We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists



122,000





Our authors are among the

TOP 1%





WEB OF SCIENCE

Selection of our books indexed in the Book Citation Index in Web of Science™ Core Collection (BKCI)

Interested in publishing with us? Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected. For more information visit www.intechopen.com



Chapter

Living Function-Resilient Society in the Centenarian Era: Living Safety Technology Based on Connective, Artificial Intelligence

Yoshifumi Nishida and Koji Kitamura

Abstract

In the centenarian era, it has become even more imperative to address the physical and cognitive changes faced by children, the elderly, and disabled persons. We need a "living function resilient society," which ensures they enjoy safe living environments in ways that allow them to maintain active social participation levels despite the changes. To build such a society, more attention should be paid to problems: diversity in life function and intervention needs, gap between efficacy and effectiveness, fragmentation of living data and support service and variety in privacy exposure. To deal with these issues, this chapter describes a new approach referred to as "connective AI" that allows individual lives to be connected with each other and efficacy to be scaled to effectiveness by computerizing places of living in accordance with the private policy of individual facilities and connecting them with each other through a network. As a concrete example of connective AI, this chapter introduces smart living labs that are developed by the National Institute of Advanced Industrial Science and Technology (AIST) in cooperation with children's hospitals, rehabilitation hospitals, intensive care homes for the elderly, and private homes.

Keywords: living function, health monitoring, living laboratory, handrail, wearable device, RGBD camera, social participation, nursing care support

1. Introduction

A society that fosters resilience to changes in living function (a "living function-resilient society") is required now. We need social and industrial systems that ensure safety and high-level community involvement when we experience changes in cognitive function, physical function, or family function as we move toward an aging society (a dementia society). **Figure 1** shows the current age distribution of the Japanese population and that of accident rates, birth, and caregiving. Rapid, mental, and physical developments occur during infancy. Women experience significant changes during pregnancy and around birth. There are times when they or their child or parent needs nursing care. Changes in their physical and mental functions or in being able to care for someone in



Figure 1. Changes in living function and a living function-resilient society.

the family occur rather frequently in the family context. When viewed in terms of changes in living function, this means that a society will emerge in which we have to address changes in living function over generations, from a parenting generation that deals with development in children to a caregiver generation that deals with the declining living function of the elderly. The UN's 2030 Agenda for Sustainable Development, adopted in 2015, indicates the need to ensure the safety of people of all ages and the physically and intellectually challenged, ensure access to services, and implement urban design with consideration of safety and accessibility [1].

Figure 1 shows a snapshot of the current Japanese society. Significant changes will occur in a short period of 10 years or so: Japan's aging population will continue to grow until 2025 as the baby boomer generation grows old. As a result, our society will have a rapidly growing population that will need support in daily living. Compared to 2015, the elderly people aged 75 or over will increase by 5,000,000, and the number of dementia patients will increase by 2,000,000. China, as a driving force in the global economy, is also faced with an aging population: the proportion of its population aged 65 and over will be 16% by 2030. So China is likely to have the same issues as Japan, incurring enormous social costs. Today, Japan's social costs associated with dementia are huge, at US\$ 127 billion. The costs are projected to reach US\$ 181 billion in 2025 in Japan and US\$ 2 trillion in 2030 globally. Thus, the issue of how society can develop adaptability to changes in living function will be increasingly important and is a key issue leading to a new growth strategy to develop adaptability (resilience) to changes in living function as a social mechanism separate from the issue of individual efforts.

In recent years, low-cost sensors, storage devices, and cloud computing services have become widely available. Artificial intelligence (AI) based on big data is rapidly advancing. These developments will make it possible to build a society that fosters resilience to changes in living function (a "living function-resilient society") that can adapt flexibly to changes in diverse physical and cognitive functions of children, women, the elderly, and the physically and intellectually challenged and allow people to exploit their potential to the fullest. There is an expectation that in the next 10 years, a new industry that helps translate the need for living function resilience into innovation will grow significantly.

