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Analytic Hierarchy Process (AHP) in Dynamic Configuration as a Tool for Health Technology Assessment (HTA): The Case of Biosensing Optoelectronics in Oncology

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The Analytic Hierarchy Process (AHP) is a methodology, based on both mathematical and psychological approaches, exploited to analyze and solve complex problems, in order to make the best decision. AHP is also widely employed for the evaluation of healthcare systems. It works by splitting the decision problem into a hierarchy of more easily-comprehended sub-problems, each of which can be independently analyzed. Starting from these assumptions, our work aims to implement a dynamic framework for the AHP methodology, able to overcome the static nature of the technique, taking into account the evaluations associated with criteria and sub-criteria as a function of time. In the context of this paper, the Dynamic AHP is implemented as a tool for Health Technology Assessment (HTA). Indeed, the proposed case study concerns the evaluation of a new health technology for the thyroglobulin assay in patients with differentiated thyroid cancer. To this aim, we have defined the decision problem and formalized criteria and sub-criteria hierarchically; then, in order to deal with the problem from a dynamical point of view, i.e., to take into account the time dependence of criteria and sub-criteria, we developed several System Dynamics models, one for each criterion. In this context, it is shown that the Dynamic AHP approach provides a dynamic evaluation of the system, which allows to identify the best decision

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by exploiting the information on the possible evolution of the problem due to its time behavior, rather than taking the decision at a fixed time point, as the Static AHP does.

Keywords: Analytic hierarchy process; dynamic AHP; health technology assessment; HTA; multicriteria decision-making.

1. Introduction

The Analytic Hierarchy Process (AHP) is one of the most commonly exploited multi-criteria decision-making (MCDM) approach; it was developed in the 1970s by Saaty[1] to solve complex problems. When a decision has to be taken, it assesses a set of alternatives through pairwise comparisons by deriving priority scales.

AHP is also widely employed for the evaluation of healthcare systems.[2–7] Indeed, in the literature, there are several papers which propose AHP to define the priorities and criteria which allow the correct evaluation of the medical technologies.[8–11] When the complexity of the problem increases, as for choices regarding the healthcare system, the optimized solution depends on many different factors, often in conflict with each other. Using the AHP methodology, the decision-making process is driven by the adoption of criteria conveniently identified and selected.

However, the AHP approach presents some limitations; among them, an important drawback is represented by the independence of the sub-criteria, which are considered unrelated to each other. Another important limit is its static nature that does not make it suitable for medium/long-term decisions in dynamic environments. As a consequence of its static nature, AHP provides the optimal result at a given moment for a settled situation. Of course, when a dynamic situation is dealt with, priorities obtained at a specific time t can change at time $t + \Delta t$. This problem could be addressed by using the dynamic judgments method, as described by Saaty.[12–15] In this case, judgments changing over time are represented as functions of time, but this procedure requires the prediction of future trends.[12–17]

The combination of AHP with other mathematical models allows to enhance its performance by overcoming the previous mentioned limitations. The adaptation of the Static AHP to an environment which changes over time is generally called Dynamic AHP.[4,22–30]

In the light of these considerations, the aim of this paper is to propose a dynamic view of the AHP methodology for the assessment of tangible and intangible elements in a long-term decision-making scenario. This can be done by considering the long-term evolution of an assessment,[2] in order to take into account the changes (time by time) of AHP weights criteria. To this end, the AHP can be supported by the system analysis theory, that allows us to insert into the models the time evolution of the weights associated with each alternative provided by the Static AHP. This paper indeed provides an integrated approach combining AHP with a System Dynamic (SD) simulation technique.[4,18–21] In particular, the proposed approach is used to achieve a Health Technology Assessment (HTA) goal, i.e., the evaluation of optoelectronic systems in Oncology (cancer of the thyroid), compared with each other and with respect to a conventional fluidic system.

2. Methods

2.1. *The case study*

The case study is focused on the assessment of two new health technologies used in Oncology based on optofluidic systems (see Fig. 1). These systems combine the use of optical fibers, electronics and fluid dynamics for the determination of the levels of thyroglobulin (Tg) during thyroid needle aspiration. Generally, there are many different treatments for the thyroid cancer. Thyroglobulin is a large glycoprotein (660 kDa) localized in follicular thyroid colloid. Considering that the thyroglobulin sensitivity limit is above 100 ng/mL, biosensors with fiber-optic transducers should be characterized by high sensitivity and high selectivity, to reveal even small concentration and to avoid the analysis being affected by other substances, in the lymph node, irrelevant to the detection of nodules sink.

