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Review Article

Intelligent Mobile Applications: A Systematic Mapping Study

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Smart mobiles as the most affordable and practical ubiquitous devices participate heavily in the enhancement of our daily life by the use of many convenient applications. However, the significant number of mobile users in addition to their heterogeneity (different profiles and contexts) obligates developers to enhance the quality of their apps by making them more intelligent and more flexible. This is realized mainly by analyzing mobile user's data. Machine learning (ML) technology provides the methodology and techniques needed to extract knowledge from data to facilitate decision-making. Therefore, both developers and researchers affirm the benefits of combining ML techniques and mobile technology in several application fields as e-health, e-learning, e-commerce, and e-coaching. Thus, the purpose of this paper is to have an overview of the use of ML techniques in the design and development of mobile applications. Therefore, we performed a systematic mapping study of papers published on this subject in the period between 1 January 2007 and 31 December 2019. A total number of 71 papers were selected, studied, and analyzed according to the following criteria, year, sources and channel of publication, research type, and methods, kind of collected data, and finally adopted ML models, tasks, and techniques.

1. Introduction

Today, no one can deny that the most used ubiquitous systems are mobile devices. At the first of their apparition, they were mainly used to send and receive calls, SMS, MMS, and emails. However, nowadays mobiles are widely used in several challenging domains such as e-learning, e-health, e-commerce, e-travel, and e-coaching. Consequently, from a simple container of thin clients, mobiles are transformed to a container of a huge number of mobile applications offering various services of our daily life.

The total number of mobile app downloads has increased from 63 billion in 2015 to 2054 billion in 2018. Also, it is expected that in 2022 this number will reach 2582 billion [1]. Moreover, since 2015, mobile phone usage exceeded desktop Internet usage, and by 2025, connected users will reach 75% of the world's population [2]. Therefore, it is expected that by 2025 mobile data will constitute 18% of the global Datasphere [2].

This transformation and this variation on targeted business areas in addition to the large number of targeted users make mobile apps design and development one of the hottest topics in software engineering [3–6]. Recently, mobile user satisfaction and assistance became also a primary interest of both researchers and developers. The objective is to develop very attractive and easier mobile apps to facilitate and improve the quality of several services [7–9].

Therefore, following a user-centric approach from the beginning of the mobile app design and development process became inevitable. One of the ultimate objectives of this approach is to adapt mobile apps (interface and/or logics) to diversifications in user profile, context changes, and also the history of previous actions [8, 10]. This adaptation to user's data must last over time to provide an intelligent interaction with mobile users and to continuously improve the quality of provided services [10].

Machine Learning (ML) techniques are widely used to extract knowledge from data and can be used in the field of mobile application design and development to ensure intelligent interactions with mobile users. Therefore, many works present the benefits of combining ML techniques and mobile technology in several application domains. For

instance, in [11] the authors present the need in developing smarter, more personalized and efficient patient-centric m-Health models. Also, they present the current and future roles of machine learning in making intelligent decisions based on the patient's data. In [12] the authors affirm that the future of learning is the synergy of mobility, interaction, and machine learning because by combining them it is possible to create intelligent and interactive mobile models that provide innovative learning scenarios. In [13] the authors define the analysis of mobile phone datasets and networks as one of the most relevant topics in today's m-commerce research. The objective is to improve the quality of provided services by developing user-centric m-commerce apps that exploit the power of ML techniques in the analysis of user-profiles and behavior.

Recently, the introduction of machine learning techniques in the creation of intelligent mobile apps is the subject of several research works of which the number keeps increasing year by year. This new orientation towards mobile applications is encouraged by the growth in performance of smartphones in terms of CPU power, RAM capacity, and energy storage, and also it is due to advances in the field of cloud computing that provide an on-demand cloud services of data storage and computing power [14]. Thus, to structure this research axis and to facilitate the information extraction about various available publications, it becomes imperative to carry out a literature study.

To the best of the authors' knowledge, there is no existing literature review that focuses on ML-based intelligent mobile apps. Thus, the goal of this work is to have an overview of research studies done in the area of the design and the development of mobile applications that provide intelligent interactions with mobile users using machine learning techniques. Mainly, we want to discover the level of maturity of works concerning this research axis, the frequency of publications, the most targeted application fields, the most used machine learning techniques, and for which purposes they were used. To this end, we carry out a Systematic Mapping Study (SMS) as a review approach that structures available researches and results in a particular research area [15, 16]. Therefore, the identified works will be classified and categorized according to some research questions, which will frame the literature study to be carried out. The results are often presented visually to facilitate their interpretation [15, 16].

We, therefore, selected and studied 71 papers published in the period from 1 January 2007 to 31 December 2019. The objective of this SMS is to make classification and contributions counting of selected papers. Particularly, we need to have a clear vision about (1) the most frequently used ML techniques in the development of intelligent mobile apps, (2) the application domains that have been covered in the literature, (3) where the literature has been published, and (4) which kind of mobile user data are collected and analyzed.

The rest of this paper is organized as follows. Section 2 presents the SMS methodology and different rules on which we are basing our study to perform this work. The results of the study are then described and discussed in Section 3, while Section 4 presents some implications for researchers and practitioners. The limitations of the study are then presented in Section 5. Finally, Section 6 gives conclusions and future works.

2. Research Methodology

To have an overview of the state of research in a specific topic and to decide on the axes where to dig, a literature study is requested. However, researchers in the fields of Software Engineering (SE) often do not follow systematic approaches in carrying out their literature studies. Recently, several guidelines have been proposed to structure a literature study in the field of SE by applying either a Systematic Mapping Study (SMS) or a Systematic Literature Review (SLR) [15–20]. As described in [15, 16] an SMS offers a superficial overview of a particular topic by providing a count and classification of research works published in this topic. This is often done visually using graphics. An SMS will help in structuring the research topic in question and will also allow better conduct of subsequent research work as SLR [15, 16]. Compared to SMS and as described in [17–20] SLR allows further literature study by performing an in-depth analysis of identified works. Therefore, an SLR is an SMS that includes some additional steps; for instance, it reviews the adopted methodology in each work and assesses the obtained results [15, 16].

Figure 1 shows the SMS process as it was described in [15, 16]. The process consists of five steps: (1) defining the Research Questions (RQ) of the study; (2) extracting keywords and defining the search string of the study; (3) extracting the relevant researches through scientific digital databases; (4) selection of relevant papers for the study; (6) data extraction from selected papers.

The RQ defines the purpose of the study that aims at structuring the body of knowledge related to a specific topic. In this direction, each research question must have a clear objective that is related to the subject of the study and must specify explicitly which data will be extracted from the selected papers [15, 16].

