



RIGA TECHNICAL
UNIVERSITY

Māra Pudāne

AGENT-BASED HUMAN GROUP AFFECTIVE STATE MODELLING

Summary of the Doctoral Thesis



RTU Press
Riga 2023

RIGA TECHNICAL UNIVERSITY
Faculty of Computer Science and Information Technology
Institute of Applied Computer Systems

Māra Pudāne

Doctoral Student of the Study Programme “Computer Systems”

**AGENT-BASED HUMAN GROUP AFFECTIVE
STATE MODELLING**

Summary of the Doctoral Thesis

Scientific supervisor
Associate Professor Dr. Sc. ing.
Egons Lavendelis

RTU Press
Riga 2023

Pudāne, M. Agent-based Human Group Affective State Modelling. Summary of the Doctoral Thesis. Riga: RTU Press, 2023. 48 p.

Published in accordance with the decision of the Institute of Applied Computer Systems of 20 September 2022, Minutes No. 12300-1-e/6.

This work was supported by the European Social Fund within the project “Support for the implementation of doctoral studies at Riga Technical University”, Riga Technical University Doctoral Grant programme, and the European Social Fund within project No. 8.2.2.0/20/I/008 “Strengthening of PhD students and academic personnel of Riga Technical University and BA School of Business and Finance in the strategic fields of specialization” of the Specific Objective 8.2.2 “To Strengthen Academic Staff of Higher Education Institutions in Strategic Specialization Areas” of the Operational Programme “Growth and Employment”.



NATIONAL
DEVELOPMENT
PLAN 2020



EUROPEAN UNION
European Social
Fund

INVESTING IN YOUR FUTURE

<https://doi.org/10.7250/9789934229688>
ISBN 978-9934-22-968-8 (pdf)

DOCTORAL THESIS PROPOSED TO RIGA TECHNICAL UNIVERSITY FOR THE PROMOTION TO THE SCIENTIFIC DEGREE OF DOCTOR OF SCIENCE

To be granted the scientific degree of Doctor of Science (Ph. D.), the present Doctoral Thesis has been submitted for the defense at the open meeting of RTU Promotion Council on 24 October 2023 16:15 at the Faculty of Computer Science and Information Technology of Riga Technical University, 10 Zunda Street, Room 206.

OFFICIAL REVIEWERS

Professor Dr. sc. ing. Jānis Grabis
Riga Technical University

Professor Dr. paed. Sarma Cakula
Vidzeme University of Applied Sciences, Latvia

Professor PhD, Nuno Manuel Garcia dos Santos,
University of Lisbon, Portugal

DECLARATION OF ACADEMIC INTEGRITY

I hereby declare that the Doctoral Thesis submitted for review to Riga Technical University for promotion to the scientific degree of Doctor of Science (Ph. D.) is my own. I confirm that this Doctoral Thesis has not been submitted to any other university for promotion to a scientific degree.

Māra Pudāne (signature)

Date:

The Doctoral Thesis has been written in Latvian. It consists of an Introduction, 5 chapters, Conclusions, 61 figures, 25 tables, 4 appendices; the total number of pages is 187, not including appendices. The Bibliography contains 204 titles.

ABSTRACT

For centuries, emotions have been considered a negative side-effect of rational thinking; however, it is undeniable that affective states, including emotions, moods, and personality, impact human reasoning and, consequently, group behaviour. Affective states influence how humans make decisions, what actions they choose to perform, and how group structure and relationships among individuals develop over time. Group affective state is also closely related to seemingly inexplicable factors, such as group productivity and working atmosphere. With the research on emotion benefits in psychology and the increasing role of computer technologies in everyday life, the studies on emotion modelling in computer systems have developed in number and quality over the past 30 years.

Individual emotions and group affective interaction modelling in computer systems give multiple benefits, including those that refer to experiment repeatability in environments where there are many variables (i.e., it is impossible to repeat the same experiment on the same human group without changing any parameters), and modelling of borderline cases, that can breach ethics constraints or be dangerous, for example, in case of the aggressive crowd. Specifically, emotion modelling can be used when developing believable virtual teams that are comprised of people and their virtual peers – one such application is intelligent tutoring systems.

