Hojjatollah Farahani · Marija Blagojević · Parviz Azadfallah · Peter Watson · Forough Esrafilian · Sara Saljoughi

An Introduction to Artificial Psychology

Application Fuzzy Set Theory and Deep Machine Learning in Psychological Research using R

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Preface

Don’t You Know the Statistics? Don’t be Afraid and Enter

In science we try to build up a picture of the world. With the advancement of science, certainty has been isolated day by day and dark clouds have cast doubt on its beauty and radiance, and the certainty of Holy Grails turned upside down. Scientists have worked hard to push certainty out of the heart of mathematics. This effort was not very successful, and the advancement of science did not only increase human knowledge of phenomena but also expanded our knowledge of the limitations of scientific knowledge.

It shook the body of certain scientific principles, and the use of most of the tools of world representation have been shown to be problematic.

Until the twentieth century, science dealt with the certainty of Aristotelian logic. Now there was a world in which something could be both A and Not-A. Thus the death knell rang for the dominant 2000-year-old Aristotelian thought and instead of a comprehensive description of the world by drawing fixed and unique maps whose lines were in harmony with the day-to-day world, science made a set of maps, maps that were different but which gave a flexible understanding of the world.

Science is emerging in the postmodern world where scientific reading is not a fixed machine, rather it is creative and dynamic and readers create meaning in their minds based on thoughtful or lived experiences. Therefore, an author is no longer the final reference and refuge of the work or the only true creator. The reader does not suffer in passive silence in the ruthless wave of information, rather he is the one who gives life to the text. The data is silent and vague, and the mind of the reader ignites and speaks to them. In this new scientific worldview, we are not neutral observers of phenomena, which is neither possible nor desirable, but have become participants in the world.

Bohr, one of the great thinkers of quantum physics, believes that measurement questions the world and that question changes the answers. So what we are seeing are not phenomena, but, as Heinberg puts it, the genius of physics. What we see is not reality, but reality that is intertwined with the method of studying it. So we can say that what we see is the product of the science of measurement. In other words, the process of recognizing a phenomenon causes it to occur, but to what extent? We do not know. With this view, certainty is slowly receding from the world of science, and uncertainty is rising above thought. Psychological scientists, who are skilled in crossing the boundaries of science and brain activity, are not spared from this dramatic change. They found inadequate behavior and adopted a qualitative methodology for trapping elusive, dynamic, and meaningful phenomena. As we get closer to reality, precision decreases and vice versa.

Although a group with flexibility and scientific breadth combined these two methodologies, this hybrid was not inherited certainty at all, and this method gave rise to inherent uncertainty of the phenomena, and the struggle between precision and reality continued.

David Appelbaum has written a beautiful book called *The Stop*, in which he made a subtle statement which we express here. In this book, he compares the speed of seeing and examining things as experienced by a blind person by touch. Although the blind person cannot see, he says that this not-seeing also has its advantages, because the blind person sees things that a seeing person does not because he moves cautiously and slowly and, as a result, he finds his way through obstacles with a different touch and method and gains a new understanding. Perception is a trace of a hidden meaning; a perception often deepens, albeit slowly. So it can be said that although fast methods of understanding have their advantages, standing and looking calmly and evolving perception is also important. More attention should be paid to the development of a new methodology and extension of the current one. Therefore, it is hoped that mind researchers, psychologists, and all those with a research mindset will use multifaceted methods.

Behavioral scientists therefore have a reliable basis for relying and looking at psychological phenomena to be able to grasp the pearl of truth, but there is doubt about the nature of truth. The transition from classical (nineteenth century) certainty to the uncertainty of the present century was necessary as understanding evolved. This transition was not straightforward but enabled us to get nearer to the truth.

Developing theories in quantitative and qualitative research is the main purpose of this book.

We know that researchers' inference involves probability and uncertainty, so we talk about decay of the Holy Grail of perceived truths. It should be said that probability is an uncertainty about the existence or non-existence of phenomena, while what is examined in this book is a representation of another type of uncertainty, that is, the degree of certainty about existence or non-existence of phenomena rather than naively assuming a phenomenon's non-existence.

Most of us, however, have the same uncertainty in terms of the likelihood of the results obtained by doing research in psychology. We are aware of research findings but do not always believe that its results present a true understanding of psychological problems. However, the goal is not to reduce their value in any way. Because uncertainty is everywhere!!

Inference was created to model human thought, in order to obtain more dynamic and consistent findings with reality by using approximate and fuzzy reasoning.

