IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received July 9, 2019, accepted July 25, 2019, date of publication July 29, 2019, date of current version August 13, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2931835

Anticipatory Computing for Human Behavioral Change Intervention: A Systematic Review

CHUNPEI LIN[1], GUANXI ZHAO[2], YENCHUN JIM WU[3,4], AND HAILIN LI[5]

[1]School of Business Administration, Huaqiao University, Quanzhou 362021, China
[2]Business Management Research Center, Huaqiao University, Quanzhou 362021, China
[3]Graduate Institute of Global Business and Strategy, National Taiwan Normal University, Taipei 106, Taiwan
[4]College of Innovation and Entrepreneurship, National Taipei University of Education, Taipei 106, Taiwan
[5]East Business Management Research Center, Huaqiao University, Quanzhou 362021, China

Corresponding author: Yenchun Jim Wu (wuyenchun@gmail.com)

This work was supported in part by the National Social Science Foundation of China under Grant 18BGL096 and Grant 18ZDA062, and in part by the National Natural Science Foundation of China under Grant 71771094.

ABSTRACT With the rapid development of computer and communication technology, anticipatory computing has been identified as one of the most important factors affecting human behavioral change. The future of anticipatory computing will not be bright if it fails to provide useful help to human life and work. Anticipatory computing applied to behavioral change intervention (BCI) is full of challenges and is a research topic of increasing interest and importance. This paper provides an overview of the concept of anticipatory computing, BCI, as well as anticipatory computing for the BCI and offers a multistage literature analysis. Also, a systematic analytical framework articulated from the existing literature is presented to reveal the progress and details of anticipatory computing for the BCI. This framework is divided into four dimensions: 1) sensing and context inferring; 2) context prediction; 3) behavioral guidance and intervention, and; 4) application. Based on our literature analysis, 11 elements of anticipatory computing for BCI are identified and discussed in terms of principles, enablers, and activities. Afterward, contributions and possible future directions for research are summarized at the end of this paper.

INDEX TERMS Anticipatory computing, behavioral change intervention, context prediction, intelligent intervention, sensing and context inferring.

I. INTRODUCTION

Anticipatory computing (AC) is rapidly becoming the focus of computer science and technological development [1]. With characteristics such as data technology advantages and prediction abilities, AC shows great development prospects and potential in realizing human behavioral change intervention (BCI). Wearable devices are a typical field of its application. Gartner Inc. forecast that 310.4 million wearable devices would be sold worldwide in 2017, an increase of 16.7 percent over 2016, and Allied Business Intelligence Research reported that the 2018 estimate of global wearable device market was $12.6 billion [2]. Wearable devices can collect high-resolution data on human behavior (HB) on an unprecedented scale (location, physical activity, voice and audio environment, proximity to objects, collocation with other devices, environmental indicators and more) through their pervasiveness and ability to passively log the user context [3], which is profoundly changing the way people work and live.

Compared with previous methods, AC devices can be more convenient for continuously collecting, recording, and updating the user's behavior trajectory, thus improving the timeliness, reliability, and accuracy of solutions and suggestions [4], [5]. However, there is still a long way to go in making use of AC to provide systematic solutions or suggestions for human behavioral change [6]. BCI through AC is a systematic project that requires the linking of human activities with AC sensing devices and information processing terminals through the appropriate approaches. The process involves resolving complex problems, such as the connection of users and their devices using sensors, the recognition and conversion of user activity traces, the demands of differentiated calculation methods and models derived from users' needs for personalized user experience, data quality, and system performance reliability. Additionally, because the research on AC remains preliminary, various difficulties are

The associate editor coordinating the review of this manuscript and approving it for publication was Tao Zhang.

2169-3536 © 2019 IEEE. Translations and content mining are permitted for academic research only.
Personal use is also permitted, but republication/redistribution requires IEEE permission.
See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

encountered in its practice. Problems such as the proficiency requirements for equipment and program operation, data leakage and abuse, prediction accuracy, and accountability regarding improper intervention results are yet to be resolved. Therefore, the use of AC to realize BCI requires a discussion between academia and industry.

The potential of and prospects for AC in BCI have gradually attracted scholarly attention, which has accumulated rich knowledge through numerous research methods. As early as 1980s, with the rise and use of internet technology, anticipatory systems began to be mentioned by some scholars [7]. Subsequently, many scholars studied the implementation process from the perspective of computer science [8]–[10]. In the twenty-first century, many scholars began to link AC with behavioral change prediction and intervention, which became the subject of heated discussion after 2010 [11]. Among them, Pejovic and Musolesi [12] reviewed recent research on anticipatory mobile computing and concentrated on the design and implementation of anticipatory mobile systems. However, they only commented on related research on AC in the computation implementation process, and few reviews have been conducted from the perspective of behavioral intervention. Pantic *et al.* [6] specifically discussed the four phases of anticipatory computing and advocated the transformation of computer-centric design into human-centered human-computer interaction design. Nadin [1] integrated the definition and process of AC with a number of scientific experimental cases, emphasizing that anticipatory computing would have to be embodied (in effective agents, robots, artefacts, etc.) in order to be expressed in action. Moreover, AC devices, such as smart phones, provide some innovative methods of behavioral intervention. In recent years, AC devices have been constantly commercialized and tested and face new opportunities and challenges [13]. Hence, it is necessary to systematically review the current research status, so as to understand the key factors and future directions for their successful application [1], [14].

Against that background, our research makes three contributions. First, this article describes and discusses AC for BCI and crosses the two fields of computer science and behavioral science. Second, based on the four dimensions of AC and the division of three time periods, we propose a systematic analysis framework covering the entire process of AC for BCI development in the past 19 years and the development priorities of each part. Third, based on our review of the literature, we propose 11 key elements, which are discussed in detail for AC devices and their designers and users. The rest of the paper is organized as follows. First, a general overview of AC and BCI is provided from the perspectives of computer science, psychology, and management to illustrate the nature and concept of AC, BCI, and AC for BCI. Based on this overview, diverse perspectives are integrated into a summary of characteristics of AC for BCI, and these characteristics are further elaborated in a systematic analytical framework. Multiple researchers then retrieved and filtered all the literature on AC for BCI in multiple databases. Then, relevant studies are discussed and reviewed in an attempt to identify the elements that are key to the success of AC for BCI based on the time axis and dimension. Next, the paper concludes with suggestions for further research on AC for BCI.

II. THEORETICAL BACKGROUND

A. ANTICIPATORY COMPUTING

The concept of AC can be traced to 1985 and the research of eminent mathematical biologist Robert Rosen, who proposed the concept of an anticipatory system and described it as "a system containing a predictive model of itself and/or its environment, which allows it to change state instantly in accord with the model's predictions pertaining to a later instant" [7]. With the recent developments in computer science and communication technologies, scholars are reconsidering the role of AC in human life and its application for behavioral control. Nowadays, the definition of AC is becoming clearer, and the majority of scholars [1], [7], [15]–[17] regard it as a process of making a sensible behavioral decisions based on expectations of the past, present, and future. AC not only includes collecting, handling mass data, and predicting the user's future situation but also making intelligent decisions that benefit participants [13], [18].

The existing literature on AC generally can be divided into three categories: (1) how to optimize and improve the prediction methodologies (e.g., statistical models, algorithms) and computer technology to achieve superior anticipation [1], [19]; (2) how the anticipatory system works, including mobile sensing, human–computer interaction (HCI), machine learning, and context prediction [8]–[10], [20], [21]; and (3) the application areas of AC, especially anticipatory mobile computing, which has attracted great interest in academic and practical circles with the advent of the smartphones [22]–[24].

AC is generally believed to possess four major functions: sensing, context inferring, context prediction, and intelligent actioning [6], [25], [26]. The first three functions are technical features of AC, among which HCI and machine learning are the basis for context inference, and the combination of mobile sensing and predictive modeling increases the potential for context prediction. Intelligent actioning is an application function of AC. In the course of BCI, AC can assist participants by introducing intelligent decision-making or by providing tailored suggestions to guide positive behavioral changes and check the effectiveness of intelligent intervention through constant monitoring and feedback. A small difference exists between tailored suggestions in AC and message tailoring. Tailored messages are personalized based on assessments of individual characteristics and needs and/or specific targeted outcomes [11], but tailored suggestions in AC are a further extension based on analysis and evaluation, involving intelligent guidance and intervention in users' future behavior. What's more, tailored messages according to people's development stages can enable people to focus on self-determined motives and intrinsic goals, which is beneficial in their acceptance of behavioral change [27].