While such models reap many benefits, they do not exist due to high interdisciplinarity. The study presented in the Thesis integrates existing models and interaction mechanisms found in psychology research, using multi-agent systems as a tool for affective interaction mechanism implementation. Multi-agent systems belong to a field based on the distributed intelligent computing paradigm; it includes interaction protocols at the whole system level and intelligent agents at the single agent level.

Chapter 1 of the Thesis analyses agent-based modelling for human group affective state dynamics modelling, creating a compatibility matrix based on multiple studies. Chapters 2 and 3 are interdisciplinarity. Chapter 2 describes single human affective behaviour modelling; Chapter 3 formalises affective interactions among agents and reviews how those interactions are implemented in current models. Further, in Chapter 4, fully affective multi-agent system requirements are defined, and a design for such a system is created. Because of the complexity of the model, multiple artefacts have been produced to see how the Thesis confirms the hypothesis: an affective agent module can be used to implement a fully affective multi-agent system and is a tool that can be used for crowd simulation. Finally, a board game scenario has been developed specifically for the Thesis validation. In the final section, the experiments have been described, and the results analysed.

The Thesis results are published in 11 publications, 8 of which were presented at international conferences.

Table of Contents

Introduction	6
1. Multi-agent systems and agent-based modelling	11
1.1. Affective agents and multi-agent systems	11
1.2. Agent-based modelling and model classification for design purposes	12
1.3. Using ABM to simulate human group	14
1.4. Summary and conclusions	15
2. Simulation of human affective processes	16
2.1. The role of emotions and emotion theories	16
2.2. The models of affective agents	17
2.3. The aspects of affective agent model analysis	17
2.4. Affective agent model comparison and analysis	19
2.5. Summary and conclusions	20
3. The simulation of affective interactions	21
3.1. Emotions as social information	21
3.2. Emotional contagion mechanisms	21
3.3. Emotion effects on the group level	23
3.4. Comparative analysis of existing affective group models	24
3.5. Using MAS and ABM mechanisms to model human affective interaction	24
3.6. Summary and conclusions	26
4. Human group modelling approach	27
4.1. Affective agent requirements, architecture, and algorithms	27
4.2. The domain-independent design of CME	30
4.3. Emotional contagion among agents	32
4.4. Summary and conclusions	34
5. The implementation and validation of the solution	35
5.1. The validation of the design and experiment plan	35
5.2. Demonstration agent	37
5.3. Crowd modelling scenario	38
5.4. Board game scenario	38
5.5. Validation based on macro-pattern characteristics and rational consequences	39
5.6. Model restrictions and further research	40
5.7. Summary and conclusions	42
Conclusions	43
List of references	45

INTRODUCTION

It is well-accepted that human reasoning consists of rational and affective – or emotional – components. However, researchers' beliefs regarding the meaning of emotions and the necessity to research affective processes have varied over time (Hudlicka, 2011). Only in the second half of the 20th century did the idea of the necessity of emotions develop. The beginning of emotion research related to computers arguably started with R. Picard's book “Affective Computing” in 1997; this book summarised the existing studies and was primarily focused on human–computer interaction and emotion recognition (Picard, 1997). Over time, the research domain of affective computing has expanded, and current topics in affective computing include human emotion simulation model development, among other research. Emotion modelling and simulation in computer systems allow not only to find new interdisciplinary use cases and to enhance existing computer applications but also to extend the academic basis in psychology and sociology.

To have these applications, one of the critical properties a model must possess is believability or correspondence to reality. It is essential that the Thesis does not research visual believability; instead, it looks at the behaviour believability of an individual human and especially that of a human group. Some studies already examine such models, but most focus on emotion simulation in an individual human; however, emotions have internal and social roles. A believable human group behaviour model would enable new use cases:

- generating virtual groups for virtual reality and serious games purposes;
- prediction of groups' affective state dynamics;
- group research, including finding dependencies between various parameters.

