Profiling of low back pain patients for the design of a tailored coaching application

Abstract— **Low back pain is a major public health problem that is the leading cause of disability in most countries. The recommendations are to propose personalized physical activity programs according to the individual characteristics (motivation, preferences, attitude towards physical activity) of each patient. However, the current management of low back pain includes rehabilitation programs that are costly and/or not always personalized. The objective of this research is to better understand the characteristics of people with chronic low back pain to identify typical profiles to inform the design of a tailored coaching mobile application. We selected eight concepts and associated scales to characterize the population: general health status (MYMOP), treatment burden (TBQ), quality of life (EQ-5D-5L), level (IPAQ), fears and beliefs (FABQ-AP) and motivation (EMAPS) for physical activity, emotional state (PHQ-9) and feeling of self-efficacy (FC-CPSES). These questionnaires were administered online via an e-cohort of low back pain patients. 193 patients with chronic low back pain were included. A clustering analysis allowed us to distinguish 4 profiles: (1) "Unmotivated," characterized by the lowest motivation and the highest amotivation toward physical activity (i.e., they do not understand why it is useful), (2) "Cautious" with low motivation and having the highest fears and beliefs toward physical activity, (3) "Depressed" with good intrinsic motivation but also a significant level of depressive symptoms, and (4) "Confident" also showing good intrinsic motivation and having the highest self-efficacy. These four profiles of patients will be used to design a coaching mobile application tailored along the priorities (e.g., physical activity, pain management) and types of motivational messages displayed on the tailored mobile application.**

Index Terms: **Chronic low back pain—e-coaching—motivational profiles—hierarchical ascendant classification**

I. Introduction

Low back pain is a major public health problem that is increasing as the population ages. This disease is the first cause of disability among employees. The probability of returning to work is only 20% after one year of sick leave and 0% after 2 years. In most cases, the main recommended treatment is adapted physical activities and therapeutic exercises. The challenge is to motivate patients to adopt a health behavior (e.g., regular physical activity, attitude towards pain) that will allow them to manage their disability. In this perspective, health professionals use the bio-psycho-social model to support patients [1]. This multidimensional approach encompasses the physical aspect as well as psychological and environmental factors based on a shared medical decision and multi-professional rehabilitation programs. However, the current management of chronic low back pain includes costly and sometimes insufficiently personalized rehabilitation programs, which reduces their effectiveness [2]. A stratified approach could significantly improve patient outcomes and is associated with clear economic benefits [3]. According to the Internal Association for the Study of the Pain (IASP), low back pain, with its multiple treatment modalities, is an ideal candidate for personalized management.

Digital interventions such as web-based health (eHealth) or mobile health (mHealth) applications have great potential to improve population health and the efficiency and reach of healthcare delivery [4]. Several studies have already been conducted on their use with people suffering from chronic diseases such as low back pain. These demonstrated a significant positive effect on disease monitoring, self-reporting, education, promotion of physical activity [5] as well as improvement of short-term pain and disability in patients with chronic low back pain [6]. Although there are many apps available for self-management of low back pain, their effectiveness in improving patient outcomes is rarely empirically evaluated [7]. Recent evaluations of commercially available apps have revealed that the vast majority are not based on a scientific framework [8]. Thus, the informatics literature emphasizes the need for personalized and behavioral science-based systems to support health behavior change [4]. In this context, the personalization of persuasive systems for behavior change is growing [9][10] but the preliminary step of defining relevant profiles is not always detailed.

Our work aims to design a tailored coaching smartphone application supporting patients' behavioral change towards physical activity and the management of their pathology. The objective of this study is to determine if motivational profiles of low back pain patients can be defined to propose tailored and automated coaching through the mobile application. Such profiles would allow, for example, to tailored motivational messages displayed by the mobile application as well as priorities in terms of proposed activities (e.g., knowledge allowing to change attitude towards physical activity and/or pain).

In this paper we present the method and results of a motivational profiling of patients based on their psychological characteristics.

