River Publishers Series in Computing and Information Science and Technology

ARTIFICIAL INTELLIGENCE

ACHIEVEMENTS AND RECENT DEVELOPMENTS

Editors:
Anatolii I. Shevchenko
Yuriy P. Kondratenko

River Publishers

Artificial Intelligence: Achievements and Recent Developments

RIVER PUBLISHERS SERIES IN INFORMATION SCIENCE AND TECHNOLOGY

Series Editors:

K.C. CHEN
National Taiwan University, Taipei, Taiwan
University of South Florida, USA

SANDEEP SHUKLA
Virginia Tech, USA
Indian Institute of Technology Kanpur, India

The "River Publishers Series in Computing and Information Science and Technology" covers research which ushers the 21st Century into an Internet and multimedia era. Networking suggests transportation of such multimedia contents among nodes in communication and/or computer networks, to facilitate the ultimate Internet.

Theory, technologies, protocols and standards, applications/services, practice and implementation of wired/wireless networking are all within the scope of this series. Based on network and communication science, we further extend the scope for 21st Century life through the knowledge in machine learning, embedded systems, cognitive science, pattern recognition, quantum/biological/molecular computation and information processing, user behaviors and interface, and applications across healthcare and society.

Books published in the series include research monographs, edited volumes, handbooks and textbooks. The books provide professionals, researchers, educators, and advanced students in the field with an invaluable insight into the latest research and developments.

Topics included in the series are as follows:-

- Artificial intelligence
- Cognitive Science and Brian Science
- Communication/Computer Networking Technologies and Applications
- Computation and Information Processing
- Computer Architectures
- Computer networks
- Computer Science
- Embedded Systems
- Evolutionary computation
- Information Modelling
- Information Theory
- Machine Intelligence
- Neural computing and machine learning
- Parallel and Distributed Systems
- Programming Languages
- Reconfigurable Computing
- Research Informatics
- Soft computing techniques
- Software Development
- Software Engineering
- Software Maintenance

For a list of other books in this series, visit www.riverpublishers.com

Artificial Intelligence: Achievements and Recent Developments

Editors

Anatolii I. Shevchenko

Institute of Artificial Intelligence Problems of Ministry of Education and Science and National Academy of Sciences of Ukraine, Ukraine

Yuriy P. Kondratenko

Petro Mohyla Black Sea National University; Institute of Artificial Intelligence Problems of Ministry of Education and Science and National Academy of Sciences of Ukraine, Ukraine

River Publishers

Published, sold and distributed by:
River Publishers
Alsbjergvej 10
9260 Gistrup
Denmark

www.riverpublishers.com

ISBN: 978-87-4380-097-2 (Hardback)
978-87-4380-096-5 (E-book)

Contents

Preface

The monograph provides an overview of the main achievements and recent results in artificial intelligence (AI) technologies and systems including new theoretical findings and successful examples of AI practical implementation in different industrial and special areas (medicine, robotics, military sphere, re-building processes, etc.).

This monograph "Artificial Intelligence: Achievements and Recent Developments" consists of twelve research-oriented chapters presented by invited well-known scientists from the People's Republic of China, Ukraine, the United Kingdom, and the United States of America.

The chapter "Artificial Intelligence: Achievements and Prospects," by A. Shevchenko, M. Klymenko, and L. Baranovska, describes the current state of AI achievements and its influence on the transformation of research, social and technological processes, etc. The chapter focuses on perspectives and priority tasks of AI development and implementation. New regulatory initiatives are discussed at various levels to control AI applications and support the creation of new AI technologies, possible solutions, hardware, and algorithmic means for optimizing computations and modeling cognitive abilities.

In "Decision Support in the Field of Cyber Security Through the Use of Generative Artificial Intelligence," D. Lande, I. Svoboda, A. Feger, and L. Strashnoy present the methodology of forming causal networks through the repeated application of large language models (LLMs) with their visualization and analysis. The authors propose to create and subsequently combine two networks: first – starting from the node representing the initial state of the problem (the root cause); second – starting from the goal, working backward. The combined causal network serves as the foundation for creating desired scenarios.

V. I. Slyusar in the chapter "Applications of Large Language Models in the Military Sphere" explores the transformational impact of LLMs on modern military operations, particularly in the context of hybrid and conventional warfare. The focus is on the role of LLMs in improving decision-making, intelligence analysis, and operational efficiency. The author analyzes the future potential of LLMs for enhancing decision support systems and proposes the application of multi-agent LLMs in military technology and virtual reality (VR). The integration of LLMs into VR enables the creation of personalized, adaptive, and realistic training, significantly improving the preparation of military personnel. The chapter also examines the capabilities of multimodal LLMs for processing images, audio, and video data, as well as their use in autonomous systems and cybersecurity.

The chapter "Optimization-oriented Synthesis of Rule Bases of Intelligent Systems: Application Features for Complex Plants' Control," by Yue Zheng, Jianjun Wang, Oleksiy Kozlov, Galyna Kondratenko, and Anna Aleksieieva, addresses the optimization-oriented synthesis of rule bases (RBs) of intelligent fuzzy logic systems. The proposed approach allows the creation of fuzzy systems with an optimal set of consequents and a reduced number of rules in RBs in terms of incomplete source information due to highly efficient sequential search procedures of structural-parametric optimization. The effectiveness studies were conducted for two different intelligent control systems, particularly, for a mobile robotic platform and a floating dock.

In "The Nearest Results of Artificial Intelligence Application in Biology and Medicine: Development Trends and Implementation Risks," O. P. Mintser discusses the implementation of artificial intelligence in medicine, which is limited to a relatively small number of practical areas. The purpose of the study is to conceptualize the reasons for limitations in the use of AI, as well as the prospects and risks of AI implementation.

Ie. V. Sidenko and co-authors of the chapter "Artificial Intelligence Technologies for Efficient Solving Recognition Tasks" focus on using convolutional and recurrent neural networks for solving various recognition problems across diverse sectors. The authors analyze AI efficacy in medical diagnosis, transportation logistics, military operations, and others. By examining successful cases of AI implementations, this study highlights the role of AI in enhancing classification and recognition capabilities in real-world scenarios. Additionally, prospects for AI development, considering potential improvements and advancements to current technologies, are discovered.

The chapter "Hierarchical Decision Support System for Increasing Maritime Safety Based on Optical Color Computing Architecture," by V. Timchenko, V. Kreinovich, Y. Kondratenko, and I. Demidov, considers the basic principles of constructing logical components of the architecture of optical color computing based on estimating the dispersion of truth operands.

To implement the proposed optical architecture, a real-time changing multifactor database was generated to assess the safety of navigation in limited water areas with heavy vessel traffic. A three-level decision support system has been developed to control traffic safety and organize port ship maintenance. Possible logical operations for obtaining estimates for a specific set of input data are modeled and the effectiveness of the proposed approach due to the speed and parallelism of optical color computing is assessed.

A. V. Bukalov in the chapter "Artificial Intelligence: Effective Socionic Models of Psycho-Informational Processes and Quantum Computers" reviews theoretical and experimental studies of the quantum nature of the psyche and consciousness and discusses the author's results showing the connection between quantum and mental processes. The author introduces the concept of an elementary unit (quantum) of consciousness and proposes calculating the degree of consciousness of any living organism. Analysis of the presented data leads to the conclusion that adequate modeling and reproduction of mental processes with the manifestation of consciousness and multifunctional intelligence is possible only on quantum computers with a structure corresponding to the real structure of the psyche. It is well described by the extended information model of the psyche, proposed by the author, in socionics (or psychoinformatics) as the theory of information metabolism. The author developed the basic socionic model, introducing the coordinating function of consciousness and the description of the internal structure of mental functions, and showed that the hierarchy of these functions can be modeled as a special system from several specialized quantum processors.

Y. Zaporozhets and A. Ivanov, in "Cognitive Methodology as AI Tool for Investigation of Phenomenological Ground of Melt Electromagnetic Treatment," focus on using artificial intelligence (AI) methods to improve the efficiency of various technological and production processes in the foundry industry. Many experiments have ascertained that the melt treatment with electric current (ECT) in certain modes effectively improves structural parameters and quality of castings.