For this paper, two different types of optical fiber transducers (biosensors) were considered:

- The first biosensor is the *Lab on Fiber* (LOF) that provides integration and nanoscale patterning on the tip of the fiber layers of metallic materials.[31] The resulting structures are plasmonic crystals capable of trapping light at a specific wavelength of resonance.
- The second biosensor, called *Long-Period Gratings* (LPG), involves the use of long-wheelbase patterns inscribed within the core of the fiber, covered with nanoscale layers of functional polymeric materials.

Both the technologies are composed of two parts, controlled by the same software: an Opto system, which is responsible for the analysis of a biological fluid removed with

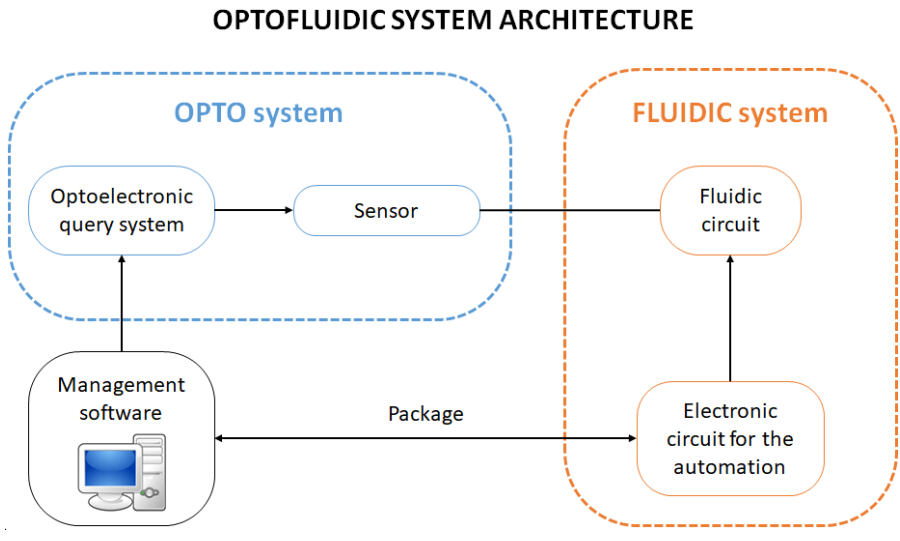


Fig. 1. Representation of the architecture of the optofluidic system.

needle aspiration, and a Fluidic system that has the task of managing the body fluids taken and ensuring proper analysis performance.

We compared these two biosensors with each other and with the conventional Cytological Analysis.

2.2. *The proposed methodological approach*

First, it is necessary to define the HTA problem.[32–34] In our case: "What technology is better to adopt for the thyroglobulin assay in patients with differentiated thyroid cancer?"

Then, all criteria and sub-criteria that will be used for the evaluation have to be defined. For example, to assess the technical aspects of the new biomedical devices to be introduced, different indicators/sub-criteria are considered, such as technological efficiency, reliability, safety and others. The selected criteria and sub-criteria are given in Table 1.

Each criterion, together with its sub-criteria, is treated as a dynamic system in which the weight of each criterion/sub-criterion at the time t_i influences its value at the time t_{i+1}. To this aim, we adopted the SD logic[21] (see Appendices A.1–A.4 for details about the SD tools), which allows us to model the behavior of complex systems over time.[35,36]

This methodological approach is iterated for all the selected criteria: organizational, economic, clinical and social–ethical–legal. Finally, the implemented model is validated both on real and simulated data.

The flowchart shown in Fig. 2 summarizes the implementation of the HTA approach by means of the proposed Dynamic AHP methodology, i.e., the combination of Static AHP and SD. The AHP is applied at time zero to define criteria and sub-criteria and calculate the global weights for each of them. Then, the SD simulation is applied to update, at each time step, the values of the global weights computed by the initial application of AHP in order to obtain the final priority vector of preferences for each of the alternatives considered.

2.3. *Data processing using the AHP*

A pairwise comparison matrix of the selected criteria, shown in Table 2, is built on the basis of the judgments provided in collaboration with the National Research Council staff dealing with biosensoristic systems.

Table 1. Criteria and sub-criteria.

