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Scientifically validated applications for monitoring the practice of physical activities and energy expenditure using the smartphone accelerometer: a integrative review

Aplicativos cientificamente validados para monitorar a atividade física e o gasto de energia usando o acelerômetro de smartphone: uma revisão integrativa

Aplicaciones científicamente válidadas para monitorear la práctica de actividades físicas y el gasto energético utilizando el acelerómetro del teléfono inteligente: una revisión integrativa

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Abstract
Introduction: Mobile technologies, especially smartphone applications, have contributed a lot in the area of health and physical activity, but there is an increasing concern with the validation criteria of these tools. It is extremely important to know if the physiological parameters used are safe and reliable to promote and monitor the practice of physical activity. With technological innovation, it is possible to process the data of accelerometer to measure energy expenditure. Objective: this study searched for evidence of scientific validation in Apps that uses smartphone's accelerometer as energy expenditure indicator. Method: The keywords, inclusion and exclusion criteria were defined. The selected articles were categorized using an adapted questionnaire. Result: In a total of 1923 articles, eight articles meted all inclusion criteria that developed and validated apps for physical activity analysis. Conclusion: The results induced the effectiveness of smartphone's accelerometer to recognize physical activity and energy expenditure. It can be used to encourage healthy and safe practices, leading to improvements in quality of life. The limited number of articles with scientifically validated Applications indicates the need for more research.
Keywords: Apps; Smartphone; Energy expenditure; Accelerometers; Physical activity.

Resumo
Introdução: As tecnologias móveis, principalmente os aplicativos para smartphones, têm contribuído muito na área da saúde e atividade física, mas existe uma preocupação crescente com os critérios de validação dessas ferramentas. É extremamente importante saber se os parâmetros fisiológicos utilizados são seguros e confiáveis para promover e monitorar a prática de atividade física. Com a inovação tecnológica, é possível processar os dados do acelerômetro para medir o gasto de energia. Objetivo: este estudo buscou evidências de validação científica em aplicativos que usam o acelerômetro de smartphone como indicador de gasto de energia. Método: foram definidos os descritores, critérios de inclusão e exclusão. Os artigos selecionados foram categorizados por meio de questionário adaptado. Resultado: em um total de 1923 artigos, oito artigos atenderam a todos os critérios de inclusão que desenvolveram e

validaram aplicativos para análise de atividade física. Conclusão: Os resultados induziram a eficácia do acelerômetro do smartphone em reconhecer a atividade física e o gasto energético. Pode ser usado para estimular práticas saudáveis e seguras, levando a melhorias na qualidade de vida. O número limitado de artigos com aplicações validadas cientificamente indica a necessidade de mais pesquisas.
Palavras-chave: Apps; Smartphone; Gasto energético; Acelerômetros; Atividade física.

Resumen
Introducción: Las tecnologías móviles, especialmente las aplicaciones para teléfonos inteligentes han contribuido mucho en el área de la salud y la actividad física, pero existe una preocupación creciente por los criterios de validación de estas herramientas. Es de suma importancia saber si los parámetros fisiológicos utilizados son seguros y fiables para promover y controlar la práctica de la actividad física. Con la innovación tecnológica, es posible procesar los datos del acelerómetro para medir el gasto energético. Objetivo: Este estudio buscó evidencia de validación científica en aplicaciones que utilizan el acelerómetro de los teléfonos inteligentes como indicador de gasto de energía. Método: Se definieron las palabras clave, los criterios de inclusión y exclusión. Los artículos seleccionados se categorizaron mediante un cuestionario adaptado. Resultado: En un total de 1923 artículos, ocho artículos cumplieron con todos los criterios de inclusión que desarrollaron y validaron aplicaciones para el análisis de la actividad física. Conclusión: Los resultados indujeron la efectividad del acelerómetro de los teléfonos inteligentes para reconocer la actividad física y el gasto de energía. Se puede utilizar para fomentar prácticas saludables y seguras que conduzcan a mejoras en la calidad de vida. El número limitado de artículos con aplicaciones validadas científicamente indica la necesidad de realizar más investigaciones.
Palabras clave: Apps; Smartphone; Gasto energético; Acelerómetros; Actividad física.

1. Introduction

According to the World Health Organization (WHO), 6% of deaths worldwide are due to physical inactivity, ranking fourth in the global risk of mortality. People who are insufficiently active have a 20% to 30% increase in the risk of all causes of mortality (Organization, 2009). Physical inactivity is also related to the onset of chronic non-communicable diseases (CNCDs), such as cardiovascular disease, hypertension, obesity, diabetes, colon cancer, osteoporosis and depression, which makes measuring physical activity (PA) in real life a relevant research topic (Warburton et al., 2006). For this, it is important that the PA evaluation methods identify the type and measure the energy expenditure (EE), duration and intensity (Hills et al., 2014).

Information and communication technologies (ICT) present a series of innovations capable of assisting in the evolution of healthy lifestyles and enhancing public health initiatives (Guillén et al., 2009). New technologies have provided knowledge in the area of health and quality of life, which make them accessible and facilitate the sharing of clinical information (Goulart et al., 2006). The development of mobile computing in recent years and the use of smartphones has favored solutions that use sensors and applications (Apps) for the benefit of health and well-being (Junior et al., 2011).