The design and development of such a model is a complex task from psychology, sociology, as well as computer science perspectives. The complexity in social science is associated with a precise definition of the related concepts. The correct tools and paradigms must be chosen from the computer science perspective. Another challenge is the formalisation of psychology and sociology theories. In computer science, agent-based modelling is the most promising approach to modelling human groups, characterised by simple interactions between components (i.e., agents) and simple agent behaviours. The affective behaviour of a human group is defined by multiple types of interactions that differ based on communication intention and other characteristics. Some of these interactions have a specific socially accepted sequence (such as reaction to others' emotions). These factors complicate the affective interaction modelling in addition to complexities in message interpretation.

The multi-agent system approach studies more complex interactions among intelligent agents and would allow designing a more elaborate system. For this reason, one of the main aspects of the Thesis is a study of the relationships among agent-based models and multi-agent systems.

Wooldridge (2009) has stated that two issues must be solved when designing a multi-agent system: what agents will be put in the multi-agent system, that is, what will be the structure and

behaviour of these agents, and the interactions among agents. This approach corresponds to the agent's affective behaviour modelling and affective interaction modelling.

On a single-agent level, as a result of multiple studies, many affective behaviour models have been developed; these models vary in emotion theories used, how abstract they are, and the stage of maturity (Marsella et al., 2010). Albeit some studies systematise these models, there is no systematisation based on believability and functionality.

There is a different situation with the research that focuses on emotions as a social information source. There are only some studies that examine the affective interactions; these studies are sparse and distributed in a variety of domains: crowd modelling (Dey & Roberts, 2007), agent life extension in a multi-agent environment (Kazemifard et al., 2012), and training scenarios (Korecko et al., 2014). The lack of such research is related to the social effects of emotions being a comparatively new direction in psychology and sociology. Albeit there exist some models that allow modelling affective behaviour, there is no research that would systematise and simulate all the mechanisms used in human affective interaction.

Based on the laid arguments, the **hypothesis** was formulated for the Thesis: *A human group's affective state dynamics can be modelled believably by combining the agent-based modelling approach with affective reasoning and interaction models.*

The following **thesis statements** were defined for the defence:

- Combined with appropriate approaches, a multi-agent paradigm is suitable for modelling human groups from rational and affective perspectives.
- Existing affective agents do not model all the functions necessary for ensuring affective behaviour.
- Existing affective interaction modelling methods do not model all the interaction mechanisms necessary for the human group affective behaviour simulation.
- The set of methods developed allows to model all the functions related to emotions.
- The set of agent interaction-level methods allows modelling affective interactions.

To defend the Thesis statements and prove the hypothesis, the author of the Doctoral Thesis has formulated the **goal**: *to develop a human group affective state simulation approach.* Six tasks are formulated to achieve this goal:

1. Study the agent-based modelling approach in the context of intelligent agent paradigm.
2. Perform a comparative analysis of the existing human affective behaviour simulation models.
3. Perform a comparative analysis of the existing human group affective behaviour simulation models.
4. Develop the design of an affective multi-agent system that implements affective behaviour on a single agent level and on agent interaction level.
5. Implement an affective agent that allows the modelling of affective reasoning at an individual level.
6. Develop an affective multi-agent system that implements affective behaviour and interactions.

The **research object** is affective multi-agent systems, and the **research subject** is agent-based affective interaction simulation models. The Thesis studies models that focus on human interaction simulation rather than those that are focused on human-computer interaction.

The following **theoretical research methods** were used:

- A *theoretical study* was used to create three overviews on agent-based models, individual's affect modelling, and human group affect modelling in Chapters 1, 2 and 3 of the Thesis; as a result of the theoretical study, the aspects for analysis were defined. Then, a *systematic literature review* and *comparative analysis* for agent-based models, affective agent models, and affective multi-agent simulation models was performed; it resulted in agent-based model classification, class compatibility matrix, and affective multi-agent system comparison from the perspective of emotional role implementation.
- *Design* and *modelling* were used to formalise the necessary concepts, define the requirements, and develop the affective agent and affective multi-agent system design in Chapter 4.