Implementation of this promising technology of melt treatment requires a deep study of the elements' interaction mechanisms of the weakly structured complex system "ECT-of-Melt" (CSEM) at all levels of its hierarchical relationships and chains of interactions. One of the most important AI approaches was used to study the phenomenological ground of the CSEM – the cognitive methodology of modeling, which is based on structuring knowledge in a specific subject domain (SD). Ontological analysis of the SD using taxonomic models ensured the creation of an ordered information platform for constructing a cognitive model (CM) of the CSEM. The CSEM CM has several essential peculiarities, particularly a multi-level hierarchical structure that covers more than a hundred concepts – vertices of the corresponding graph and about 2000 edge-connections. Such a CM cannot be used in computer models in the form of a conventional cognitive map (CMp). Therefore, the connection matrix of the primary CM was subjected to decomposition into a set of partial adjacency matrices. On their base, a hierarchical network scheme of interconnections between concepts was developed. The result of the presented development is the completion of the set of AI tools with the help of which it is possible to compile a wide range of algorithms for the cognitive study of the phenomenological basis of ECT, targeted at revealing the most effective modes of ECT of melts and obtaining high-quality castings.

The chapter "Some Aspects of the Application of Artificial Intelligence for the Recovery and Development of Ukraine," by S. Kovalevskyy, considers the AI application for the recovery and development of Ukraine, which suffered from military conflicts. The main focus is on the integration of AI into various areas of the country's life, including public administration, economy, infrastructure, health care, and education. Specific technological solutions are proposed, such as agent systems, neural networks, and decision support systems, which contribute to increasing the efficiency of recovery processes and ensuring sustainability in the conditions of post-war development. Challenges related to the implementation of AI are also discussed, including ethical, legal, and organizational aspects.

Olga Kosheleva, Vladik Kreinovich, and co-authors in the chapter "Two Is Enough, but Three (or More) Is Better: In AI and Beyond" underline that the most successful AI technique is deep learning – the use of neural networks that consist of multiple layers. It is well known that neural networks with two data processing layers are sufficient for approximating any function with a given accuracy. However, using three or more data processing layers (deep learning) makes the neural networks much more efficient. Authors show numerous examples from AI that this is a general phenomenon: two is enough but three or more is better. The authors discuss the fact that this phenomenon is universal and provide a possible explanation for such a phenomenon.

The chapter "How Free Can Artificial Intelligence Be?," by O. V. Bilokobylsky and T. V. Yeroshenko, addresses the issue of freedom in the field of AI by proposing two key perspectives: (a) whether AI can possess freedom and, if so, to what extent; (b) the conditions necessary to preserve human freedom in interactions with AI. It is argued that current AI paradigms (symbolic, perceptron, and generative), grounded in physicalist and communicative views of the mind, lack access to ontological reality, rendering them neither rational nor free. Consequently, the focus shifts to ensuring conditions for rational human social activity by mitigating AI's potential negative impacts. To achieve this, the authors propose a methodology for embedding main imperatives into AI legislation and policy.

The chapters of the monograph have been structured to provide an easy-to-follow introduction to the topics addressed, including the most relevant references, so that anyone interested in this field can get started.

This book may be useful for researchers and students who are interested in recent developments of modern control systems, robust adaptive systems, optimal control, fuzzy control, motion control, identification, modeling, differential games, evolutionary optimization, reliability control, security control, intelligent robotics, and cyber–physical systems.

We would like to express our deep appreciation to all authors for their contributions and to reviewers for their timely and interesting comments and suggestions. We certainly look forward to working with all contributors again soon.

Editors:

Anatolii I. Shevchenko, Prof., Dr.Sc., Corresponding Member of the National Academy of Sciences of Ukraine, *Director of the Institute of Artificial Intelligence Problems, Ukraine*

Yuriy P. Kondratenko, Prof., Dr.Sc., Corresponding Academician of the RACEF and Royal European Academy of Doctors - Barcelona 1914 (Spain), *Head of Intelligent Information Systems Department at Petro Mohyla Black Sea National University, Ukraine*

List of Figures

List of Tables

List of Contributors

Aleksieieva, Anna, *Petro Mohyla Black Sea National University, Ukraine*

Baranovska, L., *Institute of Artificial Intelligence Problems, Ukraine*

Bilokobylsky, O. V., *Institute of Artificial Intelligence Problems of MES and NAS of Ukraine, Ukraine*

Bukalov, A. V., *International Institute of Socionics, Ukraine*

Demidov, I., *Admiral Makarov National University of Shipbuilding, Ukraine*

Feger, Anatolii, *National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute" (NTUU "KPI"), Ukraine*

Ivanov, A., *Institute of Pulse Processes and Technologies of the NAS of Ukraine, Ukraine*

Jianjun Wang, *Yunzhou (Yancheng) Innovation Technology Co., Ltd, China*

Klymenko, M., *Institute of Artificial Intelligence Problems, Ukraine*

Kondratenko, Galyna, *Petro Mohyla Black Sea National University, Ukraine*

Kondratenko, Y., *Petro Mohyla Black Sea National University, Ukraine*; *Institute of Artificial Intelligence Problems, Ukraine*

Kosheleva, Olga, *University of Texas at El Paso, USA*

Kovalevskyy, S., *Department of Innovative Technologies and Management, Donbas State Engineering Academy, Ukraine*

Kozlov, Oleksiy, *Petro Mohyla Black Sea National University, Ukraine*

Kreinovich, Vladik, *University of Texas at El Paso, USA*

Lande, Dmytro, *National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute" (NTUU "KPI"), Ukraine*

Mintser, O., *Shupyk National Healthcare University of Ukraine, Ukraine*

Saliutin, M., *Petro Mohyla Black Sea National University, Ukraine*

Shevchenko, A., *Institute of Artificial Intelligence Problems, Ukraine*

Sidenko, Ie., *Petro Mohyla Black Sea National University, Ukraine*

Skarga-Bandurova, I., *Oxford Brookes University, United Kingdom*

Slyusar, V. I., *Central Research Institute of Armaments and Military Equipment of Armed Forces of Ukraine, Ukraine; Institute of Artificial Intelligence Problems, Ukraine*

Strashnoy, Leonard, *University of California, Los Angeles (UCLA), USA*

Svoboda, Igor, *National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute" (NTUU "KPI"), Ukraine*

Timchenko, Victor, *Admiral Makarov National University of Shipbuilding, Ukraine*

Yeroshenko, T. V., *Institute of Artificial Intelligence Problems of MES and NAS of Ukraine, Ukraine*

Yue Zheng, *Yancheng Polytechnic College, China*

Zaporozhets, Y., *Institute of Pulse Processes and Technologies of the NAS of Ukraine, Ukraine*

Zhukov, Y., *C-Job Nikolayev, Ukraine*

List of Abbreviations

ABPA	Allergic bronchopulmonary aspergillosis
AHP	Analytic hierarchy process
AI	Artificial intelligence
AIS	Abbreviated Injury Scale
ANN	Artificial neural network
ANP	Analytic network process
API	Application programming interface
ASIC	Application-specific integrated circuits
BAP	Biologically active point
BDA	Big data analysis
BDI	Belief-desire-intention
BEN	Behavior with emotions and norms
BN	Big negative
BOD	Behavior-oriented designers
BP	Big positive
CCR	Concept connections register
CGA	The Cancer Genome Atlas
CISO	Chief Information Security Officer
CM	Cognitive model
CNN	Convolutional neural network
CoT	Chain-of-thought
CPU	Central processing unit
CV	Computer vision
DARPA	Defense Advanced Research Projects Agency
DBEM	Database on Melts ECT Modes
DL	Deep learning
DM	Data mining
DMN	Default mode network
DP	Digital pathology
DSS	Decision support system
ECT	Electric current treatment

EEG	Electroencephalography
EMF	Electromotive force
FCM	Fuzzy cognitive map
FCN	Fully convolutional network
FIM	Functions of information metabolism
FL	Federated learning
FLOP	Floating point operations per second
FPGA	Field-programmable gate array
FPV	First person view
GAC	Geodesic active contours
GDPR	General Data Protection Regulation
GenAI	Generative AI
GEO	Gene Expression Omnibus
GH	Global Health
GPR	Ground-penetrating radar
GPU	Graphic processing unit
HNCut	Hierarchical normalized cuts
IAIP	Institute of Artificial Intelligence Problems
ICH	Intracerebral hemorrhage
IDS	Intrusion detection systems
IED	Improvised explosive device
IoT	Internet of Things
ISHAM	International Society for Human and Animal Mycology
IT	Information technologies
IVAS	Integrated visual augmentation system
KB	Knowledge base
KDD	Knowledge discovery in database
LAM	Large action model
LLaMA	Large Language Model Meta AI
LLM	Large language model
LRN	Local response normalization
LT	Linguistic term
MFR	Masked face recognition
ML	Machine learning
MMS	Molten metal system
MoE	Mixture of experts
MRI	Magnetic resonance imaging
NAS	Neural architecture search