To identify keywords and formulate search strings from the research questions, SMS uses the PICO (Population, Interventions, Comparison, and Outcomes) model, which consists of four key components: population, intervention, comparison, and outcomes. Population refers to a specific SE role, type or application area. Intervention refers to software technology or methodology that addresses specific issues in SE. Comparison identifies the technologies, techniques, tools, methods, or strategies to be extracted and compared. Finally, outcomes should be related to the factors of the importance of the intervention to practitioners. The terms used to describe each component are then used to define the search string of the study [15, 16].

The defined search strings will be used to extract the relevant researches covering the subject of the study; this is mainly done through Scientific Digital Databases (SDDB). However, the search string must be adapted to the search roles in each SDDB [15, 16].

Inclusion and exclusion criteria must be used to retain only the researches that match the subject of the study; these

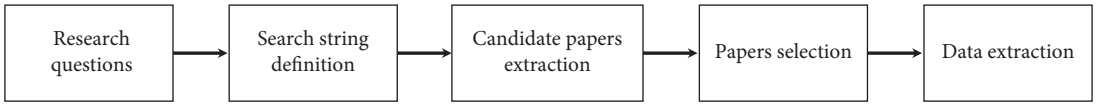

Figure 1: Description of the systematic mapping study process. The process starts with the definition of research questions and ends with the data extraction operation.

criteria will be applied to the titles and abstracts of extracted researches. Nevertheless, we can have some researches that need a full review of the content before deciding about their inclusion or exclusion [15, 16].

Finally, the retained researches must be exploited to extract the data that responds to the specified research questions [15, 16].

2.1. Research Questions. The aim of this study is to have an overview of published works about the use of ML techniques in the realization of intelligent mobile apps. For that, we define six RQ that are presented in Table 1 and that cover the scope of developing intelligent mobile apps. Each research question is accompanied by an explanation that presents the rationale behind its adoption by the authors.

2.2. Search Strings. To find the keywords of the study we follow the PICO model presented in [16]. As shown in Table 2, for each component we have a number of sentences that describe the subject of study. To extract keywords from these sentences we used roles proposed in [16] that classify keywords in many sets; each one is concerned with one component of PICO model. Table 3 presents the extracted keywords from PICO components.

After defining the keywords sets, we reorganize them to six groups as presented in Table 4, with each group containing keywords that either are synonyms, present different forms of the same word, or are terms that have similar or related semantic meaning within the domain of intelligent mobile applications [18]. The definitive search string is obtained by concatenating words from groups as follows: (design OR development) AND (mobile OR user OR "mobile user") AND (intelligent OR adaptive OR reactive OR responsive) AND (application OR interface) AND (analyze OR learn OR predict) AND (interaction OR "user experience" OR data OR behavior OR desire OR satisfaction). The Boolean OR is used to assemble terms in the same group and the Boolean AND is used to join groups of terms.

2.3. Candidate Papers. The defined search string was used to search primary studies from four digital libraries: IEEE Xplore, ACM Digital Library, ScienceDirect, and Springer Link, since they were the most commonly used to publish SE studies [21].

2.4. Paper Selection. This section identifies the inclusion/exclusion (IC/EC) criteria we used to assess the relevance of the primary studies retrieved by applying the search string to the four digital libraries. IC/EC criteria were applied to the title and abstract of each paper. Doubtfully, we use the full-text to decide upon a paper whether it will be included or excluded. As presented in Table 5, we identified three inclusion criteria and four exclusion criteria:

2.5. Data Extraction. To collect all relevant data from the selected studies and in order to provide answers to the different RQs defined in Table 1 we used the template presented in Table 6. It provides a description of different data items that will be extracted from the selected papers. Each data item is provided with its name, with its data type, and also with the research questions to which they refer.

Publication Channel refers to a regularly published journal or to an academic event such as conference, workshop, symposium, or seminar.

Publication Source refers to the effective name of the journal or the academic events that have published each selected paper.

Research type refers to a classification of selected studies in relation to the stage of completeness of the realized work. Petersen et al. in [15, 16] and Wieringa et al. in [22] define five types of research studies as follows: Evaluation Research (ER), Solution proposal (SP), Validation Research (VR), Philosophical Papers (PP), and Opinion Papers (OP). SP paper presents a novel technique or an improvement of an existing technique and argues for its relevance without a validation. VR makes an In-depth analysis of a note implemented solution proposal. ER provides an empirical study of a problem or an implementation of a technique in practice. PP presents a new way of looking at things or a new conceptual framework. Finally, an OP gives an opinion about what is wrong or good about something, how we should do something [15, 16].

Study Field refers to the application business field of the study such as e-Learning, e-Commerce, e-Government, and e-Health. A study that does not specify the application domain is classified as Generic.

Study Context refers to the context in which the study was carried out. In [17], Kitchman and Charters have defined four contexts: Academic, Organization, Industrial, and Government.

ML Model refers to the model of learning that is used to extract knowledge from data. In this work, we consider five types of ML models: Supervised Learning (SL), Unsupervised Learning (UL), Semi-Supervised Learning (SSL), Active Learning (AL), and Reinforcement Learning (RL) [23, 24]. SL algorithms learn from training data sets that provide examples about relations between data inputs and the target outputs and generalize results as a model that can predict outputs from new inputs [23, 24]. UL algorithms attempt to identify similarities between inputs, which help in their categorization [23, 24]. Learning algorithm attempts to

Table 1: Definition and description of the research questions of the study.

ID	Research question	Rationale
RQ1	In which years, sources, and publication channels papers were published?	To identify where studies concerning this field of research can be found and whether there are specific publication channels; it also indicates when effort regarding this research area was made
RQ2	Which research types are adopted in selected papers?	To provide an overview of different types of research outlined in the literature regarding the application of ML in intelligent mobile apps development
RQ3	Which application fields are targeted in selected papers?	To determine in which application fields ML techniques were carried out and researchers were interested
RQ4	Which contexts are targeted in selected papers?	To determine in which context different studies were performed
RQ5	Which kinds of data are collected from mobile devices?	To identify which data are interesting researches to perform data analysis with ML techniques
RQ6	Which ML models, tasks, and techniques are used to analyze mobile data?	To determine which kind of ML techniques researchers were often interested in

Table 2: Description of our PICO components that matches the intelligent mobile interaction.

Component	Description
Population	Intelligent mobile interaction studies
Interventions	(i) User-oriented mobile application (interface) design and development (ii) User experience oriented mobile application design and development (iii) Adaptive, reactive, or responsive mobile application design and development
Comparison	We compare studies on intelligent mobile interaction area by identifying and comparing the different approaches and techniques used to collect mobile user data and behavior, to analyze and learn from mobile user data and behaviors, or to predict user desires
Outcomes	Maximize user satisfaction in interaction with mobile applications

Table 3: The sets of the extracted keywords from the PICO components.