As a data-driven and computation-based computer algorithm science [28], AC must be embodied in certain devices (e.g., agents, robots, artifacts, smart phones) in order to be expressed in action [16]. Moreover, these devices usually have the following core attributes. First, they are equipped with sensors (e.g., accelerometer, microphone, GPS) through which the users' data can be captured and collected for prediction. Second, they have a hardware foundation for storing a certain scale of data [29]. Third, a set of machine language, algorithms, and procedures are embedded in these devices [12], [16], [30] to analyze user behavioral patterns, obtain contextual inferences, and predict their future behavior using relevant data [12], [22]. Finally, these devices often have good HCI, which is embodied mainly in direct manipulation and authorization [1].

B. BEHAVIORAL CHANGE INTERVENTION

The basic unit of activity theory analysis is human activity, focusing on the interaction of human activities and consciousness in context [31]. Behavior is a general term to express actions in people's daily lives, encompassing all purposeful human activities. Early research on behavioral science can be traced back to the Hawthorne experiment, which was undertaken at the Western Electric Telephone Manufacturing Factory at Hawthorne, near Chicago, between 1924 and 1933 [32]. The experiment shows that by controlling for some conditions of the working environment (e.g., lighting conditions), employees working behavior changed [33]–[35]. The results of this experiment have had a positive and far-reaching impact on human management activities. And most scholars focus their attention on practice that ''can change the behavior of individuals or groups,'' which indirectly contributes to the development of behavioral change research [36]–[38].

A recent review shows that by 2014 the number of theories of behavioral change had reached 83 [39]. These theories determine the different levels of behavior of a person under the interaction of individuals, society, and the environment [40]. Also, the process of behavioral change can be divided into three stages: awareness of a problem, deciding what to do, and commencing a behavior [27]. These studies provide directions for behavioral change intervention and drive many scholars to pay attention to behavioral change interventions. As the Behavioral Change Wheel shows, by identifying the source of behavior to determine its effective goals, BCI can change behavior by altering abilities, opportunities, and motivations [41].

The theory on BCI used earlier was derived from Prochaska and DiClemente [42], [43], who proposed the transtheoretical model and stages of change, also known as the Stages of Change. The model points out that human behavioral change is a complex, gradual, and continuous process, divided into five stages: pre-intention, intention, preparation, action, and maintenance. The first three stages are mainly related to individual cognitive changes involving sociology, psychology, and other disciplines [44], with the last two stages related to behavioral adjustment and maintenance based on individual cognitive changes. Hence BCI can be regarded as the process of guiding people's behavioral change by formulating corresponding behavioral intervention strategies and plans, and it can be further divided into many activities, such as monitoring, learning, and providing tailored BCI [45].

C. ANTICIPATORY COMPUTING FOR BEHAVIORAL CHANGE INTERVENTION

Traditionally, BCI revolves around advice, support, and relevant information, such as body diagnosis instructions, professional care, and behavioral training, which is frequently applied in medicine [42]. However, this traditional approach is subject to a participant's time, budget, and geographic location [45]. In this study, ''AC for BCI'' is a dynamic intervention process, in which participants can be encouraged and supported to change behavior that will promote and maintain a lifestyle through anticipatory systems [46]. AC-based BCIs include continuous interviews and surveys of participants, enabling the anticipatory system to predict and respond to participants' behavioral changes more intelligently, such as providing tailored recommendations based on participants' questions, helping participants set targets and trace their progress, which achieve a more desirable result in a more timely and effective way [47].

According to the number of participants, AC for BCI can be divided into group-based BCIs and individual-based BCIs. Group-based BCIs primarily use AC in smart cities for dynamic urban traffic control, pavement monitoring, and hazard surveillance [48]. Individual-based BCIs primarily concern intelligent personal assistant technology and preventive health care. Intelligent personal assistant technology uses built-in sensors in AC devices to obtain web browsing history, calendars, and online social contacts to predict user intentions and display relevant contents in real time [14]. BCIs in preventive health care establish and develop human behavioral patterns through AC and actively provide guidance in treatment methods, thereby achieving superior health-care results. For example, AC can monitor and guide patients' treatment with depression or obesity [24], [26], [49].

III. METHOD

Although Rosen proposed the concept of AC in 1985, it was not quickly applied to behavioral science. After the internet economic bubble burst in 2000, many internet companies faced a transformation and began to focus on the effects of the internet on human life [50]. Mobile perception, HCI, machine learning, and situational prediction have also become the focus of academic attention [9], [51]–[53], which are important components of AC [22]. In order to systematically evaluate the progress of AC for BCI, we collect papers about AC for BCI published between 2000 and 2018 from multiple sources. We categorize the relevant documents collected at the end and the research status of the past 19 years, including

TABLE 1. Literature search of computerized databases.

Step	ACM (AC or BCI terms)	IEEE Xplore (AC or BCI terms)	Pubmed, Medline (AC terms)	Science Direct, Web of Science (AC or BCI terms)	Wiley-Blackwell (AC or BCI terms)
1	Anticipatory computing/ system	Anticipatory computing/ system	Patient/individual/ person/ anticipatory behavior	Anticipatory system/computing+ human behavior	Anticipation/anticipatory+ behavior
2	AC "adaptive dynamics"/ "embodied experience"/ "interactivity"	AC "Language competence"/ "learning"/ "context awareness"	AC "integrated computation resources"/"shared data"/"information generation"/ "interactivity"	AC "knowledge acquisition"/ "understanding"/ "learning"	AC "Integrated computation resources"/"interactivity"/"information generation"
3	Sensing/context inferring/prediction/ Intelligent actioning	Sensing/context inferring/prediction/ intelligent actioning	Behavior intervention/guidance	Sensing/context inferring/prediction/ intelligent actioning	Sensing/context inferring/prediction/ intelligent actioning
4	Delimiters: Date of publication: 2000-2018; English language	Delimiters: Date of publication: 2000- 2018; English language	Delimiters: Date of publication:2000-2018; English language	Delimiters: Date of publication:2000-2018; English language	Delimiters: Date of publication:2000-2018; English language

the research focus, the areas of concern, and the development process according to the timeline. Then based on the research status we make suggestions on future research.

A. SEARCH STRAGETY

AC is primarily published in computer science journals, while human behavioral intervention based on AC is generally published in health-care and social science journals. Therefore, we searched for articles on databases including ACM Transactions, Medline, IEEE Xplore, Web of Science, Wiley-Blackwell, Science Direct, and PubMed. Additionally, Google Scholar provides academic articles from various research publishers, so we also used it as an additional platform to avoid omissions caused by a limited search scope.

B. SAMPLE AND CRITERIA

The criteria of the research were based on the concepts of AC and HB, especially AC developed to intervene in HB. We selected two criteria for our research sample. First, the sample must include either AC or HB. At the same time, some terms related to AC or HB were considered, such as predictive computing, anticipatory mobile computing, and anticipatory systems. Second, according to nine preconditions of AC proposed by Nadin [1], specific conditions or supporting factors—such as sensing, context inference, context prediction, and intelligent actioning—were highlighted. Finally, the implementation of BCI (e.g., behavioral monitoring, learning, and providing customized information) was used as the supporting condition to analyze how AC intervenes and actively changes HB and its potential application in BCI.

C. LITERATURE SEARCH

The research was based on the retrieval process of Yudatama *et al.* [54], which included selecting five subject-related databases, retrieval of subject words for each database, synonyms, language, and other screening conditions and divided the retrieval process into four steps. A systematic search was conducted in August 2018 using AC, BCI, and related search terms (S1, Table 1). The search yielded 23,998 papers. Step 2 was a conditional screening of the AC literature abstracts based on the three preconditions of the implementation of AC (e.g., adaptive dynamics, embodied experience, and interactivity) and its nine subdimensions (context awareness, integrated computation resources, shared data, probability and possibility model, information generation, learning, language competence, knowledge acquisition, and understanding) [1]. Step 3 was screening of abstracts on BCI and the four dimensions of BCI, such as sensing, context inference, context prediction, and intelligent actioning [12], [45]. To meet the criteria, restrictions were placed on the language and years published in Step 4.

