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Editors:

Regina Ferreira

José Amoroso

Fernando Santos

Filipe Rodrigues

Miguel Jacinto

Pedro Sobreiro

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Avenida Mário Soares, 110, 2040-413 Rio Maior

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INDEX

01. Editorial.....	4
02. Interview.....	5
03. Article.....	8
04. Publications.....	19
05. R&d activities.....	21
06. Calls and funding.....	22
07. Schedule.....	23

01

EDITORIAL

This is the 34th newsletter of LQRC-CIEQV and the 3rd within the scope of the coordination that involves 3 Polytechnic Institutes, Santarém, Leiria, and Setúbal. Through research, we intend to contribute to the production of knowledge and innovation that promotes the improvement of the quality of life of human beings. The newsletter is, therefore, a way to disseminate the research, among others, carried out by our researchers.

Research activity has undergone an extraordinary development in quantity and quality in recent years, specifically of researchers from Polytechnic Higher Education. To achieve this goal it is necessary that researchers count on long-lasting and constant support. This is the way.

This issue comes within the scope of the scientific area of "organizational dynamics". In this sense, it presents an article that deals with the problem of sustainability and profitability of organizations that work in the context of sports, exploring a dynamic perspective and how it can be used in sports management. It identifies moments of client abandonment and the use of the indicators obtained supports decision-making for the development of new approaches to combat abandonment and contribute to a greater sustainability of sports organizations and sports practice.

This issue also includes the interview conducted with the collaborating researcher Elsa Vieira, in addition to the dissemination of articles published by our researchers. We want to extend our sincere thanks to Pedro Sobreiro and all the researchers and who contributed to this edition of the Newsletter.

These are reasons for a good read!



Regina Ferreira ^{1,2}

¹ Higher Health School of Santarem – Polytechnic Institute of Santarém

² Life Quality Research Centre

02

INTERVIEW

— Entrevista a Elsa Vieira



Elsa Vieira ^{1,2}

¹ Sport Sciences School of Rio Maior – Polytechnic Institute of Santarém

² Life Quality Research Centre

Brief curricular presentation

Elsa Vieira is Adjunct Professor at Sport Sciences School of Rio Maior – Polytechnic Institute of Santarém (ESDRM-IPSantarém). She has a PhD in Management from the University of Beira Interior, a Master's in Business Sciences from the University of Porto and a degree in Management from the Catholic University of Portugal. She is a collaborator member of CIEQV – Organizational Dynamics scientific area. She has published several scientific papers and abstracts with peer review, book chapters, presentations at conferences and congresses, in the field of management and sports management.

What are your goals as a CIEQV member?

As a collaborating member of CIEQV, my main aim is to contribute to the development of the scientific area - organizational dynamics, namely, management and sports management. More specifically, contribute with scientific papers, participate in conferences, and interact with other researchers, within the scope of studying individual and collective dynamics and their association with quality of life, as well as social influence on individual and organizational interactions.

What are your most important research projects? Develop one of the indicated projects.

As for the most important research projects, I mention the following:

- Methodology for applying the blue ocean strategy, recommended by Kim and Mauborgne (2005). According to these authors, the blue ocean strategy materializes in an unexplored market, where demand can be created and where there are opportunities for high growth and profitability. To clarify the “path” to follow to achieve a blue ocean strategy, the strategies implemented by gyms/health clubs were identified, then the relationship between implemented strategies and the financial performance of gyms/health clubs was analyzed, subsequently, the current value proposition offered by gyms/health clubs based on the dimensions of service quality and finally, the attributes to be reduced, eliminated, elevated and created are investigated to achieve an innovative business idea.
- “Emerging Forms of Employment in Sport – FORMS” – project that aims to investigate new forms of employment in the sport sector. This project is coordinated by the European Observatoire of Sport and Employment (EOSE) in cooperation with five partner institutions. This project is coordinated by Professor Abel Santos and has as members Alfredo Silva, Elsa Vieira and Pedro Sobreiro.

Knowing that knowledge must be transferred to society, how can the area of scientific research and professional intervention in which you are involved contribute to uniting theory with practice?