II. Background

A. *Tailoring and profiling*

Several researchers have worked on the design of so-called persuasive technologies [11] with the objective of promoting health behaviors and determining design and evaluation frameworks [12]. Recently, Oinas-Kukkonen developed the concept of a behavior change support system (BCSS) for health [13] and proposed the Persuasive System Design (PSD) model [14] to better frame research and design activities in this area. The authors go even further by proposing a categorization of the main persuasive strategies to be applied when designing persuasive systems, initially proposed by Fogg [11]. This taxonomy distinguishes two strategies that are often confused: personalization and tailoring. Personalization consists in offering content or services that are customized to the user's individual preferences. Tailoring proposes an adaptation according to various factors potentially relevant to a group of several users. These strategies are widely recommended in the literature, especially for the design of systems promoting physical activity [9][15]. In 2014, researchers proposed seven key tailoring concepts for real-time physical activity training systems [16]. The most used concepts are feedback, goal setting, user targeting and inter-human interaction. Concepts such as self-learning, context awareness and adaptation are less used [17]. Many opportunities are therefore available to design a system adapted to a user or a group of users. Tailoring has the advantage of being able to propose an automatic adaptation based only on the data allowing to identify the user's profile. These profiles must be based on relevant factors to accompany users in their process of behavioral change.

For chronic low back pain, a schema of factors associated with the patient, his interaction with the therapist and the clinical pathways has been presented with the aim of proposing a more adapted approach [18]. The authors state that subgroups of patients have been considered according to clinical characteristics that represent mainly a mechanical or non-mechanical pain profile [19]. However, the authors have not yet demonstrated a positive effect of this categorization on a health service adjustment. Until now, studies aimed at classifying low back pain patients were based on the type of treatment to be adopted based on clinical factors determined by physical therapists [20][21]. This work has led to changes in the adaptation of different clinical treatments, but it does not consider the motivational and/or behavior change characteristics of patients. Regarding chronic pain in general, automatic classification has nevertheless revealed certain correlations concerning the psychological health of the patient and his or her adherence to treatment [22]. In his thesis, Dekkers [23] proposed a method of profiling orthopaedics patients based on clinical, psychological and communication characteristics with the aim of proposing tailored health care services. He thus presents 3 profiles:

- "Optimistic" characterized by high preoperative health, low anxiety, limited coping behavior, no preference for personal and emotional communication, and good communication skills.
- "Manager" characterized by low preoperative health, higher pain scores, use of multiple coping strategies (including seeking support and distraction), and highest communication skills, preferences, and self-efficacy.
- "Modest" characterized by more anxiety, a higher tendency to pain catastrophizing, a relatively high preference for emotional communication over participatory and open communication, and lower communication skills and self-efficacy.

Importantly, these profiles are based on the results of analysis of clinical, psychological, and communication data from patients rather than on the experience of healthcare professionals. This work has identified specific design guidelines for these subgroups for the development of digital patient applications [24]. In the field of physical activity, several studies have already proposed motivational profiles [25] based on self-determination theory (SDT) [26][27]. This theory distinguishes between intrinsic (or self-determined) motivation, extrinsic (or controlled) motivation and amotivation (or lack of motivation). Self-determined motivation implies that the individual feels completely free to make choices, whereas controlled motivation implies that one's actions are influenced and guided by external pressures [26]. Thus, SDT considers that there are different forms of behavioral regulation that can be represented on a continuum of self-determination ranging from amotivation to intrinsic motivation. The results of work on motivational profiles based on SDT have provided a basis for effective strategies to develop exercise adherence by focusing on the types of motivations individuals have [25]. Although several studies have attempted to identify profiles with the aim of proposing tailored support, no study to our knowledge has focused on identifying profiles based on factors impacting motivation or, more broadly, the process of behavior change in patients with chronic low back pain.

B. Behavior change

Improvement in the symptomatology of chronic low back pain often requires a change in the patient's lifestyle, particularly about physical activity and attitude towards pain [28]. In social psychology, a distinction is made between attitude and behavior. The former is conceived as a general evaluation (positive or negative) of a person towards an object [29]. Whereas behavior is defined by the actual observable actions of the individual. Behavioral theories and models therefore aim to identify the factors that influence attitude and behavior change.

The literature on health behavior change is extensive and includes approaches based on several theories and models that operate at multiple levels, including individual, interpersonal, group, and community [30]. Nevertheless, these different theories are often limited to determinants of intention that do not always translate into behavior change [31]. For the design phase of our intervention, we rely on the Health Action Process Approach (HAPA) model of behavior change [32] because of its approach, which is adapted to the health context and considers other determinants than intention to support behavior change.