IV. RESULTS

A. SEARCH RESULTS

We conducted our search on electronic databases, such as ACM Transactions, IEEE Xplore, PubMed, Medline, Science Direct, Web of Science, and Wiley-Blackwell, for articles with keywords or titles containing AC, BCI, or related terms, and identified 23,998 articles. The results were screened based on the concept of AC and its nine preconditions [1] and obtained 4,848 articles related to AC. After deleting duplicate results, 446 articles remained, of which 355 were

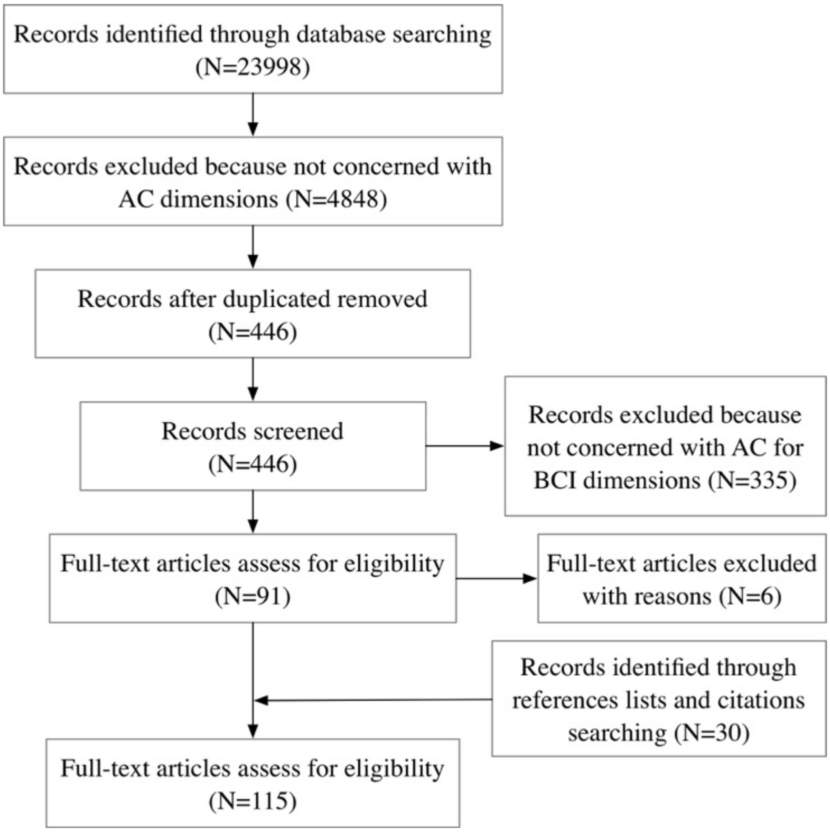


FIGURE 1. Search strategy and results.

excluded because of irrelevance to AC or BCI. Finally, six articles were omitted based on limitations such as publication time or language. Together with 30 articles obtained from 'snowball sampling' during the reading process, 115 articles that matched the search strategy were selected for full-text analysis. The detailed process is shown in Fig 1.

Two researchers (ZGX, LHL) screened 115 articles using the steps in Fig. 1. To ensure the reliability of the coding, the two researchers acted as coders independently to evaluate the correlation between the articles obtained and the research topic (AC and BCI). Each article was coded as 1, 2, or 3, in which 1 indicates the lowest correlation, and 3 indicates the highest. The reference standard is the correlation of the literature content with any dimension of sensing, context inferring, context prediction, behavioral guidance and intervention, and application [6], [22], [25]. Large differences in scores of some literature and the inability to score others were discussed and resolved with the senior researcher (LCP). Table 2 shows the final scores of 115 articles by ZGX and LHL, and the kappa value is 0.895. According to the kappa rating of Landis and Koch [55], the consistency within the coding team (kappa > 0.8) is good.

B. DATA ANALYSIS

The two researchers (ZGX, LHL) respectively searched each article and used Pejovic and Musolesi's cord category [12] as a framework to reveal the research progress on AC for BCI. The 115 articles that met the joint search criteria were categorized based on the four dimensions of AC for BCI: sensing and context inference, context prediction, behavioral guidance and intervention, and application.

With the rapid development of computer science and communication technology, such as pervasive computing, artificial intelligence, big data, and motion-sensing technologies, the function of AC in behavioral prediction and intervention began to receive great attention in 2011 [11], and since 2015 the applications of AC for BCI have been constantly tested and promoted [22]. Therefore, the research progress on AC for BCI can be divided into three stages. The first stage (2000-2010) is exploration of AC, in which many scholars discuss the concept and ideas on its design, involving sensing, context inference, and context prediction. The second stage (2011-2014) is trials of AC for BCI, and more attention was paid to behavioral intervention through AC in scenario

TABLE 2. The results of the kappa coding.

Frequency		PYL 1	PYL 2	PYL 3	Total
ZGX	1	40	2	0	42
ZGX	2	1	34	2	37
ZGX	3	1	2	33	36
Total		42	38	35	115

TABLE 3. The proportion of four dimensions of AC for BCI.

	Publications and Proportions			
	Sensing and context inference	Context prediction	Behavioral guidance and intervention	Application
2000-2010	9 (7.8%)	10 (8.7%)	5 (4.3%)	6 (5.2%)
2011-2014	12 (10.4%)	13 (11.3%)	11 (9.6%)	14 (12.2%)
2015-2018	27 (23.5%)	18 (15.7%)	22 (19.1%)	22 (19.1%)
Total	48 (41.7%)	26 (35.7%)	38 (33.0%)	42 (36.5%)

experiments with the gradual popularization of wearable devices. The third stage (2015-2018) is the realization of AC for BCI, and an increasing number of sophisticated terminal equipment was developed with high-precision sensors, combined with novel algorithmic procedures. Considering that each of the 115 documents retrieved may contain multiple aspects of these four dimensions, this paper uses the proportional form to classify them according to the three stages and four dimensions. Each percentage in Table 3 is that the number of documents in a certain time period and a certain dimension accounts for a total of 115. Total means that the number of documents classified into a certain dimension accounts for a total of 115. Based on these 115 papers, we propose a systemic analytical framework to illustrate the key points and main ideas in Table 4.

A total of 48 papers (41.7%) were related to sensing and context inference, which mainly discusses the issue of how AC understands and describes ''what the user does.'' Analyses were conducted from the perspectives of the interpretation process, sensory interface, and supporting framework. Sensing and context inference comprise the front end of AC and refer to the AC system's understanding of the context [26]. During the interpretation process, AC identifies the raw information in the environment through speech analysis, motion tracking, object identification, and other approaches and infers higher-level conceptual expressions or reconstructs user behavior and key features of the environment to clarify contexts, behavior, or intentions [22], [56], [57]. The contextual knowledge, goals, and clues extracted from user scenarios are key resources for social reasoning and have crucial implications for the accuracy of interpreting users and their contexts [58]. The sensory interface is the carrier used by the anticipatory system to interact with users and collect their contextual information. According to the specific contextual differences, it can be divided into four categories: geographic, link, traffic, and social [18]. The sensory interface in the mobile anticipatory system is often controlled by users and automatically records and transmits clues about usage scenarios through the sensor during social interaction. The supporting framework provides hardware and software support for AC to interpret users and their contexts, and a good support framework is helpful to ensure the quality of information and data collected from users [59], [60].

A total of 26 papers (35.7%) contained discussions of context prediction, which mainly investigates how AC infers and predicts ''what the users may do next'' by focusing on contextual tools and learning mechanisms. Mobile terminals such as robots and smartphones are crucial sources of users' personalized information and can be used to predict their behavioral track through built-in autonomous learning mechanisms [61]–[64]. And they are rapidly developing and becoming mainstream instruments for AC, integrating functions such as information collection, activity monitoring and behavioral prediction [22]–[24]. In terms of learning mechanisms, AC emphasizes that contextual prediction should learn from users' past activities and predict their future behavior and emotional states [12]. Such predictions are simple ''outputs of predictive models,'' rather than foresight [65]. And these models were guided by specific forecasting goals, such as users' surroundings, emotions, and behavioral trajectories, and supported by diversified computing methods [14], [66]–[71].

Papers relevant to behavioral guidance and intervention totaled 38 (33.3%) and mainly discussed how AC guides and intervenes in users' behavioral decisions to explain ''what should be done by them.'' And these studies focus on the mechanism and effectiveness of behavioral guidance and intervention through AC. An intervention model based on different methods has been proposed to guide driver behavior and avoid possible conflicts by predicting the future traffic state [70], [72]. Another intervention model embedded in smartphones can provide appropriate suggestions and interventions for patients suffering from depression by monitoring their cognitive context and analyzing their cognitive and emotional factors based on high-performance sensors and powerful computing capacity [23]. Not all intervention mechanisms work, and their effectiveness needs to be considered. Designers may need to do the following to enable the intervention mechanism to work effectively: building a common platform for coordination, high personalization through comprehensive recognition and prediction models, and investigation for optimal timing, relevance filtering, and the type of guidance [74]. At the same time, negative results and relevant accountability issues brought about by the failure of the intervention mechanism need to be taken seriously [22], [81]. A total of 42 papers (36.5%) were related to application,

TABLE 4. The focus and main ideas of four dimensions during the three stages.