Technical aspects	Organizational aspects	Economic aspects	Clinical aspects	Social–legal–ethical aspects
Reliability	Procedural complexity	Investments	Efficiency	Respect for social
Technology	Human resources	Usefulness	Effectiveness	Respect for principles
Technological safety	—	ROS	Side effects	Respect for legal issues

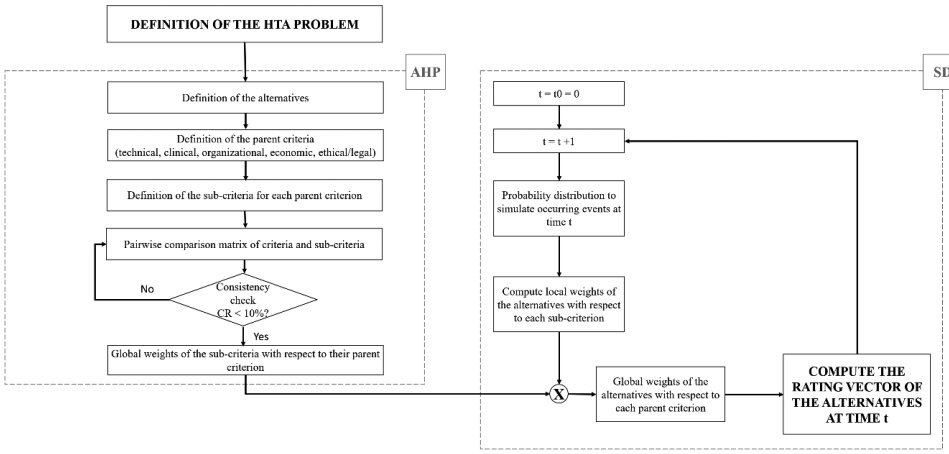


Fig. 2. Flowchart of the Dynamic AHP process.

Table 2. Matrix of pairwise comparisons of the criteria.

	Technical aspects	Organizational aspects	Economic aspects	Clinical aspects	Social–legal–ethical aspects
Technical Aspects	1	1/3	1/7	1/5	1/5
Organizational Aspects	3	1	1/5	1/3	1/3
Economic Aspects	7	5	1	3	5
Clinical Aspects	5	3	1/3	1	3
Social–legal–ethical Aspects	5	3	1/5	1/3	1

For the matrix shown in Table 2, the Random Index (RI) is equal to 1.12 (see Appendix A.5 for more details) and, the maximum eigenvalue ($\lambda_{\max}$) associated with the matrix has been calculated (by using Matlab), to check the consistency ratio (CR):

$$\lambda_{\max} = 5.3185;$$

$$n = 5;$$

$$\mathrm{CI} = (\lambda_{\max} - n)/(n-1) = (5.3185 - 5)/4 = 0.0796;$$

$$\mathrm{CR} = \mathrm{CI}/\mathrm{RI} = 0.0796/1.12 = 0.0711 = 7.11\% < 10\%.$$

Since the acceptable level of inconsistency is 10%, and the CR of the matrix of the pairwise comparisons of the criteria is lower than this threshold, it can be considered consistent (see Appendix A.5 for more details).

The global weights vector of the selected criteria is calculted by means of the Static AHP using the data given in Table 2. As well described in the wide literature about AHP and MCDM,[37–44] by iterating this process for each sub-criterion, after some manipulations (see Appendix A.5), it is possible to calculate the global and local weight vectors for each sub-criterion.

2.4. *The dynamic AHP*

Once obtaining the global weights of the sub-criteria, the weight vector is used as an input variable in the simulation model to which it belongs. In particular, the global weights of the sub-criteria, which have been calculated through the Static AHP, are updated by multiplying them with the output of the simulation model (see Fig. 2).

The Powersim Studio software has been used for the simulation. The period chosen for the simulation goes from 1/1/2015 to 1/1/2025 (i.e., 10 years have been simulated), and the time step is equal to 1 h. In our model, each vector represents one of the three alternatives that have been considered: Cytological Analysis (conventional method), LOT Biosensor (optofluidic system) and LPG Biosensor (optofluidic system).[31]

The inputs of the simulations are represented by time-dependent variables (number of tests required by patients, number of analyzed biological samples, rate of arrival in the labs, number of finished tests and number of completed reportings) deployed as a well-known Poisson distribution, i.e., a probability function used to model the number of events occurring within a given time interval. It is the most suitable function to model technical, organizational, clinical and social–ethical–legal aspects. An exception is made for the economic aspect. Five simulation models, for the five considered criteria (technical, organizational, clinical, economic and social–ethical–legal), are then developed.

The outputs of the simulations represent the new local weights of the alternatives with respect to the sub-criteria. Finally, these local weights are multiplied by the global weights of the sub-criteria, previously calculated through the Static AHP, in order to obtain the updated vector of the global weights of the alternatives.

Hence, by applying the Dynamic AHP a new priority vector, containing the preferences for the alternatives, is obtained at each time point.

After the implementation of the simulation model, a comparison between the results obtained with the proposed dynamic procedure and those obtained with the static procedure was performed for each simulation model (Table 3). Table 3 shows that the new dynamic method has highlighted results that cannot be obtained with a static procedure, such as the traditional AHP. For example, after a few years of simulation the first alternative is preferable to the third, contrary to the indications obtained with the Static AHP.