NCD	Noncommunicable disease
NDVI	Normalized difference vegetation index
NEAT	Neuro-evolution of augmenting topologies
NER	Named entity recognition
NGVA	NATO Generic Vehicle Architecture
NLP	Natural language processing
NPU	Neural processing unit
OCC	Ortony, Clore, and Collins
PAM	Partial adjacency matrix
PCC	Prothrombin complex concentrate
PMEP	Phenomenological Map of Melt ECT Processes
PMS	Project management systems
PSSH	Physical symbol system hypothesis
QC	Quantum computing
RAG	Retrieval augmented generation
RB	Rule base
ReLU	Rectified linear unit
RNN	Recurrent neural network
ROI	Region of interest
S.A.R.A.H.	Smart AI Resource Assistant for Health
SaaS	Software-as-a-service
SD	Subject domain
SM	Semantic modeling
SME	Small- and medium-sized enterprise
SN	Small negative
SoC	System-on-chip
SOLO	Segmenting objects by locations
SP	Small positive
SQL	Structured query language
SVM	Support vector machine
TPN	Task-positive network
TPU	Tensor Processing Unit
TST	Ten Second Triage Tool
UAVs	Unmanned aerial vehicles
UN	United Nations
USC	University of Southern California
VGG	Visual geometry group
VoIP	Voice Over Internet Protocol
VPU	Vision processing unit

VR	Virtual reality
WME	Weapons and military equipment
WSI	Whole slide imaging
WTDS	War trauma dataset
YOLO	You only look once

2

Decision Support in the Field of Cybersecurity Through the Use of Generative Artificial Intelligence

Dmytro Lande[1], Igor Svoboda[1], Anatolii Feger[1], and Leonard Strashnoy[2]

[1]National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute" (NTUU "KPI"), Ukraine
[2]University of California, Los Angeles (UCLA), USA
E-mail: dwlande@gmail.com; i.svoboda@kpi.ua; feher.anatolii@gmail.com; lstrashnoy@gmail.com

Abstract

This chapter is dedicated to the methodology of forming causal networks through the repeated application of systems based on large language models (LLMs), as well as the visualization and analysis of these networks. The generated causal networks provide the possibility of further transitioning to scenario analysis. The chapter discusses the potential of emulating a group of experts by repeatedly applying similar prompts to LLMs. The methodology is based on using causal networks formed by LLMs. It is proposed to create and subsequently combine two networks: the first network is formed starting from the node representing the initial state of the problem (the root cause); the second network is formed starting from the goal, working backward. The combined causal network serves as the foundation for creating desired scenarios.

Keywords: Decision support, large language models, virtual experts, causal networks, semantic networking.

2.1 Introduction

In today's world, decision-making in complex systems is becoming an increasingly important and challenging task due to the growing volume of data, the variety of situations requiring analysis, and the increasing number of interdependent factors. Traditional decision-making approaches, such as analytical methods, heuristics, and expert systems, while still relevant, often demand significant resources, particularly the involvement of a large number of experts. However, recent advancements in artificial intelligence, particularly large language models (LLMs), open new possibilities for addressing this issue.

Traditionally, the decision-making process in complex systems has relied on the work of experts who build models and analyze complex data to find optimal solutions. However, practice shows that these methods have several limitations. The biggest challenge lies in ensuring access to a sufficient number of competent experts who can provide comprehensive and objective analysis. This becomes especially critical in cases where the number of factors and their interactions is so large that it requires substantial intellectual and time resources. Moreover, experts may hold different views on the same issues, leading to conflicting opinions and, consequently, difficulties in reaching consensus decisions.

2.1.1 The role of large language models in decision-making support

With the emergence of LLMs, such as GPT-4, new prospects have appeared in the field of decision support. These models can process vast amounts of information, extract knowledge, and construct complex semantic networks that describe cause-and-effect relationships between various concepts [1, 2]. This significantly reduces reliance on a large number of experts, replacing their work with a more automated approach.

Large language models like GPT-4 have become innovative tools in artificial intelligence, capable of substantially influencing decision support processes. Their ability to process and analyze massive amounts of textual information, as well as generate coherent and logical responses to user queries, opens new possibilities for improving traditional approaches to data analysis and decision-making. Procedures where LLMs can be applied in decision support include automating data collection and analysis, forming semantic networks, simulating expert work, reproducing hierarchical decision-making models, scenario analysis, and forecasting, among others.

One of the greatest advantages of LLMs is their ability to simulate expert work through repeated prompt processing. By applying various approaches to query formulation, it is possible to replicate the opinions of different experts, creating diverse perspectives on the same problem. This reduces the dependency on engaging large numbers of human experts, particularly in cases where finding such specialists is difficult or too costly.

Large language models (LLMs) are capable of supporting decision-making processes, including complex hierarchical models such as the analytic hierarchy process (AHP) [3, 4]. Using LLMs, it is possible to model the process of comparing various decision options, taking into account a wide range of criteria. LLMs can also generate scenarios based on existing data, predicting possible decision outcomes.

By repeatedly applying prompts to LLMs, coherent semantic networks can be created that account for different perspectives. At present, individual experts can act as mentors, guiding the work of "virtual experts" powered by LLMs. Furthermore, the application of LLMs enables the creation of event development scenarios based on the constructed semantic networks, which allows for forecasting potential outcomes and making well-informed decisions.

2.1.2 Literature review

Among the works related to decision support systems theory, it is important to mention the work of T. Saaty, who developed the analytic hierarchy process (AHP) [4] and the analytic network process (ANP) [5]. This work is dedicated to improving such methods through the application of large language models (LLMs).

A review [6] is dedicated to the revolution in information technology sparked by the advent of large language models. A significant contribution to the development of decision support methods based on artificial intelligence was made by the classic work [7]. Numerous publications, including [2], are devoted to describing the principles and various applications of LLMs. This paper analyzes LLMs from the perspective of mathematics and computer science.

The review of the capabilities and applications of LLM technology in various industries, and the description of how businesses should approach the integration of generative AI into their business models, is presented in the book [8] and works [9–11]. Another important direction – researching hierarchical models that use LLMs for decision-making strategy development – is reflected in the work [12], which poses new questions to LLMs at each stage of the decision-making process. The work [13] is dedicated to managing next-generation networks based on the use of LLMs.

Research in the field of LLMs for decision-making and semantic network construction is at the forefront of scientific development. In the work [1], methods for forming domain models using LLMs are explored, introducing the concepts of "semantic networking" and the "swarm of virtual experts." This section is dedicated to the development of these areas.

Causal networks are a powerful tool for modeling complex systems, where it is necessary to account for interconnections between various elements and their mutual influence. Such networks can be built both manually, using traditional methods, and automatically with large language models. Traditional approaches to constructing causal networks mainly rely on expert knowledge, logical analysis, and statistical methods. With the development of machine learning technologies and LLMs, new approaches to automating the creation of causal networks have emerged, including the automatic detection of connections, the use of LLMs for building semantic networks, and the combination of expert knowledge with LLMs, such as the dynamic networking approach based on bidirectional search [14].

Causal networks are a critical tool in modern conditions where complex interconnections must be considered and well-informed decisions must be made. New approaches involving LLMs allow for the automation of network formation, improving the efficiency and accuracy of analysis, as well as providing a deeper understanding of complex systems, which is crucial for decision-making in various fields.

2.2 Semantic Networking

LLM-based systems have vast potential in extracting key concepts and named entities. In particular, the authors in [1] demonstrated how to create networks of connections between characters in literary works and domain networks with "general-specific" type connections.

This work is dedicated to describing a methodology for forming causal networks through repeated queries to LLMs, specifically ChatGPT (https://chat.openai.com/), as well as visualizing and analyzing these networks using Gephi (gephi.org) – the most popular free-license graph visualization software [15] – and the GrapViz-based software suite [16]. CSV format is suitable for uploading data to both Gephi and GrapViz.

The created causal networks will enable scenario analysis. The main challenge of conducting scenario analysis based on causal networks lies in the creation of such systems, which traditionally requires significant resources and expert involvement.