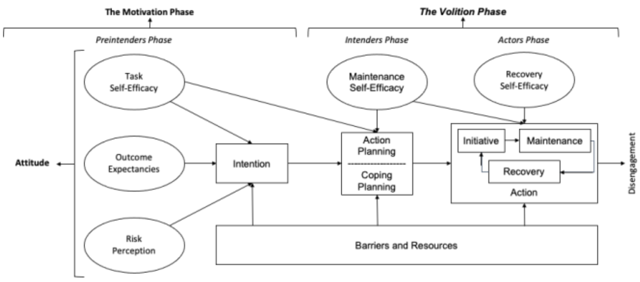

Fig. 1. The Health Action Process Approach (HAPA) model [32]

The Health Action Process Approach (HAPA) model suggests that the adoption, initiation, and maintenance of health behaviors must be explicitly conceived as a process that includes at least a motivation phase and a willingness phase. The former corresponds to the construction of the intention to change behavior, primarily influenced by risk perception and outcome expectations. The second phase is subdivided into a planning phase, an action phase, and a maintenance phase. It is important to note that perceived self-efficacy as well as barriers and resources play a crucial role in all phases of the model.

Several recent studies have attempted to list these barriers and resources to physical activity in chronic low back pain [33][34]. Boutevillain proposes to divide them into 3

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categories: Physical, Psychological and Socio-environmental (Table I).

TABLE I. SUMMARY OF LOW BACK PAIN PATIENTS' BARRIERS AND RESOURCES TO PHYSICAL ACTIVITY [33][34]

	Physical	Psychological	Socio-environmental
Barriers	- Pain - Co-morbidities	- Lack of motivation - Lack of perceived benefits - Fears and false beliefs - Lack of knowledge - Depression	- Lack of time - False recommendations - Poor organization - Profession
Resources	- Back support (ex: lumbar belt)	- Will/Desire - Self-esteem	- Supervision by a health professional - Monitoring of the PA - Group practice

Because of its adaptive and everyday nature, a mobile application can address certain socio-environmental barriers, but it is also important to consider psychological barriers to promote behavior change. Moreover, we can link some of the psychological barriers and facilitators identified in the case of low back pain with the factors described in the HAPA model influencing behavioral intention. The barrier "lack of perceived benefits" directly impacts "outcome expectations", while "lack of knowledge" or "false beliefs" could impede patients' "risk perception". The "self-esteem" facilitator may refer to the sense of self-efficacy impacting throughout the behavior change process. Another psychological barrier more specific to low back pain is highlighted here: "depression". According to the HAPA model, all these factors play a role during the motivational phase, which could explain the presence of the "lack of motivation" barrier. Finally, this research allows us to identify the psychological factors impacting on the process of behavioral change in low back pain patients. The following sections aim at identifying motivational profiles of patients by considering these psychological factors to propose them a tailored digital support promoting regular physical activity.

III. METHOD

A. Participants and procedure

All participants were recruited between July 2020 and October 2021 via an e-cohort of low back pain patients through which we sent validated questionnaires in French. A total of 193 participants were included in the study. They were assured that there were no right or wrong answers, and that the data collected would remain anonymous and be used for research purposes only.

B. Tools and measures

First, we analyzed some socio-demographic data to characterize our sample with respect to the general population of low back pain patients: age, gender, occupational status, and duration of low back pain. Then, with the help of healthcare professionals who are experts in the management of chronic low back pain, various standardized scales were selected to characterize our sample in a clinical manner: general health, quality of life, treatment burden and physical activity level. In addition, we selected several scales to measure the psychological factors identified in the literature review (Table I) that potentially impact the process of patient behavior change: patients' sense of self-efficacy, level of depression, motivation, and fears and beliefs about physical activity.

1) Clinical characteristics

a) General health status

The MYMOP [35] is a generic patient-specific outcome tool for assessing general health. It provides an individualized approach and measurement of symptoms and activities affected by the symptoms. The patient identifies the two symptoms that most affect their health status and then rates them on a scale of 0 (not at all bothersome) to 6 (extremely bothersome). Next, the patient chooses an activity that was affected by the first symptom and rates the activity again on a scale of 0 to 6 during the previous week. Finally, the patient can rate his or her well-being on the same scale (0 = Best that can be to 6 = Worst that can be).