The following **applied research methods** were used:

- The result of *prototyping* is the implementation of three applications that are described in the last chapter.
- *Experimental analysis* was done in the last chapter to compare the model to expected behaviour.

The **scientific novelty** of the Thesis:

- An approach for modelling affective human interaction based on the mechanisms used in multi-agent systems, including methods for emotion dynamics computation, multi-level affect integration, agent communication modelling, as well as affective agent architecture.
- The use of the proposed approach to develop various affective multi-agent systems.
- A classification of agent-based models from multi-agent systems' perspective and the compatibility matrix of agent-based models' classes based on best practices.
- Affective interaction classification from the perspective of agent communication.

The **practical significance**: A module for modelling affective agents in a multi-agent system and a tool for emotion modelling in crowds of varying structures have been developed; both use cases are based on the approach defined in the Thesis. Agent-based model class compatibility matrix can be used to design and build agent-based models.

The author of the Thesis has presented the Thesis results at the following **conferences**:

- Third Northeast Regional Conference on Complex Systems (NERCCS 2020), April 1–3, 2020. “The Spread of Consumers' Emotions as Function of the Social Network Structure”, poster presentation, Buffalo, U.S.A. (online).
- International Conference on Applied Mathematics & Computational Science (ICAMCS), January 19–21, 2018. “Agent-based model of anger contagion and its correlations with personality un interaction frequency”, presentation, Budapest, Hungary.
- The 5th IEEE Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE'2017), November 24–25, 2017, “Classification of Agent-Based Models from the

Perspective of Multi-Agent Systems”, poster presentation, Riga, Latvia (awarded as the Best Poster).

- Seventh International Conference on Affective Computing and Intelligent Interaction (ACII2017), October 23–26, 2017. “Affective Multi-Agent System for Simulating Mechanisms of Social Effects of Emotions”, presentation, San Antonio, U.S.A.
- 58th International Scientific Conference of Riga Technical University, section “Applied computer systems”, October 12, 2017, “Agent-Based Simulation of Human Emotional Interaction”, presentation, Riga, Latvia.
- International Conference on Agents and Artificial Intelligence (ICAART 2017), February 24–26, 2017, “Emotion Contagion among Affective Agents: Issues and Discussion”, presentation, Porto, Portugal.
- 57th International Scientific Conference of Riga Technical University, section “Applied computer systems”, October 13, 2016, “Emotion Modelling for Simulation of Affective Student-Tutor Interaction: Personality Matching”, presentation, Riga, Latvia.
- 9th International Conference on Intelligent Systems and Agents, July 22–24, 2015. “Collaborative Human-Like Multi-Agent Systems: an Overview, presentation, Las Palmas, Spain.

The following **publications** are published on the topic of the Thesis:

- **Pudāne, M.**, Brooks, B., Radin, M. The Spread of Supply Chain’s Consumers’ Emotions as Function of Their Social Network Structure. In: ICTE in Transportation and Logistics 2020. Lecture Notes in Intelligent Transportation and Infrastructure. Springer Nature Switzerland AG, 2020. pp. 61–68. (indexed in ISI Web of Science) (author's contribution 80 % – design and implementation of the solution).
- **Pudāne, M.**, Brooks, B., Houston, R., Radin, M. Agent based model of anger contagion and its correlations with personality and interaction frequency. *International Journal of Education and Information Technologies*, 2018, 12, pp. 7–12 (indexed in ISI Web of Science) (author's contribution 70 % – design and implementation of the solution).
- **Pudāne, M.** Classification of Agent-Based Models from the Perspective of Multi-Agent Systems. In: Proceedings of Advances in Information, Electronic and Electrical Engineering AIEEE’2017, Latvia, Riga, November 24–25, 2017. Riga: 2017, pp. 1–6 (indexed in SCOPUS and ISI Web of Science).
- **Pudāne, M.** Affective Multi-Agent System for Simulating Mechanisms of Social Effects of Emotions. In: Proceedings of Seventh International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW), United States of America, San Antonio, October 23–26, 2017. San Antonio: 2017, pp. 129–134 (indexed in SCOPUS and ISI Web of Science).
- **Pudāne, M.**, Lavendelis, E. General Guidelines for Design of Affective Multi-Agent Systems. *Applied Computer Science*, 2017, 22, pp. 1–8 (indexed in SCOPUS and ISI Web of Science) (author's contribution – 60%).
- **Pudāne, M.**, Radin, M., Brooks, B. Emotion Contagion among Affective Agents: Issues and Discussion. In: Proceedings of 9th International Conference on Intelligent Systems and