Differences highlighted for each considered aspect (criteria and sub-criteria) are discussed in Sec. 3.

2.5. *Comparison of the results and model validation*

The model validation can be performed by comparing the simulated data with real historical data, i.e., the values assigned to the sub-criteria in a period of time that goes from the introduction of the technology to the year before the simulation has been run. In particular, the differences between data series have been estimated.

Table 3. Comparison of results obtained by Static AHP and Dynamic AHP at time t_0 shows that at the time the deliverables produced by the simulation of above approaches highlight a preference for the LPG Biosensor.

			Cytological analysis	Biosensor LOT	LPG Biosensor
Technical Aspects	Technological aspects	DYNAMIC AHP	0.016515	0.000000	0.000785
		AHP STATIC_To	0.011400	0.003200	0.002700
	Reliability	DYNAMIC AHP	0.003390	0.012001	0.001909
		AHP STATIC_To	0.011400	0.003200	0.002700
	Technological Safety	DYNAMIC AHP	0.001406	0.002197	0.002197
		AHP STATIC_To	0.000420	0.001620	0.003760
Organizational Aspects	Procedural complextiy	DYNAMIC AHP	0.001550	0.048600	0.017052
		AHP STATIC_To	0.009600	0.028800	0.028800
	Human Resources	DYNAMIC AHP	0.007472	0.002989	0.002989
		AHP STATIC_To	0.010500	0.001490	0.001490
Economic Aspects	Investments	DYNAMIC AHP	0.016418	0.019941	0.019941
		AHP STATIC_To	0.005120	0.025600	0.025600
	Useful	DYNAMIC AHP	0.059418	0.077187	0.063395
		AHP STATIC_To	0.022800	0.096100	0.081100
	ROS	DYNAMIC AHP	0.037961	0.080524	0.118515
		AHP STATIC_To	0.027000	0.096100	0.113900
Clinical Aspects	Clinical Efficiency	DYNAMIC AHP	0.025655	0.032394	0.045351
		AHP STATIC_To	0.008000	0.045000	0.050300
	Effectiveness	DYNAMIC AHP	0.188933	0.027405	0.048697
		AHP STATIC_To	0.011800	0.041900	0.049700
	Side Effects	DYNAMIC AHP	0.020149	0.008407	0.005944
		AHP STATIC_To	0.025800	0.004600	0.004100
Ethical and Legal Aspects	Respect of social aspects	DYNAMIC AHP	0.012800	0.004800	0.009600
		AHP STATIC_To	0.016320	0.005440	0.005440
	Respect of the legal issues	DYNAMIC AHP	0.004371	0.002667	0.004662
		AHP STATIC_To	0.007700	0.001800	0.002200
	Respect for ethical principles	DYNAMIC AHP	0.015047	0.045000	0.045003
		AHP STATIC_To	0.009540	0.047700	0.047700
TOTAL		DYNAMIC AHP	0.089695	0.340228	0.548556
		AHP STATIC_To	0.177000	0.402550	0.419000

However, for the case study in analysis, historical data are available only for the first alternative (Cytological Analysis), which is currently employed; while the other two alternatives refer to prototype systems for which historical data are not available. Therefore, for these systems, a simulation was carried out. Indeed, once obtaining the input data distributions, the simulation proceeds by generating random values from these distributions. Each simulation model describes the time-dependent variation of the priorities of the three alternatives with respect to each sub-criterion of the model.

3. Results

By employing the "traditional" Static AHP, the following priority vector is obtained:

- Cytological Analysis: 0.1774
- LOT Biosensor: 0.40255
- LPG Biosensor: 0.419

The Static AHP highlights a slight preference for the LPG Biosensor (overall weight = 0.419). By employing the Dynamic AHP, once you have entered all the necessary data and started the simulation, the model will process the data for every time step totaling 87.600 vectors (24 h a day, 365 days a year for 10 years of simulation). After getting through the five simulation models (see Figs. S1–S5 of the Supporting Information for the results about each single simulation model), the global weight vectors of the alternatives per sub-criterion are obtained.

In the case of technical aspects (Fig. S1 — Technological efficiency, Reliability, % of Failure and Safety), the alternative that has the highest priority is the LPG Biosensor, followed by the LOT Biosensor and finally by the Cytological Analysis. This is mainly due to the fact that Cytological Analysis has intervention times for maintenance and repair operations greater than the two biosensors.