The science of psychology is full of linguistic variables that require an approximate, indefinite, and obscure method of their own kind so that we do not fall into imitation models in studying the psychological phenomena of these multi-faceted concepts. These multi-faceted concepts may be interpreted and examined in different ways which is fine. What is annoying, however, is the dominance of a particular method or a particular way of thinking and its application to the inference of data in research.

In this book, we have considered the methodology of approximate inference in psychological research from a theoretical and practical perspective. Quantitative variable-oriented methodology and qualitative case-oriented methods are both used to explain the set-oriented methodology which we call fuzzy psychology. As stated in the opening sentence of the book, it does not matter if you do not know much about mathematics or statistics, because statistical and mathematical intuitions are key here and they will be learned through practice. What is important is to understand the method and its application to new, dynamic, and elusive phenomena.

Finally, your comments on this book are very welcome, so please do not hesitate to share them with us.

In the end, remember Montagne's short but deep saying "What do we know?" The human world is indeed full of uncertainty, whose beauty we have not been able to define and explain.

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Contents

1 In Search of a Method 1
1.1 What Is Artificial Psychology? 1
1.2 In Search of a Method 4
1.3 From *p*-value to *p*-war 5
1.3.1 *p*-value as Evidence to Confirm or Unconfirm a Null Hypothesis 6
1.3.2 Reverse Interpretation of the *p*-value 7

2 Artificial Psychology 9
2.1 Artificial Psychology 9
2.2 Why Artificial Psychology? 11
2.3 Artificial Psychology in Practice 22
2.4 Interpretability and Explainability in a Knowledge-Based Approach 25
2.5 Achilles' Heel in Psychology 26

3 Fuzzy Set Theory and Psychology 31
3.1 Fuzzy Set Theory and Psychology: Theoretical View 31
3.2 The Gray World of Mind 32
3.3 The Fuzzy Logic Under Psychological View 34
3.4 Why Fuzzy Logic Theory? 37
3.5 What Is the Fuzzy Map? 41
3.6 Fuzzy Modelling of Psychological Systems 43
3.7 Properties of Fuzzy Sets 44
3.8 Types of Fuzzy Sets (Membership Functions) 46
3.9 Practical Example Using R 47
3.10 Fuzzy Set Composition 51
3.10.1 Practical Example Using R 52
3.11 Mamdani Fuzzy Inference System 54
3.11.1 Mamdani Fuzzy System Steps 57
3.11.2 Practical Example Using R 59

3.12 Toward Fuzzy Rule Mining 66
3.12.1 Adaptive Network-Based Fuzzy Inference System (ANFIS) 68
3.12.2 Genetic Cooperative-Competitive Learning (GCCL) 75
3.12.3 Structural Learning Algorithm on Indefinite Environment (SLAVE) 77

4 Fuzzy Cognitive Maps 81
4.1 Fuzzy Modeling of Human Knowledge: Toward Fuzzy Cognitive Maps in Psychology 81
4.2 Modeling Based on Psychological Knowledge 83
4.3 Optimization in FCMs 90
4.4 Scenario Analysis in FCMs 92
4.4.1 Practical Example Using R 92

5 Network Analysis in AP 99
5.1 Network Analysis in AP 99
5.2 Structural Analysis of Psychological Network 101
5.3 Steps in Network Analysis 103
5.4 Descriptive Statistics of Networks 104
5.5 Network Accuracy 106
5.6 Accuracy of Centrality Indices 107
5.7 Network Science in Psychology 107
5.8 Network Science in Cognitive Psychology and Neuroscience 108
5.8.1 Complex System 108
5.8.2 The Brain as a Complex System 108
5.8.3 Brain Connectome 110
5.8.4 Various Scales for Network Analysis of the Brain 111
5.8.5 Networks in the Brain 112
5.8.6 Definition of a Brain Graph 115
5.8.7 Brain Network Identification and Analysis in Graph 118
5.8.8 The Brain's Important Networks 119
5.8.9 Applications of Graph in Cognitive and Behavioral Science 121
5.8.10 Machine Learning in Analysis of Resting-State fMRI (Rs-fMRI) Data 123
5.9 Designing Conceptual Networks 125
5.10 Sample Size in Network Analysis 126
5.11 Moderated Psychological Network Analysis 127
5.11.1 Practical Example Using R 127