b) Quality of life

The EQ-5D-5L [36] is a questionnaire to measure quality of life across 5 dimensions: mobility, self-care, usual activity, pain, and anxiety. Health states in the EQ-5D-5L can be summarized using a 5-digit code representing each dimension or represented by a single synthetic U(E) number that reflects the degree of quality or severity of a health state according to the preferences of the general population of a country or region. Each of the dimensions is judged on a scale from 1 (no problems) to 5 (extreme problems) and is weighted according to the values specific to the country or region of the sample studied. The matrix of values applicable to France was published in February 2020 [37], allowing us to calculate the U(E) score for our sample. A last item, the EQ VAS is a self-reported score between 0 and 100 where patients are asked to evaluate their health status themselves. It is conceptually different from the U(E) index because it represents only the patient's point of view.

c) Treatment burden

The TBQ [38] is the only instrument that measures treatment burden in a comprehensive manner, independent of pathology or treatment. It consists of 13 items assessed on a Likert scale ranging from 0 (no problem) to 10 (major problem). It assesses the burden of taking medication, self-monitoring, laboratory tests, visits to the doctor, the need for organization, administrative tasks, following advice on diet and physical activity, and the social impact of treatment. The item scores can be added together into an overall score, ranging from 0 to 130.

d) Physical activity level

The IPAQ [39] assesses participants' overall physical activity and sedentary time during the past 7 days. This questionnaire looks at the practice of intense and moderate physical activities, walking, as well as the time spent sitting (sedentary), whether during leisure activities, at work, in daily life or during transport. A weighting is attributed to each of the physical activities allowing to calculate, according to the number of days of activity per week and the time spent in minutes, a MET-minutes/week score. Thanks to this score, this questionnaire also allows to classify the subjects according to 3 levels of activity: inactive (1), moderate (2), high (3).

2) Motivational characteristics

a) Sense of self-efficacy specific to chronic pain

The FC-CPSES [40] is a validated 33-item self-administered questionnaire. Patients are asked how confident they are in performing certain activities at the present time. Each item is measured using a numerical scale ranging from 1 (not at all confident) to 10 (completely confident). The total score for the Chronic Disease Self-Efficacy Scale can be obtained by averaging the 33 items and ranges from 1 to 10. Higher scores indicate higher self-efficacy. Ten subscale scores can also be calculated using the same method: Exercising regularly (items 1-3); getting information about the disease (item 4); getting help from the community, family, or friends (items 5-8); communicating with the doctor (items 9-11); managing the disease in general (items 12-16); doing chores (items 17-19); social/recreational activities (items 20 and 21); managing symptoms (items 22-26); managing breathlessness (item 27); and controlling/managing depression (items 28-33). This scale was adapted to the context of chronic pain patients following cross-cultural adaptation guidelines.

b) Level of depression

The PHQ-9 [41] is a short 10-item scale used to diagnose and measure the severity of depression. Each item is rated on a severity scale ranging from 0 to 3 producing a total score ranging from 0 to 27. The last question asks the respondent to what extent the identified problems have interfered with work, home, or social life. However, responses to this item are not scored or included in the total score. Based on this score, the respondent is assigned an interpretation (1-4: minimal depression; 5-9: mild depression; 10-14: moderate depression; 15-19: moderately severe depression; and 20-27: severe depression). But the authors do not rule out the possibility of using the total score as a continuous variable.

c) Motivation for physical activity

The ÉMAPS questionnaire [42] allows a self-evaluation of motivation in 18 items. This tool, which can be used daily and for all populations, aims to better understand the motivation of individuals to engage in physical activities from a health perspective by evaluating the different behavioral regulations identified by the SDT (intrinsic motivation, integrated regulation, identified, introjected, extrinsic motivation and amotivation) by a score ranging from 1 to 7.

d) Fears and beliefs about physical activity

The FABQ [43] is a questionnaire divided into 2 subscales that focuses specifically on the fears and avoidance beliefs of low back pain patients regarding physical activity and work. In our study, we used only the scores obtained on the subscale concerning fears and beliefs about physical activity. Each item presents a fear or belief that the respondent must evaluate on a scale ranging from 0 (completely agree) to 6 (completely disagree). The total score is obtained by adding the item scores. A score of 15 or more is considered high [44], indicating that fears and avoidance beliefs are more strongly held towards physical activity. The global score of this scale is often treated as a continuous variable in the literature [45].

C. Statistical analysis

To account for the overall results of our sample, we conducted descriptive analyses using the mean (m) and standard deviation (s) as primary indicators. Each of the scales was analyzed following the recommendations presented in the previous section. Regarding motivational characteristics, we continued the analyses with the objective of identifying homogeneous groups of patients.