This expansion has created opportunities for monitoring relevant data in non-clinical environments (Appelboom et al., 2014). The average speed of data traffic per smartphone in 2018 was 13.2 megabits per second (Mbps), compared to 17.7 Mbps per month in 2019, and average usage grew by 25.4% in 2019 (*Cisco Annual Internet Report - Cisco Annual Internet Report (2018–2023) White Paper*, [s.d.]). Given these data, software companies for smartphones constantly launch and update Apps in the segment of PA and health. Currently, more than 100,000 mHealth Apps are available on the Android and iOS mobile store. And the forecast is that this number will grow with the development of technologies and health care, but there is a growing concern with the scientific validation criteria of these tools, since little information based on research for the development of Apps is available. In addition, star ratings and comments about Apps published on the Apple Store and Play Store are subjective and come from suspicious sources (Kuehnhausen & Frost, 2013; Pires et al., 2020). The choice of Apps based on popularity has little or no significant scientific information (Girardello & Michahelles, 2010). Meanwhile, much of the published literature on the topic focuses on technical aspects of websites that do not assess the quality of these resources (Aladwani & Palvia, 2002; Olsina & Rossi, 2002; Seethamraju, 2004). In the PA and health segment, the use of instruments that assess the individual's activity level and his / her EE is extremely relevant, as it allows the collection of more accurate information about the users' daily lives and their physical needs. It is extremely important to know what extent this means of promoting and monitoring the practice of PA is really safe when developed without the use of scientific parameters by health professionals. In view of this concern, the following questions arise: which are the Apps that have undergone scientific validation? And if reliable data are presented that can be used by users without putting their health at risk? In order to answer these questions, the objective of this study is to present Apps that have undergone scientific validation in the PA and quality of life aspect and that use the accelerometer sensor of the smartphone itself to measure the EE.

2. Methodology

2.1 Research strategies

The research was carried out by searching the electronic databases Pubmed, ScienceDirect, Web of Science, Scopus, IEEE Xplore and CINAHL. The Google Scholar database was not used due to the large number of works that appeared during the search, and the impossibility of adding filters for a more refined search focused on articles of our interest. The search in the databases was carried out using the following keywords: Apps, smartphone, energy expenditure, accelerometry, physical activity, smartphone software, mobile application. The keywords were selected according to the most frequent terms, which were translated according to the research language (Portuguese, Spanish and English). The search terms were based on Boolean logic using the combination of the following terms in English: ((smartphone software) OR (mobile application) OR (smartphone apps) OR app) AND (energy expenditure) AND (accelerometry OR accelerometer) AND (physical activity).

2.2 Inclusion criteria

One of the initial criteria was to include only studies that analyzed or developed Apps that used the accelerometer on the smartphone itself to measure the EE and submitted the Apps to criteria for scientific validation. However, no articles were found that were in agreement with the initial intention, therefore, studies that developed validation tools or evaluated some Apps were also included. These studies used Apps related to health and quality of life and were developed for the iOS and Android operating system and can be used by children, adults or the elderly, as well as Apps developed specifically for a disease. The search was expanded to articles written in English, Portuguese and Spanish and were analyzed retrospectively from 2010 to 2020. This period was selected considering that in 2010 smartphones were launched commercially with more accurate internal accelerometers capable of collecting data related to EE. The selection and evaluation of the studies were carried out through a questionnaire adapted to categorize and classify the articles that met the criteria of this integrative review.

2.3 Exclusion criteria

The exclusion criteria were applied to studies that were not developed on the iOS and Android operating system.

2.4 Data extraction and synthetization

In the initial selection and evaluation of the articles using the form adapted from (Fournier et al., 2020) (Attachment 1), those who had no relation to the subject according to the title and abstract were excluded. In the second stage of the selection, the complete texts were obtained and, afterwards, the studies were selected, independently, by two researchers.

The selected articles were categorized using a questionnaire adapted from (Fournier et al., 2020) (Attachment 2):

Based on completing this questionnaire, the following classification criteria were proposed:

A) It presents very relevant data, low risk of bias, meets all inclusion criteria and obtains "yes" in response to all questions;