6 Deep Neural Network 145
6.1 Deep Neural Network (DNN) 145
6.2 Neural Network 146
6.3 Neuron 146
6.4 Artificial Neural Network (ANN) 149
6.5 Types of Training 154
6.6 Usage of Neural Network 155
6.7 The Artificial Neural Network Structure 156
6.8 Modeling an Artificial Neural Network 158
6.8.1 Classical Optimization Methods 159
6.8.2 Intelligent Optimization Methods 160
6.9 Types of Data in Machine Learning Algorithms 160
6.10 Basic Concepts 161
6.11 Types of Artificial Neural Networks 164
6.12 Comparing Multilayer Neural Network with Regression 165
6.12.1 Practical Example Using R 167
6.13 Hyper-Parameter Tuning 172
6.14 Evaluation of DNNs 173
6.15 Interpretability and Explainability in DNNs 175
6.16 Difference between LIME and SHAP 178
6.16.1 Practical Example Using R 178

7 Feature Selection in AP 187
7.1 Feature Selection Problem 187
7.2 Feature Categorization 188
7.3 General Procedure of Feature Selection 188
7.4 Feature Selection Methods 190
7.4.1 Practical Example Using R 191
7.5 Metaheuristic Algorithms 194
7.6 An Introduction to the Genetic Algorithm 196
7.7 Basics of the Genetic Algorithm 197
7.8 The Initial Design of the Genetic Algorithm 198
7.9 Feature Selection Using the Genetic Algorithm 199
7.10 The Genetic Algorithm's Application in Artificial Psychology 201
7.10.1 Practical Example Using R 202
7.11 The Genetic Algorithm's Application in Neural Network Sciences 203

8 Bayesian Inference and Models in AP 207
8.1 Bayesian Inference and Models in Artificial Psychology 207
8.2 Bayesian Statistics in a Nutshell 208
8.3 A Critique on the Use of p-value 210
8.3.1 Significance or Existence of a Network 213
8.3.2 Practical Example Using R 213

8.4 Naïve Bayes Classifier 215
8.5 Cross-validation 217
8.5.1 A Practical Example Using R 218
8.6 Bayesian Binary Logistic Regression 220
8.6.1 A Practical Example Using R 221
8.7 Bayesian Network Analysis 225
8.7.1 A Practical Example Using R 229
8.8 Bayesian Model Averaging 231
8.8.1 Practical Example Using R 233

References 237

Index 251

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Peter Watson holds three degrees in Mathematical Statistics including a Ph.D. (Manchester). He has been providing statistical support in various ways to the research at CBSU, the Cognition and Brain Sciences Unit in Cambridge (and its predecessor, the Applied Psychology Unit) since 1994 (and prior to that fulfilling a similar role at the MRC Age and Cognitive Performance Research Centre in Manchester). He is the co-author of over 100 papers and lectures at the University of Cambridge. He is a statistical referee for several journals including *BMJ Open* and the *Journal of Affective Disorders*. He has also been a major contributor of articles to the on-line CBSU statswiki web pages which receive upwards of 100,000 visits annually. He has also been secretary, since 1996, of the Cambridge Statistics Discussion Group and chair and meetings organiser for the SPSS users group (ASSESS) since 2001 and has also been a member of the Clinical Trials Advisory Panel for Alzheimer's Research UK.

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Chapter 1
In Search of a Method

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1.1 What Is Artificial Psychology?

Artificial psychology (AP) is a highly multidisciplinary field of study in psychology. AP tries to solve problems that occur when psychologists do research and need a robust analysis method. Conventional statistical approaches have deep-rooted limitations. These approaches are excellent on paper but often fail to model the real world. Mind researchers have been trying to overcome this by simplifying the models being studied. This stance has not received much practical attention recently.

Promoting and improving artificial intelligence helps mind researchers to find a holistic model of mental models. This development achieves this goal by using multiple perspectives and multiple data sets together with interactive and realistic models. This comprehensive, holistic, and interactive view may lead to a new research line in the near future. AP can open up a new horizon for mind researchers from clinical to theoretical psychologists to find a more realistic model. This horizon is rooted in a multidisciplinary approach updating our view along with the development of the related sciences leading to the finding of new results even from old datasets and models. AP has some assumptions. Satisfying these assumptions helps find a more precise and deeper way of modeling for artificial psychologists.