Agents (ICAART 2017), Portugal, Porto, February 24–26, 2017. Porto: 2017, pp. 328–334. (indexed in ISI Web of Science) (author's contribution 70 % – design of the solution).

- **Pudāne, M.**, Lavendelis, E., Radin, M. Human Emotional Behaviour Simulation in Intelligent Agents: Processes and Architecture. *Procedia Computer Science*, 2017, Vol. 104, pp. 517–524 (indexed in SCOPUS and ISI Web of Science) (author's contribution – 95 %, the second author is the Thesis supervisor, the third – a consultant).
- Petroviča, S., **Pudāne, M.** Emotion Modelling for Simulation of Affective Student–Tutor Interaction: Personality Matching. *International Journal of Education and Information Technologies*, 2016, Vol. 10, pp. 159–167. (indexed in ISI Web of Science) (author's contribution – 50 %).
- Petroviča, S., **Pudāne, M.** Simulation of Affective Student–Tutor Interaction for Affective Tutoring Systems: Design of Knowledge Structure. *International Journal of Education and Learning Systems*, 2016, No. 1, pp. 99–108. (author's contribution – 50 %).
- **Pudāne, M.**, Lavendelis, E., 2015, Collaborative Human-Like Multi-Agent Systems: an Overview. In: *Proceedings of 9th International Conference on Intelligent Systems and Agents (ISA 2015)*, Gran Canaria Las Palmas, Spain (indexed in SCOPUS and ISI Web of Science) (author's contribution is 95 %, the second author is the Thesis supervisor).

On the topic of the Thesis, a publication has been accepted for publishing:

- **Pudāne M.**, Affective multi-agent system: modelling and simulation of social and rational effects of emotions. In: *Proceedings of International Scientific Conference on Information Technology and Management Science*, 2023.

The author of the Thesis has six scientific publications on other topics, three of those related to viable multi-agent system modelling and validation.

The scientific publications that are related to the Thesis are on the following topics: agent-based-model class compatibility matrix, affective interaction classification, affective agent architecture, as well as crowd modelling from various aspects and board game scenarios that allow proving the macro-level behaviour of the model.

1. MULTI-AGENT SYSTEMS AND AGENT-BASED MODELLING

The purpose of this chapter is to describe concepts related to human behaviour and human group behaviour modelling. The chapter discusses affective agents, multi-agent systems (MAS), and agent-based modelling (ABM) and defines the theoretical basis for the design of agent-based models.

1.1. Affective agents and multi-agent systems

In artificial intelligence, an agent is a system that perceives its environment through sensors and acts upon it through actuators (Russel & Norvig, 2010). The paradigm of intelligent agents is based on the concept of rationality: the agent chooses the action that will yield the best result among the possible actions (Russel & Norvig, 2010). An affective agent, in its essence, is an extension of a rational agent where emotions are used as an additional parameter that can be used as a performance measure, percept (Becker-Asano, 2008), or considered otherwise when making decisions (Gratch & Marsella, 2004). This brings the conclusion that affective agents and rational agents will both use similar or the same architectures and reasoning methods. The affective agents, in addition, must have a computational model of emotion (CME) – an abstract functional unit that contains affect processing and storing mechanisms.