This report identifies issues in building living function resilience and discusses, on the basis of our research, the potential for AI and the Internet of things (IoT) in building a living function-resilient society.

2. Issues in building a living function-resilient society

2.1 Variety in living function and intervention needs (one-size-fits-all issue)

The variety in living function needs to be acknowledged. A one-size-fits-all or universal intervention strategy is not necessarily effective: we need a mixed strategy combining universal, selective, and individual strategies [2]. We must have a basic understanding of what issues are involved in designing interventions based on a mixed strategy and where they arise. However, we do not fully understand them. We need to reveal the whole picture of issues associated with changes in the living function of the elderly and to base intervention design (precision intervention [2]) on that picture. To this end, we must have a system that collects data on changes of living functions and issues stemmed from the changes.

In the area of nursing care, providing one-to-one care services using human labor is considered ideal. In reality, it is difficult to provide services in terms of social costs. On the other hand, a universal strategy does not allow the variety in living function to be addressed. Precision care, which is defined as intermediate between universal and one-to-one strategies, is important. The use of AI technology may make it possible to align the variety in living function with individual adaptability by properly dividing the variety in living function into segments and selecting services that match each segment.

2.2 Gap between efficacy and effectiveness

Various intervention approaches have been proposed. An approach that is shown to have efficacy under laboratory conditions or under specific circumstances may have no effectiveness in other situations, such as the local community or society more broadly [3]. This is an issue of a lack of understanding of a local community or an individual life as a complex system and of error arising from the incorporation of a simplified model used in laboratory research into a complex system [4]. It is suggested that researchers act to hear user requests with a serious mind, for example, by conducting a complete interview survey. The issue is often discussed in terms of attitude or mindset in conducting research. However, we think that this discussion misses the point and that it is not a matter of mindset and effort but is a scientific issue arising from lack of science and technology and methodology for dealing with complex systems in field settings. Recently, it has been pointed out that the incremental approach (incrementalism) has a limit and design should be implemented in a manner that allows scaling (big change). We need to put in place in individual lives and facilities a system to evaluate the effectiveness of interventions and make continuous improvements. We need a method of designing and evaluating effective interventions in complex life systems that are present in individual lives and in facilities and in communities.

2.3 Fragmented living data and support services

Data on life are fragmented by facility and life situations. For example, data on illness, data on living function change, data on daily activities, and data on accidents/incidents exist in different facilities. It is necessary to use the data in an integrated manner and thereby to evaluate the variety in living function among children and elderly people, identify issues associated with the variety, and evaluate potential solutions. More importantly, we need a method of detecting their changes in daily life.

In addition to data fragmentation, services as solutions are fragmented. A collective impact model has been proposed to achieve effectiveness by collectively using stakeholders and social resources with a common purpose [5]. There is a need for a system for implementing the collective impact model based on the data.

2.4 Variety in privacy exposure

The definition of personal information has been changing. Besides that, there are a variety of ideas about privacy exposure. This means that there is a "one-sizefits-all" issue also in privacy policy; we need a system and technology to control information according to the variety of ideas of individuals and facilities about privacy, instead of developing a privacy policy common to all people and facilities. For example, there are facilities that are positive about installing cameras to prevent abuse of the elderly.

3. Problem solving by connective AI

3.1 Description of connective AI

To address issues in the variety in living function, intervention needs, data fragmentation, and variety in privacy exposure, we believe in the importance of an approach referred to as "connective AI" that allows individual lives to be connected with each other and efficacy to be scaled to effectiveness by computerizing places of living in accordance with the private policy of individual facilities and connecting them with each other through a network. We believe that connective AI is essential to building a living function-resilient society.

While our lives and living environments have individuality and are different from each other, there are many similar phenomena and environments. Skillful processing of information should make it possible to share information and convert it into knowledge. As pointed out by Herbert Simon, a physical phenomenon is essentially nonlinear when viewed hierarchically. We can develop a science based on the assumption that a physical phenomenon in the target layer can be modeled by associating it with feature quantities in the sublayers.