The assumptions of AP are discussed here. First, we assume that the mind is filled with uncertainty. The uncertainty is the cost we are paying for living in the real world. We are usually trying to proceed through this uncertainty by considering the most certain fact as a truth. It is important to note that uncertainty not only occurs in nature but also in almost all man-made systems. Second, we assume that the mind is continuous. In other words, we assume a continuous consciousness in which the brain acts holistically and outputs behaviors discretely (Huette et al., 2012); therefore, there is not a sharp dividing line between emotion and cognition. The brain is a grey matter that constructs mental systems not separated by solid lines. These ambiguous areas are the ones mind researchers are trying to handle by the use of

statistical models. The third assumption is that the mind is a complex system; human mentality is made up of complicated systems. Even the simplest system and phenomena are complex. This complexity can be captured and interpreted by a dynamic model. The fourth assumption is that there is always a proxy between mind and data. It is not possible to study mental activities directly. Brain data needs to connect to some psychological constructs and behaviors. Therefore, we need to use multiple sources of data in a single model at the same time. Conventional statistical techniques use rigorous mathematical models. These models require comprehensive and complete data for analysis and prediction. In the real world, we are facing big, imperfectly measured data as well as nonlinear relationships in complex systems. The fifth assumption is that brain data is highly dimensional data. This implies that the dataset has many features even in small sample sizes. This problem commonly occurs in psychological research, especially in clinical, cognitive psychology, and neuroscience, where we need to deal with $P > n$.

In summary, psychologists need new analysis models to help them model complex mental systems. Artificial psychology uses intelligent models that satisfy these assumptions (Fig. 1.1).

One technique used in applied computing is to emulate the strategies involved in the intelligent systems or models for problem-solving. Intelligent models are related to the human way of thinking and interpretation. These models use fuzzy logic, artificial intelligence, and genetic algorithms both individually or together.

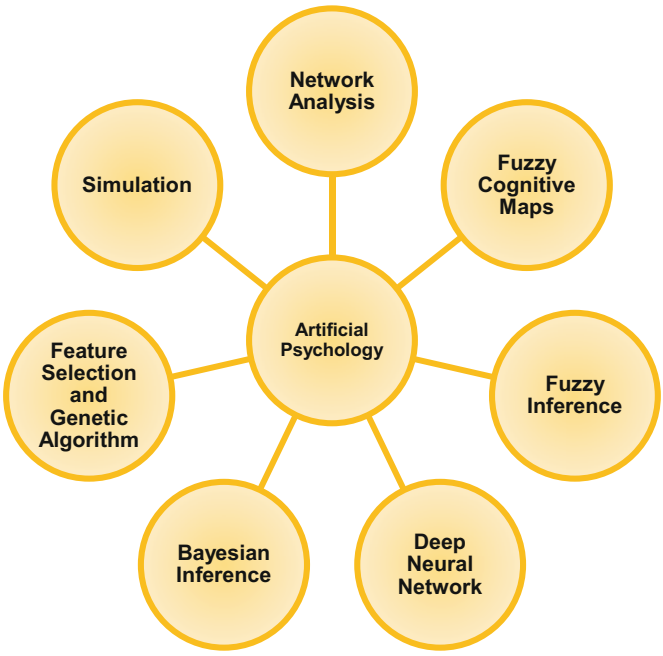

Fig. 1.1 Artificial psychology as a multidisciplinary field

1.2 In Search of a Method

Science aims to clarify concepts systematically, and its core is replicability. The ambient world is full of concepts, some of which are determinable or almost determinable, such as country borders and per capita income. Others, however, that are more prominent and studied in the social and behavioral sciences are different, such as depression, suffering, grief, love, and selective attention.

There is an infinite set of these concepts and they are very vague, scattered and elusive and assume highly diverse intertwined forms. The models designed by researchers to acquire an approximate understanding of these concepts represent the efforts of science to clarify them. Models are an approximate simplified understanding of reality and do not deal directly with reality. Models are always an approximation of reality outside of them. These models test theories and hypotheses about different concepts.

If psychological reality is vague and elusive, how should it be examined then?

Such a reality cannot be understood well by a single method. Therefore, research methods must develop like any other science, and there is no harm in employing a multitude of methods and, sometimes, methods of other disciplines for more accurate proximity to concepts.

Perhaps the principles and assumptions of many of the existing methods and future ones will probably require revision, even the methods introduced in this book. The dominance and hegemony of a particular method is remarkably alarming and dangerous.

It should be borne in mind that methods are not the only means of achieving reality, but they are the containers of reality, and the research findings take shape from them. Furthermore, these findings from the method occasionally become so extreme that they annoy some researchers.

