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The Interdisciplinary Impact of the Quantification of Everything Method

Constantinos Challoumis [1,*]

[1] Philips University of Nicosia & National and Kapodistrian University of Athens, Athens, Greece

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ABSTRACT

The Quantification of Everything (Q.E.) methodology is a three-step process designed to transform theoretical concepts into mathematical representations and validate the resulting models through the principle of multiple axiomatics. This methodology integrates algorithms and computational techniques, often involving many estimations. Its application spans various scientific disciplines; in this context, its use in economics has been illustrated. A distinctive feature of the Q.E. methodology is its ability to convert empirical theoretical concepts into tractable mathematical forms by utilizing virtual quantity data. This function is especially useful in domains such as the social sciences, where empirical data may be limited or entirely unavailable. By enabling the generation of virtual datasets to test theoretical models, the methodology offers a structured approach for translating qualitative insights into quantitative terms and deriving corresponding mathematical expressions. The Q.E. methodology is a robust and adaptable framework applicable across all epistemic domains.

1. Introduction

Based on the paper "The Q.E. (Quantification of Everything) Method: Transforming Qualitative Data Across Scientific Disciplines" [1]. Axiomatic analysis is founded on the assumption that the validity of an initial hypothesis is initially unknown. This foundational premise is essential for the critical examination of any economic theory. The hypothesis serves as the starting point for developing and evaluating economic models [2]. Consequently, axiomatics seeks to address the underlying structure of economic analysis by verifying whether the initial hypothesis is upheld within the context of the model under investigation.

If the hypothesis is satisfied, the model is deemed consistent with its foundational principles, thus validating the axiomatic framework. Conversely, if the hypothesis fails to hold, the axiomatics is considered inadequate, indicating that the economic model lacks theoretical sufficiency. Therefore, the core purpose of axiomatics lies in determining whether the initial hypothesis aligns with the

* *Corresponding author.*
E-mail address: challoumis_constantinos@yahoo.com

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mathematical and economic outcomes of the analytical process. In doing so, it enables the researcher to assess the selected model's theoretical soundness and internal coherence. This method is very useful, it can be applied to any scientific field, as it converts quality into quantitative data. In that way, any science, even theoretical, can be converted to applied science. Axiomatics is founded on the assumption that the outcome of a hypothesis is initially unknown. This is crucial for scrutinizing an economic theory under examination. The hypothesis of an economic theory forms the foundation for the subsequent study of each economic model. Axiomatics aims to address the theoretical underpinnings of economic analysis and to verify that the initial hypothesis of the model is satisfied. If the hypothesis is confirmed, then the model is consistent with the principles of the analysis framework.

The Q.E. (Quantification of Everything) theory is based on the philosophy of multiple axiomatics. The hypothesis and conclusions are pivotal for clarifying each economic theory by confirming that the conclusions are consistent with the initial hypothesis. Multiple axiomatics allow for the re-modification of models through feedback. Feedback plays a crucial role as it enables the adjustment of the initial hypothesis based on the conclusions, thereby providing more accurate models. Feedback is the driving force behind iterations, enhancing the precision of the models.

Set of iterations $G = \{1, \dots, n\}$: Here, $n \in N$ represents the number of iterations for the generator.

Estimating equation $M = f(x_i)$: In this equation, $x_i \in R$ are the variables, and $f(x)$ is the function applied to these variables.

Forming equation $E_n = f(x_i) \cdot G$: This represents the forming equation after multiple iterations, where the function of $f(x_i)$ has repeatedly applied over the set G.

The new set of estimations $E'_n = f\left(x_{\{i \pm 1\}}\right) \cdot G$: This denotes a new set of estimations obtained by modifying the variable of x_i, either adding or subtracting one.

Final chosen equation $C_h = \{E_n, E'_n, \dots\}$: The final chosen equation is derived by comparing them, E_n, E'_n and others to determine which equation best fits the theoretical background and hypothesis of the model.