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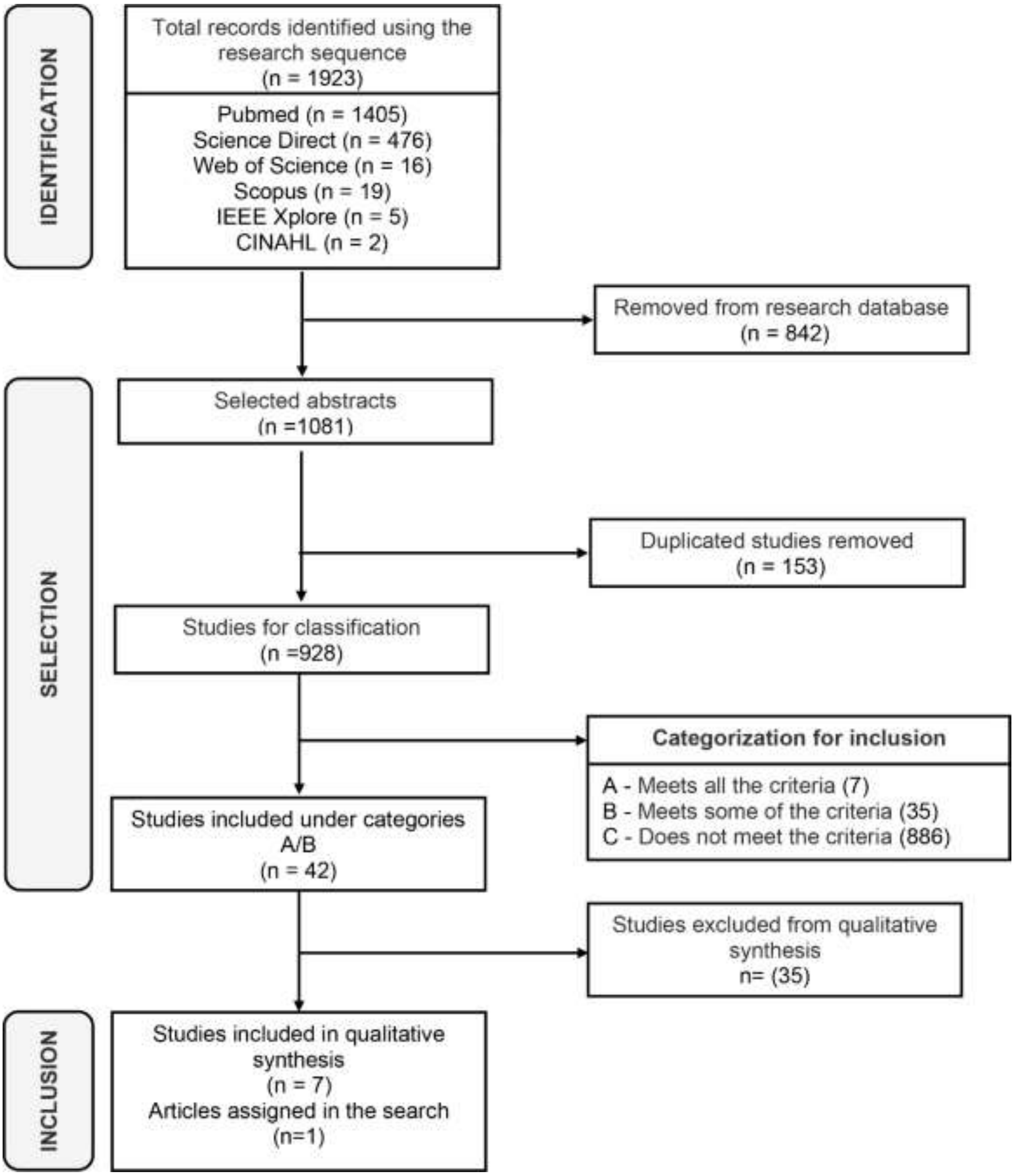
B) Presents relevant data, moderate risk of bias, meets some inclusion criteria, gets "yes" in response to at least two questions;

C) Does not present relevant data, high risk of bias, does not meet the inclusion criteria and obtains "yes" in response to a maximum of 1 question.

An initial survey of 1923 articles were carried out. Articles classified in category "A" and "B" were included and articles classified "C" were excluded.

Figure 1 shows the information flowchart, according to the selection and classification criteria.

Figure 1. Research flowchart indicating the methodology applied in conducting the integrative review.



Note. Consort flow diagram. Source: Authors’ own diagram.

It is observed that in Figure 1 the scarcity of studies that validate Apps that used the smartphone's internal accelerometer as a tool for data collection and EE measurement. From the initial survey, 7 articles were selected that met the inclusion criteria and another 1 that was not found in the searches due to the keywords, but of great importance to be cited in this work.

3. Results and Discussion

The study categorization and classification instrument were used effectively and contributed to the selection of articles. Eight articles were selected that met the inclusion and exclusion criteria. These studies described the development and validation of Apps with the smartphone's own internal accelerometer.

The selected articles, after applying the categorization and classification forms, will be presented below with their respective search strategies for validating the Apps. Draw 1 illustrates the answers to the selection criteria formulated for scientific articles obtained from indexed databases.

Draw 1. Answers to form questions for each of the eight articles included in the integrative review.