In the case of organizational aspects (Fig. S2 — Procedural complexity and Human resources), for Cytological Analysis it can be seen that the Procedural complexity decreases over time because the personnel are reduced (a biologist was initially involved in performing Cytological Analysis, successively the biosensors had been used), hence fewer examinations have to be processed, this yielded to a reduction in the necessary time. Of course, an opposite situation has occurred for the two biosensors.

In the case of economic aspects (Fig. S3 — Investments, Profit and ROS), due to the higher purchase cost, the LOT Biosensor requires higher investments. In general, the two biosensors have a larger profit than Cytological Analysis, this is due to the higher revenues and the greater investment made. Furthermore, the profit related to these systems has an increasing trend over the years because the reagents' cost decreases with an exponential law. Conversely, the reduction in the profit of Cytological Analysis is determined by the increase in personnel costs over the years.

In the case of clinical aspects (Fig. S4 — Clinical efficiency, % of Intrinsic errors, Effectiveness, % of Average efficiency and Side effects), the two biosensors have a higher clinical efficiency than Cytological Analysis mainly because with the new biosensor technologies the number of repeated examinations is certainly lower. It can also be noted that the efficiency of Cytological Analysis decreases over time due to the increase in the intrinsic error related to the number of examinations that must be repeated.

In the case of ethical and legal aspects (Fig. S5 — Respect for social aspects, Respect for legal aspects and Respect for ethical aspects), the Cytological Analysis indicator decreases over time because it increases the number of examinations not

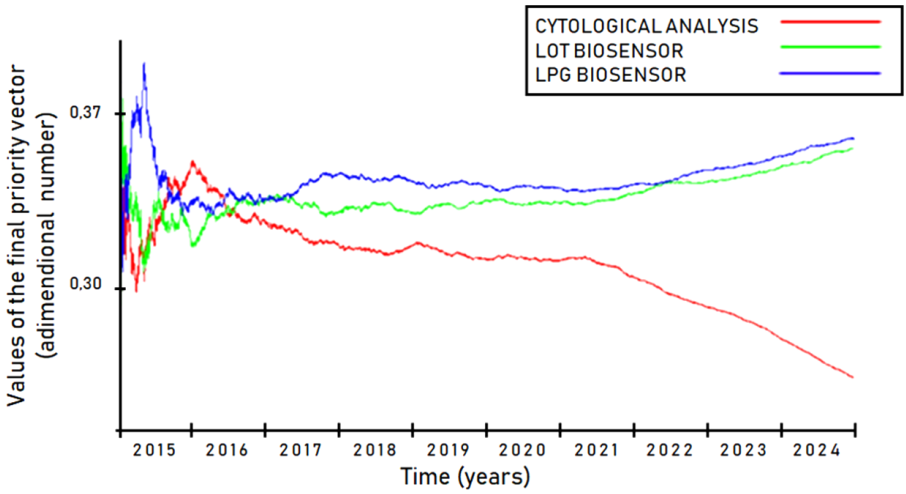


Fig. 3. Trends in final priority vector.

executed due to the higher costs for patients, who instead can access to the LOT Biosensor, which is a cheaper alternative.

It is important to note that the differences between the values assumed by the priority of the three alternatives are rather small, so there is no indication about the best system but only about the preferable one.

The time-dependent trend of the final priority vector, which represents the preferences between alternatives, is displayed in Fig. 3.

Figure 3 shows that at the time $t = 0$ there is a preference for the LPG Biosensor (overall weight = 0.55), followed by the LOT Biosensor (overall weight = 0.34) and by the Cytological Analysis (overall weight = 0.089). At the end of the simulation, the LPG Biosensor still has the highest priority (overall weight = 0.55), outdistanced very little from the LOT Biosensor (overall weight = 0.36), while the Cytological Analysis is the least preferable (overall weight = 0.27). Despite the fact that both Static AHP and Dynamic AHP provide the same result, the second one was able to show the dynamic evolution of the different alternatives. Criteria and factors vary over time, so that the best decision can be consequently time-dependent. In this analysis, even though the LPG Biosensor results are preferable both at $t = 0$ (as for the Static AHP) and t=final decision, the Dynamic AHP shows that it is not preferable over all of the considered timespan. Indeed, for a short period, the Cytological Analysis is the best choice; then, the two optoelectronic alternatives, which are characterized by an increasing trend, become far more preferable than the Cytological Analysis and get very close to each other in terms of global weight (Fig. 3).

To help in making the best decision it is useful to consider the cumulative sum of the weights of the final priority vector (Fig. 4), because the final sum of these preferences may take the same value by referring the decision to a stalemate. However, also this analysis shows that the preference is for the LPG Biosensor.