2. Literature Review

The axiomatic approach is grounded in the convergence between hypotheses and conclusions. An extension of this framework (multiple axiomatics) represents an evolution of the classical axiomatic model. The key distinction lies in the repetition and iterative validation between hypotheses and conclusions, allowing for refined adjustments and consequently more precise economic models. This refinement is operationalized through the Quantification of Everything (Q.E.) method, which integrates fuzzy logic, rational frameworks, and behavioral insights to construct and evaluate economic theories. Within this context, fuzzy logic plays a critical role in the generator stage of the process, wherein random values are produced and various equations are compared. These comparisons often involve the addition or subtraction of independent variables to test the consistency and behavior of the model under investigation. Fuzzy logic, introduced by Lotfi A. Zadeh in his seminal 1965 paper "Fuzzy Sets", initially met resistance due to the limited mathematical formalization available at the time. This hindered its acceptance in much of the Western academic community. However, in Japan, fuzzy logic was rapidly adopted and successfully implemented in technological applications, primarily because it delivered practical results, regardless of whether rigorous mathematical proofs existed. During the 1980s, Japanese manufacturers extensively employed fuzzy logic in consumer electronics, whereas its acceptance in the United States only gained momentum toward the end of that decade.

The controversy surrounding fuzzy logic was highlighted by William Kahan, a colleague of Zadeh, who criticized the theory for promoting imprecise reasoning. This critique echoes philosophical objections from Aristotle, whose principles (particularly the Law of Non-Contradiction and the Law of the Excluded Middle) assert that any proposition must be either true or false, disallowing intermediate truth values [3,4]. Despite these historical objections, contemporary advancements in Artificial Neural Networks and Machine Learning have revived interest in fuzzy logic. These modern frameworks demonstrate the relevance and applicability of fuzzy logic beyond neoclassical assumptions and behavioral constraints, offering more nuanced models of decision-making and systemic behavior. Accordingly, randomization within the Q.E. method originates from the conceptual foundation of fuzzy logic. The interpretative and analytical processes that follow (repeated across trials) enable the identification and validation of the most suitable model for the theory under consideration [5-7].

3. Methodology

The concept of the Q.E. theory is based on a methodology that stands on the determination of mathematical equations subject to conditions that are also considered. One more important thing is the determination of the upper and lower limits of the values of the independent variables. Forasmuch as the dependent variable represents the behavior of the selected model, depending on a generator that produces random values for all the independent variables to configure the interaction between them and their behavior under different conditions. The random numbers that are used to determine the behavior of the equations in comparison with the subtracted or added variables to the equations are used for the determination of the behavior of the model. At least the basic study includes two facets, which are:

i. The analysis of the behavior of the model depends on the scrutiny of the structural characteristics of each model, accordingly allowing, in that way, the extraction of general conclusions about the model that is under examination.
ii. The frequency analysis behavior scrutinizes the behavior of the dependent variables, but from the view of the number of appearances of a variable compared to another variable, it estimates the impact that one independent variable has on one or more other independent variables on the dependent variable.

The dependent variables are those that are modified from the generator [8]. Thereupon, the generator produces values for the dependent variables. The extracted values of the generator allow the creation of magnitudes, which are the basis for comparisons and the analysis of mathematical equations. In that way, it is plausible to quantify quality data and theoretical terms. Moreover, according to this methodology, the created magnitudes allow proceeding further to econometric analyses. In general, it is a methodology for the quantification of quality data. Thus, using the Quantification of Everything (Q.E.) methodology is plausible in clarifying the behavior of any model and determining its standalone behavior, or its comparative behavior, between different models. Therefore, this methodology as an index permits the study of the following issues:

i. It is possible to scrutinize and examine theoretical themes, from qualitative analysis to quantitative analysis.
ii. The creation of magnitudes can be used for any other analysis using that data as an axis for further estimations with different scientific tools, and sciences.
iii. Consequently, the created magnitudes permit an econometric analysis.

iv. If they are not determined, these units are considered "virtual units". The term "virtual units" means they are used only for each study and for comparability analysis.

This methodology of transforming quality data into quantitative data allows a completely different approach to theoretical studies, as it permits the mathematical determination of terminologies and their study in a different scientific field.