Set	Component	Keywords
1	Population	Intelligent, mobile, interaction
2	Interventions	User, application, interface, design, development, user experience, adaptive, reactive, responsive
3	Comparison	Approaches, techniques, mobile user, data, behavior, analyze, learn, predict, desire
4	Outcomes	User, satisfaction, interaction, application

Table 4: Grouping of identified terms in six groups depending on whether they are similar or they are often used together.

Terms	G1	G2	G3	G4	G5	G6
Intelligent			*			
Mobile		*				
Interaction						*
User		*				
Application				*		
Interface				*		
Design	*					
Development	*					
User experience						*
Adaptive			*			
Reactive			*			
Responsive			*			
Mobile user		*				
Data						*
Behavior						*
Analyze					*	
Learn					*	
Predict					*	
Desire						*
Satisfaction						*

describe data instead of SL algorithms that attempt to make a prediction of outputs. SSL algorithms are a subcategory of SL algorithms that are used when unlabeled data are easily available and it is difficult or expensive to have labeled data. The learning algorithm attempts to use labeled and unlabeled data when searching for a model (with less human intervention). It recursively attempts to find a model using labeled data and apply it on unlabeled data, then only detected labels with high accuracy are retained and added to the labeled data set [25]. AL algorithms are a subcategory of SL that are used in situations where there are huge data sets in which there are few labeled data for training. In such case label prediction is difficult or expensive to obtain. The learning algorithm attempts to add new labeled tuples to training data set by querying periodically a user for labels until having acceptable data set size that allows making supervised learning [23, 26]. RL algorithms are used in case of dynamic environments in which an agent tries to find the suitable action to execute in response to a specific situation or event. The agent learns behavior through his errors by trying different possibilities until he finds a suitable action to perform [23, 27].

Table 5: Inclusion and exclusion criteria.

Category	Criteria
Inclusion	Studies presenting methods and techniques to develop intelligent mobile applications that support intelligent interactions with users
	Studies presenting methods and techniques to analyze mobile user data
	Studies published between 2007 and 2018
Exclusion	Studies not presented in English
	Studies not accessible in full-text
	Books and gray literature
	Studies that are duplicates

Table 6: Data extraction template.

Data item	Name	Value	RQ
1	ID	Integer	—
2	Authors	Set of names of the authors	RQ1
3	Title	Title of the paper	RQ1
4	Publication channel	Kind of publication channel	RQ1
5	Publication source	Name of publication source	RQ1
6	Year	Calendar year	RQ1
7	Research type	Which research strategy was followed	RQ2
8	Study field	In which business fields the research was applied	RQ3
9	Study context	In which context the research was conducted	RQ4
10	Data collection strategy	Which kinds of data were collected from mobile users	RQ5
11	ML model	Which machine learning approach was adopted	RQ6
12	ML task	Which data mining tasks were used by selected papers	RQ6
13	ML technique	Which data mining techniques were used by selected papers	RQ6

ML techniques refer to the algorithms that are used to perform the learning task. These algorithms can be categorized into many ML Tasks for each of the ML models [23, 24]. For instance, SL model contains classification task and regression Task, and UL model contains association task and clustering task. SSL and AL models are considered as variants of the SL model; consequently, they use the same ML tasks [23, 24]. Figure 2 presents an inventory of ML techniques most used in practice and grouped by ML models and ML tasks.

3. Results and Discussion

This section presents the findings related to this systematic map. Firstly, we introduce an overview of the result of the selection process; and secondly, all the results for each research question are presented.

3.1. Overview of the Selected Studies. Our search in the fourth digital libraries provided 9238 candidate papers. However, 9167 papers were excluded after applying the exclusion criteria, thus leading to the identification of 71 articles regarding the use of ML techniques in intelligent mobile app design and development.

Table 7 shows the number of selected papers in each step of the selection process. In fact, the duplicate papers were first discarded and only one study was considered. Besides, the papers reporting the same study were also excluded and only the most recent one was included. Then, all papers not written in English or not accessible in full-text were excluded. Finally, many papers required a full-text review before deciding about their inclusion or exclusion.

The number of selected papers is respectable and reflects the importance of the research topic addressed in this study. Also, this number will allow conducting the study with acceptable data size that will give a credible overview of the targeted research topic. The complete list of selected studies with their relevant data is provided in Table 8.

3.2. RQ1: In Which Years, Sources, and Publication Channels Papers Were Published? Figure 3 presents the variation in the number of selected papers over the years between 2007 and 2019. It shows that the average annual growth rate of publications is 30% for each year. Nearly, two-thirds (66.2%) of the studies were published in the second half of the observed period between 2013 and 2019. Moreover, 11 papers were published in 2019, which is a significant number if it is compared to other years. Consequently, it is very clear that researchers are becoming more and more interested in this research area. This trend is justified by many other works. For instance, Garousi et al. have conducted a research about trends in SE; their work showed that mobile subject is the second hottest research topic in SE area [99]. Also, Karanatsiou et al. have affirmed that mobile app development is counted among the most frequent research topics in SE. Finally, Zhu et al. affirm that the improvement of mobile performances in terms of processing power and data storage capacity in addition to the advances in cloud computing has a role in the support machine learning algorithms by the mobile devices. They also highlight new challenges in

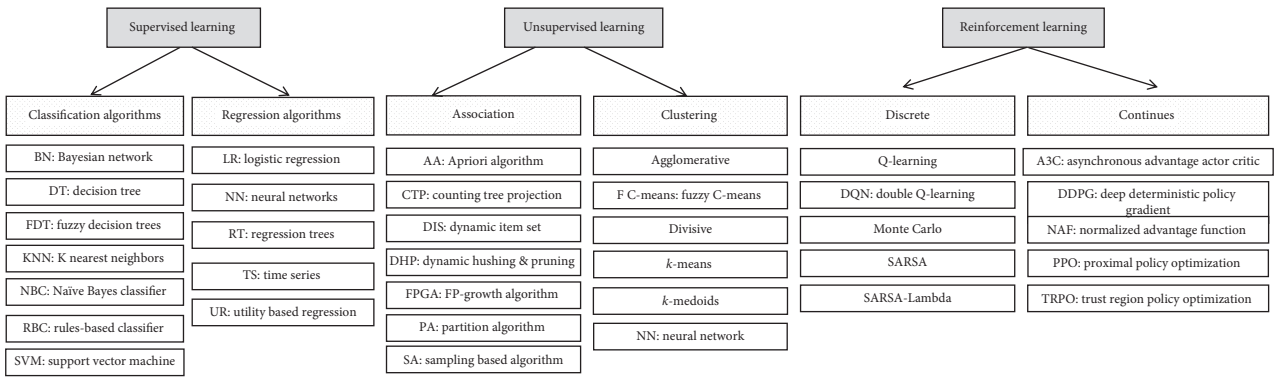

Figure 2: Data analysis techniques grouped by ML models and tasks.

Table 7: The number of retained papers after each step of our selection process.