Cluster analysis consists of four steps: selection of cluster variables, decision of the clustering procedure, determination of the number of clusters, and validation of the cluster solution [46]. To distinguish motivational profiles based on psychological factors that can impact the behavior change process of low back pain patients, we identified 10 variables to be included in the clustering analysis. These 10 variables are: the chronic pain-specific self-efficacy score, the depression score, the 6 scores for the different behavioral regulations identified by the SDT, and the fear and belief score for physical activity. In this study, all the measures were included as a continuous variable. The scale scores were standardized by the center-reduced method. To validate the selection of variables, it is important to study their correlations between them, here with Pearson's coefficient, in order to avoid problems of multicollinearity in cluster analyses [47]. According to Hair and al [48], only correlations greater than 0.90 suggest that the variables have strong collinearity. In terms of deciding on the clustering procedure, the main methodology used is cluster analysis. This data reduction technique can be used in the health care context to segment patients to identify homogeneous groups [46][49]. More specifically, Hierarchical Ascending Classification (HAC) is a method that allows one to visualize the progressive clustering of data. One can then get an idea of an adequate number of classes into which the data can be grouped. Thus, the appropriate number of clusters is determined here in an exploratory hierarchical cluster analysis (Ward's clustering method with squared Euclidean distance) [49]. This technique relies on the examination of the dendrogram and the agglomeration coefficient to determine the appropriate number of clusters. Then, to validate the cluster solution determined by HAC, a non-hierarchical cluster analysis with the k-means method was conducted [48]. Finally, to analyze the motivational characteristics of each group, a one-factor multivariate analysis of variance (manova) was conducted with the cluster as the independent variable and the motivational variables as the dependent variables. All analyses were performed with Rstudio v.1.1.463.

IV. RESULTS

A. Overall description of the sample

1) Socio-demographic and clinical characteristics

A total of 193 participants responded to all questionnaires. The average age of the sample was 54 years (s = 13 years) and the vast majority were women (74%). On average, the duration of low back pain was 15 years, but with a large standard deviation (s = 12 years). Regarding the professional situation, 44% indicated that they were employed, 22% were on disability and 19% were retired. Concerning the clinical characteristics, the results are consistent with our population of low back pain patients.

a) General health status

With a mean score of 4,75 (s = 1,23) for symptom 1, the participants indicate that discomfort is present. The results for symptom 2 are quite similar, with a mean score of 4.26 (s = 1,47), as well as the discomfort caused by symptom 1 towards an important activity for the patients with a mean score of 4.26 (s = 1,70). The details of the symptoms and activities reported are consistent with the case of low back pain. Our participants report having mainly osteomuscular pain. But as a 2nd symptom, psychological discomfort seems to become more important. The average well-being score was 3,74 (s = 1,21), which reflects a rather negative feeling of well-being. Finally, we find in our participants a mean MYMOP score of 4,25 (s = 1,12).

b) Quality of life

The results of the EQ-5D-5L show an average profile of 22232, corresponding to mild problems for mobility, usual activities, self-care and anxiety and moderate problems for pain. The average VAS EQ score was 57,54 (s = 21,67). Overall, our participants report a relatively low quality of life score. These results are consistent with those of the U(E) score (maximum score of 1) which is also relatively low with a mean of 0,70 (s = 0,27).

c) Treatment burden

The average TBQ score is 60.19 (s = 33,68). In addition, only 39% of our participants report being able to continue the same investment of time, energy, and money for life.

d) Level of physical activity

As for the level of physical activity measured by the IPAQ, the distribution is rather homogeneous with most participants with a moderate level (53%) against respectively 23% for the inactive and high levels.

2) Motivational characteristics

a) Sense of self-efficacy specific to chronic pain

The self-efficacy measurement scale shows that our population is generally relatively confident with a score of 6,08 (s = 1,53). This is consistent with the data presented by Lacasse and al [40] who obtained a mean of 6,11 (s = 1,47) for their sample of chronic low back pain patients before intervention.

b) Level of depression

With a mean score of 9,98 (s = 6,12) for the PHQ-9, we can consider moderate depressive symptoms in our participants.