Therefore, at this point, the three basic points that the hypothesis and the mathematical determination need to complete their simplest form for the establishment of quality data:

i. The first step is about the hypothesis. At this point, the scope of the analysis of each study is discussed. Thus, a mathematical determination is the main point of this step.
ii. The second step is about the generator, which produces the values for the independent variable. This procedure takes into consideration the upper and lower limits, which are used for the production of values through randomization. This technique allows the formation of quality data into a quantified form. Thence, after a crucial number of irritations, it is plausible to sketch the appropriate mathematical equation. In that way, the behavior of the equation is under study. Therefore, the procedure needs at least two mathematical equations, with a lack of some variables, or more variables in the existing equation, to understand how the equation reacts in different forms.
iii. The third step gives the conclusions, and through feedback with the hypothesis, it is plausible to confirm an existing theory, or to submit a new scientific view [9,10].

The first step determines the scope of the study. The structural theoretical elements are used to specify the mathematical point of view under examination. Then, the hypothesis happens at this level, and the mathematical modeling is based on the theoretical background, which is under development or already exists and is checked for verification. This level is crucial for the next two steps. This is because this step shows the orientation of the study for the next two levels. From a programming view, it must be defined as the variables and the number of iterations. Multiple compilations of the program define the iterations, and this is the reason why this level is critical for the study. This initial step is connected with the last step through the feedback (Figure 1).

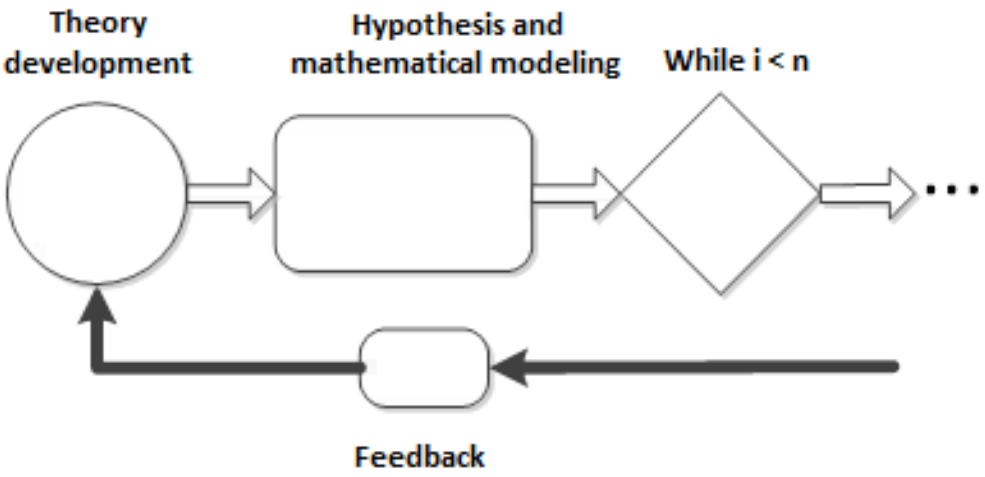


Fig. 1. Flowchart of hypothesis and mathematical modeling

Pseudocode for the hypothesis and the mathematical modeling (Figure 2).

```
<lib>                                   //definition of library
integer n = …;                          //initialization of values;
integer number;
float number;
main{
While i<n {…} or For {…}                //creation of loop
equation 1=…                            //definition of the equations
equation 2=…
…
equation n=…
end;
}
```

Fig. 2. Pseudocode for the hypothesis and the mathematical modeling

In Figure 1 and Figure 2, there is a general view of the basic parts needed for the definition of the mathematical equations and the configuration of the hypothesis which will happen through the third step, combined with this initial step. This step requires an understanding of the structural characteristics of the theory. The terminology "structural characteristics" is about the same key points of the theory, which permit the specification of those things that could be analyzed as variables. The number of iterations is modified by compiling the program, and in general, a high number of iterations allows a good quality of modification of the chosen mathematical model. However, because the result is plotted to extract conclusions, sometimes the high number of iterations makes it more difficult to represent the model's behavior. Therefore, not always a high number of iterations is considered to be fine for the study, but it should be found by more than one compilation, the best-fitted approach. One practical way to better organize the results is to make a border by programming like the following instance (Figure 3).

```
Pseudocode to organize the data
…
for(x<n) {                              //creation of a border
      for(y<m) }
```