Database	Returned studies	Year filter (2007–2018)	Title/Abstract review	Full-text review	Add manually	Retained studies
IEEE	1694	1356	36	19	5	24
ACM	3223	2475	36	16	5	21
SCDirect	560	500	16	2	3	5
Springer	3761	3229	47	16	5	21

exploiting massive data distributed over a large number of edge devices including smartphones [100].

Figure 3 shows also that almost every year the number of papers published in conferences is more important than the other channels. Moreover, Figure 4 shows that 54% of selected papers were published in conferences, while 40% were published in journals. Finally, only 4% were published in symposium and 2% were published in workshops. The high percentage of conference papers is explained by the fact that researchers often report their primary results at first in conferences, then synthesize them in a journal article after validation [101, 102]. Therefore, researches on the topic of intelligent mobile applications have not reached yet the required level of maturity and they still have several axes where to fetch. Also, the percentage of papers published in journals shows that there are some validated results that can be exploited in future works.

Table 9 presents the publication sources where there were published at least two of the selected studies. Thus, the most frequent publication source is "Lecture Notes in Computer Science" with a percentage of 16.9%, succeeded by "ACM International Joint Conference on Pervasive and Ubiquitous Computing" with 4.23%. Finally, we find "IEEE Transactions on Learning Technologies," "International Conference on Advanced Learning Technologies," "Personal and Ubiquitous Computing," "Procedia Computer Science," and "Universal Access in the Information Society" with 2.81% for each of them. All these publication sources are considered to have a high-ranking, thing that reflects the high quality of most of the selected studies.

3.3. RQ2: Which Research Types Are Adopted in Selected Papers? Figure 5 shows that ER (Evaluation Research) is the most adopted research type with a percentage of 44%, succeeded by SP (Solution Proposal) with a percentage of 26% and VR (Validation Research) with a percentage of 24%. Finally, PP (philosophical paper) is the less adopted research type with 6%.

ER are more dominant, and this means that several studies have proposed final solutions that are evaluated and experimented in practice. These studies can be reviewed in-depth in future works as SLR. Like ER, VR are also pertinent and can be considered in future SLR studies. Other research types must be ignored in subsequent work [14]. The codominance of SP, VR, and PP to the detriment of ER reflects that the majority of proposed solutions are not implemented or experimented in real context. SP works propose implemented solutions that are not yet experimented. However, VR propose new implemented and experienced solutions; nevertheless, experiments are realized as simulations, prototyping, or experiments in a lab. Finally, PP works present a new conceptual framework solution that is not yet either implemented or experienced [16, 17]. ER works are already experimented and validated; that is why they are published equally in journals and conferences as shown in Figure 6. Figure 6 shows also that SP and VR are often published in conferences. This is because these works are firstly reported as primary results in conferences, then they will be synthesized and reported in journals after validation [101, 102].

3.4. RQ3: Which Application Fields Are Targeted in Selected Papers? Figure 7 shows that every year the total number of papers that focus on a specific field is greater than those that are generic. Moreover, only 22% of selected papers have proposed generic solutions that can be applied on several fields and 78% are oriented to a specific field. Therefore, we note that researchers are focusing more and more on specific

Table 8: Data extracted from the selected papers.

ID	Ref	RQ1 Publication channel	Year	RQ2 Research type	RQ3 Study context	RQ4 Study field	RQ5 Data collection strategy	ML model	RQ6 ML tasks	ML techniques
1	[28]	Conference	2019	VS	Academic	e-Learning	Context	SL	Classification	ANN
2	[29]	Journal	2019	VS	Academic	e-Health	Context, interactions, profile	SL	Classification	ANN
3	[30]	Conference	2019	SP	Academic	e-Health	Context, interactions, profile	SL	Classification	ANN
4	[31]	Conference	2019	ES		Recommendation	Context	UL	Clustering	K-means
5	[32]	Conference	2019	VS	Academic	e-Learning	Interactions	UL		ANN
6	[33]	Conference	2019	ES	Academic	Recommendation	Interactions	RL		Q-learning.
7	[34]	Journal	2019	ES	Academic	e-Learning	Context, interactions	SL + UL	Clustering, classification	K-means, SVM
8	[35]	Journal	2019	SP	Academic	e-Learning	Context, interactions	UL	Association, clustering	AR, K-means
9	[36]	Journal	2019	ES	Academic	e-Coaching	Context	SL	Classification	MM
10	[37]	Conference	2019	SP	Academic	e-Commerce	Context, interactions	SL	Classification	RBC
11	[38]	Journal	2019	ES	Academic	e-Learning	Context, interactions	SL	Classification	ANN, SVM
12	[39]	Conference	2018	VS	Government	Generic	Interactions, preferences, profile	RL	—	Q-learning
13	[40]	Conference	2018	ES	Academic	e-Learning	Interactions	SL	Classification	ANN
14	[41]	Conference	2018	SP	Government	Entertainment	Interactions, preferences	SL	Classification	RF
15	[42]	Journal	2018	VS	Organization	e-Health	Context	SL	Classification	RBC
16	[43]	Conference	2018	ES	Organization	Recommendation	Interactions	SL	Regression	KNN, NBC
17	[44]	Journal	2018	ES	Industrial	e-Health	Context, profile	SL	Classification	RBC
18	[45]	Conference	2017	SP	Organization	e-Health	Context	SL	Classification	DT
19	[46]	Conference	2017	ES	Academic	Gamming	Context	SL	Classification	RBC
20	[47]	Conference	2017	SP	Academic	e-Coaching	Feedbacks	SL	Classification, regression	DT, LR
21	[48]	Conference	2017	ES	Academic	fs management	Interactions			MCDM
22	[49]	Conference	2017	SP	Academic	Generic	Context, feedbacks, profile	SL	Regression	SVM
23	[50]	Journal	2017	PP	Organization	Generic	Context	SL	Classification	
24	[51]	Journal	2017	ES	Organization	e-Coaching	Context, interactions	SL	Classification, clustering	DT, HAC
25	[52]	Journal	2017	ES	Organization	e-Coaching	Interactions			
26	[53]	Conference	2016	SP	Organization	Generic	Context, interactions			
27	[54]	Conference	2016	SP	Organization	e-Coaching	Context	SL	Classification	SVM
28	[55]	Conference	2016	ES	Organization	Recommendation	Context, interactions	SL	Association	AR
29	[56]	Symposium	2016	SP	Academic	Generic	Context, interactions	SL	Classification, clustering	ANN, K-means
30	[57]	Conference	2016	SP	Academic	Generic	Interactions			
31	[58]	Journal	2016	ES	Organization	e-Learning	Context, profile			
32	[59]	Conference	2015	ES	Organization	Notification management	Context	SL	Classification	NBC, RF
33	[60]	Conference	2015	SP	Academic	Gamming	Emotion		Classification	
34	[61]	Conference	2015	ES	Academic	Natural language processing	Context, interactions	SL	Regression	LR
35	[62]	Conference	2015	VS	Academic	Recommendation	Context	SL	Classification	SVM
36	[63]	Journal	2015	ES	Academic	Gamming	Interactions	SL	Clustering	K-means
37	[64]	Journal	2015	ES	Academic	e-Learning	Context	SL	Classification	RBC

Table 8: Continued.