There are multiple types of agent architectures. Due to the multi-layer processing of events related to agents' emotions (e.g., physical and cognitive processing), the most suitable architectures for modelling affective agents are layered or hybrid architectures. Layered architectures can incorporate *reactive* and *cognitive* architectures, including *deductive* (logic-based) architectures and *practical reasoning* (Belief-Desire-Intention (BDI)) architectures (Chin et al., 2014; Wooldridge, 1999; 2009).

To simulate human group affective behaviour, more than one agent is necessary; the paradigm of MAS entails using multiple communicating agents in a single system (Wooldridge, 2009). ABM is a well-established approach for modelling distributed behaviour and the consequent processes, and as a result, it is used in social, economic, ecological, and other complex system research (Helbing & Baliatti, 2013). In the Thesis, it is concluded that ABM is an application of the MAS system, which enables using MAS concepts in agent-based models.

There are two abstraction levels in MAS: (1) a level that models the internal structure of the agents and (2) at least one level that models agent interaction with other agents (Lavendelis, 2009; Luck et al., 2005; Wooldridge, 2009). Further in the Thesis, the terms used by Wooldridge (2009) are used: micro-level – to denote the internal workings of an agent and macro-level – to denote the system as a whole.

Interactions among agents in MAS have three viewpoints: technical message transferring, syntactic correctness, and semantic interpretation (Wooldridge, 2009). For agent interaction implementation, there is a FIPA ACL standard that defines the structure of the message (syntax); the interpretation of the message (or semantics) is ensured by knowledge structures (ontologies) and communication act sequences (protocols).

Since the design of MAS is complex and consists of multiple levels, there is a variety of development platforms: made specifically for the ABM, as well as generic. The author of the Thesis has extended the classification of Macal and North (2014) and distinguishes the software among four categories: (1) desktop tools for ABS development, (2) large-scale agent development environments, (3) MAS development platforms, and (4) general programming languages. Based on the compatibility with FIPA standards, availability of the documentation, as well as tools used in the study on agent-based models in this chapter, for further analysis, three tools were chosen: JADE (Bellifemine et al., 2001), NetLogo¹, and RePast (North et al., 2008). Based on the criteria, JADE has the most favourable result; for this reason, JADE was chosen to develop the Doctoral Thesis applications.

1.2. Agent-based modelling and model classification for design purposes

From the perspective of modelling, ABM and equation-based modelling (EBM) are contradicted (Wilensky & Rand 2015; Helbing & Balmelli 2015). The most crucial difference between the two is that EBM uses a top-down modelling approach, while ABM describes the systems bottom-up – which allows the development of simulation models based on the properties of individuals. ABM is especially suitable to implement and explain the emergence, systems' ability to adapt, and model systems that contain heterogeneous elements (Wilensky & Rand, 2015), including socio-technical systems (Macal, 2016) and systems that include human behaviour modelling (Bonabeau, 2002). The validation of the ABM, especially once human behaviour modelling is involved, is a complex task. It is considered that if the results of the model correspond to real-life behaviour, it is a proof-of-concept (Wilensky & Rand, 2015), which in turn corresponds to TRL (Technology Readiness Level) 3².

The drawbacks of ABM are related to the computational power consumption and vagueness of the design process (Wilensky & Rand 2015; Bonabeau 2002). As a solution to the last problem, a few development methodologies are defined; however, the development steps in these methodologies are still abstract (Helbing & Balmelli, 2013; Macal & North, 2010; Nikolic & Ghorbani, 2011); the design process lacks more precise good-praxis-based methods.

There are multiple existing classifications of the semantics of agent-based models, as ABM applications are diverse and include various domains. By gathering existing classifications (Bonabeau, 2002; Helbing & Balmelli, 2013; Macal, 2016) and reviewing more than 90 agent-based models, the author of the Thesis has concluded that there are no classifications that allow analysing models from the MAS perspective. Such a classification would enable making design decisions, e.g., choosing the appropriate agent architecture, thus furthering agent-based model design approaches. The classification would also unify the concepts and terms used to describe and compare agent-based models.