Fig. 3. Pseudocode to organize the data

Figure 2 and Figure 3 describe the first step in its basic form. Depending on the compiler used to serve this scope, the program is adjusted accordingly into code. Thus, concluding in this first step:

i. Definition of the dependent, and the independent variables.
ii. Definition of the mathematical equations, which are under examination.
iii. Definition of a table to organize the data.
iv. It should be mentioned again that an important element about the study of the mathematical model to extract easier conclusions is to use similar equations.

Analyzing the last bullet, one effective technique to extract easier conclusions is to add or subtract from each equation for the system's behavior; therefore, it is plausible to use a series of equations to reach a clear conclusion. Follows a flow chart (Figure 4) about this issue:

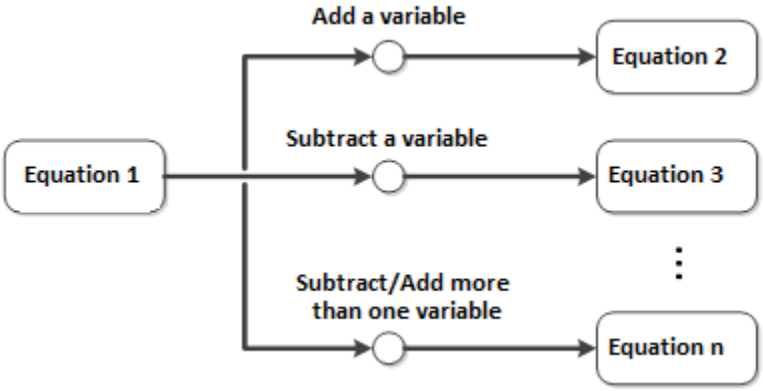


Fig. 4. Flowchart of the similarity of equations

The previous scheme (Figure 4) shows the similarity between the equations [11]. The interpretation of this technique shows that a similarity check exists, which permits the specification of the appropriate equation. The gradual transformation of equations allows the anticipation of the appropriate equation. The next paragraph analyzes the generator, which is the mainstream element for producing these values that are necessary to extract conclusions for the mathematical model. After defining the mathematical equations and clarifying the hypothesis, it is plausible to proceed to the establishment of the generator [12,13].

This second step is more technical than the other two steps, and the reason is that at this level, there is the generator, which is the mainstream source of this procedure (Figure 5). The generator produces randomized values that have a scale of limits [14,15]. The calling scale of limits means that there is at least one limit, but each variable has its own limit. The limit of each variable can be the same as that of the other variables. However, the limits express the conditions that are subject to the mathematical equations. Therefore, the conditions in any mathematical equation are important for quantifying data quality. Ergo, the conditions have a key role in the quantification of the data, as through them comes the determination of the behavior of the equation [16,17]. The randomization of the values of the generator uses limits based on the conditions of the mathematical equation under examination [18-20].

```
Pseudocode to generate values
<lib>                                   //definition of library
float c1, c2,…cn;                       //definition of limit
int i;
main(){
x1 [i]= rand (i,j,k);                   // production of random values in table
…
u1= c1*x1;                              //definition of limit for a variable
u2=c2*x2;                               //definition of limit for another variable
end;
}
```

Fig. 5. Pseudocode for behavior analysis of the generator mechanism

Thus, the development of the generator using the special limits of each variable and the structure of the behavior of the model is completed. After that, it is plausible to proceed to the frequency analysis of the behavior of the generator mechanism. Thence, in the frequency analysis, the number of appearances of one independent variable compared to the other independent variables. Two basic techniques could be applied. The first is by multiple comparisons between the two equations, completing all the possible combinations. Another way to estimate the frequency of the independent