ID	Ref	RQ1 Publication channel	Year	RQ2 Research type	RQ3 Study context	RQ4 Study field	RQ5 Data collection strategy	ML model	RQ6 ML tasks	ML techniques
38	[65]	Journal	2014	ES	Government	Entertainment	Context, preferences	SL	Classification	Tp, CBFM
39	[66]	Journal	2014	VS	Academic	e-Health	Context	SL	Classification	RBC
40	[67]	Conference	2014	PP	Academic	Data visualization	Context			
41	[68]	Conference	2014	ES	Organization	Entertainment	Context, interactions	SL	Classification	DT, KNN
42	[69]	Journal	2014	ES	Organization	e-Health	Context	SL	Classification	RBC
43	[70]	Journal	2014	PP	Government	Generic	Context	SL	Classification	RBC
44	[71]	Workshop	2014	ES	Academic	e-Commerce	Preferences, feedbacks	AL	Regression	UR
45	[72]	Conference	2013	VS	Academic	Generic	Context, interactions	SL	Classification	RBC
46	[73]	Conference	2013	ES	Academic	Generic	Interactions	SL	Clustering	K-means
47	[74]	Conference	2013	SP	Academic	e-Learning	Context, interactions	SL	Association	AR
48	[75]	Conference	2013	VS	Government	Gamming	Interactions	SL	Classification	ANN
49	[76]	Journal	2013	ES	Government	Generic	Preferences	SL	Classification	KNN
50	[77]	Journal	2013	ES	Academic	e-Health	Context	SL	Classification	RBC
51	[78]	Conference	2012	ES	Government	e-Health	Context	SL	Regression	FBA
52	[79]	Journal	2012	SP	Academic	e-Learning	Profile, interactions	SL	Classification	ANN, FL
53	[80]	Conference	2012	SP	Government	e-Learning	Context, preferences, profile	SL	Classification	DT
54	[81]	Conference	2012	VS	Academic	e-Learning	Preferences, profile	SL	Clustering	K-means
55	[82]	Journal	2012	VS	Organization	Smart home	Feedback, interactions	RL		Q-learning
56	[83]	Journal	2012	SP	Organization	e-Travel	Context, preferences	SL	Classification	SVM
57	[84]	Journal	2011	VS	Academic	Recommendation	Context, interactions	SL	Classification	NBC
58	[85]	Conference	2011	VS	Academic	Gamming	Interactions	SL	Classification	CN
59	[86]	Conference	2011	VS	Academic	e-Learning	Context, profile	SL	Classification	ANN, FL
60	[87]	Conference	2011	ES	Academic	e-Learning	Profile			
61	[88]	Journal	2011	ES	Government	e-Learning	Preferences	SL + UL	Clustering, classification	DT
62	[89]	Conference	2010	ES	Academic	e-Travel	Context, interactions	UL	Clustering	FBA
63	[90]	Conference	2010	SP	Academic		Profile	SL + UL	Clustering, classification	ANN, K-means
64	[91]	Conference	2010	SP	Government	e-Health	Context	SL	Classification	ANN, FL
65	[92]	Journal	2009	ES	Government	e-Learning	Context, interactions, profile	SL	Classification, regression	RBC, MM
66	[93]	Conference	2009	ES	Academic	Generic	Context	SL	Classification	NBC
67	[94]	Journal	2009	PP	Academic	e-Learning	Context, profile	SL	Classification	
68	[95]	Journal	2009	VS	Government	Generic	Interactions	UL	Clustering	FBA
69	[96]	Conference	2008	VS	Organization	E-commerce	Interactions	SL	Association	FBA
70	[97]	Journal	2008	VS	Industrial	Generic	Interactions	SL	Regression	SPA
71	[98]	Conference	2007	VS	Academic	Recommendation	Profile	SL	Classification	NBC, FL, MM

fields. Figure 8 shows the variation in application fields adopted in selected papers. It shows that the most targeted application fields are e-Learning with 24% and e-Health with 17%.

The dominance of e-Learning and e-Health mobile applications can be explained by the fact that they have a massive social and economic impact on consumers and enterprises than other fields. They create better living

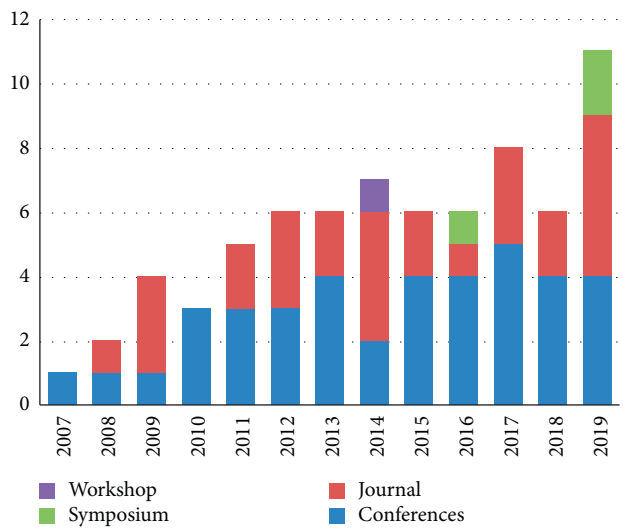

Figure 3: Distribution of selected papers over the period 2007–2018.

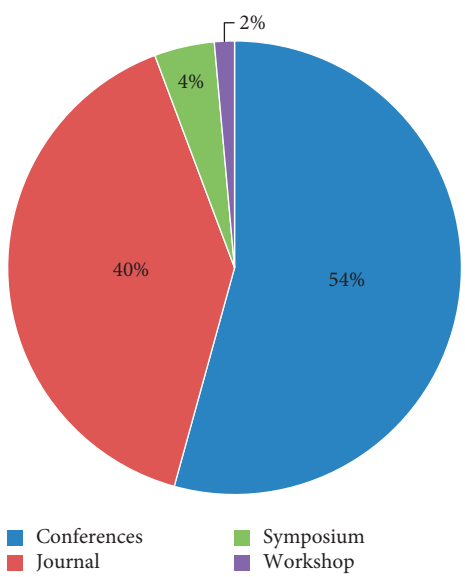

Figure 4: The percentage of each publication channel in selected papers.

Table 9: Most frequent publication sources in the selected studies.