c) Motivation for physical activity

We note that "Intrinsic Motivation" (m = 4,03 ; s = 1,83) and "Identified Regulation" (m = 4,84 ; s = 1,64) are the most pronounced in our participants, while Extrinsic Motivation (m = 1.78; s = 1.13) and Amotivation (m = 1,99 ; s = 1,29) are the lowest. Compared to the results of Boiché and al [42] with a sample of 490 patients with chronic diseases (Chronic Obstructive Pulmonary Disease, cardiovascular disorders, breast cancer, type 1 or 2 diabetes, obesity, chronic low back pain, spinal cord injury) our sample has lower results for intrinsic motivation, integrated, identified, and introjected regulation, equivalent for external motivation and higher for amotivation.

d) Fears and beliefs about physical activity

Regarding fears and beliefs towards physical activity, we find a mean score of 14,52 (s = 6,07) which means that on average our participants do not have strong fears and beliefs towards physical activity [44].

TABLE II. DESCRIPTIVE STATISTICS OF MOTIVATIONAL CHARACTERISTICS

Motivational characteristics (*n* = 193)	***m***	***s***	***Cronbach alpha (α)***
Self-efficacy (FC-CPSES) (score/10)	6,08	1,53	0,94
Motivation for PA (EMAPS) (score/7)			
Intrinsic Motivation	4,03	1,83	0.90
Integrated Regulation	3,68	1,93	0.90
Identified Regulation	4,84	1,64	0.90
Introjected regulation	3,80	1,79	0.83
Extrinsic Motivation	1,78	1,13	0.77
Amotivation	1,99	1,29	0.82
Fears and beliefs about PA (FABQ-AP) (score/24)	14,52	6,07	0.77
Depression (PHQ-9) (score/27)	9,98	6,12	0.87

B. Identification and description of clusters

1) Clusters identification and validation

The correlations between the variables ranged from -0,59 to 0,80, implying that there is no problem of multicollinearity in the cluster analyses [48]. Furthermore, the results regarding the different types of motivation testify to the presence of a continuum of self-determination [26] extending from amotivation to intrinsic motivation. Indeed, the subscales show the highest positive correlations, while the farthest subscales show the highest negative correlations. The correlations presented also show that depressive symptoms ($p < 0,05$) and sense of self-efficacy ($p < 0,001$) are significantly related to all types of motivation. Whereas fears and beliefs towards physical activity were significantly related ($p < 0,05$) only to integrated, introjected and external regulation.

The results of examining the HAC dendrogram and the agglomeration coefficient indicated that a four-group split is most appropriate. The k-means method revealed similar groups to the HAC confirming the four-cluster solution [48].

TABLE III. TABLE OF CORRELATIONS BETWEEN CLUSTERING VARIABLES

Motivational Variables	1	2	3	4	5	6	7	8
1. Self-efficacy								
2. Intrinsic Motivation	0,36**							
3. Integrated Regulation	0,34**	0,79**						
4. Identified Regulation	0,35**	0,78**	0,79**					
5. Introjected regulation	0,24**	0,76**	0,80**	0,77**				
6. Extrinsic Motivation	-0,31**	-0,32**	-0,18*	-0,25**	-0,17*			
7. Amotivation	-0,38**	-0,53**	-0,50**	-0,59**	-0,45**	0,43**		
8. Fears and beliefs about PA	-0,25**	-0,14	-0,18*	-0,12	-0,16*	0,18*	0,10	
9. Depression	-0,56**	-0,27**	-0,27**	-0,28**	-0,21*	0,35**	0,32**	0,30**

Note. * $p < 0,05$; ** $p < 0,001$

TABLE IV. DESCRIPTIVE STATISTICS OF CLUSTERS

Motivational Variables	Cluster 1 (N=72)		Cluster 2 (N=33)		Cluster 3 (N=56)		Cluster 4 (N=31)	
	m	*s*	*m*	*s*	*m*	*s*	*m*	*s*
Self-efficacy (score/10)	7,13	1,26	5,65	1,29	5,22	1,32	5,67	1,34
Motivation for PA (score/7)								
Intrinsic Motivation	5,01	1,48	5,64	1,00	2,06	0,91	3,65	1,03
Integrated Regulation	4,61	1,55	5,73	0,87	1,81	1,03	2,79	1,07
Identified Regulation	5,82	0,83	6,18	0,53	2,90	1,30	4,68	0,88
Introjected Regulation	4,46	1,43	5,92	0,82	2,01	0,89	3,30	1,14
Extrinsic Motivation	1,24	0,50	1,80	1,02	2,52	1,49	1,64	0,78
Amotivation	1,33	0,69	1,43	0,58	3,25	1,49	1,80	0,80
Fears and beliefs about PA (score/24)	12,19	5,95	13,94	5,62	15,23	6,12	19,26	3,29
Depression (score/27)	4,92	3,46	13,30	5,21	12,53	5,88	13,52	4,38