2.2.1 Forming the network based on a simple hierarchical query to LLM

The method for forming a causal network can begin with an example. Suppose we are interested in the issue of data leakage, and we ask the LLM to provide known causes of this phenomenon. The central node of the future network should be the concept of "data leakage." Successfully completing this query will determine the second level of the hierarchy – concepts related to data leakage, i.e., its causes. For each such concept, we also define a set of influencing factors. This process can go on indefinitely, but for this example, we will stop at three levels. Despite the hierarchical formation of such a causal network, the resulting network will not strictly adhere to a hierarchical structure.

A system like ChatGPT can assist in obtaining the contents of a CSV file. You can use the following prompt:

→List the causes of data leakage in cybersecurity. The reason is to use no more than three words. The results should be presented in the format "cause;data leakage." Each such entry – from a new line

The system responds approximately as follows (at the beginning of each pair, the cause is listed first, followed by the consequence – data leakage – after the semicolon):

- *human error; data leakage*
- *weak passwords; data leakage*
- *insider threats; data leakage*
- *misconfigured systems; data leakage*
- *etc.*

Subsequent queries will focus on the terms in the response, with prompts that follow the original structure, such as:

→List the causes of human error in cybersecurity. The reason is to use no more than three words. The results should be presented in the format "cause; human error." Each such entry – from a new line

The combined CSV file containing ChatGPT's responses is then passed for analysis and visualization. The resulting network is weakly connected and incomplete, with concepts that may not accurately represent the causes and effects. This is a network obtained from querying only one artificial expert.

2.2.2 Forming a network based on hierarchical queries from a swarm of virtual experts to ChatGPT

ChatGPT can produce different answers at various stages of text processing, which, from a human logic perspective, are entirely "reasonable." Each of these responses can be considered as coming from a virtual expert. By generalizing the responses of multiple such experts, we can obtain a more complete and accurate answer. To implement the swarm of virtual experts, we repeatedly ask the same queries, as in the previous case, for both the first and second levels of the hierarchy. After obtaining responses, they are combined into a single CSV file and passed on for analysis and visualization. In practice, the network can grow until it is sufficiently complete, as judged by a human expert.

The most influential nodes in this network (highest Out-Degree) are:

- *human error (7)*
- *social engineering (4)*
- *weak passwords (3)*
- *phishing attacks (2)*
- *unpatched systems (2)*
- *insider threats (2)*

The network formed in the previous example may contain inaccurate information due to errors made by ChatGPT during individual queries. Assuming that the probability of the same errors occurring is low, we can exclude from the network concepts that appear less frequently than a set threshold. In the following example (Figure 2.1), concepts that appeared fewer than two times were excluded.

The most influential nodes in this network (highest Out-Degree) are:

- *human error (5)*
- *social engineering (3)*
- *phishing attacks (2)*
- *unpatched systems (2)*

Based on expert evaluations, it can be concluded that the primary causal network, created through the simplest hierarchical queries to ChatGPT, includes a large number of concepts, which are relatively weakly connected. However, due to its completeness, it could serve as good "raw material for further analytical processing." Such a network is most suitable for subsequent scenario analysis.

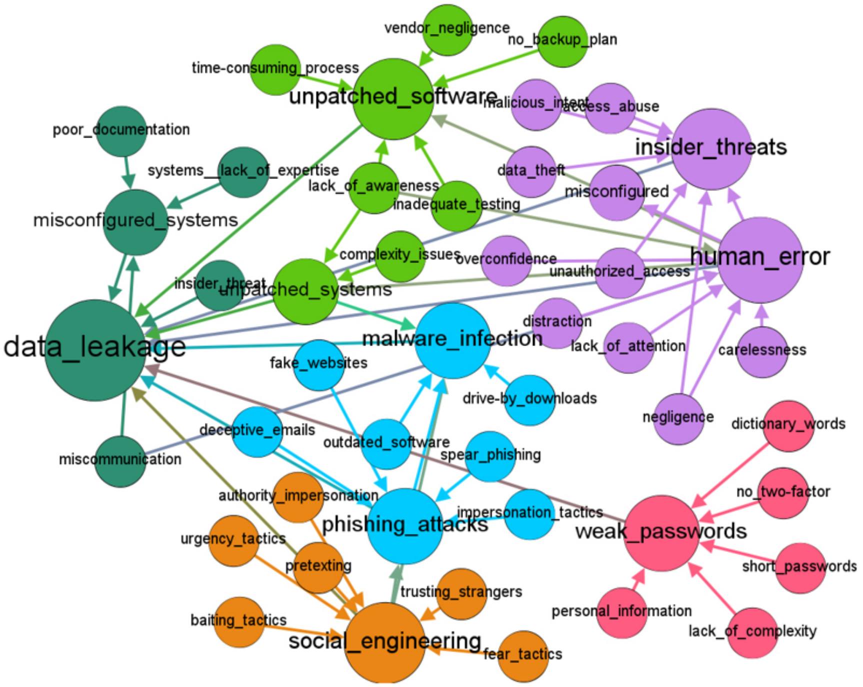

Figure 2.1 Directed causal network formed by generalizing the hierarchical queries from a swarm of virtual experts to ChatGPT.

2.3 Dynamic Networking Based on the Bidirectional Search Approach

2.3.1 Method description

The dynamic networking method is based on a bidirectional algorithm for forming causal networks, namely the formation and subsequent merging of two networks – the first network is built from the node representing the initial state of the problem (root cause), and the second from the node representing the goal to be achieved through the desired scenario [17]. The authors named the proposed algorithm "dynamic networking," which is close to the "bidirectional search" method, whose essence is to move from the initial state to the goal and from the goal to the initial state, in order to speed up the process of finding the optimal solution. The main idea is to connect the two processes once they "meet" at some stage.

The formed causal networks provide a direct transition to scenario analysis. In practice, the greatest difficulties in conducting scenario analysis based on causal networks lie in creating such networks, which in traditional cases require significant resource expenditure and the involvement of experts. After this, numerous scenarios for achieving the goal are generated, ranked according to various criteria. The initial state (root cause) and the goal are considered as input data for building future scenarios. Three sources of information may be used: (1) the ChatGPT system itself; (2) resources from the Internet; (3) documentation from the client (insight). Sources (2) and (3) are optional and may not be used for the initial formation of the network.

According to the proposed approach, the network is first formed based on the "initial state." The following steps may be used for this:

1. A prompt is formed to the LLM, suggesting decomposing the "initial state" and obtaining "partial initial states."
2. After obtaining the "partial initial states," they can be filtered according to the client's needs through dialogue, allowing the client to exclude those they consider unnecessary. In the absence of the possibility of dialogue, the approach of a "swarm of virtual experts" can be used to select the most significant states.
3. This step is optional and increases the reliability of the network. Roles of virtual experts for the chosen subject area are selected from LLM. Possible roles suggested by the system may include roles such as: business owner, partner, technical specialist, financier, etc. If this step is not performed, one can proceed directly to step 4.
4. Based on the "partial initial states" (or the latest in terms of the hierarchy of concepts), we ask LLM what "consequences" that improve the overall situation can be obtained from the presence of these concepts. As a result, LLM will provide a set of consequence concepts. These concepts are connected by directed edges from the corresponding latest concepts in the hierarchy.
5. Request from LLM what "consequences" can arise from the "consequences" obtained in the previous step, which will improve the overall state.

Each request to LLM can be applied several times on behalf of different virtual experts to duplicate important connections and reduce the weight of non-essential ones.

Simultaneously, the second half of the network is constructed as follows:

1. Using LLM, roles of virtual experts for the chosen subject area are selected. If this step is not performed, one can proceed to step 2 and simply use the general assessments of LLM.
2. Causes that may lead to the "goal" are queried from the AI system on behalf of the selected virtual experts. A subnetwork is built, in which directed edges lead from the concepts of "causes" to the "goal."
3. On behalf of the selected virtual experts, the causes of each cause concept obtained in step 2, which may lead to the goal, are queried. And so on.

The procedures are terminated once the first subnetwork, merged with the second half of the network, forms a connected component. In practice, it is recommended to continue building the network for one or two more steps on each side, supplementing the created network.