Regarding the investigation of presenting a proposal for a methodology to achieve a business idea in accordance with the blue ocean strategy, it is extremely relevant for managers. With this investigation it is concluded that most gyms/health clubs adopt a similar business model, with the same range of products/services, that is, the same value proposition, making it more difficult to persuade and attract new members to the industry. The blue ocean strategy gives great importance to the structure of the four fields of action (eliminate, reduce, elevate, and create) to achieve new demand, this project starts from the importance-performance analysis, then evaluates the difference between importance and performance in quality attributes and then identifies the attributes to increase, reduce, eliminate and maintain in a new business. Finally, it is also possible to mention the contribution of this study in measuring the six strategic options to reconstruct the boundaries of the gym/health club sector, namely through: the analysis of alternative industries, strategic groups, customer groups, complementary products and services, the functional-emotional stimulus of the industry and the temporal context.

Regarding the FORMS project, it is pertinent to highlight the identification of new forms of work: employee sharing, job sharing, voucher-based work, interim management, casual work, ICT-based mobile work, platform work, portfolio work and collaborative employment. It is worth highlighting the relevance of characterizing new forms of work for employees and employers.

Considering that the LQRC-CIEQV promotes research on the quality of life, what are the practical implications of the research it develops?

Regarding the practical implications of the research, the possibility of finding new business ideas for gyms that enhance greater adherence to physical activity, promoting the population's quality of life. Within the scope of the project on emerging forms of employment in sport, one of the contributions will be the identification of good practices and recommendations on emerging forms of employment.

03

ARTICLE

– Predicting dropout and survival analysis in physical activity



Pedro Sobreiro ^{1,2},

¹ Sport Sciences School of Rio Maior – Polytechnic Institute of Santarém

² Life Quality Research Centre

Abstract

Physical activity is essential for people to keep a healthy lifestyle, in addition to the dimension of physical activity we also have the problem of sustainability and profitability of organizations that work in the context of sport. To contribute to the sustainability of organizations, we can approach customer dropout with an analytical perspective to support the development of measures to increase customer retention. The use of historical customer data allows knowledge extraction through techniques based on machine learning, which enables the construction of predictive models. In the construction of predictive models, we can develop an analysis with a static perspective where we predict dropout at a given moment in time, or with a dynamic perspective, where we consider that the risk of dropout varies over time. We present an example, exploring a dynamic perspective and how can be used in sport management. Survival analysis allows you to find moments where dropouts occur, and the use of the indicators obtained support decision-making for the development of new approaches to counteract dropout and contribute to a greater sustainability of sports organizations and sports practice.

Keywords: Retention; Machine learning; Decision trees; Survival analysis; Sport management.

Introduction

Physical activity is fundamental to a healthy lifestyle (Haskell et al., 2007; Warburton et al., 2006). In Europe, 40% of citizens (more than 172 million) do physical activity at least once a week and 7% (more than thirty million) 5 times a week or more, where 14% support physical activity is developed in sports center (Eurobarometer, 2018). The need to increase the number of people engaging in physical activity can be addressed as a problem of adherence to sports activities, where there is a lack of research that addresses sport as an opportunity to take part massively in active behaviors (Henderson, 2009). However, to increase sports practice, it is mandatory to keep those who are already developing physical activity, which is one of the main problems that sports managers deal with today (MacIntosh & Law, 2015). The problem requires several approaches that aim to reduce dropout, increase adherence, and recognize physical activity as a priority. Cervelló et al. (2007) states that dropout occurs when participation in training or competitions ends, that occurs in the first year with a dropout rate between 40-50% (MacIntosh & Law, 2015). The impact of customer churn is greater than just the financial dimension in health clubs, considering that regular physical activity promotes and maintains health and reduces the risk of chronic diseases and premature mortality (Haskell et al., 2007), contributing to their prevention (Warburton et al., 2006).

Customer churn is a problem that also has an impact on the organization's performance, namely (Amin et al., 2017): (1) negative impact on the organization's overall performance; (2) decrease in sales; (3) competitors gain dissatisfied customers with promotions; (4) lost revenue; (5) long-term negative impact on customers; (6) increases uncertainty that reduces the ratio of new customers; (7) costs of attracting new customers greater than their maintenance; and (8) threatens the company's image in a competitive market and diminishes the customer base.