2) Clusters description

The averages obtained by each cluster allowed us to give a name to each group. Thus, the first cluster labeled "Confident" includes 72 individuals (37%) and the second cluster named "Depressed" includes 33 individuals (17%). These clusters have high intrinsic, integrated regulation, identified and introjected motivation in contrast to clusters 3 and 4 named respectively "Unmotivated" (n = 56, 29%) and "Cautious" (n = 31, 16%). The "Confident" profile stands out because of its high self-efficacy score and its low depression score. The "Depressed" profile had, on average, mild to moderate depressive symptoms, as did the "Unmotivated" and "Cautious" profiles. The "Unmotivated" group is distinguished by the highest amotivation score and has high fears and beliefs about physical activity [44]. Nevertheless, the "Cautious" profile shows the highest score of fears and beliefs towards physical activity.

To analyze the motivational characteristics of each group, a one-factor multivariate analysis of variance (manova) was conducted with the cluster as a four-modality independent variable and the six types of motivation as dependent variables. The results showed significant differences between the four clusters [F(18,558) = 15,908 ; p < 0,001]. Univariate results then showed that the four groups differed on intrinsic motivation [F(3,189) = 89,72 ; p < 0,001], integrated regulation [F(3,189) = 92,665 ; p < 0,001], identified regulation [F(3,189) = 123,602 ; p < 0,001], introjected regulation [F(3,189) = 93,273 ; p < 0,001], external regulation [F(3,189) = 17,243 ; p < 0,001], and amotivation [F(3,189) = 44,895 ; p < 0,001]. Overall, the results of the Newman-Keuls post-hoc tests confirmed the distinction between each group.

Several anova's combined with Newman-Keuls post-hoc tests were then conducted to analyze differences between the four clusters in identified psychological barriers and facilitators (sense of self-efficacy, fears and beliefs towards physical activity, depressive symptoms). The first analysis showed that there were significant differences between the four groups regarding self-efficacy [F(3,189) = 26,528 ; p < 0,001]. More specifically, the results of the post-hoc tests showed that the individuals in the "Confident" profile had the highest self-efficacy scores compared to the other three profiles and this was significant (p < 0,001). Between the "Depressed", "Cautious" and "Unmotivated" groups, the results do not show significant differences in the feeling of self-efficacy.

Then, the results of the anova with fears and beliefs towards physical activity as a dependent variable also revealed a significant effect [F(3,189) = 11,914 ; p < 0,001]. The "Cautious" profile had the highest scores of fears and beliefs towards physical activity significantly compared to the "Unmotivated" profiles (p < 0,01), "Depressed" (p < 0,001) and "Confident" (p < 0,001). However, the "Unmotivated" profile also had significantly higher scores than the "Confident" profile (p < 0,05).

Finally, concerning the results of the anova with depressive symptoms as the dependent variable, the results showed significant differences between the clusters [F(3,189) = 44,213 ; p < 0,001]. The "Confident" profile had significantly lower scores (p < 0,001) than the other profiles, whereas the differences between the "Unmotivated", "Cautious" and "Confident" profiles were not significant.

V. DISCUSSION

The objective of this study was to determine groups of low back pain patients from a cluster analysis to propose profiles on which to base the future design of a tailored mobile application.

This typology is built according to the types of motivation of the individuals and their sensitivity to certain psychological factors that can have an impact on their behavioral change process. Clustering analysis allowed us to determine 4 patient profiles that we named by their characteristic: Unmotivated, Cautious, Depressed and Confident. Table I shows that only fears and beliefs towards physical activity are not significantly correlated with all types of motivation, unlike the level of depression or the feeling of self-efficacy. It seems that this factor has a greater or lesser impact depending on the type of motivation of the patients. The hypothesis that fears and beliefs are among the factors influencing only the attitude and thus the behavioral intention of patients but not the direct behavior could explain this phenomenon. In contrast, the feeling of self-efficacy and depressive symptoms would be involved in each phase of the behavior change process. From a theoretical point of view, our results show some consistency with those of Dekkers [23]. The Confident profile has several similarities with the Optimistic profile, and the Cautious profile could join the Managers profile. Thus, the Unmotivated and Depressed profiles could be a decomposition of the Modest profile. This new approach could bring a new vision to the medical practice already established with the Dekkers profiles.