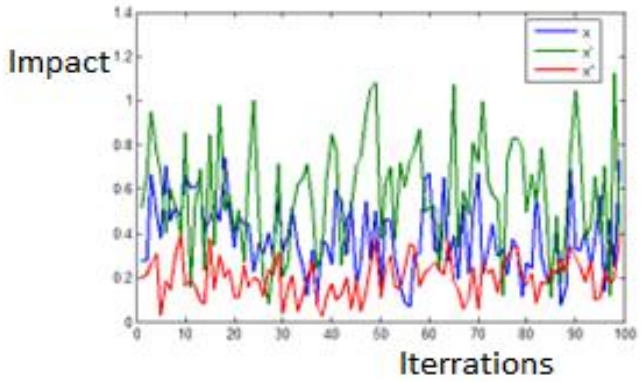
variables is by using a constant limit. This last technique is more empirical and is based on iterations, meaning that usually many compilations are made to determine the appropriate limit. The constant limit is determined better using the last step. Figure 6 presents pseudocode for the frequency.

```
if u1< constant;                                    // definition of frequency
        frequency1= frequency1+1;
else
        frequency2=frequency2+1;
```

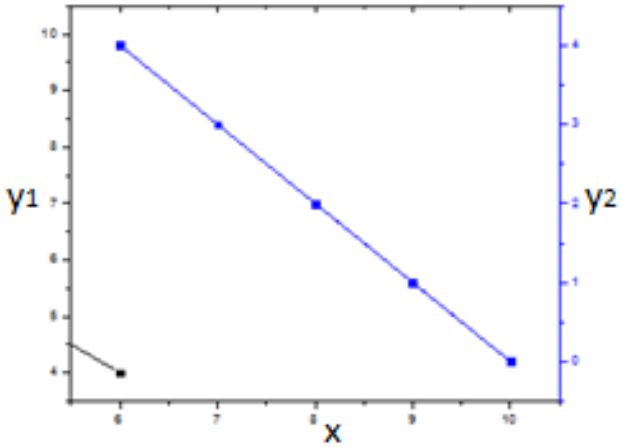
Fig. 6. Pseudocode for the frequency

The previous pseudocode for the frequency analysis behavior gives the frequency between independent variables under examination. The previous technique is based on the use of a constant limit.

Then, in Figure 7, there is an example of the behavior analysis. The changes in an equation after changes in some of its variables. In the second diagram are the results of a frequency analysis of behavior, where it has been determined from the x-axis, the y_1, and the y_2 axes the level of appearance between frequencies. The blue line is a different frequency than the black line which is another frequency; thus, it is plausible to determine the impact factor of the one independent variable to the other.



(a)



(b)

Fig. 7. (a) Instance of the plot of behavior analysis, (b) Instance of the plot of frequency analysis behavior

According to Figure 8, the analysis procedure functions as a connector between the hypotheses and the results. Hence, the results are used as an indicator of the hypotheses. The establishment of a theory depends on the compatibility of results with the initial assumptions of each economic model.

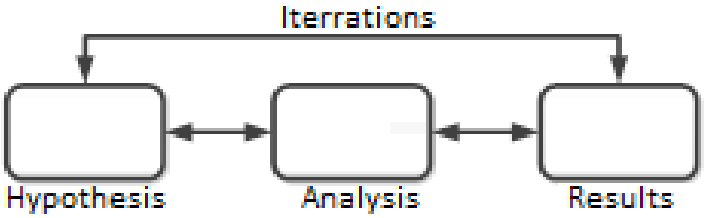


Fig. 8. The mechanism of the classic form of axiomatics

The feedback as it is obtained from Figure 9, is the basis for the confirmation of the hypothesis, and based on that, it has been modified again to the initial model and some parameters to be consistent with the scope of the research. The feedback is responsible for the iterations needed to clarify the exact mathematical equation until it is consistent with the theoretical structure.