	2000-2010 (main ideas)	2011-2014 (main ideas)	2015-2018 (main ideas)
Dimension: Sensing and context inference **Focus:** What does the user do?	Motion-sensing system and related supported framework were prepared for prediction [57, 58].	1. Inferences of current and future environments are necessary components of BCI [12]. 2. The HCI between users and the anticipatory system becomes the key for sensing and context inferring [69, 72].	1. More explanations of the process of anticipatory systems were given [22, 73]. 2. AC frameworks and system mechanisms were proposed [18, 59, 74].
Dimension: Context predict **Focus:** What might the user do next?	The concept of context prediction was analyzed and the idea of intelligent furniture detection is proposed [60, 65].	Prediction methods were developed, such as pervasive computing and adaptive computing (Pejovic & Musolesi, 2014), and prediction models were proposed based on specific scenarios, e.g., traffic and emotions [68, 69, 70].	The prediction models and methods were improved continuously (Pérez-D'Arpino & Shah, 2015), and the context prediction vehicles were developed, e.g. robots, smartphones [22, 61, 67].
Dimension: Behavior guidance and intervention **Focus:** What should be done?	Guidance and intervention for HB in the development of AC were emphasized [71].	AC opened up a new path for analyzing human behavior, but the intervention was only conducted when certain conditions occur [11, 70]. And the methods for decision-making and frameworks for intervention systems were explored [1].	Time and methods of guidance or intervention are becoming a hot spot and the effectiveness of intervention based on machine learning gains widespread attention and needs to be improved further [5, 23, 75].
Dimension: Application **Focus:** Are the users really doing it?	The potential and prospects of AC in positively changing human behavior began to be mentioned [76].	Attempts have been made to enable AC to intervene in human life with the popularization of smartphones, wearable devices [77], and preventive health care is a hot spot of AC for BCI [78].	Intelligent anticipatory agents for dynamic environments were emphasized [59], and the application of AC for BCI needs to be further improved from the perspective of the designer, participants, and policy makers [64, 75, 79].

which mainly talk about the application fields of AC for BCI. In the early 2000s, AC was successfully applied to robot navigation, hand-eye coordination, learning, and action planning [53] and was also capable of narration and music creation [82]. Since 2011, the application of AC for BCI has included intelligent personal assistant technology, preventive health care, urban traffic management, and ambient intelligence. MindMeld and Google Now are typical applications of intelligent personal assistants, which predict user intentions and display relevant real-time content by acquiring the user's web browsing history, calendar, and online social contacts. Preventive health care establishes and develops human behavioral patterns through AC and actively provides guidance on treatment methods, thereby helping the user to achieve better health-care results [14], [24], [83].

The problems accompanying the acceleration of urbanization, such as traffic, pollution, and crime, plague modern cities, but the motion sensing of AC can mitigate traffic, monitor roads, detect hazards, and provide safety guidance [48], [71], [84], [85]. AC can also be applied to ambient intelligence for generating personalized responses to users [61], [86], including in-home health care and smart food management [87].

V. DISCUSSION

The purpose of the research is to link AC and BCI in theory and practice. Through a content analysis of 115 articles, we propose an analytical framework with four dimensions and three stages to organize research progress on AC for BCI. What is more, we also find that AC is increasingly integrated with human behavior, constantly improving people's daily lives and work. However, the factors affecting AC's implementation of BCI are not clear enough. Drawing on the ideas of Scholl *et al.* [88], as shown in Figure 2, 11 key elements of AC for BCI were identified through literature-base content analysis and subsequently described. We calculated the proportion of 11 key elements in 115 papers. These elements are interrelated, including principles, enablers, and activities. Principles are the foundation of BCI and include three key elements that represent the level of knowledge and ability to perform AC, including researcher ability (25.2%), diversification and personalization of research subjects (34.8%), and cooperation (24.3%). Enablers consist of four key elements, which are conditions that promote the complete and efficient implementation of BCI in both scientific background and social background, including hardware development (47.8%), software development (66.1%), legal guidelines and regulations (20.0%), and computer ethics (11.3%). Activities consist of four key elements, which are information and behaviors that target the results, including information continuity (38.3%), information integrity (58.3%), user authorization (39.1%), and user engagement and feedback (30.4%). On the one hand, these 11 key elements as a whole cover all the details of the AC for BCI process. On the other hand, the elements are related to each other and interact. They are not independent. The goal of the entire process is to make the interaction of human behavior with anticipatory computing more practical and actionable.

A. PRINCIPLES

1) RESEARCHER ABILITY

As seen in the literature analysis, the implementation of anticipatory computing is not easy, and it is often difficult for several researchers to complete the development of software and hardware (e.g., algorithm programs and sensor devices). Researchers need to be equipped with sufficient specialized knowledge to finish in-depth tasks. More importantly, they need to develop the ability to integrate knowledge of different disciplines (e.g., medicine, computer science, engineering).

2) DIVERSIFICATION AND PERSONALIZATION OF RESEARCH SUBJECTS

In life, people are in various industries (e.g., automotive, retail, agriculture), and it is necessary to make completely different judgments for each career task in an anticipatory system (e.g., the driver's intelligent planning of driving routes). Everyone is an independent individual, and their growth experience, social background, beliefs, financial status, values, hobbies, and personal needs are different. Hence, to enable users to obtain the expected guidance, the personalized HCI should be provided through AC.

3) COOPERATION

Various cooperation needs to be satisfied when AC is used for BCI. Collaboration among researchers facilitates the integration of interdisciplinary knowledge. And an interdisciplinary research team is more likely to reduce cognitive bias in the design process of AC. To allow participants to be deeply involved in AC experiments, researchers need to establish partnerships with them, characterized by trust, mutual concern, and understanding. In addition, participants need to have enough confidence in AC devices (e.g., smartphones to obtain cognitive content and emotional factors for depressed patients) to facilitate the collection processing of their data.

B. ENABLERS

1) HARDWARE DEVELOPMENT

The information gathering process of AC needs the support of hardware equipment (e.g., robots, smartphones, intelligent building, computers). Intelligent mobile wearable devices (e.g., smart watches, smart running shoes) are currently hot spots, but the development of hardware sensing devices is still limited. Few devices carry high-performance sensors and processors, and using these devices is not easy for participants. Intellectualization is the key direction for hardware development of AC.

2) SOFTWARE DEVELOPMENT

Intelligent software (e.g., algorithms, models, programs, systems) is the core of AC for collecting and processing information. The definition of intelligent interaction system includes interaction between the sender and the receiver, with the use of personal smart devices and the support of intelligent conditions. However, most software currently in use can only meet users' basic physical and psychological needs (e.g., blood pressure, heartbeat, mood monitoring) or provide a certain anticipatory judgment (e.g., a decentralized approach to vehicle routing prediction). With more diverse personalized needs, more intelligent interventions and guidance are needed (e.g., users accept the intelligent recommendations without making subjective judgments), which requires researchers to develop software at a deeper level.

3) LEGAL GUIDELINES AND REGULATIONS

The third wave of technology has spawned many business practices that are closely related to information and communication technologies, but the relevant concepts that emerged in this wave are constantly evolving, which places further normative requirements on relevant legal norms and regulations. In the future, the definition of the relevant concepts (e.g., environmental intelligence, the Internet of Things, universal computing, mobile computing) needs to be further clarified, and the relevant legal policies should be introduced or improved (e.g., legal liability for improper intervention treatment) and licensing agreements (e.g., data collection and sharing protocols).

4) COMPUTER ETHICS

As a product of human social progress and scientific and technological development, AC must be consistent with the core values and goals of human development and harmonious with the long-established ethical human civilization. To better promote and implement AC for BCI, it is necessary to improve the ethics of computer science workers, system designers, and developers and distributors (e.g., setting up computer science ethics courses and strengthening scientific ethics promotion on campus).