3.2 Smart living lab coevolving with connective AI

As **Figure 2** shows, to work with connective AI in concrete terms, we at the National Institute of Advanced Industrial Science and Technology (AIST) have developed a smart living lab in cooperation with children's hospitals, rehabilitation hospitals, intensive care homes for the elderly, and private homes. The term "smart living lab" here means (1) a place where we identify needs in field settings with user participation and adaptively explore whether new proposals to meet the needs are acceptable to the users in these "living labs" and (2) a place where we collect data, using AI and sensors, on activities of daily living of users (including children as non-main users) with a variety in living function (a smart field).

A system that allows daily life data fragmented in these places to be shared is essential to understanding the variety in living function. We need a new approach for information processing (AI for reality) to clarify real conditions. A system to





link the verification of efficacy at the laboratory level to verification of effectiveness in facilities and communities is essential to developing solutions to support daily life. There is a strong need for a direction (reality for AI) for support technology to be put in place. We need to develop a living ecosystem suitable for individuals by combining stakeholders involved and social resources. We need to understand a field system as a complex system from a system science perspective and develop solutions that scale to different field settings. The next section describes connective AI technology being developed at AIST to build a living function-resilient society and smart living lab activities using the technology.

4. Attempt to demonstrate safety in daily life using AI and IoT technology

4.1 Raising awareness using data scattered across multiple organizations in an integrated manner (issue identification)

A recent text mining technique allows us to process quantities of data that are too big for humans to process. It has the potential for social function, which can be referred to as awareness (issue identification). Using data on medical treatment costs and situations resulting in injury from the Japan Sport Council, we at AIST are developing a technique that automatically analyzes situations that may result in severe injury. This technique identifies phrases unique to situations resulting in severe injury from free descriptive text, based on the assumption that treatment costs increase with increasing severity of injury. It is called "severity cliff analysis [6]." As shown in **Figure 3**, when similar situations are plotted in descending order of treatment costs, a cliff appears where the treatment costs change sharply. The technique allows us to identify the inflection point of the cliff and analyze what causes the severity of injury to increase. Using this new technique, we analyzed injuries in school environments. Among injuries that involve running and tripping, the severity of injury is higher for hurdle running than for rope jumping and running on flat ground, because it involves hurdles. We investigated measures to prevent hurdle injury and found a hurdle with a top bar that opens like a double door when struck by the foot, which is in use at high schools in Miyagi Prefecture. Thus, severe injuries can be significantly reduced by taking effective preventive measures like this.

The technique allows us to understand in detail situations that result in severe injury by compiling incident data scattered across multiple organizations into big data for analysis by AI. Consequently, we can develop new prevention measures and associate them with existing measures. With data available only at some organizations (some schools, care facilities, etc.), we cannot know the overall occurrence and extent of severe injuries. As a result, known preventive measures remain isolated, and their widespread introduction is delayed. A new approach to improving situations in real-life settings by identifying problems and connecting them with solutions will be increasingly important in the future.

4.2 Monitoring changes in living function using IoT technology

Elderly people typically lose cognitive and motor functions with age and experience increasing challenges in daily life. There is a need for IoT sensors to detect changes in the living function of individual elderly people as they occur and to call for appropriate interventions. A recent projection for the next 10 years holds that smart homes will provide a market for sensors to support not only home security but also healthcare and safety in the home.

We developed a sensor to make it possible to measure how fast the elderly can walk and how well they can walk unaided. The sensor is designed to be built into an object used in daily life, in this case a handrail [7]. It collects only relevant data (maintaining privacy) and does not need to be attached and detached. We verified the basic functions of the sensor in the living lab at AIST and then installed it in the home of an 88-year-old woman who lives alone. Our study will verify the efficacy of the sensor through long-term monitoring.