A dropout is an event that represents an option, which may represent a withdrawal of a member. The decision to renew a monthly fee falls under the heading of repeat purchases (Bhattacharya, 1998), which can be organized into two categories: (1) membership to have access to the organization's articles (e.g., Automobile Club Portuguese) (2) complete choice when the service is available to the customer regardless of whether or not they are members (e.g., members of a club).

This event can be contextualized in a contractual or non-contractual scenario (Ascarza, 2018; Gupta et al., 2006), where in contractual scenarios it is possible to understand the cash flow generated by its customers (Xue et al., 2021) and have access to subscription and usage records (Verbeke et al., 2014). In the context of physical activity performed in clubs or health clubs, it is common to find contractual configurations, where usually the dropout represents a loss of revenue, considering that the customer

stops paying. When faced with contractual configurations, the customer has the possibility to choose whether to withdraw or not, which means that they can renew or not (Prasasti & Ohwada, 2014). In these cases, customer dropout represents an explicit end to a relationship, which is more penalizing than in non-contractual scenarios (Risselada et al., 2010) and which has implications for the profitability of organizations by increasing marketing costs and reducing sales (Amin et al., 2017).

Developing an approach to managing customer churn is key to developing measures to realize customer retention (Ascarza, 2018). A successful approach requires retention strategies that rely on the accuracy of the prediction and simultaneously on the timing when it occurs (Alboukaey et al., 2020). Overall, it is fundamental to try to identify the customer's future decision to support the development of actions that counteract the probability of dropout at an early stage (Nie et al., 2011). To resolve this issue, the Predictive learning could be an option, however, after the appearance of the artificial intelligence (Friedman, 1994), Machine learning emerged as a modern extension of predictive analytics (Ongsulee et al., 2018), that is understood as an automated process for extracting patterns from data (Kelleher et al., 2015), that generalizes from the data used to train the model. More recently, it has emerged Deep Learning which is considered to be a part of the Machine Learning (Dargan et al., 2020), trying to mimic the behavior of the human brain (Agrawal et al., 2018). It is considered that the Machine Learning encompasses Deep Learning, and it's understood that is a consequence of predictive models. In this context, organizations typically address the problem using historical data, through the construction of a binary model (dropout/non-dropout) to try to predict customer dropout (Verbeke et al., 2012).

The importance of the problem for organizations in keeping customers has led to the development of research in areas such as marketing, statistics and management, where several models have been created to understand or predict customer churn at the next contract renewal (Ascarza & Hardie, 2013). Ascarza and Hardie (2013) explored a model to address customer churn in contract/subscription/membership scenarios to gain access to an underlying service. The problem of customer dropout and the impact on the sustainability of organizations requires the development of approaches and the use of tools to support decision-making by those responsible for organizations that work in the context of sport, based on the assumption that customers are the most valuable asset they have (Athanasopoulos, 2000; Jones et al., 2000).

In this context, how can we use historical customer data to predict customer dropout and support decision-making to develop preventive measures to prevent customer dropout in the context of a contractual setup?

How can we address the problem?

The problem can be addressed using an analytical approach through the analysis of existing data, considering that in contractual scenarios the company has access to records of the customer's subscription and interactions (Verbeke et al., 2014).

Customer analysis is key to developing business and marketing intelligence (Sheth et al., 1998), using historical data to identify trends and patterns (Berry & Linoff, 2004). This process can also be known as data mining, i.e., the extraction of knowledge from existing data (Han & Kamber, 2012), which allows us to answer business-related questions, that are traditionally time-consuming (Hung, 2006). Commonly used approaches use techniques such as statistics, machine learning, pattern identification, databases, data visualization, algorithms, and high-performance computing (Han et al., 2012), to extract useful information or detect patterns in data through automated or semi-automated methods (Berry & Linoff, 2004; Han & Kamber, 2012), usually applied to demographic, socioeconomic, interactions with the organization, sentiment, spatial-temporal, and social networks (Sobreiro et al., 2021).

The information that many organizations have about customers can support managers in decision-making, allowing for a greater understanding of customers, supported through the development of analyses on existing data (Nie et al., 2011). Analyses that can also be performed to predict the customer's intention to dropout or not (García et al., 2017). Machine learning can be used to predict customer churn (Sobreiro et al., 2021), using automatic pattern extraction to develop customer retention strategies based on existing data (Kelleher et al., 2015).