Both obtained partial networks are constructed based on the first source (LLM resources) and, if possible, the second (Internet) and third (insight). After forming both subnetworks, they are merged. All routes from the start to the goal are selected. The weights of these routes are calculated − this is a separate problem that has long been solved using optimization methods. It should be noted that LLM excels at solving this problem. After that, with the involvement of a human expert, the most important routes are determined in the form of a sequence of network nodes − the list of causes and consequences is provided to the client. In this case, LLM can beforehand provide several narrative chains ranked by formal criteria. If the user wants to rank the obtained narrative chains based on substantive criteria, they can also input appropriate prompts to LLM, such as "Rank the obtained narrative chains by price criteria."

2.3.2 Mathematical model

Basic Concepts and Notations

Let us define the basic concepts and notations:

- Graph: $G = (V, E)$, where V is the set of nodes (concepts), and $E \subseteq V \times V$ is the set of directed edges (connections).
- Initial state v_0 and goal v_f: Nodes representing the initial state of the problem and the desired goal.
- Partial states: Nodes representing intermediate concepts or sub-tasks.
- Virtual experts: A set of functions or algorithms that perform the role of experts in the system.

Formation of Subnetworks

Subnetwork from the initial state:

- Initial state: v_0.
- Recursively generate a subnetwork from v_0, adding vertices $v_1, v_2, ..., v_n$ and edges $(v_0, v_1), (v_1, v_2), ...$ at each step. Let $V_0 = \{v_1, v_2, ..., v_n\}$ be the current step, and $E_0 = \{(v_0, v_1), (v_1, v_2), ...\}$ be the index of added vertices. At each step, filtering based on the significance of states can be used.

Subnetwork from the goal:

- Initial node: v_f.
- Recursively generate a subnetwork from v_f, adding vertices $u_1, u_2, ..., u_m$ and edges $(v_f, u_1), (u_1, u_2), ...$.

Let $V_f = \{v_f, u_1, u_2, ..., u_m\}$ be the current step, and $E_f = \{(v_f, u_1), (u_1, u_2), ...\}$ be the index of added vertices.

Combining subnetworks:

The final network is formed by combining the subnetworks generated from the initial state and the goal:

$$G = \left(V_0 \bigcup V_f, E_0 \bigcup E_f\right). \tag{2.1}$$

If $v_i \in V_0$ and $u_j \in V_f$ are identical, they are merged, and the weights of edges are summed.

Selection of optimal routes:

- A route P is a sequence of nodes $v_0 \to v_1 \to \cdots \to v_f$.
- The weight of a route is calculated as the sum of the weights of edges:

$$w(P) = \sum_{(v_i, v_j) \in P} w(v_i, v_j), \tag{2.2}$$

where $w(v_i, v_j)$ is the weight of the edge between nodes v_i and v_j.

- Optimal route: A route with the minimum sum of weight values:

$$P_{\text{opt}} = \arg\min_P w(P). \tag{2.3}$$

Each request to LLM can be modeled as a function $f_{\text{GPT}}(v_i)$, generating a set of possible next nodes $\{v_j\}$ and corresponding connections (v_i, v_j).

Construction of the final network:

The algorithm for constructing the final network can be represented as a recursive process of graph formation:

1. Construction of the subnetwork from the initial state:

$$G_0 = \mathrm{BuildNetwork}(v_0, f_{\mathrm{GPT}}). \tag{2.4}$$

2. Construction of the subnetwork from the goal:

$$G_f = \mathrm{BuildNetwork}(v_f, f_{\mathrm{GPT}}). \tag{2.5}$$

3. Combination of subnetworks: $G = G_0 \bigcup G_f$.

Selection and ranking of routes:

After constructing the complete network, standard optimization methods (e.g., Dijkstra's algorithm) can be used to select and rank the best routes, or qualitative criteria can be applied by consulting experts, whether real or virtual.

2.3.3 Example of forming a causal network through dynamic networking

As a simplified demonstration of scenario generation using the proposed method, let us consider the task of market capture in the mobile communications sector by a specific mobile operator in a particular region. To achieve this, we generate a causal network in which we treat "mobile operator" as the initial state and "market capture" as the goal, or the final state. At the decomposition stage of the initial state, we introduce the prompt:

Prompt: Decompose the concept of "mobile operator." Provide 10 main entities (no more than three words each).

As a result, ChatGPT provides the following responses:

- *communication Services*
- *wireless connection*
- *telephone infrastructure*
- *cellular networks*
- *transfer data*
- *etc.*

Using the "swarm of virtual experts" approach, we repeat the request multiple times. After that, we simulate a client by applying a prompt that includes all the responses:

Prompt: Select the 10 most important from the already named entities: Communication Services; Wireless Connection; Telephone Infrastructure; Cellular Networks; Transfer Data; Communication Subscribers; Tariff Plans; Technical Support, etc.

Next, queries are made for each partial initial state. For simplicity, we will consider only two roles: the general role and the partner role.

Prompt (Role 1, Concept 1): What consequences might arise from the mobile operator having favorable tariffs? Name 10 consequences – concepts with no more than three words each.

Prompt (Role 2, Concept 1): What consequences could result from the mobile operator having favorable tariffs from the partner's perspective? Name 10 consequences – concepts with no more than three words each.

Prompt (Role 1, Concept 2): What "consequences" might arise from the mobile operator having high-quality communication? Name 10 consequences – concepts with no more than three words each.

Prompt (Role 2, Concept 2): What are the consequences of the mobile operator having high-quality communication from the partner's perspective? Name 10 consequences – concepts with no more than three words each.

This process continues for all defined concepts in a hierarchical manner according to the specified algorithm.

Next, we form a second subnet, which should formally conclude with the state of "market capture." Of course, we construct this network from the end. For this, the following prompts are introduced:

Prompt (1, Goal): List 10 reasons why mobile operators capture markets in small villages. Each reason should consist of no more than three words. Provide the answer in the format "reason; market capture." Each entry is a separate statement. Provide concepts without explanation.

Prompt (2, Goal): Name 10 reasons that could lead to market capture by mobile operators in a small town from the partner's perspective. Each reason should consist of no more than three words. Provide the answer in the format "reason; market capture." Each entry is a separate statement. Provide concepts without explanation.

Next, for each of the reasons, according to the algorithm, queries of the type are introduced:

Prompt: Name 10 reasons that could lead to innovations to capture the mobile operators' market in a small town from the partner's perspective. Each reason should consist of no more than three words. Provide the answer in the format “reason; Innovation.” Each entry is a separate statement. Provide concepts without explanation.

Thus, according to the above algorithm, a second subnet related to the target state is formed. By combining the two networks, defined by the unconnected responses from the ChatGPT system, we obtain a joint network, which subsequently serves as the basis for forming narrative chains.

2.3.4 Formation of narrative chains by formal criteria

To form narrative chains according to the constructed model, the following prompt is entered into ChatGPT:

Prompt: Based on the constructed network, issue several chains leading from the “mobile operator” node to the “market capture” node.

LLM response:

- Chain 1: Mobile operator; Quality of service; Loyalty of subscribers; More subscribers; Capturing the market
- Chain 2: Mobile operator; Marketing strategies; Partnership relations; Partnership success; Capturing the market
- Chain 3: Mobile operator; Wide coverage; More customers; Capturing the market
- Chain 4: Mobile operator; Flexible rates; Subscriber loyalty; More customers; Capturing the market
- Chain 5: Mobile operator; Innovations; Unique services; Capturing the market

2.3.5 Ranking of narrative chains by significant characteristics

Below are the results from the ChatGPT system, which ranks the obtained narrative lines according to the following criteria: price factor, time, and implementation risks. To rank the chains by price factor, the following prompt is entered:

Prompt: Expertly rank the given chains in terms of the price factor.

In response, the LLM provides:

- Chain 2: Mobile operator; Marketing strategies; Partnership relations; Partnership success; Capturing the market
- Chain 5: Mobile operator; Innovations; Unique services; Capturing the market

- Chain 1: Mobile operator; Quality of service; Subscriber loyalty; More subscribers; Capturing the market
- Chain 3: Mobile operator; Wide coverage; More customers; Capturing the market
- Chain 4: Mobile operator; Flexible rates; Subscriber loyalty; More customers; Capturing the market

2.3.6 Visualization and analysis of networks

When using traditional tools for analyzing and visualizing network structures, such as Gephi or Neo4j, analysts face two main issues:

1. The need to install software products, which is not always possible, especially when working with mobile devices, new operating systems, or in environments with restrictions on installing third-party software.
2. The necessity to understand the functioning of these systems, dealing with dozens of parameters, graph layout modes, clustering, and so on.