Studies	Criteria			
	1) Does the study meet the analysis requirements and present data that prove the scientific validation of the application?	**2)** Will the studied variables serve as a reference for safe use and with a lower rate of inconsistencies in the data?	**3)** Did the App developers use appropriate ways of defining variables, ways of measuring and presenting results?	**4)** The results of the study provide the reliability of the App?
(Easton et al., 2014)	Triaxial accelerometers on the HTC and Samsung platforms were validated by comparing the measurements of the accelerometer with indirect calorimetry data.	The app is consistent for walking speeds of 4, 5 and 6 km / h and then for running speeds of 8 and 20 km / h with a 0% gradient with each stage separated by 3 minutes of active recovery	The authors clearly define the variables used in the experiment in the experimental protocol. That is, duration of the protocol, speed, speed gradient and measurements collected by indirect calorimetry	The EE reliability and acceleration measured between the tests performed were assessed using intraclass correlation coefficients (ICC). The Bland-Altman method was not used to correct the concordance.
(Dunton et al., 2014)	The authors evaluated the App's performance with the ActiGraph accelerometer monitor (ACT + MT) and also the ActiGraph (ACT) separately.	The software is fully customizable and flexible to accommodate different activity thresholds or time and movement intervals.	The App uses motion detection and the transition between these states for self-report surveys.	The self-report can be used to increase the physical activity data collected by the accelerometer, filling gaps in the accelerometer data collection.
(Pande et al., 2015)	The collected data used an Android App and a COSMED K4b2 calorimeter was used to validate the readings and measure the actual energy expenditure.	It used data combining the readings of accelerometer and barometer sensors, as it allows obtaining greater correlation and precision for reference of values.	A generic regression model was developed to estimate energy expenditure that produces up to 96% correlation with actual energy expenditure.	The results were compared with the latest generation calorimetry equations and consumer electronic devices (Fitbit and Nike + FuelBand).
(Costa et al., 2016)	The developed equations used a TriTracR3D to verify the linear relationship between the accelerometer data and the energy expenditure estimation.	The collected data set made it possible to develop reliable tools for comparing results.	The collected data sets were analyzed using the energy expenditure equations already validated.	The study presents comparison tables of results with reference values correlated with energy expenditure.
(Guidoux et al., 2017)	The EE was compared with the Armband and Actiheart sensors validated in other studies.	Transformed acceleration data into PA and EE levels with different smartphone placements.	An EE measurement function was defined considering different PA categories.	It presented relevant results of accelerometry relating them to the tables in the Compendium of Physical Activities.

(Maddison et al., 2017)	It performed the comparison with indirect calorimetry and a stand-alone accelerometer and verified the validation of the collected data.	It presented valid measurement of PA at low and moderate levels of intensity.	The authors suggest that the measurement has the estimates of equivalent groups and made a comparison with the EE by indirect calorimetry and with the EE estimate from the ActiGraph movement counts, making an association between measurements and absence of systematic bias.	It uses indirect calorimetry as a reference and the integration of GPS data.
(Rodriguez et al., 2019)	Two smartphones were used in the study, and next to them a GT3X + accelerometer to validate and compare the results of the tests performed.	Four different algorithms have been proposed to calculate the activity count, resulting in a sampling period of 20 ms (50 Hz). There was some variability due to the time constraints of smartphones.	The authors used 4 different algorithms for further offline analysis using Matlab, namely: time domain filtering, histogram, power spectrum bands and accelerometer signal area	This study indicated the levels of physical activity defined conventionally in the literature can be measured with smartphones. Tests classified one of the most efficient algorithms used.
(Faria et al., 2019)	The authors analyzed the GT3X ® ActiGraph accelerometer and Google Fit ® smartphones when measuring the GE compared to the gold standard measurement of the Cortex Metamax 3B® ergospirometer	This study investigated the validity of the GT3X® ActiGraph accelerometer and Google Fit® smartphones in estimating the energy expenditure of individuals who suffered a stroke during a brisk walk on the ground.	Pearson's correlation coefficients were used to verify the associations between energy expenditure measures in kilocalories (kcal), estimated by the devices and those obtained with the Cortex Metamax 3B ® ergospirometer.	The results of the present study demonstrated that the GT3X ® ActiGraph accelerometer and the Google Fit ® smartphone app compared to the gold method during a brisk walk on the ground, did not provide valid measurements of EE in individuals with chronic stroke

Source: Authors.

The work of (Easton et al., 2014) verified the validity and reliability of the EE measurement using triaxial accelerometers incorporated in the High-Tech Computer Corporation (HTC) platforms and Samsung smartphones. Two tests were performed: i) Walking test at speeds 4, 5 and 6 km / h, and ii) Running test at speeds of 8, 10, 12, 14, 16, 18 and 20 km / h, or up to voluntary exhaustion. The test time was 3 min at each speed and for speeds above 10 km / h there was a 3 min recovery. The acceleration was recorded in the three axes of movement of the accelerometer of each device and was expressed as the magnitude of the vector (VM). To analyze the reliability of the accelerometry and EE data, the results of both tests were evaluated using intraclass correlation coefficients (ICC). The relationship between EE and the VM acceleration was established using Pearson's correlation coefficient, with significant statistical values for $P <0.05$. This work showed that the triaxial accelerometers embedded in Samsung and HTC devices are reliable and valid in tests of fast running and measuring EE. The EE result was significantly correlated with HTC VM ($r = 0.98$, $p <0.001$) and Samsung VM ($r = 0.99$, $p <0.001$).