Machine learning is used to develop predictive models of churn that generalize the relationship between churn or non-churn, and historical data to predict future customer behavior, which is influenced by the input data and the algorithm used to develop the model (De Bock & Poel, 2011). The commonly used approach attempts to detect patterns related to customer churn.

The process for understanding when customers churn or what are the factors related to churn seems like a logical approach to developing preventative actions before a customer churns. Identifying, for example, customers who are likely to terminate the contract in order to be offered concessions or offers to retain it (Sivasankar & Vijaya, 2019).

Usually, existing studies approach the problem as a technical analysis or probability of events occurring, using artificial intelligence to predict the probability of a customer churning where it seeks to optimize predictive models without considering a business problem underlying the problem. This perspective

leads us to consider the interpretability, in addition to considering the prediction or not of dropout, we must also consider the possibility of extracting information that allows the development of actions, for example, information that we can use to develop measures in the context of marketing for the development of personalized ads (Kim et al., 2001).

The use of decision trees has the advantage of supporting the extraction of actionable information (Kim et al., 2001; Pan et al., 2007). Pan et al. (2007) suggests the use of the profiles identified in the decision trees most susceptible to dropout, to develop actions for retention. Pinheiro and Cavique (2018) proposed, for example, the adoption of workflows according to existing profiles, determined by decision trees.

Another type of approach we can use is survival analysis. The motives are related to the goal in the development of the survival analysis, which is to determine the probability of an event happening or not (e.g., customer dropout or not), the focus is given to the analysis of the time until dropout occurs, exploring its relationship with different variables. The main difficulty is related to the fact that at a given time, only some individuals have dropped out and the others have not.

Survival analysis, originating from biomedical statistics, is especially suited to the study of the moment when an event occurs in longitudinal data (Singer & Willett, 1993). This type of approximation allows you to examine not only whether an event occurred, but also how long it took to occur. However, the main advantage is related to the concept of censorship, which indicates the number of cases that are not complete for the dropout event, for example, the non-dropout customer that are also incorporated into the analysis. These customers are still active, and we don't know if the dropout event has occurred, which is considered censorship. Survival models incorporate this and improve the weather prediction for the event used, for example, in regression models, which only consider customers who have already dropped out, instead calculating the probability of the event occurring at a given time.

The survival analysis also considers individuals who have not yet dropped out, using the concept of censorship. Censorship indicates, for example, customers who have not yet given up, and who are incorporated into the analysis. This means that there are still active customers for whom we don't know if a dropout event has occurred. Censoring and incorporating uncertainty, instead of predicting the time of the event in regression models, survival models allow you to predict the probability of an event happening at a given time.

The time of dropout is represented by T , which is a non-negative random variable, which indicates the time period of the event occurring for a randomly selected individual from the population. T represents

the probability of an event occurring in each time period, given that it has not yet occurred in a previous time period, known as the discrete-time hazard function (Singer & Willett, 1993).

There are several challenges to identifying time related to quitting, considering the dynamic behavior of the customer intention to quit (Alboukaey et al., 2020), considering that this can change over time. The importance of understanding when dropout may occur is a dimension of the problem that must be considered, considering a temporal perspective, however few studies have addressed the problem with this perspective (Perianez et al., 2016; Burez & Vandenpoel, 2008).

Predicting dropout through survival analysis

This approach has advantages of developing a dynamic approach, as opposed to dropout prediction where we predict the risk of dropout at a given time. Here we consider that the risk of dropout varies over time. Survival models make it possible to capture a temporal dimension (Perianez et al., 2016), rather than considering only a binary outcome (dropout / non-dropout).

The simplicity in the use and interpretation of the Kaplan-Meier survival curve allows you to easily identify trends over time. The survival curve represents the probability of survival from a given point in time.

To construct the survival curves we need to determine the probability of survival p_i which is calculated with:

$$p_i = \frac{r_i - d_i}{r_i}$$

As an example, let's consider the customers of a sports facility, where r_i represents the number of customers who survived at the beginning of the period, d_i represents the number of customers who dropout during that period of time. With these elements we can build a table with the probabilities of survival.