Figure 4 shows how the sensor works and its installation. The sensor comprises two strain gauges fixed above and below a steel bracket secured to the wall. When the subject puts her hand on the handrail, the downward load is detected by the strain gauges.

We conducted a verification test of the sensor in a real-world setting. We installed several sensors on a handrail in the hallway in the subject's house (**Figure 4**, right). **Figure 5** (left) shows a sequence of images of the subject walking while holding the handrail. We collected data continuously for 24 months and plotted the subject's walking speed by using the installation's position-estimation capability (**Figure 5**, right).

We plotted the monthly median walking speed to reveal any changes in the walking pace from January 2016 to December 2017. As **Figure 6** shows, it changed substantially over the period: it decreased from February to August as physical strength declined, increased again from September to November, but declined again from January to March. The subject told us that she initially lost physical strength but regained it from September, but knee pain caused increasing difficulty in walking from January 2017. In May 2017, she broke her thighbone and was admitted to a hospital. In August 2017, she discharged from the hospital. Our results show that the sensor can detect some problems in daily life, although not the cause.

The walking pace of the elderly decreases with advancing age, along with walking patterns such as stride length, walking pace, and lower limb muscle strength.

Such declines increase the need for in-home support services for people who retain a strong need to remain in their own home. Low-cost monitoring of health and mobility would allow quick identification of risks to safety such as by falls. Such monitoring of individual elderly people would allow the timely implementation of appropriate interventions as a form of precision care or individualized care. Continued advances in AI and IoT will support this.



Figure 3.

Severity cliff analysis, using big data, to identify factors involved in situations resulting in severe injury.



Figure 4. Handrail-type IoT sensor (left, configuration; right, picture).



The subject using the handrail (left) and motion data obtained (right).



Figure 6.

Results of 15-month monitoring of walking pace as a health indicator.

4.3 Supporting community involvement of people with different living functions by using a daily life database

If we can detect changes in walking pace and other changes in daily life, what is the best way to use this information? One way is to provide services that support community involvement according to changes in living function.

To understand the living conditions and living function of the elderly, we interviewed elderly participants at home and collected data on their living conditions as a technological element for providing tailored support for community involvement. We developed a system to describe daily life data in terms of relationships between elements such as community involvement, experience, emotions, people, things, and activities related to community involvement [8]. We included elements and experiences used to describe daily life in the International Classification of Functioning, Disability and Health. **Figure 7** shows an example of graphically represented life data of an elderly person at one time point. The plot represents the overall life structure. Such graphic representation allows an understanding of the entire life structure,

including the relationships between individual elements, the use of graphic structure analysis, and numerical representation of the degree of similarity between individual graphic structures and searching on life data. Using this method, we have developed a life database of more than 70 elderly people.

The use of graphic representation of daily life allows calculation of the degree of similarity between individual graph structures and identification of those who have a similar life structure. **Figure 8** shows the life structures of 20 elderly people and plots the degree of similarity between them. It reveals groups concentrated at the top left corner of the graph, where the life structures have a degree of similarity, along with one person at the right edge (G15) and one at the bottom edge (G10), both substantially different from the others. The placement of G15 indicates that that person mostly feels happy about community involvement but sometimes feels sad, angry, or worried about it. The placement of G10 indicates that the person has mostly negative feelings such as loneliness, sadness, and anger. Such graphical representation allows us to identify elderly people with a different life structure from the majority who might therefore require interventions to support them in changing their living conditions.

For example, when we design an intervention to improve living conditions, by using a life structure distance space (or life structure manifold), we can identify people with similar life structures and encourage them to become involved in community activities, instead of putting together people with very different life structures. If a person's life structure later changes, we can again encourage community involvement with people with more similar life structures. This is a scientific approach to changing people's life structure step-by-step to bring it closer to what they want or by revising goals. We think that this approach will lead to a data-based scientific approach (life design methodology) to process design to achieve a desirable life structure.