The study by (Dunton et al., 2014) describes Mobile Teen, an application (App) developed for a smartphone. This App uses the objective assessment method and the self-report through the context-sensitive momentary ecological assessment (CS-EMA), informed by sensors, and end-of-day recovery (recall) through sensors. The physical activity information obtained by the self-report collected through the App can be used to increase the reliability of the objective data collected by the smartphone's internal accelerometry sensor. The data collected by the App has a great importance to improve research and practice of physical activity. It appears that self-report data can significantly improve understanding of any failure of the accelerometer, as well as information about how the smartphone is transported. With this, researchers can understand the importance of placing the smartphone on the body for the assessment of activity using the smartphone's internal accelerometer.

The collected information can be used to adjust the EE estimates for activities that are not well collected by motion sensors positioned on the waist such as cycling and weight training. The data reported by the accelerometer and the recall can be used to differentiate types of activities, such as doing homework or playing football, which can appear identical when examining objective intensity data. The contextual and psychosocial information collected by the App can be used to test hypotheses about environmental, social, motivational and emotional correlates in real time. Making it possible to compare the individual's state during physical activity and after, and in the absence of activity. Smartphone Apps like these have the potential for large-scale intervention studies. It is noteworthy that the study by (Dunton et al., 2014) is a qualitative study.

The study by (Pande et al., 2015) analyzed the EE estimate using sensors embedded in a smartphone (accelerometer and barometer sensor), for activities such as walking, standing, going up or down stairs. A generic regression model was developed that provides a correlation up to 96% of the EE estimate in relation to the real value. The portable metabolic system COSMED K4b2 was used as a reference instrument to measure the EE of physical activities. Simultaneously, the smartphone's accelerometer and barometer sensor, which contained customized software, recorded the events and recorded the data in a csv file. The research used as resource vectors (FV: feature vectors) user demographic information, accelerometer sensor data and barometer values, which are useful to recognize activities and improve data accuracy. At the end of the study, a significant result was observed in the data obtained from the junction of the barometer sensor and the accelerometer sensor, as they allow, with the use of PV, to obtain greater correlation and precision for the EE reference values. Obtaining the RMSE value, which is the mean square error, was 0.70.

(Costa et al., 2016) proposed to explore available and accessible technologies, which do not require extra equipment to assess physical activity. The solution presented in the study, improves the use of common technologies, such as accelerometer sensors that are present in smartphones. A linear and a nonlinear model was used to estimate EE in activity. And as a reference value, a MET calculation was used, where a very accurate estimate of EE per minute can be obtained. The set of information collected allowed access to data from different PAs and on different devices, enabling the development of reliable tools to compare the individual's evolution over time. After analyzing the data, an average correlation of EE was observed between the reference values and the linear model. The work also analyzed activity recognition using a subset of the classifiers available in Weka version 3.8.0. Through the tests carried out, the combination of the Multilayer Perceptron (MP), with the implementation of the decision tree (J48), obtained the best results to identify each of the activities. Activity recognition was performed to assess the efficiency of the accelerometry values in an absolutely unrestricted environment. The application worked with acceptable accuracy for a limited set of activities (running, volleyball, handball, basketball and futsal).

The study by (Guidoux et al., 2017) aimed to use the advantages of accelerometers embedded in smartphones, to provide EE estimation model with a new signal transformation function. The individuals who participated in the study wore an Android smartphone (Samsung Galaxy xCover or LG Nexus4) in their left pocket. At the same time, they used the Pro3 SenseWear Armband® monitor (Bodymedia version 6.0, Pittsburgh, PA, USA) on the right arm triceps, and below the chest the Actiheart® sensor (CamNtech, Cambridge, UK). In this study, an energy consumption verification function (Pred EE) was developed considering the duration, the metabolic cost and four categories of PA related to intensity and associated with Metabolic Equivalent Tasks (MET). 1. Very light: it is associated with very low intensity activities, such as sitting or lying down. 2. Light: it is associated with low intensity activities such as slow walking. 3. Moderate: Activities such as slow or fast walks and going downstairs are associated. 4. Vigorous: includes more intense activities, such as running or climbing stairs. To create an effective function, the method consists of classifying the signals collected by the accelerometer and transforming them into intensity categories, associating each category with the MET, which is the energy cost of an activity. The comparison between Pred EE and Actiheart® shows that the time spent in category 1 was significantly underestimated by 10.1% ($p = 0.0006$). in relation to activities in categories 2 and 3, they were slightly overestimated by Pred EE, 7.9% and 4.2%, respectively ($p = 0.004$ and $p < 0.0001$, respectively). Regarding the values obtained by Armband®, all four categories of activities were evaluated in a similar way.