If online analytical systems for graph visualization can help with the first problem, among which the authors believe the Lite version of the Gephi system – Gephi-Lite (https://gephi.org/gephi-lite) – and the web version of the Graphviz system – WebGraphviz (http://www.webgraphviz.com) – are noteworthy, then the need for developing a proprietary service has arisen to address the second task within the operational construction and representation of subject area models.

To solve the problem of graph visualization and analysis and to avoid the aforementioned issues, a program was developed based on the library (API) of the Graphviz system, which became the foundation for the CSV2Graph service (https://bigsearch.space/uli.html), currently available online at https://bigsearch.space/uli.html. This service provides initial analysis and visualization of graphs, where the information corresponds to the CSV format, with each record representing a pair of entities separated by a semicolon (Figure 2.2).

The program interface includes a network generated using CSV2Graph, as well as additional statistical information about this network (the number of nodes, connections, network density, and a list of all nodes and connections along with their weight values). Thus, the proposed CSV2Graph program addresses two main issues related to the use of traditional network visualization tools, such as Gephi or Neo4j: it allows working with graphs without the need to install software and simplifies the process of configuring visualization parameters.

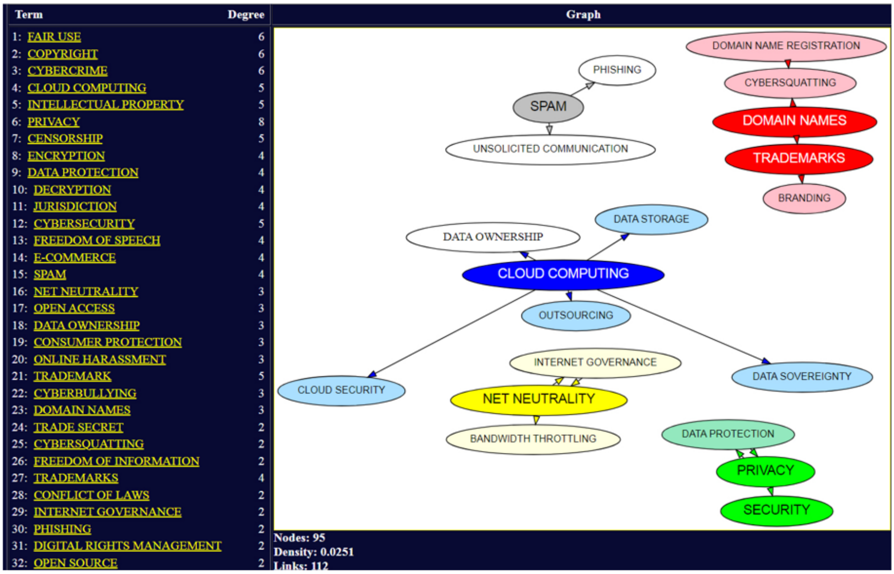

Figure 2.2 Graph generated from a CSV formatted database.

2.4 Hierarchy Analysis Method

2.4.1 Description of the hierarchy analysis method

The analytic hierarchy process (AHP) was developed by American mathematician Thomas Saaty in the 1970s and is used to structure complex problems that require consideration of multiple criteria. It helps in making decisions based on a logical and rational comparison of alternatives. AHP is a systematic approach to structuring decision-making tasks in the form of a hierarchy or network. Starting with defining the main goal at the top of the hierarchy, other elements are placed at intermediate levels. These intermediate levels consist of criteria that determine the importance of selecting an alternative and influence subsequent levels. At the lowest level are specific alternatives.

Over the years, AHP [4] and the analytic network process (ANP) [5], its evolution, have played a significant role among expert decision support methods. The widespread adoption of these methods has always been hindered by the challenge of selecting experts, who were always in short supply. Now, with the technological revolution driven by the development of LLM systems [1, 2], the possibility of addressing this challenge through so-called virtual experts [14] has emerged. The study [18] demonstrates and justifies the application of ChatGPT specifically for the field of cybersecurity.

The analytic hierarchy process, traditionally used for decision-making, can be enhanced and adapted to modern conditions through the use of LLMs and virtual experts. In this approach, AHP is integrated with LLMs, which create and process semantic networks. The use of LLMs allows for the automation of the process of creating and analyzing such networks, significantly reducing the burden on experts and increasing decision-making efficiency.

2.4.2 Implementation of AHP with LLMs

The analytic hierarchy process, traditionally used for decision-making, can be enhanced and adapted to modern conditions through the use of LLMs and virtual experts. In this approach, AHP is integrated with LLMs, which create and process semantic networks. The use of LLMs allows for the automation of the process of creating and analyzing such networks, significantly reducing the burden on experts and increasing decision-making efficiency.

In the traditional implementation of AHP, experts perform tasks such as pairwise comparison of criteria and alternatives, as well as assessing their relative importance. In the LLM-based approach, these tasks can be distributed among virtual experts, each fulfilling a specific role, such as hierarchy-building experts, pairwise comparison experts, data analysis experts, and mentor experts.

To implement AHP using LLMs for building the hierarchy and forming criteria and alternatives, "virtual experts" are engaged and assigned appropriate roles. Consider the example of applying AHP where the goal is to ensure cybersecurity. To determine the roles of virtual experts, the LLM system is prompted with the following:

Prompt: Provide five expert roles from whose perspective cybersecurity issues can be considered.

In response to this request, the system produces:

Cybersecurity issues can be considered:

- *Cybersecurity Analyst*
- *Ethical Hacker (Penetration Tester)*
- *Network Security Engineer*
- *Compliance Officer*
- *Chief Information Security Officer (CISO)*

Since this decision is deemed accurate by the authors, these "virtual experts" with these roles are subsequently used to determine the criteria for cybersecurity.

2.4.3 Criteria determination

Criteria represent a separate level of the hierarchy being constructed. The procedure for determining the main criteria for ensuring cybersecurity involves multiple interactions with the ChatGPT system on behalf of different experts, taking into account various responses and highlighting the most frequently mentioned ones (the final list of criteria can, of course, be confirmed by a human expert). Below is a prompt for determining cybersecurity criteria, formulated on behalf of the "Cybersecurity Analyst" expert, along with the corresponding response from the ChatGPT system:

Prompt: Identify the five main cybersecurity criteria from the perspective of a Cybersecurity Analyst.

Response from ChatGPT:

- *threat detection*
- *vulnerability assessment*
- *incident response*
- *security monitoring*
- *security policies*

Summarizing the responses obtained from all the aforementioned virtual experts, the criteria are as follows:

- *access control*
- *incident response*
- *security awareness*
- *security policies*
- *threat modeling*
- *vulnerability assessment*
- *encryption*

2.4.4 Definition of alternatives

To determine alternatives (the third level of the hierarchical network), a procedure is implemented that involves multiple interactions with the ChatGPT system, where the criteria from the previously defined list are specified, and possible options for their implementation are requested.

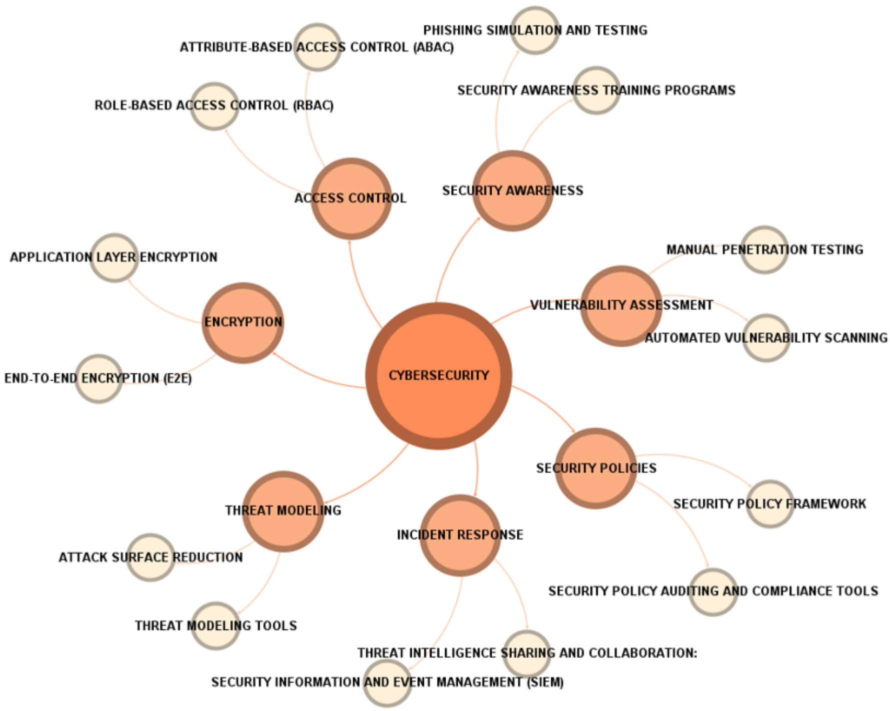

Figure 2.3 Simplified AHP hierarchy for the goal of "Ensuring Cybersecurity."