Title	Type	Libraries	Ranking	Number
ACM international joint conference on pervasive and ubiquitous computing	Conference	ACM	A*	3
IEEE transactions on learning technologies	Journal	IEEE	Q1	2
International conference on advanced learning technologies	Conference	IEEE	B	2
Lecture notes in computer science	Journal	Springer	Q2	12
Personal and ubiquitous computing	Journal	Springer	Q2	2
Procedia computer science	Journal	Elsevier	-	2
Universal access in the information society	Journal	Springer	Q2	2

conditions [103]. Mobile applications for e-Learning provide the possibility to access high-quality educational resources and educational content that is adapted to users' needs and learning speed. Mobile applications for e-Health represent a creative solution to bring health care services to more people especially in emerging countries [103].

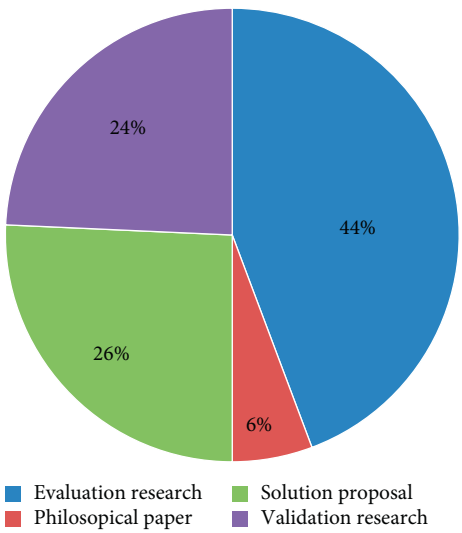

Figure 5: The percentage of each research type in selected papers.

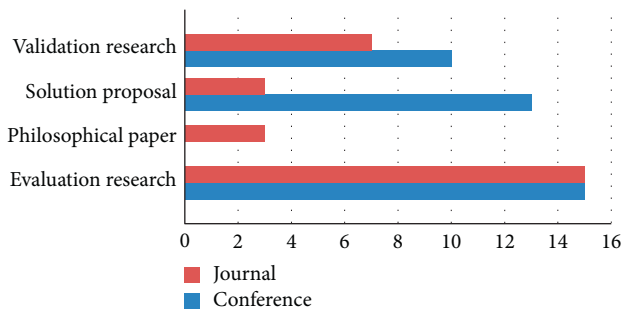

Figure 6: The percentage of research types in journals and conferences.

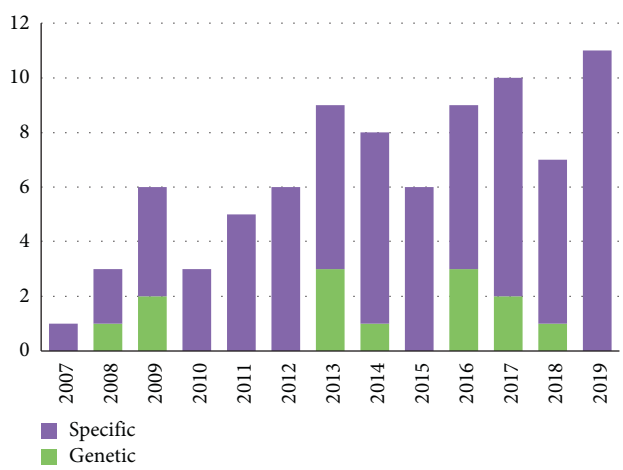

Figure 7: Distribution of selected papers over the period 2007–2018 for each application field category.

3.5. RQ4: Which Contexts Are Targeted in Selected Papers? Figure 9 shows that 47% of selected studies were conducted in an academic context, 35% were funded by organizations, 17% were adopted by government institutes, and only 1% of selected studies were conducted in an industrial context. Figure 10 shows that during the last 4 years all studies were conducted either in an academic context or in an organization context, except two studies that were conducted in government context. Figure 10 shows also that studies that were conducted in an organization context begin to be more frequent than academic studies. Moreover, in the last for years, works funded by organizations are becoming more dominant.

The growing number of projects funded by organizations can be explained by the fact that organizations (companies, enterprises) are becoming aware of the importance of mobile technologies as innovative solutions for the realization of economic and human development, so they fund many research and development projects in the area of mobile technologies [103]. Industrials are more interested in hardware and infrastructure aspects instead of the software engineering aspect, which explains the few number of research studies funded by industrials. Finally, regarding the number of works funded by governments, it can be explained by the fact that governments spending on adoption and usage of mobile technologies do not reach the expected economic and social aspirations [103].

3.6. RQ5: Which Kinds of Data Are Collected from Mobile Devices? Figure 11 shows that context data are the most collected from mobile users with a percentage of 42%, succeeded by interaction data with 33%, profile data with 13%, preference data with 8%, and feedback data with 4%. But it must be emphasized that, in the same work, several types of data may be collected from the mobile user.

Context and interaction data are the most used because they provide dynamic data about the mobile user. They can help in taking decisions that are most suitable to the current context of the user in conjunction with his previous actions. Context data give information about the current state of the user (identity, health state, mental state, physical state, psychological state, etc.) and about its environment (location, time, current activity, etc.). However, interaction data gives information about the previous user actions (apps consultation history, notification history, usage log, clicks, etc.) that can help in predicting future user actions. Profile and preference data often provide static information about the user and help to have a primary idea about the user without considering context and interaction data that are not available at the beginning of use of mobile apps. Finally, feedback data are not very important in conducting interactions with users because usually they are considered in application maintenance.

3.7. RQ6: Which Machine Learning Models, Data Mining Tasks, and Techniques Are Used to Analyze Mobile Data? Figure 12 shows that supervised learning is the most used machine-learning model in selected papers with a percentage of 73%; however, 11% have used unsupervised learning, 4% have used reinforcement learning, and 1% has used active learning. Finally, 11% of papers have not used any machine-learning model. Figure 13 shows that every year, SL is the most dominant model in selected studies. Also, it shows that there was no usage of UL techniques and

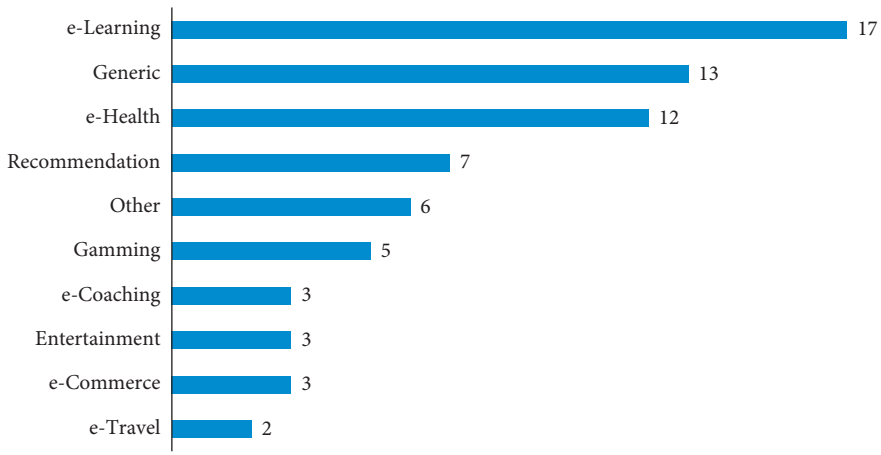

Figure 8: The number of selected studies by application field.