It is noteworthy that the present book does not attempt to discard, ignore, or devalue past or existing methods but to overcome the fear of going beyond them. The research psychologists' shared fear might result in innovation. The aim is to find a way in which elusive concepts could be understood more clearly by researchers.

We know that wrong answers are more harmful than random answers because wrong, non-random answers mislead science systematically and significantly.

From Sigmund Freud's birth in 1856 until the writing of this book (2022), the earth has rotated 60,590 times, and research methods need to rotate as well. We know that psychology did not begin from Freud's birth, but Freud is cited since he has been called one of the scientific revolutionaries.

1.3 From *p*-value to *p*-war

Statistical significance plays a significant role in scientific research by linking data to hypothesis testing from the late mid-twentieth century (Gigerenzer et al., 1990). Currently, the most commonly used statistical measures in scientific studies, despite much criticism of its use, is the *p*-value (Lyu et al., 2020). In spite of the widespread use of the *p*-value in psychological research, various studies show that most researchers and students misinterpret *p*-values. This misinterpretation is rooted in *p*-value misuse, including the statistical significance hypothesis (Ziliak & McCloskey, 2008) and p-hacking. These are the main reasons for the confidence crisis and

reproducibility crisis in psychology research. The effect size and confidence intervals (CIS) can be regarded as alternatives to the *p*-value. Although the CIS can be used to improve statistical interpretation and inference, considering it an indicator of the effect size variations, its concept has also been misunderstood by researchers and its users (Lyu et al., 2020; Harrison et al., 2020; Greenland et al., 2016; Lyu et al., 2018; Morey et al., 2016; Cumming, 2013).

The study carried out by Lyu et al. (2020) on 1479 researchers and students in various fields in China revealed difficulty interpreting the *p*-value and CIS correctly, regardless of their academic degree and career stages. That is, 89% of them made at least one error in the *p*-value interpretation, and 93% made at least one error in the CIS interpretation. The level of misinterpretation in the significant and nonsignificant *p*-values and whether the CIS included zero or not was increased. Moreover, it is noteworthy that respondents were generally confident in their (incorrect) judgments.

These results indicate that researchers have misunderstood these crucial indicators of inferential statistics. This misunderstanding causes researchers to misinterpret, using classical statistics-based methods (assuming we are pleased with the *p*-value!), and these interpretations flow from different streams into the sea of psychological research findings (Harrison et al., 2020).

These interpretations include the following:

1.3.1 p-*value as Evidence to Confirm or Unconfirm a Null Hypothesis*

This issue is what is referred to as the illusion of certainty in Gigerenzer's research (2004, 2018), as it may provoke a crisis of confidence in the psychological research findings by encouraging researchers to reach a *p*-value of ≤ 0.05 as evidence of the existence of an "effect." One of the primary sources of this crisis is publication bias. This bias results from the fact that scientific journals welcome statistically significant results (p-value ≤ 0.05).

Chang et al. (2019) state that a *p*-value is a probability of obtaining an effect at least as extreme as the effect in the sample data, assuming the truth of the null hypothesis. Considering the *p*-value in classical statistics, despite its low statistical power in both single studies and meta-analyses, may result in distrust in the actual results of psychological research. Given the statistical power in the published studies, the frequency of statistical significance in those studies is suspiciously high (Francis, 2014).

Schmidt and Oh (2016) asserted that 90% of the research reports were significant, while the average total power was 0.4. What they found is strong evidence that these studies are questionable. Test power did not increase in questionable research practices until 1962, when Cohen emphasized the "low power" issue. What was the reason for this emphasis?

We know that in classical statistics, the *p*-value is a function of the effect size and the sample size, and the sample size seriously affects the power increase:

$$(p-\text{value}) = f(\text{Effect size}, \text{sample size}) \tag{1.1}$$

Low power leads to nonsignificant results. Nonsignificant results are as important as significant ones, but their nonsignificance made it difficult for researchers to publish their papers. This publication bias is called the file drawer problem, with studies less likely to reject the null hypothesis ending up unpublished in a file drawer. Therefore, researchers have earnestly strived to increase the power of their research. Maxwell (2004) has elaborated on this issue extensively. However, it has not always been possible to obtain a sufficient sample size, so maybe this is why researchers conducted questionable research. In other words, they conducted questionable research to obtain significant results to avoid the abundance of nonsignificant results due to low statistical power (Harrison et al., 2020).