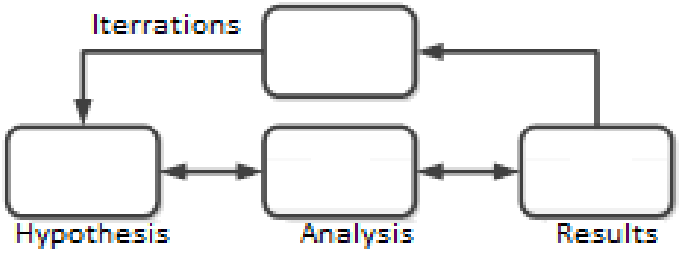


Fig. 9. The mechanism of the multiple axiomatics

3. Results

An illustrative application of the Q.E. method is demonstrated in the study "The Impact Factor of Education on the Public Sector – The Case of the U.S." Here, the monetary cycle in relation to education is analyzed using the Q.E. method and compared with econometric results and mathematical equations (Table 1).

Table 1
Compiling coefficients

Factors F	Values	Q.E. method
		Values
a_s	0.6	0.6
a_t	0.7	0.7
μ	0.9	0.9
a_r	-	-
$a_n * h_n$	0.3	-
$a_m * h_m$	-	-

The diagrammatic results are presented as follows (Figure 10). A paradigm for how to quantify quality data in history:

i. It must be defined which variables.
ii. The examination variable must be defined.
iii. The examiner should define one equation.

iv. Then the examiner must define the prior equation without the examination variable.
v. This determines the behavior of the model.
vi. This is plausible through the feedback, as the feedback is about the generator and the omitted variable.
vii. The generator thought the random variables allowed the determination of the graph, revealing to the examiner the behavior of the equation.
viii. Finally, it is plausible through the examination of all variables to determine all the possible behaviors of the initial equation and define its final form.

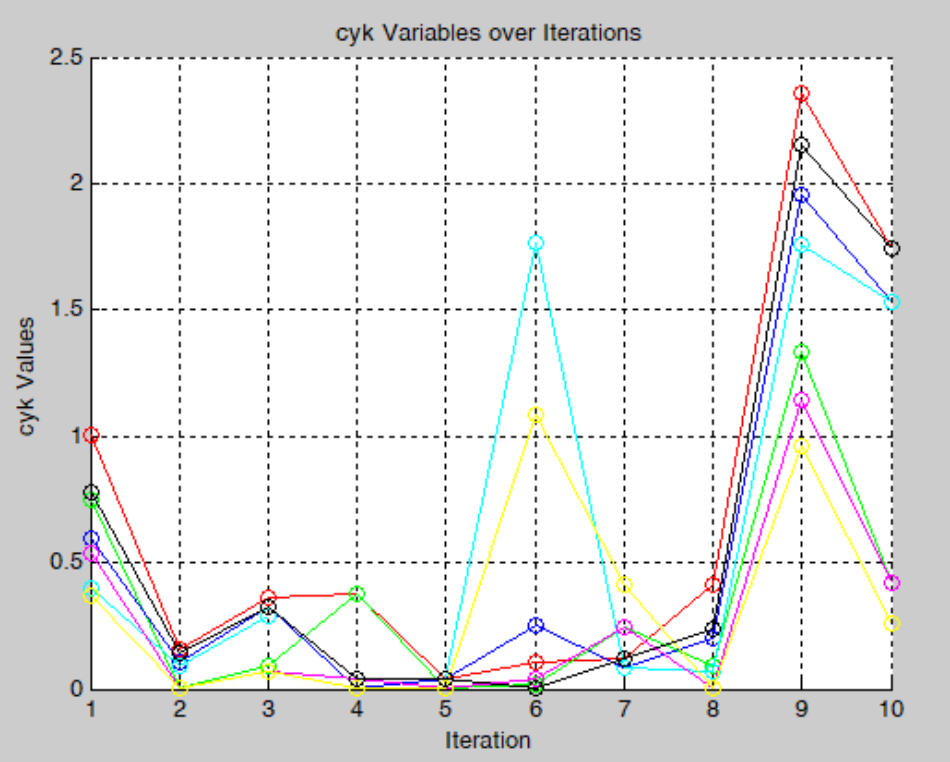


Fig. 10. The mechanism of the multiple axiomatic results

Considering the initial equation $time = events - external\ factors$ (Table 2).