Figure 9 shows the output of software that has read the life structure data of an 80-year-old woman and has searched for elderly persons with similar life structures



Figure 7. *Example of graphical representation of life structure data.*



Figure 8.

Visualization of life structure patterns (life structure distance space or life structure manifold).



Figure 9.

Software to support life design based on an enormous amount of life data and life geometric operations (digital crystal ball).

and for things that make her happy. **Figure 10** shows a group of elderly people mapping the locations of little-known community involvement events. Currently, we are working with a community association and a local elderly care management center to provide the participants with advanced support, tailored to their individual living conditions, in community involvement, by combining life design support technology and local maps and making good use of resources available in the local community.

4.4 Trial of precision care at IoT-based care facilities

In collaboration with care homes, we are undertaking a project to develop monitoring technology, tailored to individual elderly persons, to prevent accidents and detect early changes in behavior in anticipation of the time when an elderly person with declining living function needs care or support. **Figure 11** shows a system to measure the location of an elderly person with dementia and monitor his



Figure 10.

Working with a local elderly care management center and a community association to create a map to support community involvement.

or her behavior, using a beacon embedded in the sole of the person's shoe [9]. Using sensors like this, we can monitor changes in walking patterns. **Figure 12** shows a case in which monitoring over 45 days revealed a change in the walking pattern of an elderly person with dementia: the distance walked decreased greatly about half-way through the monitoring period. Later, we found that the decrease was due to a broken bone caused by a fall. This case shows how the use of sensors allows us to quantify changes in individual persons' behaviors and to accurately detect changes that can be missed.

Both wearable sensors and smartphones can collect information on individuals, but they use battery power. This is a major hindrance, because devices that require frequent battery changes are not acceptable in real-life settings. At the same time, the use of AI technology not just to find people but also to identify them has made tremendous improvements. Such "non-wearable" has begun to appear. The combination of mounted RGBD cameras and face identification software can allow unintrusive long-term monitoring of individuals, as the monitors are not worn [10]. Some facilities have started to use it. **Figures 13** and **14** show a RGBD camera and a plot of a person's walking posture captured by RGBD camera. This person's walking pace tended to be slow in the morning and to vary greatly.



Figure 11. Shoe-embedded location sensor for monitoring of the elderly.

The facility staff made the following comments on individualized monitoring:

- 1. The video of events that may not be accurately communicated by humans is recorded. This allows information on events to be shared accurately (video can be used, e.g., when passing information onto another staff member).
- 2. By watching the video of actual positioning of things and people at a care facility, instead of reading textbooks, staff awareness is raised, and crisis management training can be improved.
- 3. By watching the video, staff can know what happens when they are not on hand and can take action immediately.
- 4. Staff can monitor daily changes in the walking pace of elderly people and can associate the changes with medications, mental state (dementia), excretion, and pain. Many medications, notably sleeping pills, can cause falls. However, support tools for personal health management have not been available.
- 5. By associating the profile of an elderly person with risks, staff can know at a glance what risks the person faces, group people with similar needs for better management, and provide better care.
- 6. Being able to identify daily changes in individuals and their long-term trend, staff can determine the need for intervention and evaluate the effectiveness of intervention. The monitoring function can also be used as tool for nursing care.



Figure 12.

Results of long-term monitoring with a shoe-embedded location sensor.



Amid increasing reports of elder abuse, more facilities and users favor the use of sensors. Staff alone will not be able to monitor residents in the level of detail that this will entail. While acknowledging the need for privacy, we need to identify what services can be made possible by what sensing technology (with attendant risks to privacy). It is important to provide levels of services that suit users' needs best by preparing a variety of options for such services.

4.5 Elderly behavior library for searching for product usage by those with changing living function

Changes in living function vary among the elderly. Unlike in the case of children, this makes it difficult to classify events by age, because living function varies significantly among people of the same age. We can specify "a bed for babies up to



Figure 14.

Plot of walking pace monitored by mounted camera in a home.