For the design of the upcoming application, we located our typology on the HAPA model [32] according to the presented results. The following figure shows the positioning of the 4 motivational profiles of low back pain patients on this model.

The Unmotivated and Cautious profiles present low motivation and strong fears and beliefs [44]. Therefore, they are situated in the motivational phase, with a particular emphasis for the Cautious towards the "risk perception" factor, due to their stronger fears and beliefs. The Depressed person already has a good intrinsic motivation, but his problem is more at the level of his "barriers and resources" because of his less good mental health. Finally, the Confident has the best mental health, good intrinsic motivation, and the highest self-efficacy. We assume that he is already in the action loop, influenced by maintenance and recovery self-efficacy.

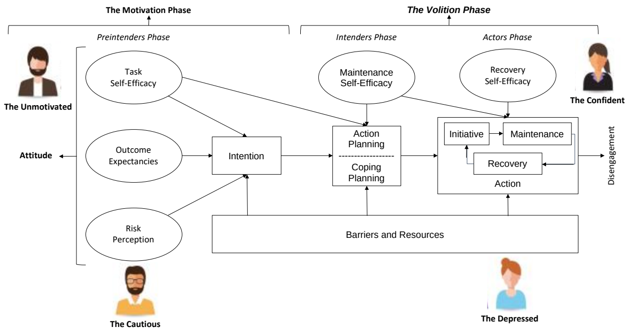

Fig. 2. Positioning on the HAPA model of the four motivational profiles resulting from our analysis

Thanks to this work, we have designed a first version of a tailored coaching application according to these profiles. This tailoring includes two aspects: content recommendation and motivational messaging. The content recommendation is to direct the Unmotivated and Cautious profiles to quizzes with the objective of changing their attitudes first and developing their intention to change their behavior. For the Unmotivated, Cautious and Depressed profiles, we recommend a wellness module including meditation exercises to reduce their depressive symptoms. The Confident profile is directly oriented towards physical activity. Concerning the motivational messages, we plan to present text messages adapted to each of the profiles according to their sensitivity to the different types of motivation presented by the SDT [26][27]. This has already been implemented through virtual agents with positive results on user appreciation [50].

Currently, the user must answer 4 questionnaires (EMAPS, FC-CPSES, FABQ-AP, PHQ-9) to measure his motivational characteristics, i.e., nearly 60 questions to be classified in one of the profiles. The aim of the rest of this work is therefore to develop an optimal screening tool like the work of Dekkers and Groeneveld [51] to classify users into one of the profiles. We consider the methodology of Classification and Regression Trees (CART) to produce decision rules to classify future cases of new patients into one of the profiles. In this way, we will be able to offer tailoring based on a user's profile when they create their profile. The evaluation of this application with end-users will allow us to verify if the tailoring choices for these profiles allow for an adapted coaching.

Finally, it is important to consider the particularities of our sample of low back pain participants who participated in our questionnaire study (e.g., 74% women) compared to the classical low back pain population. Further studies are needed to validate these clusters by including evidence of their value to the field of study. Furthermore, these profiles allow for the tailoring of the intervention according to the psychological barriers and resources of the user [33][34] but they do not consider physical and socio-environmental factors, or even the acceptance of new technologies, which should also be given special attention by the designers of the tailored motivational mobile application.

VI. Conclusion

In this study, we presented a method to identify profiles of low back pain patients to propose an automatic tailoring of a mobile application to help them change their behavior. Based on the literature, we were able to identify the factors specific to our users that impact their behavior change process. Through a cluster analysis, four profiles were distinguished. The first is the Unmotivated, who has the highest amotivation, the lowest intrinsic motivation and has strong fears and beliefs about physical activity. The Cautious has low intrinsic motivation but also low amotivation. They are characterized by the strongest fears and beliefs about physical activity. The Depressed has good intrinsic motivation. However, he also presents mild to moderate depressive symptoms like the two previous profiles. Finally, the Confident also has good intrinsic motivation. He stands out for his high score on the feeling of self-efficacy and his low score on depressive symptoms.

These profiles allow us to consider the design of a tailored application considering the psychological needs of the users to improve their self-management of their pathology.

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