C. ACTIVITIES

1) INFORMATION CONTINUITY

AC is a data-driven and computation-based computer algorithm science [28], so access to user information is critical. Because the discontinuity of human daily activities (e.g., physical location movement, discontinuous use of equipment) may have an impact on system identification and prediction accuracy, the integration of data for users in different periods is emphasized in some literature. In addition, because a user may have more than one AC device, it is necessary to integrate data from different distributed platforms in the future.

2) INFORMATION INTEGRITY

To realize the vision of AC, computer-based devices and systems need to be used by users seamlessly and unobtrusively. Some scholars have stated that an important challenge of inferring context through AC is that user-provided ''breadcrumbs''-like data may not be sufficient for mining their context. Therefore, a mobile computing device needs to be used by the user continuously, so that it is possible to collect complete information to improve the accuracy of the prediction model.

3) USER AUTHORIZATION

Another aspect of AC emphasized in the literature is user authorization. Designers and developers of AC devices should encourage users to take on the autonomy of problem solving (e.g., trying to change the current state and lifestyle). At the same time, users should also recognize the capabilities of AC devices in terms of data sensing, context inference, and context prediction, provide the authorization for AC devices, and treat them as collaborators to achieve human-machine collaboration.

4) USER ENGAGEMENT AND FEEDBACK

The limitation of using AC devices for BCI is that the final choice and execution rights are still in the hands of the user, which requires the user to participate and actively give feedback. At the same time, AC devices are expected to give users self-monitoring and behavioral autonomy to ensure that the devices serve users instead of controlling them. Most of the previous studies focused on the prediction of the users' future behavior but ignored the feedback and evaluation of such predictions (e.g., user self-assessment, evaluation of the effect of machine learning), which can constantly improve the predictive model and intelligent guidance.

VI. FUTURE WORK

With the integration and development of internet and computer technology, AC has been identified as one of the most important factors affecting human behavioral change, whether in life or in work. In the future, changes in human behavior can be predicted and guided through AC. Hence, how to apply AC to the prediction and intervention in human behavioral change is a research topic of increasing interest and importance. According to the focus in Table 4 and the 11 key elements proposed in the Discussion, we found that the research level of AC, improvement in the algorithm system, the processing of personalized information, and the degree of interaction between AC and users needed different degrees of improvement. Therefore, as shown in Figure 2, this paper proposes four possible future research areas.

1. The intelligent actioning methods in AC to support users. The final intervention in HB through AC, intelligent actioning, is the focus of anticipatory systems, although the application of AC in most literature remains in general situations, such as driving and emotion control [23], [89]. None of these mentioned approaches cover the final processing stage, namely intelligent actioning, to support users, i.e., a mechanism to change user behavior is not addressed [23]. Future research needs to improve the computational model employed in a specific situation to make it more intelligent and perform more functions than simply providing guidance.

2. The balance between information sharing and privacy protection in BCI based on AC. Real-time monitoring and diagnosis at any time anywhere may result in severe privacy problems. In particular, exchanging information on the internet may lead to risks of the leakage or abuse of user information [22], [73]. As noted by Pejovic *et al.* [26], the simultaneous development of mobile-based BCI applications and the strengthening of personal privacy protection remains a problem in AC for BCI in the future. And how to ensure users' information security and privacy while improving the comprehensiveness and accuracy of data collection will become a hot topic in computer science and behavioral science in the future.

3. The trade-offs between personalized guidance and service efficiency for large-scale participants using AC devices. The large-scale use of AC devices and the provision of personalized suggestions require massive resources and manpower. If these devices are not used effectively or the personalized suggestions are not accepted, they will lead to great waste of resources. It might be unwise to provide route guidance information to every driver [81], [90]. Therefore, one area of future research to explore is under which circumstances need the large-scale use of AC devices and users need personalized suggestions. In addition, daily behavior in social life is diverse, and distinct individuals exhibit differences even in the same category of behavior. Therefore, models and scenario simulation experiments cannot remain in the context

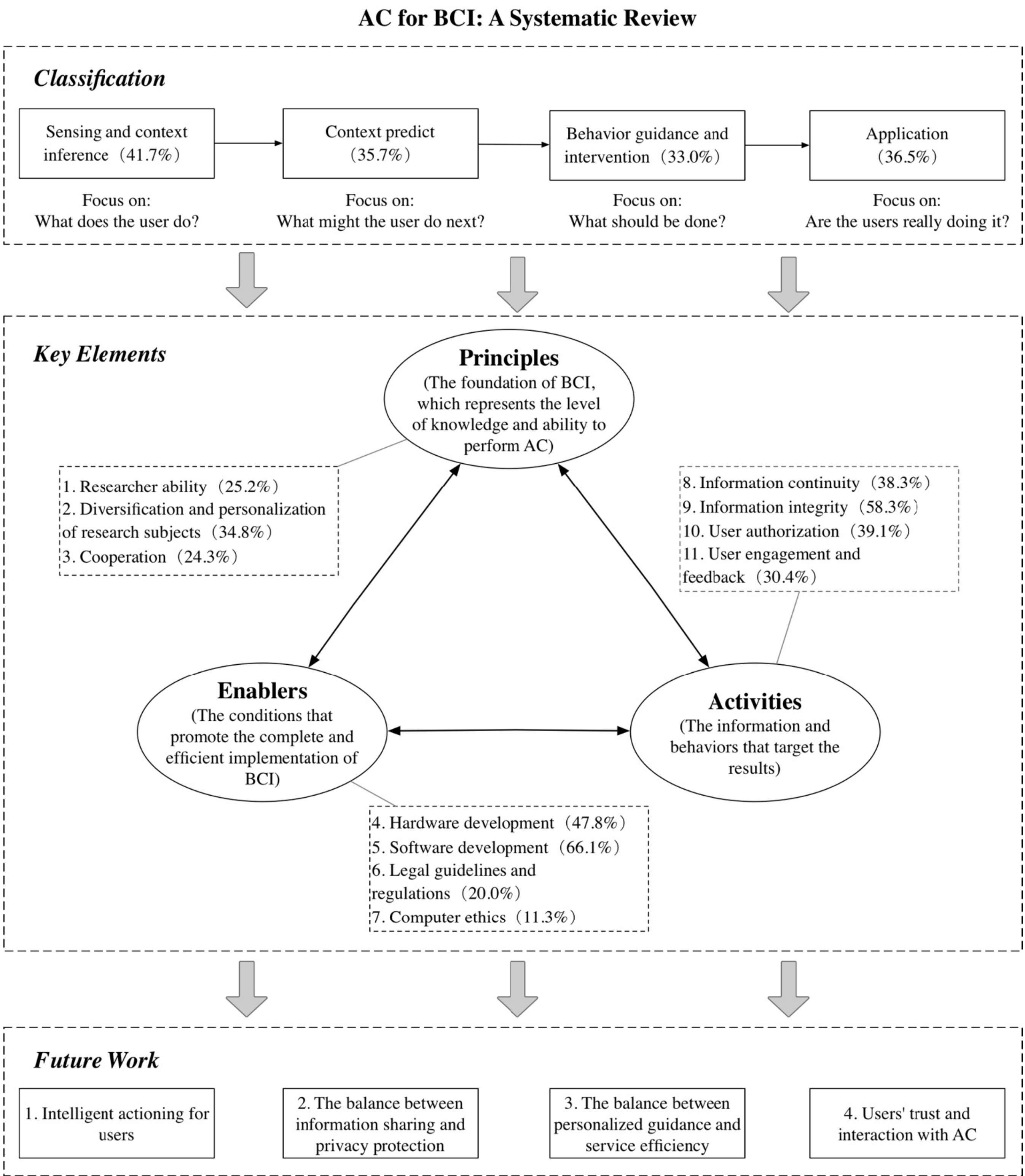


FIGURE 2. AC for BCI: A systematic review.

of general behavior and more personalized applications are necessary.

4. The effects of human-centered ideas on the design of AC devices. AC devices such as mobile wearable devices and smart home sensors have been integrated into life and work to continuously record behavioral trajectories [22]. But not everyone is willing to accept this kind of dynamic tracking. Privacy leakage risk makes users hesitate to use

AC devices [73]. For AC to penetrate the lives of users and provide them with forward-looking guidance, users need to play an important role in the design of AC devices. Users' perception and trust in AC devices and the way in which users interact with AC devices are the basic premise for the application of AC to BCI and deserve more attention in further studies.