(Maddison et al., 2017) carried out a cross-sectional two-phase study to validate the EE calculation for the smartphone App, Movn (Moving Analytics), during daily activities and human movement patterns. The first phase was carried out in the laboratory on treadmills, with light to vigorous intensities, and daily activities in free environments. The second phase was cross-validation during laboratory activities between a separate sample of participants. The protocol compared indirect calorimetry to a stand-alone accelerometer, ActiGraph Corp, which is normally used in EE research. And statistical analyzes were performed using the Statistical Package for the Social Sciences (SPSS) version 21 for Windows (IBM Corp). A multivariate regression model that included Movn activity counts and participants' body mass was the strongest predictor of the measured EE ($r = 0.83$; SEE = 1.94 kcal / min). An acceptable absolute measurement agreement was observed, within the 95% agreement limits for the EE biases, which were moderate in most intensity levels. There was slightly greater variation at faster speeds (10-12 km / h). The measurements obtained by App Movn and the EE were strongly correlated ($r = 0.91$, ICC = 0.95, both $p < 0.001$), indicating excellent agreement between the measurements. As a result of the study, App Movn provided valid measures of EE at low and moderate activity levels. However, in the most intense activities, there was a greater variation in the results.

Rodriguez et al. (2019) aimed to verify four algorithms (A1-A4) to process data from smartphone accelerometers and compare them with the results of the Actigraph accelerometer (GT3X +). The influence of the location of use of the smartphone was also investigated, and the data were compared with the Wilcoxon test. The activities carried out in the experiment were walking at low and high speed, going up and down stairs and working in the office. These activities were performed with individuals carrying two smartphones (one, on the hip; and another, in the pocket) and the GT3X + placed on the hip. The A1 algorithm was based on a posterior calculation of the area under the curve and a traditional filtering in the temporal domain. A2, using histograms, the acceleration values were calculated, used as independent variables in a standard linear regression. A3 used linear regression, but with other independent variables, bands of the power spectrum, which generates a kind of filtering in the frequency domain. And the A4 was based on a direct measurement of the area under the rectified curve of the accelerometer's raw signal. The Quade test was used to analyze the influence of the algorithm, using the Wilcoxon test with Bonferroni correction, multiple comparisons were verified. The authors used the correlation (Pearson and Spearman) and the agreement (intraclass coefficient, ICC graphs, Bland-Altmann for gross counts, and weighted kappa for activity levels) in the data obtained from the algorithm used, and compared with the counts of the GT3X +. The A4 algorithm obtained a lower error rate, and because it was the simplest, it used the least battery of the smartphone. Regarding the comparison of the GT3X + and the A4, the agreement (ICC = 0.937), correlation for raw counts (spearman = 0.927), and when classifying four or two levels of PA (weighted kappa = 0.874 or 0.923 respectively) noting good agreement results. Regarding the place where the smartphone is used, the study shows that it is not a critical parameter for obtaining the results, and that they are consistent with the results obtained in other studies. However, the use of the smartphone on the hip made it possible to better predict the counts of the GT3X +, but the difference is not statistically significant.

(Faria et al., 2019) examined the validity of the GT3X ® ActiGraph accelerometer and the Google Fit ® smartphone App in measuring EE compared to the gold method, the Cortex Metamax 3B® ergospirometer, in people who suffered stroke. The exercise performed was to walk back and forth in a 10-meter flat, straight corridor for 5 min, at maximum speed. The Shapiro-Wilk normality test and descriptive statistics were performed using the SPSS software (version 19.0). Pearson's correlation coefficients were used to verify the associations between EE measurements in kilocalories (kcal), estimated by these two devices, and also those obtained using the Cortex Metamax 3B ® ergospirometer. For correlation analysis, cutoff values were stipulated, being: 0–0.25: little or none; 0.26–0.50: reasonable; 0.51–0.75: moderate to good; and> 0.75 values from good to excellent. The results of the GT3X ® ActiGraph were about 55% higher than those obtained by the gold standard measurement. At the end of the tests, an association was found between the EE values calculated from the ActiGraph GT3X® in comparison with the gold standard values (r = 0.37; p = 0.04). The results of the Google Fit® App, did not show significant associations between the EE and the results of the gold standard method. The work concluded that the research carried out during a brisk walk with the GT3X ® ActiGraph accelerometer and the Google Fit ® smartphone App did not reach valid measurements of EE in individuals with chronic stroke. The GT3X ® ActiGraph equations are generally used to predict the EE of healthy individuals, as they may not be the most suitable for predicting the EE of individuals with stroke.

The studies presented were selected from the application of a categorization and classification instrument, which significantly helped in the selection of articles. The questions raised for this integrative review are in accordance with the inclusion and exclusion criteria determined by the author. Through this instrument, it was possible to reach the selected articles objectively. Draw 2 presents the questions applied with the respective answers to each article.

Draw 2 - Technical differences found in the articles.