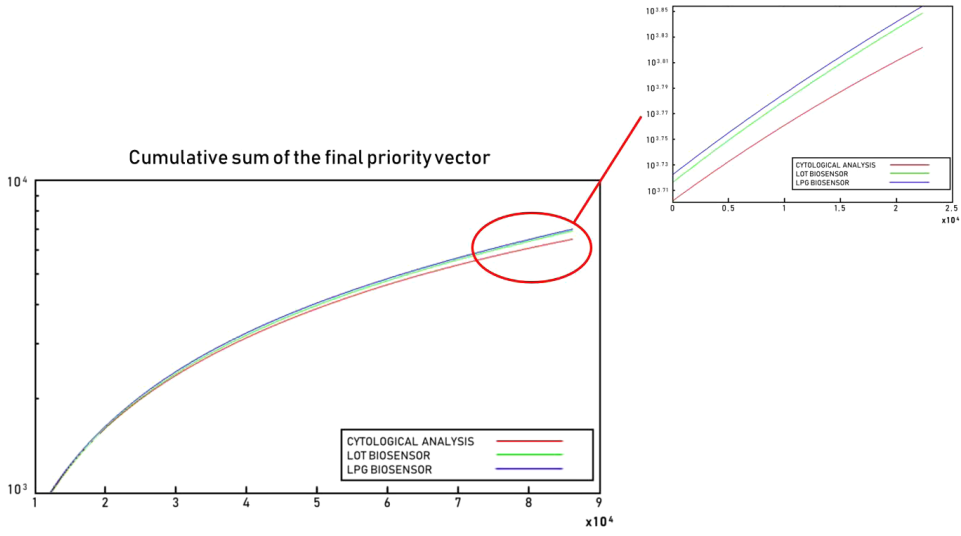


Fig. 4. Cumulative sum of the weights of the final priority vector.

4. Conclusion

The AHP is a flexible methodology which dealts with both qualitative and quantitative multi-criteria problems. It splits a given problem into different easier problems and assigns a score to each alternative solution. This decision method is employed to determine the weights of selected criteria when they are independent. The assumption of independence among the various levels of the hierarchical structure makes the methodology static and punctual. Hence, it is important the distinction between the Static AHP, traditionally used for MCDM problems, and the Dynamic AHP, a tool that integrates simulation models, such as SD, to consider the dynamism that characterizes the real systems.

This work aims to combine the Static AHP procedure with an SD model to solve a HTA problem, which is a dynamic problem where every decision taken at the time t influences the same decision at the next time $t+1$. First, we defined the decision problem, i.e., the evaluation of a new health technology for the assay of thyroglobulin in patients with differentiated thyroid cancer. Then, we defined hierarchical criteria and sub-criteria according to a Static AHP procedure. Thus, we implemented five SD models, one model for each selected criterion, whose outputs were combined with the AHP procedure to compute the final vector of priorities and display its time-dependent trend.

We demonstrated, according to the procedure validation, that the proposed methodology is reliable. More importantly, it resulted very useful since, while the Static AHP provides an analysis of the system under study at a specific time point with its best local decision, Dynamic AHP provides a time-varying analysis of the system, where the best decision in the long run can be different from all decisions

obtained at different time instants. Therefore, the Static AHP cannot be fully representative of the analyzed problem. Instead, the Dynamic AHP gives us a more comprehensive representation of the HTA problem, showing its dynamic nature and leading us to a different final priority vector of the alternatives. It supported us in facing the problem from different perspectives and in making decisions not only considering the current point of view but also taking into account a temporal evolution of the healthcare context.

Appendix A

A.1. *Outline of dynamical systems theory*

As it is well known, dynamical systems theory describes the behavior of complex dynamical systems, usually by employing differential equations, in the case of continuous dynamical systems, or difference equations.

The general stock (state variable) equation is, in principle, given by the following differential equation (A.1):

$$\dot{L}(t) = \sum R_{\text{in}}(t) - \sum R_{\text{out}}(t), \quad L(0) = L_0, \tag{A.1}$$

where $L(t)$ is the value of the state variable L at time t, L_0 is the initial value of L, R_{in} is the input stream of the state variable, R_{out} is the output stream of the state variable and $(\Sigma R_{\text{in}}(t) - \Sigma R_{\text{out}}(t))$ is the net inflow of the state variable. By integrating Eq. (A.1) between 0 and t, we obtain the time behavior of $L(t)$, see Eq. (A.2), which is also reported elsewhere[45]:

$$L(t) = L_0 + \int_0^t \left(\sum R_{\text{in}}(t) - \sum R_{\text{out}}(t) \right) dt. \tag{A.2}$$

Equation (A.2) suggests that the value of the state variable at time t is equal to its initial value plus the accumulation of the net inflow over the time period $[0, t]$.