VII. CONCLUSIONS

This paper provides an overview of the nature and concepts of AC, BCI, and AC for BCI and reviews the relevant studies in databases. Unlike other reviews [22], we offer a cross field between computer science and behavioral science and implement a multi-stage literature collection and analysis process, so this paper offers researchers and practitioners more details on AC for BCI. Also, we propose a systemic analytical framework articulated from the literature to reveal the progress and details of AC for BCI. The design framework is synthesized and divided into four dimensions: sensing and context inference, context prediction, behavioral guidance, and intervention and application. The focus of each dimension is different and will change over time. This framework, though still preliminary and in need of refinement and evaluation, covers the entire process of AC-based BCI, involving multiple steps, such as data collection, analysis, processing, and response. This framework expands the model developed by Pejovic and Musolesi [22], shifts the research perspective of AC from computer science to behavioral science, and focuses on the relationship between AC and human behavior. Finally, we identify 11 distinct dimensions of AC for BCI in the literature. They are interrelated and can be divided into principles, enablers, and activities. They address different levels of AC for BCI, mainly focusing mainly on AC devices and their designers and users. AC for BCI has become a prominent research topic and offers promising opportunities for further research.

REFERENCES

[1] M. Nadin, "Can predictive computation reach the level of anticipatory computing," *Int. J. Appl. Res. Inf. Technol. Comput.*, vol. 5, no. 3, pp. 171–200, 2014.

[2] A. McIntyre, B. Blau, and M. Reitz, "Forecast: Wearable electronic devices, worldwide," Gartner, Stamford, CT, USA, Jan. 2016. [Online]. Available: https://www.gartner.com/en/documents/3187421

[3] A. Mehrotra, V. Pejovic, and M. Musolesi, "SenSocial: A middleware for integrating online social networks and mobile sensing data streams," in *Proc. 15th Int. Middleware Conf. Middleware*, Bordeaux, France, 2014, pp. 205–216.

[4] W. Arthur, Jr., T. Tubré, D. S. Paul, and P. S. Edens, "Teaching effectiveness: The relationship between reaction and learning evaluation criteria," *Educ. Psychol.*, vol. 23, no. 3, pp. 275–285, Jun. 2003.

[5] M. M. Maheu, K. P. Drude, K. M. Hertlein, R. Lipschutz, K. Wall, and D. M. Hilty, "Correction to: An interprofessional framework for telebehavioral health competencies," *J. Technol. Behav. Sci.*, vol. 3, no. 2, p. 107, Jun. 2018.

[6] M. Pantic, A. Pentland, A. Nijholt, and T. S. Huang, "Human computing and machine understanding of human behavior: A survey," in *Proc. ICMI*, Banff, AB, Canada, 2006, pp. 239–248.

[7] R. Rosen, *Anticipatory Systems; Philosophical, Mathematical, and Methodological Foundations*. New York, NY, USA: Pergamon Press, 1985.

[8] G. Chen and D. Kotz, "A survey of context-aware mobile computing research," Dept. Comput. Sci., Dartmouth College, Tech. Rep. TR-2000-381, Nov. 2000.

[9] M. V. Butz, O. Sigaud, and P. Gérard, "Anticipatory behavior: Exploiting knowledge about the future to improve current behavior," in *Anticipatory Behavior in Adaptive Learning Systems*. Berlin, Germany: Springer, 2003, pp. 1–10.

[10] R. Perdisci, A. Lanzi, and W. Lee, "Classification of packed executables for accurate computer virus detection," *Pattern Recognit. Lett.*, vol. 29, no. 14, pp. 1941–1946, Oct. 2008.

[11] N. D. Lane, M. Mohammod, M. Lin, X. Yang, H. Lu, S. Ali, A. Doryab, E. Berke, T. Choudhury, and A. T. Campbell, "BeWell: A smartphone application to monitor, model and promote wellbeing," in *Proc. Int. Conf. Pervasive Comput. Technol. Healthcare*, Dublin, Ireland, 2011, pp. 1–8.

[12] V. Pejovic and M. Musolesi, "Anticipatory mobile computing for behaviour change interventions," in *Proc. UbiComp Adjunct*, Seattle, WA, USA, 2014, pp. 1025–1034.

[13] V. Pejovic, "Roadmap to anticipatory mobile computing," *Elektrotehniški Vestnik*, vol. 81, no. 5, pp. 247–250, 2014.

[14] A. Mehrotra and M. Musolesi, "Sensing and modeling human behavior using social media and mobile data," *Comprehensive Geograph. Inf. Syst.*, vol. 3, pp. 313–319, Feb. 2018.

[15] M. Nadin, "Anticipation," *Int. J. Gen. Syst.*, vol. 39, no. 1, pp. 35–133, Jan. 2010.

[16] M. Nadin, "Anticipation and computation: Is anticipatory computing possible?" in *Anticipation Across Disciplines*, M. Nadin, Ed. Cham, Switzerland: Springer, 2016, pp. 283–339.

[17] T. Fuller, "Anxious relationships: The unmarked futures for post-normal scenarios in anticipatory systems," *Technol. Forecasting Social Change*, vol. 124, pp. 41–50, Nov. 2017.

[18] N. Bui, M. Cesana, S. A. Hosseini, Q. Liao, I. Malanchini, and J. Widmer, "A survey of anticipatory mobile networking: Context-based classification, prediction methodologies, and optimization techniques," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 3, pp. 1790–1821, 3rd Quart., 2017.

[19] C. Meurisch, U. Naeem, P. M. Scholl, M. A. Azam, S. Günther, P. Baumann, S. Réhman, and M. Mühlhäuser, "SmartGuidance'17: 2nd workshop on intelligent personal support of human behavior," in *Proc. UbiComp*, Maui, HI, USA, 2017, pp. 623–626.

[20] N. D. Lane, E. Miluzzo, H. Lu, D. Peebles, T. Choudhury, and A. T. Campbell, "A survey of mobile phone sensing," *IEEE Commun. Mag.*, vol. 48, no. 9, pp. 140–150, Sep. 2010.

[21] I. Burbey and T. L. Martin, "A survey on predicting personal mobility," *Int. J. Pervasive Comput. Commun.*, vol. 8, no. 1, pp. 5–22, 2012.

[22] V. Pejovic and M. Musolesi, "Anticipatory mobile computing: A survey of the state of the art and research challenges," *ACM Comput. Surv.*, vol. 47, no. 3, Apr. 2015, Art. no. 47.

[23] A. Mehrotra, R. Hendley, and M. Musolesi, "Towards multi-modal anticipatory monitoring of depressive states through the analysis of human-smartphone interaction," in *Proc. UbiComp Adjunct*, Berlin, Germany, 2016, pp. 1132–1138.

[24] L. Canzian and M. Musolesi, "Trajectories of depression: Unobtrusive monitoring of depressive states by means of smartphone mobility traces analysis," in *Proc. ACM Int. Joint Conf. Pervasive Ubiquitous Comput.*, Osaka, Japan, 2015, pp. 1293–1304.

[25] H. Lu, D. Frauendorfer, M. Rabbi, M. S. Mast, G. T. Chittaranjan, A. T. Campbell, D. Gatica-Perez, and T. Choudhury, "StressSense: Detecting stress in unconstrained acoustic environments using smartphones," presented at the ACM Conf. Ubiquitous Comput., Pittsburgh, PA, USA, Sep. 2012, pp. 351–360.

[26] V. Pejovic, A. Mehrotra, and M. Musolesi, "Anticipatory mobile digital health: Towards personalized proactive therapies and prevention strategies," in *Anticipation and Medicine*, M. Nadin, Ed. Cham, Switzerland: Springer, 2017, pp. 253–267.

[27] J. P. Pope, L. Pelletier, and C. Guertin, "Starting off on the best foot: A review of message framing and message tailoring, and recommendations for the comprehensive messaging strategy for sustained behavior change," *Health Commun.*, vol. 33, no. 9, pp. 1068–1077, Jun. 2018.

[28] N. Eagle, A. S. Pentland, and D. Lazer, "Inferring friendship network structure by using mobile phone data," *Proc. Nat. Acad. Sci. USA*, vol. 106, no. 36, pp. 15274–15278, 2009.

[29] G. Miller, "The smartphone psychology manifesto," *Perspect. Psychol. Sci.*, vol. 7, no. 3, pp. 221–237, May 2012.