Below is the prompt for determining alternatives for the criterion "access control" and the response from the ChatGPT system.

Prompt: Name two primary alternative solutions for addressing cybersecurity ACCESS CONTROL criteria.

Response from ChatGPT:

- *Role-Based Access Control (RBAC)*
- *Attribute-Based Access Control (ABAC)*

As a result of the responses from the ChatGPT system to similar requests, we obtain a list of alternatives, thereby forming the entire hierarchy, as depicted in Figure 2.3 .

2.4.5 Weights of criteria and alternatives, consistency

The procedure for determining weight coefficients from pairwise comparisons can be used to assess the priorities of the criteria themselves as well as to evaluate alternatives based on pairwise comparisons conducted by experts for both criteria and alternatives. A pairwise comparison matrix is inputted. The matrices for both criteria and alternatives are formed in the same manner; so let us consider, for example, the matrix of alternative comparisons $\boldsymbol{A}$ (with elements being a_{ij}). Alternatives are compared pairwise by experts, and their responses are then aggregated (averaged overall). If a numerical assessment of the preference for alternatives A_i and A_j yields a value of preference a_{ij}, then in the reverse comparison, the preference is assessed as the reciprocal value: $1/a_{ij}$. Clearly, the preference when comparing an alternative to itself is evaluated as 1.

To determine the weight coefficients of the alternatives (or criteria, if criteria comparisons are being considered), it is sufficient to find the eigenvectors of matrix $\boldsymbol{A}$. The values of the eigenvector of this matrix corresponding to the maximum eigenvalue will serve as the weight coefficients for the criteria (the weight coefficient – the element of the eigenvector corresponds to the criterion number). However, this approach is meaningful only if the pairwise comparison matrix is consistent. To verify the consistency of the comparison matrix, a consistency ratio $\mu$is computed. It is calculated using the following formula:

$$\mu = \frac{|\lambda_{\max} - n|}{n - 1}, \tag{2.6}$$

where $\lambda_{\max}$ is determined as follows: from the values of the comparison matrix and the values of the eigenvector, a matrix $\boldsymbol{E}$ is constructed where each element e_{ij} is defined such that $e_{ij} = a_{ij}\frac{w_i}{w_j}$, where w_i, w_j are the elements of the eigenvector.

After this, the sum of the elements of matrix $\boldsymbol{E}$ is calculated for each row, and the maximum value $\lambda_{\max}$ is selected. If the alternative matrix is fully consistent, then $\lambda_{\max} = n$; otherwise, $\lambda_{\max} > n$. There is a table of consistency indices [2], which contains values of benchmark indices for different values of $n - \mu_T(n)$. If $\mu/\mu_T(n) < 0.1$ is less than the corresponding value in the consistency index table, then the alternative matrix is considered consistent.

2.4.6 Model calculation

To determine the pairwise comparison matrix of criteria, the system ChatGPT is consulted on behalf of virtual experts to assess the importance of a selected criterion relative to all other criteria. Below is an example of a prompt in which the criterion "ENCRYPTION" is compared with others:

Prompt: The values for ensuring the cybersecurity criterion "ENCRYPTION" need to be determined through expert judgment in comparison to the criteria listed below. Please provide only one generalized comparative numerical expert assessment for each criterion (in terms of times). The criteria and assessments should be presented in the form of a list. Please provide an assessment of the advantages of the "encryption" criterion for the following criteria: access control; incident response; security awareness; security policies; threat modeling; vulnerability assessment. To provide generalized numerical assessments of the impact of the "encryption" criterion compared to other criteria, you can use a scale where 1 corresponds to equal importance, less than 1 indicates lesser importance, and greater than 1 indicates greater importance.

The response from the ChatGPT system, which will serve as the basis for forming the corresponding column of the pairwise comparison matrix, is as follows:

- *access control: 1*
- *incident response: 0.7*
- *security awareness: 0.8*
- *security policies: 1.2*
- *threat modeling: 1.1*
- *vulnerability assessment: 1.2*

As a result of executing similar queries for all criteria, we obtain a pairwise comparison matrix (Table 2.1).

The matrix obtained in this way can be viewed as two matrices produced by two groups of virtual experts, based on the prompts given for comparing each criterion with every other one. Therefore, calculations were performed for each of these matrices, and the results are meaningfully close. The matrices turn out to be consistent according to the specified criterion. The

Table 2.1 Pairwise comparison matrix of criteria.

Criteria	1	2	3	4	5	6	7
1	1	0.9	0.8	0.8	1.2	0.9	1
2	1	1	0.9	0.9	0.9	1.1	0.7
3	0.9	1.1	1	0.8	0.8	0.8	0.8
4	1.2	1.2	1.2	1	1	1	1.2
5	1.1	1	1.1	1.1	1	1	1
6	1.3	1.3	1.1	1.2	1.1	1	1.1
7	1.1	1.1	0.9	1.1	0.9	0.9	1

vector of average weights for the two matrices is as follows: (0.35; 0.35; 0.35; 0.40; 0.39; 0.41; 0.38). From this, we can conclude that the criteria are close in importance, with the most influential being the fourth and sixth (security policies and vulnerability assessment).

To determine the pairwise comparison matrix of alternatives, the ChatGPT system is queried for an assessment of the importance of each selected alternative relative to all other alternatives, for example:

Prompt: You need to determine the advantages of the "application layer encryption" concept for cybersecurity compared to the concepts listed below through expert judgment. Please provide only one generalized comparative numerical expert assessment for each concept (in terms of times). The concepts and assessments should be presented in the form of a list. Please provide an assessment of the advantages of the "application layer encryption" concept for the following concepts:

- *attribute-based access control (abac)*
- *security information and event management (siem)*
- *threat intelligence sharing and collaboration*
- *role-based access control (rbac)*
- *automated vulnerability scanning*
- *etc.*

The response from the ChatGPT system, which serves as the basis for forming the corresponding column of the pairwise comparison matrix of alternatives, is as follows:

- *attribute-based access control (abac): 0.8*
- *security information and event management (siem): 0.9*
- *threat intelligence sharing and collaboration: 0.9*
- *role-based access control (rbac): 0.8*
- *etc.*

As in the previous case, calculations were performed for each of these matrices, and similar weight values were obtained. The matrices turned out to be consistent according to the established criterion. The vector of average weights for the two matrices is as follows: (0.29; 0.28; 0.24; 0.23; 0.27; 0.28; 0.24; 0.24; 0.26; 0.26; 0.27; 0.27; 0.30; 0.28). It can be concluded that the identified alternatives are close in their importance, with the most influential being the 1st and 13th (attribute-based access control and security policy auditing and compliance tools).

2.4.7 Comparison of AHP with traditional methods and through the application of LLM systems

With the advancement of technology, new opportunities for implementing AHP arise, particularly through the use of LLMs. Implementing AHP through the application of LLMs and virtual experts offers significant advantages compared to traditional methods. It ensures high consistency of results, emulates the work of a large number of experts, allows for the processing of high-dimensional tasks, accelerates the decision-making process, and makes results clearer and more accessible:

- Virtual experts can perform pairwise comparisons of a large number of criteria and alternatives simultaneously, reducing the likelihood of errors and increasing the consistency of results.
- LLM-supported virtual experts can imitate the work of many human experts, significantly lowering the costs associated with their engagement.
- The use of LLMs allows for the processing of tasks with a large number of criteria and alternatives due to automated data processing and utilization. Thanks to the automation of processes and the use of virtual experts, the speed of decision-making is significantly enhanced.
- Semantic networks provide a clearer and more visual representation of data and results. This enables users without specialized training to better understand and make decisions based on the model, increasing the overall accessibility of the approach.