By rewriting Eq. (A.2) in the interval $[t, t + \Delta t]$, with Δt being sufficiently small, we obtain

$$L(t + \Delta) - L(t) = R(t) * \Delta t, \tag{A.3}$$

where we have let $R(t) = \sum R_{\text{in}}(t) - \sum R_{\text{out}}(t)$, which is the net inflow entering the system.

By letting in Eq. (A.3) $t_i = t$ and $t_{i+1} = t + \Delta t$, we obtain the difference equation (A.4) for the general flow equation (decision variable):

$$\Delta R(t_i) = \frac{L(t_{i+1}) - L(t_i)}{\Delta t}, \tag{A.4}$$

where $R(t_i)$ is the value of the flow at time t_i, $L(t_{i+1})$ is the value of the state variable at time t_{i+1}, $L(t_i)$ is the value of the state variable at time t_i and Δt is the time interval between t_{i+1} and t_i.

A.2. *Outline of SD*

SD is a part of systems theory useful to understand the dynamic behavior of complex systems as they change over time. The basic idea behind SD is that of feedback loops that try to capture the interactions between the system's parts and how they lead to a certain overall pattern of behavior over time.

Most SD models are generated in the following four stages:

(1) *Conceptualization*

Define the purpose of the model.
Define the model boundary and identify key variables.
Describe the behavior or draw the reference modes of the key variables.
Diagram the basic mechanisms and the feedback loops of the system.

(2) *Formulation*

Convert feedback diagrams to level and rate equations.
Estimate and select parameter values.

(3) *Testing*

Simulate the model and test the dynamic hypothesis.
Test the model's assumptions.
Test the model behavior and its sensitivity to perturbations.

(4) *Implementation*

Test the model's response to different criteria.
Translate study insights to an accessible form.

However, the real power of SD is get through simulation; there exist many software packages that have been developed and optimized to this aim in the last decades.

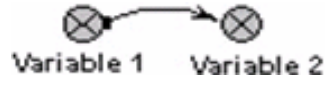
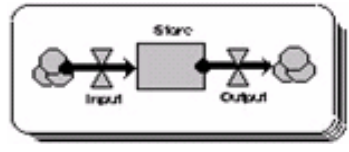
In Table A.1, the main SD logic tools to draw the model diagrams are shown.

The flow variables are instead the processes that operate to change the state of the system by acting on the stock variables and are the only way in which it is possible to act and change the stocks.

Table A.1. The SD logic tools.

Logic tool	Logical meaning	Mathematical meaning	Symbol
COMPARTMENTS (or STOCKS)	This box represents a "warehouse" of a given substance (e.g., biomass) or a quantity (e.g., time)	State variable defined by a differential equation	

Table A.1. (*Continued*)

Logic tool	Logical meaning	Mathematical meaning	Symbol
FLOW	Process that causes the increase or decrease of the variable associated to a compartment	Additive term to the differential equation. The value assigned to a flow can be both a constant or a function of a model variable	
CLOUDS	They have the same measurement units of the compartments, but without quantitative definitions. They represent factors external to the model (both source and sink)	—	
VARIABLE (or NODES)	Drawn as a node, it can represent a parameter, a calculation variable, an input or an output	Its value can be a constant or a function of other elements of the model	
INFLUENCE (or ARROW)	An arrow of influence represents the fact that a variable is used to calculate another one	var2 = f(var1)	
SUB-MODEL	This symbol is used both to divide the model into several sub-models (simpler to develop separately) and to replicate the model n times	—	

In SD, each structure (simple or complex) implies a mathematical formalization. For example, a simple mathematical problem (first-order differential equation) described in Eq. (A.5),

$$\begin{cases} \dfrac{dx}{dt} = k * x \\ x_{|t=0} = x_0 \end{cases} \quad \rightarrow \quad x = x_0 * e^{kt}, \tag{A.5}$$

can be formalized as shown in Fig. A.1.

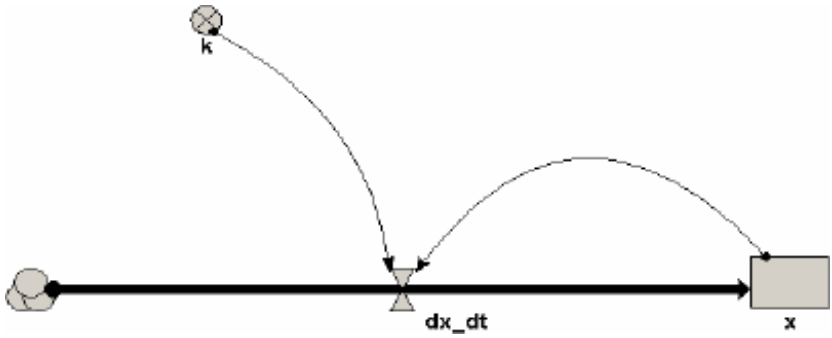


Fig. A.1. Example of SD model: The exponential equation (A.5).