Table 1 shows the probability of survival of the customers in the first 12 months with the p_i column. The median survival time was 14 months. Censorship represents customers who have not yet dropout, for example, in month 2, the value 517 in the censored column corresponds to customers with two months of membership in which the dropout event has not yet occurred during the time corresponding to the

completion of the study (between June 1, 1, 2014 and October 31, 2017), For example, customers who joined in September 2017. The probability of swimmers continuing in sport for more than six months was 73.5%, which represents a risk of dropout of 26.5% and an estimated survival of 17 months. The probability of retention of swimmers beyond 12 months was 53.0%, which represents a higher risk of dropout (47%) with an estimated survival of 22 months.

Table 1. Probability of survival in the first 12 months.

Event Month	Removed	Dropout	Censored	Risk of Dropout	pi	Estimated survival (months)
0	5	5	0	6747	.999	14
1	127	52	75	6742	.992	14
2	758	241	517*	6615	.955	13
3	439	433	6	5857	.885	15
4	372	340	32	5418	.829	16
5	346	299	47	5046	.780	17
6	319	274	45	4700	.735	17
7	406	356	50	4381	.675	20
8	268	198	70	3975	.641	20
9	240	183	57	3707	.610	21
10	294	230	64	3467	.569	22
11	206	149	57	3173	.542	22
12	103	71	32	2967	.530	22

Note: Removed – sum of customers where dropout was verified and that were censored; Censored – number of customers in which the dropout event did not occur in this period of time; Risk of Dropout – number of customers at risk of dropout; PI – probability of survival; Estimated Survival – number of estimated months of survival in the time period. Adapted from Sobreiro et al.(2022).

From the survival table we can construct the survival curves. For example, figure 1 represents the survival curve of a gym's customers. On the X axis is represented the number of months of adherence and probability of survival on the y axis. Dropout is very high in the first 12 months, ranging from a probability of survival of 54% after the first 6 months to 24% after 12 months.

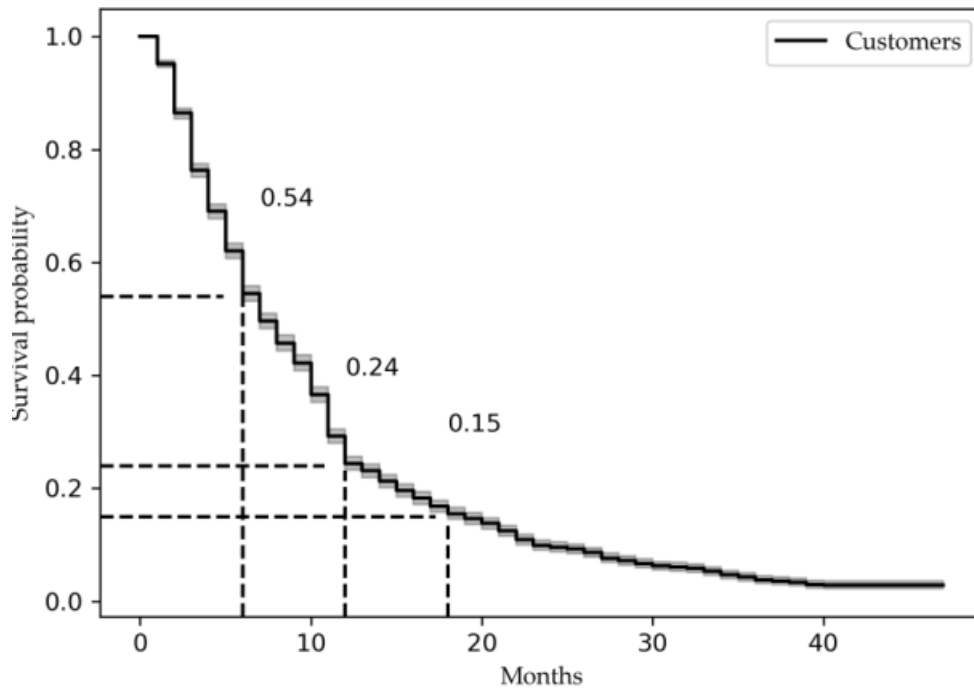


Figure 1. Kaplan-Meier survival curve.