Table 2
Compiling coefficients

Factors F	Q.E. method
	Values
Time	0.6
Events	0.7
External factor	0.9

The results are given in Figure 11. In this hypothetical scenario, the behavior of time in history is determined by the variable of factors excluding the variable external factors (which influence the clarity of studied factors), in the way the prior figure presents. There are no limitations on the Q.E. method. After determining the equation, it's plausible to make any statistical or other computational analysis. In that way, the method is objective.

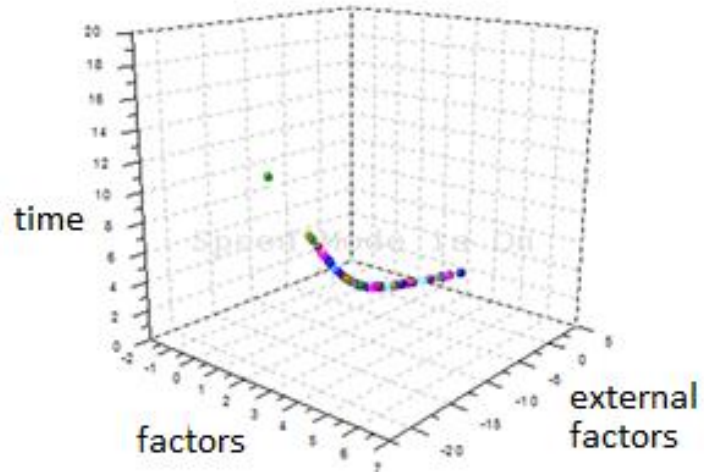


Fig. 11. The mechanism of the multiple axiomatics

4. Conclusions

This study presents and applies the Q.E. methodology as a transformative framework that converts qualitative theoretical constructs into mathematically tractable models. This methodological innovation addresses a fundamental challenge in the social sciences and other disciplines where empirical or measurable data are scarce or absent. By introducing virtual quantity data through a structured process of randomization and iterative feedback, the Q.E. method allows for developing mathematical models grounded in theoretical assumptions. A core strength of this methodology lies in its foundation on the principle of multiple axiomatics, which introduces a dynamic and recursive relationship between the initial hypothesis and the conclusions drawn. This feedback mechanism enables ongoing revision and refinement of the model, ensuring a higher degree of internal consistency and theoretical coherence. The process enhances the flexibility and adaptability of the methodology, making it suitable for evolving hypotheses and complex systems. The incorporation of fuzzy logic within the generator mechanism further strengthens the method's ability to handle ambiguity, uncertainty, and partial truths—features that are intrinsic to social, historical, and behavioral phenomena. By modeling such systems through approximate values and repeated estimations, the Q.E. methodology provides a nuanced approach to understanding and interpreting multifaceted relationships not easily captured by conventional binary logic.

The methodology's potential is demonstrated through its interdisciplinary applications, such as its use in evaluating the impact of education on the public sector and exploring theoretical models in historical analysis. These applications illustrate that the Q.E. method is not restricted to economics or formal sciences, but is equally effective in qualitative disciplines, facilitating the quantification of theoretical constructs that were previously difficult to analyze through empirical methods. Moreover, the Q.E. methodology offers a promising avenue for bridging the long-standing divide between theoretical and applied sciences. By creating and manipulating virtual data, abstract concepts and hypotheses can be subjected to computational testing, statistical validation, and econometric interpretation. This transformation enhances the scientific rigor of qualitative research and allows researchers to extract practical insights from conceptual frameworks.

In conclusion, the Q.E. method provides a systematic, flexible, and interdisciplinary tool for scientific inquiry. Integrating the Q.E. methodology with machine learning, advanced simulation, and econometric techniques may further enhance its applicability and impact across diverse scientific fields as computational tools evolve. Thus, the method significantly advances the effort to quantify knowledge across all epistemic domains.

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Conflicts of Interest
The authors declare no conflicts of interest.

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