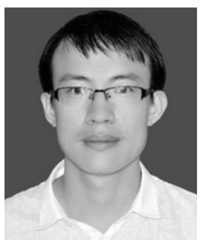
[30] D. M. Dubois, "New trends in computing anticipatory systems: Emergence of artificial conscious intelligence with machine learning natural language," *AIP Conf. Proc.*, vol. 1051, no. 1, p. 25, Oct. 2008.
[31] L. Uden, E. Damiani, G. Gianini, and P. Ceravolo, "Activity theory for OSS ecosystems," in *Proc. Inaugural IEEE-IES Digit. EcoSyst. Technol. Conf.*, Cairns, QLD, Australia, Feb. 2007, pp. 223–228.
[32] F. J. Roethlisberger and W. J. Dickson, "Management and the worker," *Acad. Manage. Rev.*, vol. 11, no. 2, pp. 459–464, Apr. 1986.
[33] H. M. Parsons, "What happened at hawthorne?: New evidence suggests the Hawthorne effect resulted from operant reinforcement contingencies," *Science*, vol. 183, no. 4128, pp. 922–932, Mar. 1974.
[34] R. Sommer, "The Hawthorne dogma," *Psychol. Bull.*, vol. 70, no. 6, pp. 592–595, Dec. 1968.
[35] R. Gillespie, "Manufacturing knowledge: A history of the hawthorne experiments," *History, Rev. New Books*, vol. 21, no. 2, p. 304, Oct. 1991.
[36] G. Wickström and T. Bendix, "The 'Hawthorne effect'—What did the original Hawthorne studies actually show? " *Scand. J. Work Environ. Health*, vol. 26, no. 4, pp. 363–367, Aug. 2000.
[37] M. Chiesa and S. Hobbs, "Making sense of social research: How useful is the Hawthorne effect?" *Eur. J. Social Psychol.*, vol. 38, no. 1, pp. 67–74, Jan./Feb. 2008.
[38] R. Crutzen, G.-J. Y. Peters, and J. Noijen, "Using confidence interval-based estimation of relevance to select social-cognitive determinants for behavior change interventions," *Front Public Health*, vol. 5, p. 165, Jul. 2017.
[39] P. Andrew, F. F. Sniehotta, W. Craig, S. U. Dombrowski, R. Lizzie, and M. Susan, "Does theory influence the effectiveness of health behavior interventions? Meta-analysis," *Health Psychol. Off. J. Division Health Psychol. Amer. Psychol. Assoc.*, vol. 33, no. 5, pp. 465–474, May 2014.
[40] M. Frese and D. Zapf, "Action as the core of work psychology: A German approach," in *Handbook of Industrial and Organizational Psychology*. Palo Alto, CA, USA: Consulting Psychologists Press, 1994, pp. 271–340.
[41] S. Michie, L. Atkins, and R. West, *The Behaviour Change Wheel: A Guide To Designing Interventions*. London, U.K.: Silverback Publishing, 2014.
[42] J. O. Prochaska and C. C. DiClemente, "Common processes of change in smoking, weight control, and psychological distress," in *Coping & Substance Use*. New York, NY, USA: Academic, 1985, pp. 345–363.
[43] J. O. Prochaska and C. C. Diclemente, "Stages and processes of self-change of smoking: Toward an integrative model of change," *J. Consulting Clin. Psychol.*, vol. 51, no. 3, pp. 390–395, Jun. 1983.
[44] J. Cheng, "Computing intentions dynamically in a changing world by anticipatory relevant reasoning," in *Intelligent Information and Database Systems*. Cham, Switzerland: Springer, 2014, pp. 361–371.
[45] N. Lathia, V. Pejovic, K. K. Rachuri, C. Mascolo, M. Musolesi, and P. J. Rentfrow, "Smartphones for large-scale behavior change interventions," *IEEE Pervas. Comput.*, vol. 12, no. 3, pp. 66–73, Jul. 2013.
[46] L. Yardley, T. Choudhury, K. Patrick, and S. Michie, "Current issues and future directions for research into digital behavior change interventions," *Amer. J. Preventive Med.*, vol. 51, no. 5, pp. 814–815, Nov. 2016.
[47] A. Fielden, "Increasing acceptance of online health information: Understanding barriers, tailoring messages and self-affirmation," Ph.D. dissertation, Dept. Psychol., Northumbria Univ., Newcastle upon Tyne, U.K., 2012.
[48] B. Hull, V. Bychkovsky, Y. Zhang, K. Chen, M. Goraczko, A. Miu, E. Shih, H. Balakrishnan, and S. Madden, "CarTel: A distributed mobile sensor computing system," in *Proc. 4th ACM SenSys*, Boulder, CO, USA, 2006, pp. 125–138.
[49] P. Klasnja and W. Pratt, "Healthcare in the pocket: Mapping the space of mobile-phone health interventions," *J. Biomed. Inform.*, vol. 45, no. 1, pp. 184–198, Feb. 2012.
[50] K. Manwaring and R. Clarke, "Surfing the third wave of computing: A framework for research into eObjects," *Comput. Law Secur. Rev.*, vol. 31, no. 5, pp. 586–603, Oct. 2015.
[51] G. Chen and D. Kotz, "A survey of context-aware mobile computing research," Dept. Comput. Sci., Dartmouth College, Tech. Rep. TR-2000-381, Nov. 2000.
[52] K. Lyytinen and Y. Yoo, "Research commentary: The next wave of nomadic computing," *Inf. Syst. Res.*, vol. 13, no. 4, pp. 377–388, Dec. 2002.
[53] W. Stolzmann and M. Butz, "Latent learning and action planning in robots with anticipatory classifier systems," in *Learning Classifier Systems*. Berlin, Germany: Springer, 2000, pp. 301–317.
[54] U. Yudatama, B. A. A. Nazief, A. N. Hidayanto, and M. Mishbah, "Factors affecting awareness and attitude of IT governance implementation in the higher education institution: A literature review," in *Proc. 3rd Int. Conf. Sci. Inf. Technol. (ICSITech)*, Bandung, Indonesia, Oct. 2017, pp. 588–592.
[55] J. R. Landis and G. G. Koch, "The measurement of observer agreement for categorical data," *Biometrics*, vol. 33, no. 1, pp. 159–174, 1977.
[56] J. Coutaz, J. L. Crowley, S. Dobson, and D. Garlan, "Context is key," *Commun. ACM*, vol. 48, no. 3, pp. 49–53, Mar. 2005.
[57] I. Escamilla, M. Torres-Ruiz, M. Moreno-Ibarra, R. Quintero, G. Guzmán, and V. Luna-Soto, "Geocoding tweets approach based on conceptual representations in the context of the knowledge society," *Int. J. Semantic Web Inf. Syst.*, vol. 12, no. 1, pp. 44–61, Jan. 2016.
[58] A. Oulasvirta, R. Petit, M. Raento, and S. Tiitta, "Interpreting and acting on mobile awareness cues," *Hum.-Comput. Interact.*, vol. 22, nos. 1–2, pp. 97–135, Dec. 2007.
[59] K. Sycara, "Agents supporting humans and organizations in open, dynamic environments," in *Proc. Int. Joint Conf. Auton. Agents Multiagent Syst.*, Bologna, Italy, 2002, p. 1043.
[60] A. Urbieta, A. González-Beltrán, S. Ben Mokhtar, J. Parra, L. Capra, M. A. Hossain, A. Alelaiwi, J. I. Vázquez, "Hybrid service matchmaking in ambient assisted living environments based on context-aware service modeling," *Cluster Comput.*, vol. 18, no. 3, pp. 1171–1188, Sep. 2015.
[61] H. Hagras, V. Callaghan, M. Colley, G. Clarke, A. Pounds-Cornish, and H. Duman, "Creating an ambient-intelligence environment using embedded agents," *IEEE Intell. Syst.*, vol. 19, no. 6, pp. 12–20, Nov. 2004.
[62] C. M. Huang and B. Mutlu, "Anticipatory robot control for efficient human-robot collaboration," in *11th ACM/IEEE Int. Conf. Hum.-Robot Interact.*, Christchurch, New Zealand, Mar. 2016, pp. 83–90.
[63] M. J. Gielniak and A. L. Thomaz, "Generating anticipation in robot motion," in *Proc. RO-MAN*, Atlanta, GA, USA, Jul./Aug. 2011, pp. 449–454.
[64] G. Hoffman and C. Breazeal, "Effects of anticipatory action on human-robot teamwork: Efficiency, fluency, and perception of team," in *Proc. 2nd ACM SIGCHI/SIGART Conf. Hum.-Robot Interact.*, Arlington, VA, USA, Mar. 2007, pp. 1–8.
[65] T. O. Staiger, P. A. Kritek, E. L. Blakeney, B. K. Zierler, K. O'Brien, and R. H. Ehrmantraut, "A conceptual framework for applying the anticipatory theory of complex systems to improve safety and quality in healthcare," in *Anticipation and Medicine*, M. Nadin, Ed. Cham, Switzerland: Springer, 2017, pp. 31–40.
[66] V. Poladian, A. Garlan, M. Shaw, M. Satyanarayanan, R. Schmerl, and J. Sousa, "Leveraging resource prediction for anticipatory dynamic configuration," in *Proc. 1st Int. Conf. Self-Adapt. Self-Organizing Syst.*, Cambridge, MA, USA, Jul. 2007, pp. 214–223.
[67] C. Pérez-D'Arpino and J. A. Shah, "Fast target prediction of human reaching motion for cooperative human-robot manipulation tasks using time series classification," in *Proc. IEEE Int. Conf. Robot. Autom.*, Seattle, WA, USA, May 2015, pp. 6175–6182.
[68] W. Gaona, E. Escobar, J. Hermosillo, and B. Lara, "Anticipation by multi-modal association through an artificial mental imagery process," *Connection Sci.*, vol. 27, no. 1, pp. 68–88, Mar. 2015.
[69] D. Sanderson and J. Pitt, "An affective anticipatory agent architecture," in *Proc. IEEE/WIC/ACM Int. Conf. Web Intell. Intell. Agent Technol.*, Lyon, France, vol. 2, Aug. 2011, pp. 93–96.
[70] P. Stahl, B. Donmez, and G. A. Jamieson, "A model of anticipation in driving: Processing pre-event cues for upcoming conflicts," in *Proc. AutomotiveUI*, Seattle, WA, USA, 2014, pp. 1–8.
[71] R. Claes, T. Holvoet, and D. Weyns, "A decentralized approach for anticipatory vehicle routing using delegate multiagent systems," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 2, pp. 364–373, Feb. 2011.
[72] P. Stahl, B. Donmez, and G. A. Jamieson, "Anticipatory driving competence: Motivation, definition & modeling," in *Proc. 5th Int. Conf. Automot. User Interfaces Interact. Veh. Appl.*, Eindhoven, The Netherlands, 2013, pp. 286–291.
[73] E. Fisher, M. Boenink, S. van der Burg, and N. Woodbury, "Responsible healthcare innovation: Anticipatory governance of nanodiagnostics for theranostics medicine," *Expert Rev. Mol. Diag.*, vol. 12, no. 8, pp. 857–870, Nov. 2012.
[74] C. Meurisch, U. Naeem, M. A. Azam, F. Janssen, B. Schmidt, and M. Mühlhäuser, "Smarticipation: Intelligent personal guidance of human behavior utilizing anticipatory models," in *Proc. UbiComp*, Berlin, Germany, 2016, pp. 1227–1230.
[75] T. Schneider and J. Hermsdörfer, "Anticipation in object manipulation: Behavioral and neural correlates," in *Progress in Motor Control*. Cham, Switzerland: Springer, 2016, pp. 173–194.
[76] M. Atzmueller, B. Fries, and N. Hayat, "Sensing, processing and analytics: Augmenting the Ubicon platform for anticipatory ubiquitous computing," in *Proc. ACM Int. Joint Conf. Pervasive Ubiquitous Comput., Adjunct*, Berlin, Germany, 2016, pp. 1239–1246.