Figure 2 represents the survival analysis considering the number of weekly visits of the customers, we can verify that the customers with 2 weekly visits present a much higher retention, with higher probabilities of survival, compared to customers who have 1 or 0 weekly visits.

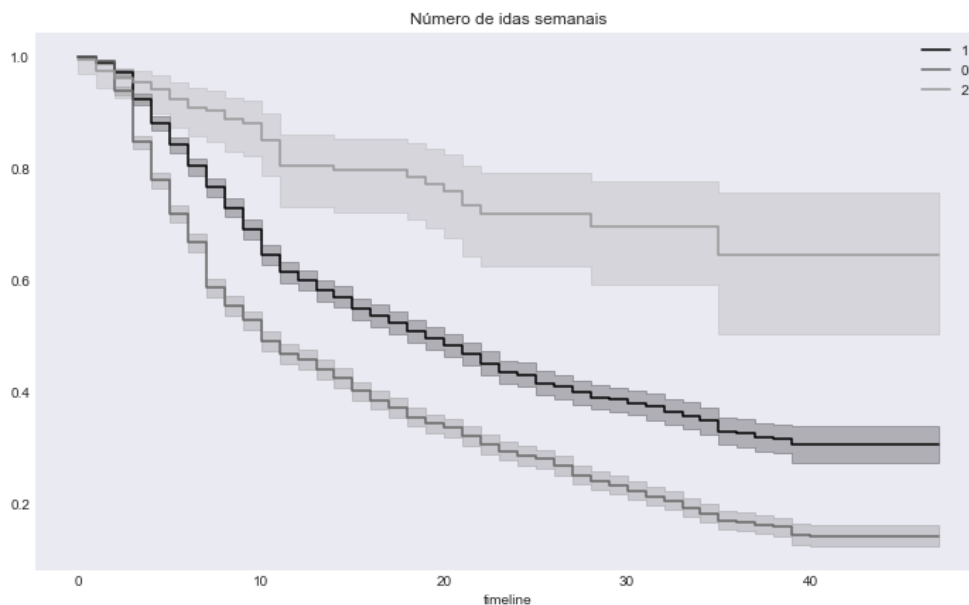


Figure 2. Survival analysis considering the number of weekly entries.

Another advantage in its determination is that it allows us to determine a revenue potential of each type of customers (enrolled in one activity or enrolled in two), for example if we consider a monthly fee of €43 and the curve corresponding to the survival of this type of customers we have a revenue potential of €857 if we multiply the probability in each month by the monthly fee value $0.99960254 \times 43 + 0.98926868 \times 43 + \dots + 0.13402511 \times 43$ over time.

Conclusion

The duration of the relationship between the customer and a company is a very important aspect, and it allows us to understand that the customer's decision to dropout changes over time. Some existing models that predict customer churn only consider the prediction at a particular point in time, not considering that it is a dynamic decision that changes over time. The customers's decision may change, in this sense it is important to also use survival analysis (Alboukaey et al., 2020).

The time perspective allows us to identify moments where retention actions can be developed. Overall, we can consider two dimensions in the prediction of dropout, one with a static perspective and the other with a dynamic perspective, considering that risk varies over time. With a static perspective, we have customer dropout predictions, which are carried out at a certain time, here we can use algorithms that are trained with test data (for model learning, where the machine learning concept comes from) to predict whether a customer dropout or not.

The time perspective allows us to identify the period in which retention actions should be developed; Therefore, the forecast should be as accurate as possible. However, the forecast should be as accurate as possible, customers who are about to churn but cannot be retained should be excluded from the countermeasures to avoid dropout, bearing in mind that their targeting may constitute a waste of scarce resources [15]. Addressing only the performance of predictive models, considering accuracy alone seems to be a reduced perspective, considering that customers with a the risk of beating may not be the best target for developing retention strategies.

It is essential to have quality data in information systems in sports organizations, combined with management guidelines for this purpose, this allows better results in obtaining fundamental indicators for decision making where information systems are fundamental. Machine learning enables the emergence and development of new analyses and approaches to support decision-making, an approach that can be complemented with models based on survival analysis to use independent variables and evaluate the impact on the time spent in sports activities or organizations.