A.3. *Example of SD code*

In order to simulate the behavior of a dynamic system, the SD includes flowcharts, equations and a simulation platform; moreover, obviously a simulation code is necessary. In particular, for the system shown in Fig. A.1, the code in SD simulation logic is as follows:

```
#include <support1.cpp>
double simile_version = 2.91;
int phasecount = 1;
double dts[2];
/*STRUCTURE TYPE DECLARATIONS */
                    class Btype : public submodeltype {
                    public:
                Btype() {
                }; /*end(procedure,structor) */
                ~Btype() {
                }; /*end(procedure,structor) */
        double natalit;
        double mortalit;
        double tasnat;
        double tasmort;
        double preda;
/* Start list here*/
                if (1 ≧ phase) {
                        Bpointer_2 = &(Desktoppointer_2 → B[loop_2]);
                                if (1 ≧ phase) {
Bpointer_2 → mortalit=Bpointer_2 → tasmort*Bpointer_2 → preda;
                Bpointer_2 → CalcoloCP = Bpointer_2 → preda*Bpointer_2 → tasnat;
                Desktoppointer_2 → TotPrede[loop_2] =Bpointer_2 → preda;
                Desktoppointer_2 → TotCP[loop_2] =Bpointer_2 → CalcoloCP;
                }; /*end(cond,1≧phase) */
```

A.4. *Example of SD applications*

Mechanical, electrical, thermal and fluid systems are all examples of dynamic systems.

Let us recall that the basic unit of SD is a feedback loop, that allows coupling the status, decision and information in the system.

The rules of operation of the internal variables of a system are, e.g., very similar to the rules exhibited by a fluid moving in a loop. A fluid moving in loops inevitably results in accumulation at each intermediate procedure. The gradual accumulation of materials produces pressure, which, in the analogy with decision-making process, influences decision makers. As a result, to decrease the pressure, decision makers are forced to use the information received to make the necessary decision and to change the flow rate according to the control strategy. However, in these conditions, the decision maker could not make the best decision.

A.5. *Implementation of the Static AHP*

The considered alternatives are: Cytological Analysis, which represents the conventional Tg-level assessment, and the two biosensors, the one with the fiber on the tip (LOT) and the one with the fiber along the surface (LPG).

As the first step of AHP, we assess the consistency of the pairwise comparison matrix (Table 2) of the selected criteria. The CR is calculated with the following equation:

$$\mathrm{CR} = (\mathrm{CI}/\mathrm{RI}), \tag{A.6}$$

where the Consistency Index (CI) is obtained according to the following equation:

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n-1} \quad \text{with} \begin{cases} \lambda_{\max} = \text{maximum eigenvalue of the matrix,} \\ n = \text{matrix dimension,} \end{cases} \tag{A.7}$$

and RI is the Random (Consistency) Index which depends on the order of the array as reported in Table A.2.

For the matrix shown in Table 2, the CR is equal to

$$\mathrm{CR} = 0.0711 = 7.11\% < 10\%.$$

The matrix can be considered consistent as long as the CR is lower than 10%.

The eigenvector associated with the matrix is then equal to

$$w_1 = [0.0703;\ 0.1403;\ 0.8582;\ 0.4194;\ 0.2509].$$

Table A.2. Array order and the respective RI.

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

By dividing each element of the eigenvector by the sum of all the elements, the following normalized vector is obtained:

$$w_{1N} = \frac{w_1}{\sum_{i=1}^{n} w_{1i}} = [0.0404;\ 0.0807;\ 0.4935;\ 0.2412;\ 0.1443],$$

which represents the vector of the local weights of the criteria.

The second step of AHP is the comparison of the sub-criteria. The vectors of the local weights of the sub-criteria are calculated analogously to the above-described procedure. Then, the global weight of the sub-criteria is calculated by multiplying the vectors of the local weights of the sub-criteria by the local weight of the corresponding main criterion, previously calculated.

The third step of AHP is the comparison of the alternatives with respect to each sub-criterion. The vectors of the local weights of the alternatives with respect to the considered parent criterion are again calculated analogously to the above-described procedure. Then, the weights of the alternatives are calculated by multiplying the vectors of the local weights of the alternatives by the global weight of the considered sub-criterion, previously calculated.

Finally, by adding all the calculated weights for each of the three alternatives, we obtain the final priority vector indicating the preferences for the three alternatives.

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