Figure 15.

Searchable library of elderly behaviors for identifying changes in living function.

24 month old," but not "a chair for persons 75 years old and older". As a means to understanding life dimensions in the elderly, we created a library of videos showing how different products (beds, chairs, wheelchairs, canes, doors, kitchen tools, handrails) are used by the elderly, depending not only on age but also on cognitive ability, physical ability, and level of care needed [11]. **Figure 15** shows snapshots of the developed library. The library was launched in March 2018. Its use requires registration. The library is a pioneering attempt to show how elderly use items, such as to identify handrails that are easy to use. We intend that it will be used to identify problems and develop solutions. If you are interested, please contact us at the address provided on the website [12].

5. Conclusions

In this report, based on our research, we describe "a living function-resilient society" as a desirable society and show the potential of AI and IoT technology to identify problems and resolve them. In terms of intelligence, to resolve issues associated with the variety in living function, we need to find innovative solutions using the variety in intelligence. Today, a society is emerging in which problems, data, and intelligence are ubiquitous. Sensing and recording technology is advancing and spreading throughout the society. Various organizations now store big data. In recent years, AI, such as data analysis technology, has been advancing. Human resources spread among universities, administrative organizations, care homes, regions, and companies can be linked to create an intelligence-ubiquitous society. New social issues emerge constantly. The type of innovation required today is the transformation of the society into an advanced interconnected society by using the ubiquity of data and intelligence in modern society to address newly emerging issues.

Intechopen

Author details

Yoshifumi Nishida* and Koji Kitamura Artificial Intelligence Research Center, National Institute of Advanced Industrial Science and Technology, Tokyo, Japan

*Address all correspondence to: y.nishida@aist.go.jp

IntechOpen

© 2019 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/3.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

References

United Nations Information Centre.
Transforming Our World: The 2030
Agenda for Sustainable Development.
2015

[2] Winston FK et al. Precision prevention. Injury Prevention. 2016;**22**(2):87-91

[3] Green LW. From research to "best practices" in other settings and populations. American Journal of Health Behavior. 2001;**35**:165-178

[4] Hanson D, Allegrante JP, Sleet DA, Finch CF. Research alone is not sufficient to prevent sports injury. British Journal of Sports Medicine. 2012;**48**(8):682-684

[5] Kania J, Kramer M. Collective impact. Stanford Social Innovation Review. 2011;**9**(1):36-41

[6] Imai K, Kitamura K, Nishida Y, Yoneyama N, Takemura H, Nakayama T. Analysis of big data on sport injuries using a severity cliff analysis technique. 17th SICE System Integration Workshop. 2016;**2016**:2903-2907

[7] Takahashi Y, Nishida Y, Kitamura K, Mizoguchi H. Handrail IoT sensor for precision healthcare of elderly people in smart homes. In: Proc. of the IEEE 5th International Symposium on Robotics and Intelligent Sensors (IEEE IRIS 2017). 2017

[8] Nishida Y. Scientifically design living: Configuration of life function using a life structure database. Information Processing. 2013;**54**(8):772-778

[9] Nishimura T, Kitamura K, Nishida Y, Mizoguchi H. Development of a nursing care support system that seamlessly monitors both bedside and indoor location. In: Proceedings of the 6th International Conference on Applied Human Factors and Ergonomics. 2015. pp. 3808-3815

[10] Murata E, Kitamura K, Oono M, Shirato Y, Nishida Y. Behavior monitoring with non-wearable sensors for precision nursing. In: Proceedings of the 8th International Conference on Applied Human Factors and Ergonomics. 2017. pp. 384-392

[11] National Institute of Advanced Industrial Science and Technology. Report on the Project to Obtain Behavior Data of the Elderly Toward a Vintage Society. 2018

[12] https://www.airc.aist.go.jp/lirt/ vintagelibrary.html (National Institute of Advanced Industrial Science and Technology, Elderly Behavior Library)