2.5 Conclusion

The chapter presents a detailed analysis of the capabilities of large language models (LLMs) in supporting decision-making in complex systems. The main idea of the article is the integration of LLMs into traditional decision-making methods, such as the analytic hierarchy process (AHP), and the implementation of new approaches to forming causal networks. It demonstrates how the proposed methodology for the automatic formation of semantic networks, which reflect causal relationships between concepts, is realized through the simulation of expert work. Thus, the use of LLMs in creating scenarios for event development and predicting possible outcomes of decisions enhances analysts' capabilities in making informed decisions. The utilization of large language models in decision-making processes provides significant advantages, including the automation of data collection and analysis, the formation of semantic networks, the simulation of expert work, support for hierarchical decision-making models, scenario analysis, and ensuring the clarity of decisions for all participants in the process.

References

[1] D. Lande, L. Strashnoy, 'GPT Semantic Networking: A Dream of the Semantic Web - The Time is Now', Kyiv: Engineering, 2023, 168 p. ISBN 978-966-2344-94-3

[2] S. Wolfram, 'What Is ChatGPT Doing ... and Why Does It Work? ', Wolfram Media, Inc., March 9, 2023, 112 p. ISBN-13: 978-1-57955-081-3

[3] V. Slyusar, 'AI as expert for Analytic hierarchy process', Research Gate discussion. 16 Nov. 2020, Available: https://www.researchgate.net/post/AI_as_expert_for_Analytic_hierarchy_process

[4] T. L. Saaty, 'The Analytic Hierarchy Process', McGraw-Hill, 1980. ISBN: 0070543712

[5] T. L. Saaty, L. G. Vargas, 'Decision Making With The Analytic Network Process', Springer, 2006. ISBN: 9781441941541, 1441941541

[6] 'ChatGPT AI Revolution 2023: A Guide to ChatGPT Technology and Its Social Impact,' Technology Summary, 2023, 64 p. ISBN 9798377089148

[7] S. J. Russell, P. Norvig, 'Artificial Intelligence: A Modern Approach', Global Edition, 4 ed., Pearson, 2021. ISBN: 9780134610993

[8] I. Nguyen , 'LLM Adoption in the Enterprise', O'Reilly Media, Inc., 2024. ISBN: 9781098151645, 9781098151621

[9] Y. Kondratenko, A. Shevchenko, Y. Zhukov, V. Slyusar, M. Klymenko, G. Kondratenko, O. Striuk, 'Analysis of the Priorities and Perspectives in Artificial Intelligence Implementation', Proc. In. 13th International IEEE Conference "Dependable Systems, Services and Technologies" (DESSERT'2023), Greece, Athens. October 13-15, 2023. DOI:10.1109/DESSERT61349.2023.10416432

[10] Y. Kondratenko, G. Kondratenko, A. Shevchenko, V. Slyusar, Y. Zhukov, M. Vakulenko, 'Towards Implementing the Strategy of Artificial Intelligence Development: Ukraine Peculiarities', CEUR Workshop Proceedings, vol. 3513, 2023, pp. 106-117, https://ceur-ws.org/Vol-3513/paper09.pdf

[11] V. I. Slyusar, Y. P. Kondratenko, A. I. Shevchenko, T. V. Yeroshenko, 'Some Aspects of Artificial Intelligence Development Strategy for

Mobile Technologies', Journal of Mobile Multimedia, Vol. 20(3), pp. 525–554, 2024. DOI:10.13052/jmm1550-4646.2031

[12] A. Handler, K. R. Larsen, R. Hackathorn, 'Large language models present new questions for decision support', International Journal of Information Management, Volume 79, 2024, 102811. DOI: https://doi.org/10.1016/j.ijinfomgt.2024.102811.

[13] A. Mekrache, A. Ksentini, Ch. Verikoukis, 'Intent-Based Management of Next-Generation Networks: an LLM-centric Approach', IEEE Network, 2024. DOI: 10.1109/MNET.2024.3420120

[14] D. Lande, L. Strashnoy, 'Hierarchical Formation of Causal Networks Based on ChatGPT', SSRN Preprint 4440629, 2023. DOI: 10.2139/ssrn.4440629

[15] Ken Cherven, 'Mastering Gephi Network Visualization', Packt Publishing, 2015. 378 p. ISBN: 1783987340, 9781783987344

[16] T. Triantoro, 'Graph Viz: Exploring, Analyzing, and Visualizing Graphs and Networks with Gephi and ChatGPT', ODSC Community, March 30, 2023.

[17] D. Lande, L. Strashnoy, O. Driamov, 'Implementation of Dynamic Networking Utilizing Generative AI Technologies', SSRN Preprint 4547440, 2023. DOI: http://dx.doi.org/10.2139/ssrn.4547440

[18] D. Lande, I. Svoboda, 'Enhancing Multi-Criteria Decision Analysis with AI: Integrating Analytic Hierarchy Process and GPT-4 for Automated Decision Support', E-preprint ArXiv. DOI:10.48550/arXiv.2402.07404

Index

About the Editors

Anatolii Shevchenko graduated from the Faculty of Physics at Donetsk State University with a major in Radio Physics and Electronics. In 1985, he defended his Ph.D. thesis, earning the academic degree of a candidate. In 1990, he completed his doctoral thesis, obtaining the academic degree of Doctor of Technical Sciences. In 1997, he was awarded the title of professor, and in 1998, he received the honorary title of Honored Scientist and Technician of Ukraine. In 2006, was elected as a Corresponding Member of the National Academy of Sciences of Ukraine in the field of Computer Systems. In 2015, he was appointed as the Director of the Institute of Artificial Intelligence of the Ministry of Education and Science of Ukraine and the National Academy of Sciences of Ukraine in Kyiv. Together with the Department of Informatics of the National Academy of Sciences of Ukraine, he initiated an international scientific journal called "Artificial Intelligence" and was appointed as its chief editor. His research interests encompass various aspects of artificial intelligence, modeling human intelligence, simulating elements of human consciousness, breakthrough technologies in the field of artificial intelligence, and multidisciplinary aspects of artificial intelligence.

Yuriy Kondratenko is a Doctor of Science, Professor, Honour Inventor of Ukraine (2008), Corr. Academician of Royal Academy of Doctors (Barcelona, Spain), Corr. Academician of Royal Academy of Economic and Finance Sciences (Spain), Head of the Department of Intelligent Information Systems at Petro Mohyla Black Sea National University (PMBSNU), Leading Researcher at the Institute of

Artificial Intelligence Problems of Ministry of Education and Science and National Academy of Sciences of Ukraine, Ukraine. He has received: a Ph.D. (1983) and Dr.Sc. (1994) in Elements and Devices of Computer and Control Systems from Odessa National Polytechnic University, several international grants and scholarships for conducting research at Institute of Automation of Chongqing University, P.R. China (1988-1989), Ruhr-University Bochum, Germany (2000, 2010), Nazareth College and Cleveland State University, USA (2003), and a Fulbright Scholarship for researching in USA (2015/2016) at the Dept. of Electrical Engineering and Computer Science in Cleveland State University. Research interests include robotics, automation, sensors and control systems, intelligent decision support systems, and fuzzy logic.

ARTIFICIAL INTELLIGENCE

ACHIEVEMENTS AND RECENT DEVELOPMENTS

Editors:
Anatolii I. Shevchenko Yuriy P. Kondratenko

This book features state-of-the-art artificial intelligence (AI) development and implementation, focusing on recent results and distinguished achievements. It analyzes AI implementation prospects, some new research tendencies and trends for AI development as well as corresponding challenges and risks. The book consists of twelve chapters in the AI field which may be conditionally divided into two groups.

One group of chapters is devoted to the overview, analysis and the discussion of (a) the world's achievements and priorities in AI's implementation, (b) the conception of the interrelation of AI and the artificial conscience, (c) the level of AI freedom (d) challenges and risks of AI implementation, (e) efficiency of deep learning and (f) socionic models of psycho-informational processes and quantum computers.

The second group of chapters presents recent developments in the AI field and successful cases of AI implementations in the different areas of human activity. Special attention is paid to efficient AI-based solutions in cybersecurity, the military sphere, biology, medicine, metallurgy, automation of industrial processes, and decision support in marine safety. In addition, this book considers the peculiarities of the AI and AI tools application for the recovery processes of the destroyed by war countries.

The monograph consists of research-analytic-oriented chapters presented by invited high-caliber scientists from different countries (Ukraine, the United States of America, the United Kingdom, and P.R. of China).

ISBN 978-87-438-0097-2

9 788743 800972

River Publishers