¹ NetLogo is available on the site: <https://ccl.northwestern.edu/netlogo/>

² According to EU project programme guidelines, available at https://ec.europa.eu/research/participants/data/ref/h2020/wp/2014_2015/annexes/h2020-wp1415-annex-g-trl_en.pdf

A multi-level classification is developed by the Thesis author (Pudāne, 2017b). The classes defined are not fully compatible; for this reason, the author of the Doctoral Thesis has created the compatibility matrix (Fig. 1.1) (Pudāne, 2017b). This matrix is useful as a guide to best-practice-based design for agent-based models and is used in the development of models described further in the Thesis.

	Flow	Organisation	Diffusion	Market analysis	Generated: arbitrarily related	Generated: preferential attachment	Generated: neighbourhood attachment	Generated: multi-layered	Generated: clustered	Acquired	Homogeneous	Structurally heterogeneous	Heterogeneous by behaviours	Heterogeneous by parameters	Reactive agents	Deductive agents	Practical reasoning agents	Hybrid agents	Lifeless entity	Living cognitive being	Living biological being	Living social being
Flow					1	3	3	0	1	3	2	1	2	3	3	1	2	0	2	3	1	1
Organisation					2	0	1	3	3	3	2	1	2	2	3	2	2	1	2	3	1	2
Diffusion					2	3	3	0	1	3	1	2	3	3	3	2	2	1	2	3	2	2
Market analysis					1	1	1	3	3	3	1	3	2	1	2	2	2	1	3	3	0	1
Generated: arbitrarily related											2	2	2	3	2	2	2	1	2	3	1	2
Generated: preferential attachment											1	0	1	3	2	2	2	1	1	2	1	3
Generated: neighbourhood attachment											2	1	2	3	3	2	2	0	2	3	3	3
Generated: multi-layered											2	0	2	3	2	2	2	0	3	3	1	2
Generated: clustered											2	2	3	3	3	2	2	1	2	3	2	2
Acquired											1	2	3	3	2	2	2	2	3	3	3	3
Homogeneous															2	2	2	0	2	2	2	1
Structurally heterogeneous													2	3	3	2	2	2	3	3	0	2
Heterogeneous by behaviours														3	3	2	2	1	2	3	2	2
Heterogeneous by parameters															2	2	2	1	2	3	2	2
Reactive agents																			2	3	2	2
Deductive agents																			2	3	1	2
Practical reasoning agents																			2	3	1	2
Hybrid agents																			2	2	2	0
Lifeless entity																						
Living cognitive being																					1	3
Living biological being																						1
Living social being																						
Legend:	0	not compatible or not used																				
	1	used in specific cases (found < 10% cases)																				
	2	compatible and used (found [10%-50%] cases)																				
	3	best practise: found > 50% cases																				
	3	best practice: other study based																				
		repetition																				
	mutually exclusive categories																					
	main diagonal																					

Fig. 1.1. The compatibility matrix of agent-based model classes.

In the meta-level, there are three groups: the classifications that describe (1) the semantics of the model, (2) the macro-level of the model, and (3) the micro-level of the model.

1. For the classification of the *semantics*, an existing study by Bonabeau (2002) is used, which formulates the following classes: flow models, organisation models, diffusion models, and market analysis models.
2. For the macro-level of the model, there are classifications *by network structure* (arbitrary related, preferential attachment, neighbourhood attachment, multilayered and clustered structure) and *by agent heterogeneity* (homogeneous, structurally heterogeneous, heterogeneous by behaviours, heterogeneous by parameters).
3. For the micro-level of the model, the models are classified based on the *semantics of an agent* (lifeless entity, living cognitive, biological, or social being) or *agent structure* (previously described architecture categories are used).

1.3. Using ABM to simulate human group

Modelling humans as cognitive and social beings includes additional challenges related to psychology, sociology, and computer science. To understand why humans behave in a certain way and create a simulation model, the corresponding psychology and sociology theories must be formalised and implemented in a model; then experiments must be organised to validate the model and compare it to the field data (Kennedy, 2012; Lee & Malkawi, 2013). At the same time, there already exists a variety of human behaviour simulation models; the Thesis scope within the research of agent-based human behaviour simulation models is depicted in Fig. 1.2.