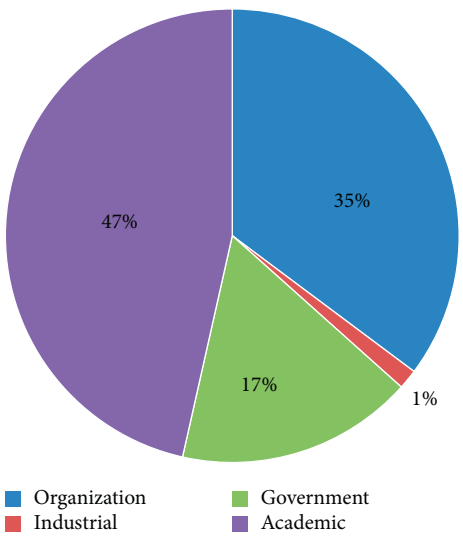

Figure 9: The percentage of each study context in selected papers.

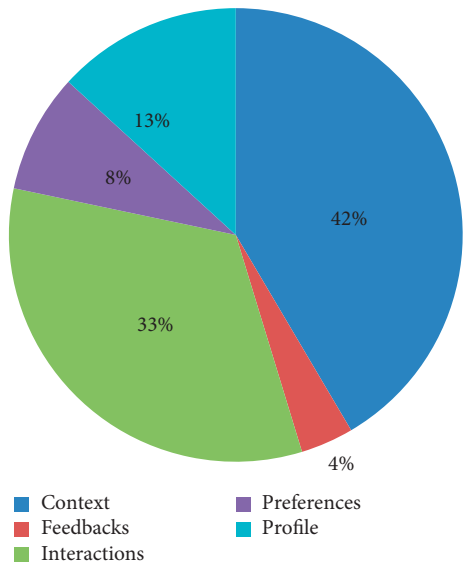

Figure 11: The percentage of each collected data type in selected papers.

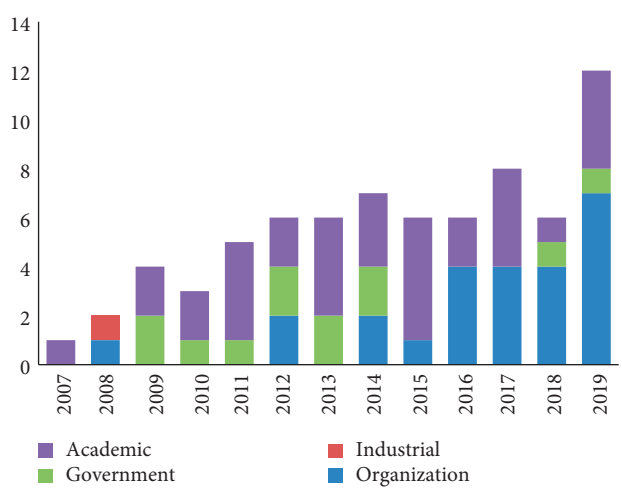

Figure 10: Distribution of selected papers over the period 2007–2018 for each research context.

there were very modest attempts to introduce UL, RL, and AL techniques in intelligent mobile apps development.

As the majority of selected studies have used supervised learning models, Figure 14 shows that classification is the most used data mining tasks with a percentage of 66%, succeeded by clustering with a percentage of 16% and regression with a percentage of 13%. Finally, the association task comes in the last range with 5%.

Table 10 presents data mining techniques that are used more than one time in selected papers. Thus, the most frequent technique is ANN that was used in 12 studies, followed by RBC technique that was used in 11 studies, K-means that was used in 8 studies, DT, SVM that were used in 6 studies for each of them, NBC that was used in 5 studies, FL and FBA that were used in 4 studies for each of them, KNN, MM, Q-learning, and AR that were used in 3 studies for each of them, and finally RF and LR that were used in 2 studies for each of them.

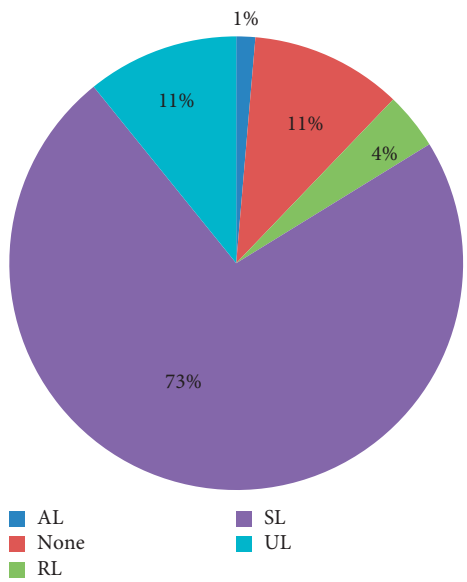

Figure 12: The percentage of each machine learning model in selected papers.

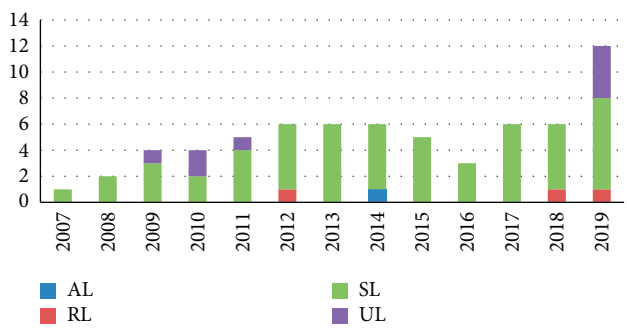

Figure 13: Evolution of Machine Learning Models usage in selected papers between 2007 and 2018.

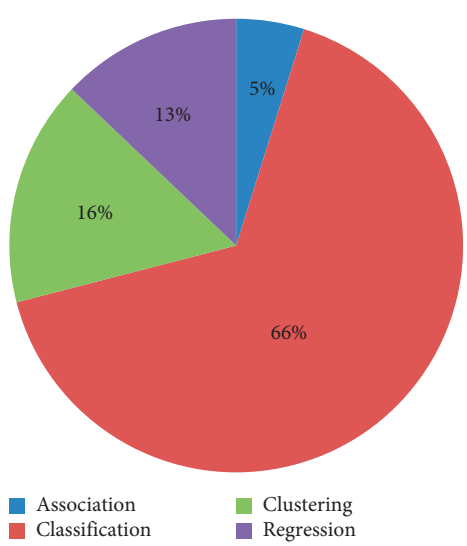

Figure 14: The percentage of adopted data analysis tasks in selected papers.

Table 10: Data mining techniques that are used by more than one of the selected papers.