	(Easton et al., 2014)	(Dunton et al., 2014)	(Pande et al., 2015)	(Costa et al., 2016)	(Guidoux et al., 2017)	(Maddison et al., 2017)	(Rodriguez et al., 2019)	(Faria et al., 2019)
Pilot Group	**	4	**	**	**	21	**	**
Experimental Group	11	6	12	18	30	42	32	30
Pilot Age	**	14/17 years	*	**	**	19/34 years	**	**
Experimental Age	*	14/17 years	22/29 years	*	22/44 years	22/29 years	*	50/74 years
Pilot Sex	**	*	**	**	**	13F/8M	**	**
Experimental Sex	2F/9M	4F/2M	*	7F/11M	15F/15M	15F/27M	13F/19M	9F/21M
Smartphone usage location	There was no specific location	*	Waist bag	Waist	Left pants pocket	Right Hip and Right iliac crest	Right pocket and Right hip	Paretic lower limb and Front pants pocket
Applications	*	Mobile Teen	*	*	eMouveRecherche	Moving Analytics (Movin)	*	Google Fit App
Operational System	Android	Android	Android	Android	Android	Android 4.3 and 2.3.3	Android	Android
Smartphone Model	Samgung (without model specification)	LG Nexus 4	Galaxy Nexus	*	LG Nexus4 and Samsung Galaxy xCover	Moto G and Samsung Galaxy Nexus S	Samgung Galaxy Trend PLUS GT-S7580	LG Nexus 5
Sampling rate	15 a 20 Hz	10 Hz	2 Hz	*	6Hz	50 Hz	50 Hz	*

Note. * Non-descriptive information in the text; ** There is no data; Source: Authors.

4. Discussion

The results of this integrative review indicate that smartphone applications developed to monitor EE through the internal accelerometry sensor are still very restricted. Even with all the advantages of having a sensor in hand, the development of validation studies is very small, with only 8 scientific articles from an initial survey of 1923 being found that could be analyzed in greater depth according to Draw 1.

The determination of EE for the human body provides important information about its level of PA and helps to prevent chronic diseases (Pande et al., 2015). EE can be measured using gold standard techniques that measure with precision and accuracy, but these methods have a high cost of application. There are alternative methods of predicting EE, these do not guarantee maximum precision, but offer better portability and accessibility, through sensors incorporated in a smartphone (Costa et al., 2016; Pande et al., 2015).

According to the authors mentioned in Draw 1, the validation methodology of the applications that monitor the practice of physical activity are different according to the applications used. (Easton et al., 2014)that although it was not found in the searches due to the authors used, it is of great importance to quote, since it validated triaxial accelerometers on the HTC and Samsung platforms, comparing the measurements of the triaxial accelerometer with indirect calorimetry data. (Pande et al., 2015), compared the data collected by the application with a COSMED K4b2 calorimeter to validate the readings and measure the EE in daily activities. In another study, (Rodriguez et al., 2019) used two smartphones, and beside them a GT3X + accelerometer to validate and compare the results of the tests performed.

We can also identify some of the variables used by the authors (Costa et al., 2016), who followed the study by (Chen & Sun, 1997), where two models of common use were proposed to estimate EE in activity: a linear and a non-linear model. The EE measured by the linear model underestimated the total energy expenditure in relation to the values obtained by the calorimeter. The non-linear model improved the calculation of EE in daily activities, improving standard errors of estimate. (Maddison et al., 2017) made a protocol for testing in a controlled laboratory environment and the other for free living to derive EE estimates from the application activity counts. For analysis, multivariate regression was performed following established methods to identify the strongest relationship between the app's activity counts, participants' characteristics and EE measured by indirect calorimetry. The criterion and convergent validity of the EE App measure were evaluated in comparison with the EE measured by indirect calorimetry during laboratory activities.

The works by (Kooiman et al., 2015; Lee et al., 2014) were not included in Draw 1 because they are studies that used accelerometers embedded not only in smartphones, but also in electronic devices. (Lee et al., 2014) investigated the accuracy of eight types of activity monitors, which were used simultaneously to analyze the EE estimate in healthy adults, the values obtained were compared with a portable metabolic analyzer, Oxycon mobile 5.0. At the end of the study, the authors observed favorable results from some monitors. In the study by (Kooiman et al., 2015) ten types of monitors in free life and in laboratory conditions were analyzed, including an App for smartphones. For comparison with the gold standard method, the Optogait system (OPTOGait, Microgate SrI, Italy, 2010) was used under laboratory conditions. ActivPAL (PAL Technologies Ltd., Glasgow, UK), which is also a gold standard method, was used in the free-living condition. Through the intraclass correlation coefficient (ICC), they reached reliability values. Three of the ten trackers obtained excellent results (ie, ICC> 0.90). And the result of the App used was low (ICC <0.60). Although of great importance in this theme, it should be noted that the works did not enter the analysis due to the inclusion criteria and the keywords that describe the work of these authors.

Another difference found in the studies reported in Draw 1 refers to the technical differences described in Table 1. For example, the sampling frequency used to capture data from smartphones was 6 Hz for (Guidoux et al., 2017) and 10 Hz for Dunton et al., 2014, and only 2 Hz in the work of (Pande et al., 2015), who reported the use of this reduced value to preserve the smartphone's battery. Other studies, such as that of (Bouten et al., 1997), show that a frequency of 0.1-20 Hz is appropriate for detection, but with a lower precision index (Bouten et al., 1997). We also found some differences summarized in Table 1, corresponding to the validation protocol, for example, (Dunton et al., 2014) validated the App through two tests, the first with 4 individuals and the second with 6, with a total of 10 research participants, the subjects' age was not clearly informed. With a relatively larger number of individuals, (Maddison et al., 2017) validated the App also from two tests, the first with 21 individuals and the second with 42, the research participants were aged 20 to 55 years old in the first test and 18 to 33 years old in the second.

