrophic lateral sclerosis - a longitudinal
741 study. *Frontiers in Neuroscience* doi:10.3389/fnins.2010.00055. Cited By 171
- 742 Nijboer, F., Furdea, A., Gunst, I., Mellinger, J., McFarland, D., Birbaumer, N., et al. (2008). An auditory
743 brain-computer interface (bci). *Journal of Neuroscience Methods* doi:10.1016/j.jneumeth.2007.02.009.
744 Cited By 244
- 745 Nojima, I., Sugata, H., Takeuchi, H., and Mima, T. (2022). Brain–computer interface training based on
746 brain activity can induce motor recovery in patients with stroke: A meta-analysis. *Neurorehabilitation*
747 *and Neural Repair* 36, 83–96
- 748 Nunnally, J. C. (1994). *Psychometric theory 3E* (Tata McGraw-hill education)
- 749 Pasqualotto, E., Simonetta, A., Gnisci, V., Federici, S., and Belardinelli, M. O. (2011). Toward a usability
750 evaluation of bcis. *Int J Bioelectromagn* 13, 121–122
- 751 Pfurtscheller, G., Guger, C., Müller, G., Krausz, G., and Neuper, C. (2000). Brain oscillations control hand
752 orthosis in a tetraplegic. *Neuroscience letters* 292, 211–214
- 753 Pichiorri, F., Morone, G., Petti, M., Toppi, J., Pisotta, I., Molinari, M., et al. (2015). Brain–computer
754 interface boosts motor imagery practice during stroke recovery. *Annals of neurology* 77, 851–865
- 755 Pillette, L., Grevet, E., Amadiou, F., Dussard, C., Delgado-Zabalza, L., Dumas, C., et al. (in preparation).
756 The acceptability of BCIs and neurofeedback: presenting a systematic review, a field-specific model and
757 an online tool to facilitate assessment. *Will be submitted soon*
- 758 Pillette, L., Jeunet, C., Mansencal, B., N’kambou, R., N’Kaoua, B., and Lotte, F. (2020). A physical
759 learning companion for mental-imagery bci user training. *International Journal of Human-Computer*
760 *Studies* 136, 102380
- 761 Rad, M. S., Nilashi, M., and Dahlan, H. M. (2018). Information technology adoption: a review of the
762 literature and classification. *Universal Access in the Information Society* 17, 361–390
- 763 Randolph, A. B. (2012). Not all created equal: individual-technology fit of brain-computer interfaces. In
764 *2012 45th Hawaii International Conference on System Sciences (IEEE)*, 572–578
- 765 Revelle, W. (2021). How to use the psych package for mediation/moderation/regression analysis. *The*
766 *Personality Project*. <http://personality-project.org/r/psych/HowTo/mediation.pdf>

- 767 Roc, A., Pillette, L., Mladenovic, J., Benaroch, C., N’Kaoua, B., Jeunet, C., et al. (2021). A review of user
768 training methods in brain computer interfaces based on mental tasks. *Journal of Neural Engineering* 18,
769 011002
- 770 Ron-Angevin, R. and Díaz-Estrella, A. (2009). Brain–computer interface: Changes in performance using
771 virtual reality techniques. *Neuroscience letters* 449, 123–127
- 772 Rondan-Cataluña, F. J., Arenas-Gaitán, J., and Ramírez-Correa, P. E. (2015). A comparison of the different
773 versions of popular technology acceptance models: A non-linear perspective. *Kybernetes*
- 774 Schaupp, L. C., Carter, L., and McBride, M. E. (2010). E-file adoption: A study of us taxpayers’ intentions.