With this type of approach, sports organizations can develop strategies aimed at customer retention, considering that they can anticipate customers at risk or when dropout occurs. Decision trees can be used to develop measures to counteract dropout in profiles with higher dropout risks. This type of information can support the development of retention strategies, contributing to a greater sustainability of organizations and simultaneously to the maintenance of physical activity. And this type of analysis allows us to extract patterns, however, aspects related to motivation or why quitting will have to be developed with other approaches that have not been described, an aspect that is complementary and very important in understanding quitting.

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04

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05

R&D ACTIVITIES

- **Invitation for publication in Healthcare journal:**

The researcher Prof. Dr. Roberta Frontini is the guest editor of a special issue with the topic: *Research and Survey on Mental Health of Children and Adolescents*. Deadline for manuscript submissions: 30 November 2023. For more information [CLICK HERE](#)

- **Invitation for publication in Healthcare journal:**

The researcher Prof. Dr. Rafael Oliveira is the guest editor of a special issue with the topic: *Supporting Athlete Development: The Role of Supporting Structures*. Deadline for manuscript submissions: 31 December 2023. For more information [CLICK HERE](#)

- **I&D projects in the scientific areas of CIEQV:**

For more information [CLICK HERE](#).

06

CALLS AND FUNDING

- Calls for support to *Turismo*, START-PME. Status: open. For more information [**CLICK HERE**](#)
- Calls for support to *Programa de Desenvolvimento Rural*, START-PME. Status: in preparation. For more information [**CLICK HERE**](#)
- Calls for support to *Plano de Recuperação e Resiliência*, START-PME. Status: open. For more information [**CLICK HERE**](#)
- Calls for support to *Programa ATIVAR.PT*, START-PME. Status: open. For more information [**CLICK HERE**](#)
- Calls for support to *Apoio à Produção Nacional*, START-PME. Status: open. Deadline: to be defined. For more information [**CLICK HERE**](#)
- Calls for support to *Programa de Incentivo para os Açores*, START-PME. Status: in preparation. For more information [**CLICK HERE**](#)
- Calls for support to *Apoios à contratação – IEFP*, START-PME. Status: open. For more information [**CLICK HERE**](#)
- [**HORIZON-EURATOM-2023-NRT-01**](#). Deadline: 8 November 2023. For more information [**CLICK HERE**](#)
- [**Cluster 2 - Culture, Creativity and Inclusive Society**](#). Deadline: 7 February 2024. For more information [**CLICK HERE**](#)

07

SCHEDULE

- **13th International Conference on Health and Social Care ICT (HCist 2023)**, 8-10 November, Porto, Portugal. For more information **CLICK HERE**
- **Jornadas Científicas da Saúde da Lusofonia**, 10 November, online. For more information **CLICK HERE**
- **44e session d'études de l'ADMEE - Canada - De l'aube au crépuscule des réformes: les apports des méthodologies de l'évaluation**, 9-10 November 2023, Château de Frontenac, Quebec. For more information **CLICK HERE**
- **27as Jornadas de Endocrinologia e Diabetes de Coimbra**, 10-11 November 2023, Coimbra, Portugal. For more information **CLICK HERE**
- **VI Jornadas de Enfermagem Perioperatória de Leiria**, 16-17 November 2023, Batalha, Portugal. For more information **CLICK HERE**
- **Congresso Internacional da Inclusão Socioprofissional**, 22-23 November 2023, Figueira da Foz, Portugal. For more information **CLICK HERE**
- **ICCE Global Coach Conference**, 29 November – 3 December 2023, Singapore, Singapore. For more information **CLICK HERE**
- **WCQR2024 - 8th World Conference on Qualitative Research**, 23-25 January 2024, São Miguel, Açores & Johannesburg, South Africa & online. For more information **CLICK HERE**
- **CONGREGA 2024 - 1st Ibero-American Congress on Engineering Asset Management**, 3-5 July 2024, Lisbon, Portugal. For more information **CLICK HERE**
- **IX Seminário Ibero-Americano CTS XIII Seminário CTS**, 8-10 July 2024, University of Aveiro. For more information **CLICK HERE**