It can also be seen that each protocol used in the works was validated for specific activities, as for example in the work of (Faria et al., 2019), brisk walking was the activity analyzed in patients who suffered a stroke and the location where the smartphone was used was on the paretic lower limb, more precisely in the front pocket. In the work of (Easton et al., 2014), two exercises were performed, walking and fast running in well-trained medium and long-distance runners. The location of use of the device was not included in the study. (Rodriguez et al., 2019) applied the tests in a greater diversity of activities. The activities were, walking at low and high speed, running, going up and down stairs, and working in the office with small movements that allowed to characterize a sedentary activity. The volunteers used two smartphones and, subsequently, comparisons were made regarding the place of use, one smartphone being used in the right pocket and the other in the right hip. The results showed a better performance with the smartphone located on the hip, however, in any of the uses, the difference is not statistically significant.

The study by (Pande et al., 2015) used the accelerometer and the barometer, because only the accelerometry sensor made it impossible to accurately determine some movements that involved changing altitude, such as going up or down stairs. The study by (Dunton et al., 2014) described that due to the single use of the accelerometry sensor, there was an absence of data collection for long periods. The data may be incomplete for some reasons, such as: forgetting to use or charge smartphones, stopped using the devices when they did not want to, during bathing or in water activities and during sleep. In addition to the limitations of the device, such as low battery life, signal interference and malfunction. Accelerometer studies in which the subjects were children and adolescents have only 50% of the data collected in just a few full days (Sirard et al., 2008; Van Coevering et al., 2005). The misuse of the smartphone by the user is an important factor in the lack of data in surveys with adolescents (Wiehe et al., 2008).

As seen, the selected studies had limitations pointed out by the authors themselves. In the study by (Costa et al., 2016) the method of recognition and classification of activities had some limitations, since a triaxial accelerometer alone was not sufficient to correctly identify some low-intensity activities, changes in altitude or activities where the device was used in a stationary position, such as cycling or elliptical. The study by (Guidoux et al., 2017) also reports the inability to differentiate activities in the sitting or standing position, and the restriction for accommodation of the smartphone in certain regions of the body or in clothing, such as large pockets located in front of pants or shorts. Some authors (Bayat et al., 2014; Kwapisz et al., 2011; Shoaib et al., 2014) defend the combined use of sensors, accelerometer and gyroscope, since most activities undergo some changes in orientation and with the gyroscope it is possible to complement the values of accelerometry in the recognition of activity. (Easton et al., 2014), showed limitation of the use of the accelerometer only in the evaluation of the EE, due to a possible vertical oscillation of the individual, which is a biomechanical characteristic of locomotion, which may overestimate or underestimate the EE of the exercise for some individuals. In addition, the device does not have the ability to recognize increased physiological demand, such as increased or transported loads. Having as a possible alternative to incorporate the combination of accelerometry with the cardiac measurement, obtaining a more accurate prediction of the EE compared to any of the measurements obtained in isolation. One of the authors tried to minimize these limitations with the use of a self-report questionnaire that generated important information to reduce the inconsistency of the accelerometry sensor data (Dunton et al., 2014).

Despite the numerous advantages of using the smartphone's internal accelerometry sensor, we found a limited number of articles with scientifically validated applications, clearly indicating the need for more research to develop new forms of data analysis. In addition to the need for comparisons with other dedicated sensors or even with specific equipment to measure EE and, thus, ensure greater reliability to internal resources.

Although this integrative review revealed the need for more research, the studies provided information that can be used in the development of a new smartphone application. As a result of the scarcity of studies, this integrative review provides an overview of the "state of the art" in the field of smartphone accelerometry sensors for measuring EE.

5. Conclusion

This study aimed to identify Apps that are scientifically validated and that use the smartphone's internal accelerometry sensor to monitor EE and thus encourage healthy and safe practices for an improvement in quality of life. In addition to being a practical tool for its use and for the prevention of NCDs and, thus, becoming a tool to help achieve the goals established by WHO. It is concluded that, even with few studies, the Apps are suitable as tools for monitoring EE through the smartphone's internal accelerometer and allow users to set goals and control the intensity of activities with EE rates. Another objective of the study was to develop an instrument for categorizing and classifying the selected articles, adapted to the needs of this integrative review. Therefore, it was concluded that the instrument developed was successful for the selection of studies, because with its effective use it was possible to identify and select carefully the articles that met the stipulated criteria. The limited number of articles with scientifically validated Apps clearly indicates the need for more research in order to develop new forms of data analysis, in addition to comparisons with other dedicated sensors or even with specific equipment for measuring EE and thus ensuring greater reliability to the internal smartphone sensors. With the development of new research and the improvement of the use of the smartphone's internal accelerometer, it will be possible to make available for use in public health, an instrument of great importance and that provides reliable data.

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