775 *Computers in Human Behavior* 26, 636–644
- 776 Sharma, N., Pomeroy, V. M., and Baron, J.-C. (2006). Motor imagery: a backdoor to the motor system
777 after stroke? *Stroke* 37, 1941–1952
- 778 Straub, D., Keil, M., and Brenner, W. (1997). Testing the technology acceptance model across cultures: A
779 three country study. *Information and Management* doi:10.1016/S0378-7206(97)00026-8. Cited By 703
- 780 Tavakol, M. and Dennick, R. (2011). Making sense of cronbach’s alpha. *International journal of medical*
781 *education* 2, 53
- 782 Terrade, F., Pasquier, H., Juliette, R., Guingouain, G., and Somat, A. (2009a). L’acceptabilité sociale: La
783 prise en compte des déterminants sociaux dans l’analyse de l’acceptabilité des systèmes technologiques.
784 *Le travail humain* 72. doi:10.3917/th.724.0383
- 785 Terrade, F., Pasquier, H., Reerinck-Boulanger, J., Guingouain, G., and Somat, A. (2009b). Social
786 acceptability: How social determinet can influence analysis of technology system acceptabiiijty
787 [l’acceptabilité sociale: La prise en compte des déterminants sociaux dans l’analyse de l’acceptabilité
788 des systèmes technologiques]. *Travail Humain* doi:10.3917/th.724.0383. Cited By 39
- 789 Thüring, M. and Mahlke, S. (2007). Usability, aesthetics and emotions in human–technology interaction.
790 *International journal of psychology* 42, 253–264
- 791 Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and
792 emotion into the technology acceptance model. *Information Systems Research* doi:10.1287/isre.11.4.
793 342.11872. Cited By 3501
- 794 Venkatesh, V. and Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions.
795 *Decision sciences* 39, 273–315
- 796 Venkatesh, V. and Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four
797 longitudinal field studies. *Management science* 46, 186–204
- 798 Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). User acceptance of information
799 technology: Toward a unified view. *MIS quarterly* , 425–478
- 800 Venkatesh, V., Thong, J. Y., and Xu, X. (2012). Consumer acceptance and use of information technology:
801 extending the unified theory of acceptance and use of technology. *MIS quarterly* , 157–178
- 802 Vilatte, J.-C. (2007). Méthodologie de l’enquête par questionnaire. *Laboratoire Culture & Communication*
803 *Université d’Avignon*
- 804 Voinea, G.-D., Boboc, R., Gîrbacia, F., and Postelnicu, C.-C. (2019). Technology acceptance of a
805 hybrid brain-computer interface for instruction manual browsing. In *PROCEEDINGS OF THE 14TH*
806 *INTERNATIONAL CONFERENCE ON VIRTUAL LEARNING (ICVL)*
- 807 Wang, Y.-M., Wei, C.-L., and Wang, M.-W. (2022). Factors influencing students’ adoption intention of
808 brain–computer interfaces in a game-learning context. *Library Hi Tech*
- 809 Wang, Y.-S., Wu, M.-C., and Wang, H.-Y. (2009). Investigating the determinants and age and gender
810 differences in the acceptance of mobile learning. *British Journal of Educational Technology* doi:10.
811 1111/j.1467-8535.2007.00809.x. Cited By 632

- 812 Wills, M. J., El-Gayar, O. F., and Bennett, D. (2008). Examining healthcare professionals' acceptance of
813 electronic medical records using utaut
- 814 Witte, M., Kober, S., Ninaus, M., Neuper, C., and Wood, G. (2013). Control beliefs can predict the ability
815 to up-regulate sensorimotor rhythm during neurofeedback training. *Frontiers in Human Neuroscience*
816 doi:10.3389/fnhum.2013.00478. Cited By 93
- 817 Wolbring, G., Diep, L., Yumakulov, S., Ball, N., and Yergens, D. (2013). Social robots, brain machine
818 interfaces and neuro/cognitive enhancers: Three emerging science and technology products through the
819 lens of technology acceptance theories, models and frameworks. *Technologies* 1, 3–25
- 820 Zulauf-Czaja, A., Al-Taleb, M. K., Purcell, M., Petric-Gray, N., Cloughley, J., and Vuckovic, A. (2021).
821 On the way home: a bci-fes hand therapy self-managed by sub-acute sci participants and their caregivers:
822 a usability study. *Journal of NeuroEngineering and Rehabilitation* 18, 1–18