1.3.2 Reverse Interpretation of the p-*value*

Another consequence of misinterpretation of the *p*-value, as Lyu (2020) states, is replication illusion. Many researchers avoid Bayesian thinking because of classical *p*-value-based statistics, the thinking that is the basis of classical inference. The reverse interpretation of the *p*-value is to consider 1 – *p*-value as the probability of successful replication of the result.

Despite these problems, the potential consequences of the lack of statistical thinking and ritual use of *p*-values have rarely been mentioned in the psychological research results, except in recent years (Lyu et al., 2020). The study of Farahani et al. (2021a, b, c) on a sample of 100 postgraduate and Ph.D. psychology students in Iran indicated that 95.7% of them make mistakes about the illusion of certainty and the replication illusion in the interpretation of the *p*-value.

The *p*-value is not well understood, and most researchers speak about it with a wrong mindset and perception. A *p*-value demonstrates the likelihood that the researcher's data will occur under the null hypothesis. This is obtained by calculating the likelihood of test statistics gained from the researcher's data (Indrayan, 2019).

It should be noted that the *p*-value is a ratio and a percentage. The *p*-value is the probability of a test statistic at least as big as the test statistic obtained from the data, assuming that the null hypothesis is correct.

Harison et al. (2020) summarized the shortcomings of using NHST (*p*-values) as follows:

1. Use of *p*-values without regarding the effect sizes and confidence intervals is not informative.
2. The potential for the use of "p hacking" by manipulating data and analyses deliberately to reduce *p*-values.
3. Simplistic dichotomous interpretations of *p*-values as either significant or nonsignificant.
4. Incorrect interpretation of $p > 0.05$ as no effect.
5. Misinterpreting statistical significance and taking it as clinical or practical significance.
6. Committing multiplicity by performing multiple statistical tests without adjusting the criterion *p*-value.

One way to improve *p*-value interpretation is to use clinical interpretation, practical interpretation, or practical significance. Apart from statistical significance, the effect size should be used for practical interpretation. Another point is that reporting inconclusive findings and null findings in articles is not harmful but valuable and strengthens the scope of scientific theories, but it should be borne in mind that what was said at the beginning of this chapter about the world not being black and white encourages researchers to choose another way to have accurate yet close-to-reality findings.

To design a different research model, a new conceptual framework is required with different measures, which will be discussed in detail in the second chapter.

Chapter 2
Artificial Psychology

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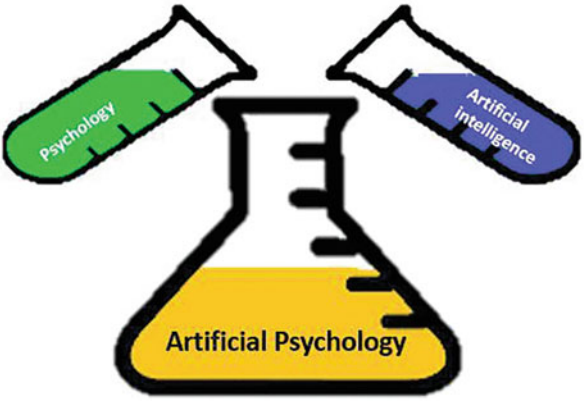
2.1 Artificial Psychology



Artificial psychology was first proposed by Dan Curtis in 1963 as a theoretical discipline. Artificial psychology is a combination of psychology and artificial intelligence. As a comprehensive definition, psychology can be called the science of studying an individual's mental processes and behaviors.

Artificial intelligence also has a wide variety of definitions, and it may not be possible to provide a comprehensive definition that encompasses all of its dimensions; however, it is a science that deals with the design of intelligent machines and systems; systems that can perform tasks requiring human intelligence (Crowder & Friess, 2010).

Here, we return to artificial psychology. The developments in psychology and artificial intelligence as of 2022 have addressed the needs of researchers. Here, artificial psychology has a theoretical framework or is simply a theory on which the artificial psychology presented in this book relies to look at the world of psychology. In other words, artificial psychology uses artificial intelligence to design, train, test, and ultimately deploy methodological models in the psychological context. This representation of artificial psychology is shown in Fig. 2.1.

This theoretical framework has features borrowed from psychology, artificial intelligence, and the psychological contexts in question. As the basis of artificial psychology, this theory is interpretable and explainable in artificial intelligence-based psychology.

Artificial psychology in this book relies on the above theory for prediction and classification to provide robust, interpretable, and explainable models. Here, artificial psychology refers to the scientific application of this theory.