[77] R. Helaoui, "Towards a proactive system based on activity recognition," in *Proc. 8th IEEE Int. Conf. Pervasive Comput. Commun. Workshops*, Mannheim, Germany, Mar./Apr. 2010, pp. 849–850.
[78] L. Da Xu, W. He, and S. Li, "Internet of Things in industries: A survey," *IEEE Trans. Ind. Informat.*, vol. 10, no. 4, pp. 2233–2243, Nov. 2014.
[79] N. Sultan, "Making use of cloud computing for healthcare provision: Opportunities and challenges," *Int. J. Inf. Manage.*, vol. 34, no. 2, pp. 177–184, Apr. 2014.
[80] M. Atzmueller, S. Doerfel, and F. Mitzlaff, "Description-oriented community detection using exhaustive subgroup discovery," *Inf. Sci.*, vol. 329, no. 1, pp. 965–984, Feb. 2016.
[81] T. Le, H. L. Vu, N. Walton, S. P. Hoogendoorn, P. Kovács, and R. N. Queija, "Utility optimization framework for a distributed traffic control of urban road networks," *Transp. Res. B, Methodol.*, vol. 105, pp. 539–558, Nov. 2017.
[82] J. Laaksolahti and M. Boman, "Anticipatory guidance of plot," in *Anticipatory Behavior in Adaptive Learning Systems*. Berlin, Germany: Springer, 2003, pp. 243–261.
[83] M. Rabbi, M. H. Aung, M. Zhang, and T. Choudhury, "MyBehavior: Automatic personalized health feedback from user behaviors and preferences using smartphones," in *Proc. Ubicomp*, Osaka, Japan, 2015, pp. 707–718.
[84] C. Han, Y. Liu, and J. Qiao, "Research on anticipatory reasoning for air traffic control," in *Proc. 9th Int. Symp. Comput. Intell. Design (ISCID)*, Hangzhou, China, Dec. 2017, pp. 427–431.
[85] M. A. Jarwar, R. A. Abbasi, M. Mushtaq, O. Maqbool, N. R. Aljohani, A. Daud, and I. Chong, "CommuniMents: A framework for detecting community based sentiments for events," *Int. J. Semantic Web Inf. Syst.*, vol. 13, no. 2, pp. 87–108, 2017.
[86] H. S. Koppula and A. Saxena, "Anticipating human activities for reactive robotic response," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Tokyo, Japan, Nov. 2013, p. 2071.
[87] G. Pan, L. Zhang, Z. Wu, S. Li, L. Yang, M. Lin, and Y. Shi, "Pervasive service bus: Smart SOA infrastructure for ambient intelligence," *IEEE Intell. Syst.*, vol. 29, no. 4, pp. 52–60, Jul./Aug. 2014.
[88] I. Scholl, J. M. Zill, M. Härter, and J. Dirmaier, "An integrative model of patient-centeredness—A systematic review and concept analysis," *PLoS One*, vol. 9, no. 9, Sep. 2014, Art. no. e107828.
[89] L. Gugerty, S. E. McIntyre, D. Link, K. Zimmerman, D. Tolani, P. Huang, and R. A. Pokorny, "Effects of intelligent advanced warnings on drivers negotiating the dilemma zone," *Hum. Factors*, vol. 56, no. 6, pp. 1021–1035, Sep. 2014.
[90] M. Rinaldi and C. M. J. Tampère, "An extended coordinate descent method for distributed anticipatory network traffic control," *Transp. Res. B, Methodol.*, vol. 80, no. 10, pp. 107–131, Oct. 2015.

CHUNPEI LIN received the B.S. degree in administration from Xiamen University, Xiamen, China, in 2007, and the Ph.D. degree in management science and engineering from the South China University of Technology, Guangzhou, China, in 2012. From 2012 to 2014, he was a Lecturer with the School of Business Administration, Huaqiao University, Quanzhou, China, where he has been an Associate Professor, since 2015. He has published more than 20 papers. His research interests include data mining and innovation management. He is also a Leader of some Natural Science Fund Projects.

GUANXI ZHAO received the B.S. degree in administration from Huaqiao University, Quanzhou, China, in 2016, where he is currently pursuing the M.S. degree in science in management and he is also a Research Assistant with the Business Management Research Center.

YENCHUN JIM WU received the Ph.D. degree from the University of Michigan. He is currently a Distinguished Professor with National Taiwan Normal University, Taiwan. He has authored over 100 peer-reviewed articles in international journals including, but not limited to, the *Academy of Management Learning and Education*, *MIT Sloan Management Review*, IEEE Transactions on Engineering Management, *Information & Management*, *Supply Chain Management*, *Journal of the American Society for Information Science and Technology*, *European Journal of Operational Research*, and *International Journal of Production Economics*. His research interests include supply chain management, technology management, and innovation and entrepreneurship. He has served on the editorial review board for many international journals.



HAILIN LI received the B.S. degree in information and computing science from Jingdezhen Ceramic University, Jingdezhen, China, in 2006, and the Ph.D. degree in management science and engineering from the Dalian University of Technology, China, in 2012. From 2012 to 2014, he was a Lecturer with the School of Business Administration, Huaqiao University, Quanzhou, China, where he has been an Associate Professor, since 2015. He has published more than 60 papers. His research interests include time-series data mining and decision-making. He is also a Leader of some Natural Science Fund Projects.