Techniques	Number of papers
ANN (artificial neural network)	12
RBC (rules-based classifier)	11
K-means	8
DT (decision tree)	6
SVM (support vector machine)	6
NBC (naïve Bayesian classifier)	5
FL (fuzzy logic)	4
FBA (frequency-based algorithm)	4
KNN (K-nearest neighbour)	3
MM (Markov models)	3
Q-learning	3
AR (association rules)	3
RF (random forest)	2
LR (logistic regression)	2

We conclude that the use of SL models (and specifically classification tasks) is a natural phenomenon because several works attempt in the majority of cases to classify users in order to know how to interact with them according to their profiles, preferences, contexts, or actions. In addition, SL algorithms are known by their simplicity because they attempt to learn from the training dataset to find model that makes conjunction between inputs and desired outputs; also, both the input and desired output data are known in advance; therefore, manual interventions to correct results are minimal [23, 24]. Finally, many SL services are now available on the cloud to facilitate the integration ML algorithm in mobile apps [27].

In many cases, UL tasks were used in the data preparation stage to make data exploration or data dimension reduction. Often, UL tasks are used before resorting to SL algorithms for prediction tasks; also, it needs more interventions than SL tasks to correct obtained results [23, 24].

RL algorithms were used in mobiles to make automation of some tasks by finding a suitable action for a specific situation or event. They were used especially for energy consumption prediction, memory allocation prediction, and mobile app usage prediction (predict users actions in interaction with mobile apps). They were less used because of their complexity by comparing them with SL and UL [23, 27].

AL tasks are the less used in mobile apps, because of their use in situations where there are huge data sets in which there are few labeled data for training. In such case label prediction is difficult or expensive to obtain [23, 26].

4. Implications for Researchers and Practitioners

This section presents some implications and recommendations for researchers and practitioners that are deduced from the analysis of data extracted from selected papers.

4.1. RQ1. Despite the important number of returned papers by the defined search string, there were a significant number

of excluded papers at each level of the selection process. This is mainly due to the fact that many research axes share the same vocabulary with mobile apps development as mobile networking, vehicle human interface interaction, and robot programming. So, researchers must define clearly the purpose of their works with terms that belong to the software engineering vocabulary. Also, many excluded papers are not described enough and do not provide sufficient details that can help in the facilitation of the selection process. So, researchers must make more effort in synthesizing their works by ensuring an acceptable level of scientific credibility that will help in evaluating correctly the quality of the work.

4.2. RQ2 and RQ3. Researchers and developers working on the development of intelligent mobile applications are focusing more and more on specific fields as e-Learning and e-Health, and this is at the expense of generic solutions. This orientation can be explained by the fact that each field has its specificities and constraints and that it is more difficult to validate more generic solutions than those that focus on specific fields. Thus, the majority of generic solutions in selected papers are not validated. So, it is recommended that future works take also this orientation of targeting a specific application field.

4.3. RQ4. The majority of selected studies are done in academic and organizational context; therefore researchers and developers still have to exert more efforts to make validation and standardization of proposed solutions, things that can encourage industrial and governments to adopt and finance more research in the area of intelligent mobile application.

4.4. RQ5 and RQ6. For the majority of selected studies, choosing a ML technique over another is not always justified. Furthermore, many works use techniques that are easy to implement but not necessarily efficient. For instance, RBC that is the second most used technique is known by its ease of implementation and interpretation but it is not the best in terms of quality [23, 24]. So, it is strongly recommended for researchers to make more effort in making proof of their choice in terms of ML techniques. On the other hand, all studies do not express clearly the nature of the logic adopted in applications. For instance, a purely user-oriented application changes its logic in conjunction with each user separately from others. Cornerwise, lightweight user-oriented application changes its logic to make global adaptations without distinction between users. So, the implemented intelligence in the two cases is not the same. Firstly, the data size is not the same; secondly, the nature of collected data is not the same (dynamic and real-time data in the first case and static and non-real-time data in the second case); thirdly the ML tasks and techniques are not the same; and finally, the degree of real-time adaptation is not the same. So, it is recommended for researchers to determine the nature of adopted logic in their solutions to have a clear idea about their contributions and to have a correct evolution of their works.

5. Limitations of the Study

Many research axes share the same vocabulary with mobile apps development as mobile networking, vehicle human interface interaction, and robot programming. So, it was very difficult to make correct keywords based on the inclusion/exclusion of papers returned by the defined search string. Therefore, it is possible that many papers have been excluded due to the lack of credible keywords or precise description. Also, given the huge number of returned papers by indexed databases, we restricted our search to only the most credible databases [19].

6. Conclusion and Future Studies

ML provides promising techniques to extract knowledge from a large dataset; the objective is to obtain patterns and models that will help in developing intelligent applications that will learn from data collected about user context, profile, and interactions. Several studies have attempted to integrate ML in the mobile field in order to provide intelligent mobile applications. Nevertheless, we do not have an overview of which techniques are used and how they are exploited in mobile apps design and development.

The aim of this paper was to define the state of research on the topic of ML techniques applied in mobile apps design and development. For this purpose, we have performed a systematic mapping study that aims primarily to respond to the research questions presented in Table 1. A total of 60 studies were selected and analyzed according to the following criteria: year, sources and publication channel, research type and methods, kind of collected data, and finally adopted ML models, tasks, and techniques.

The obtained results show that the average annual growth rate of papers publication is 25%. These papers were published in different journals and appeared at several conferences regarding computer science and software engineering fields. Evaluation search is the more dominant research type. e-Learning and e-Health are the most targeted application fields. The majority of studies are conducted in an academic context. Context and interaction data are the most collected data from the mobile user. Three-thirds of selected papers have used supervised learning models and more specifically classification tasks. Rules-Based Classifier is the most used ML technique.

Most of the studies are conducted in an academic context, a thing that reflects that either the topic is not attractive for governments and industrials or it is too difficult to apply the obtained result in real context. So, we recommend exerting more effort to make standardization and proposition tools that support ML technique application in mobile context.

Most of the studies depended closely on the application field in the sense that each domain has its own specificity in terms of the type of collected data and also in terms of its analysis objectives. Also, generic solutions cannot be

evaluated if they are not applied on a specific field. Therefore, future studies must be oriented to a specific application field.

In the majority of cases, SL techniques are used to classify users in function of their context or/and profile. This is used to adapt the application behavior or interface to the user. But for most of the selected studies, the choice of a ML technique is not always justified. Therefore, researchers must make more attempts to introduce other ML methods and assess their performance in mobile context and specifically those that are more adapted to dynamic environments as mobile. For instance, RL techniques are known for their ability to learn from user's actions and that can automatically make real-time decisions that attempt to maximize user satisfaction and all that without any training dataset.

Our future studies will be consecrated to the realization of a systematic literature review (SLR) that will make an in-depth analysis of all selected studies in addition to the studies published recently on the topic of intelligent mobile application design and development.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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