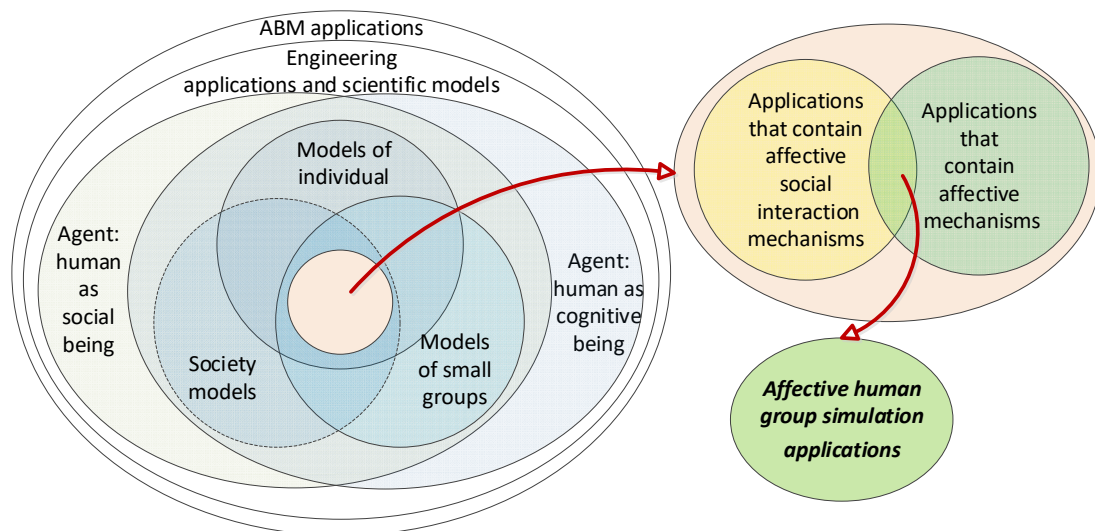


Figure 1.2. Scope of the thesis in ABM research.

From the social and cognitive perspective, a human can be modelled as a member of society, as a member of a small group, or as an individual (Kennedy, 2012). When modelling a small group, it is crucial to capture more complex agent interactions along the believable behaviour model of a single agent. There are fewer small group models compared to other model types, and they are mostly used in the research of interactions (Bristow et al., 2014). The study in the

This Thesis is related to engineering applications and scientific agent-based models, as opposed to well-visualized models (as classified by (Helbing & Balmelli, 2013)). In this study, an agent is a cognitive and social being with an affective state as a parameter. Albeit in the Thesis, the results are demonstrated in the crowd (i.e., society model) as well as a small group, the focus of the research is on individual and small group models.

Finally, when narrowing the focus to agent-based simulation models that include emotions, affective human group behaviour simulation models are those that contain both affective mechanisms in a single agent reasoning and affective social interaction mechanisms.

1.4. Summary and conclusions

Chapter 1 of the Thesis reviews concepts related to MAS, ABM, and the specifics related to human group modelling. The author of the Thesis has performed a study of existing agent-based models, which has resulted in (a) the classification of agent-based models from the perspective of MAS and (b) a compatibility matrix of the classes.

These two artefacts – the classification itself and the compatibility matrix – are also the **main results** of the chapter. They have provided the basis for identifying the scope of the Thesis, as well as further support when designing the models presented in Chapter 5.

The chapter leads to the following **conclusions**:

- Since an affective agent possesses rational reasoning properties, in the design and development of affective agents, rational agent architectures can be used.
- Considering the characteristics of various architectures as well as emotion modelling specifics, layered architectures are appropriate for modelling affective agents.
- Based on the research of ABM and MAS, the author has concluded that human group modelling would benefit from using MAS-related concepts, such as protocols, within agent-based models, as the result should be more believable.
- For the reuse of the agents, FIPA standards must be used; thus, the chosen development environment must be compatible with these standards; JADE corresponds to this and other requirements.
- The chapter also looks at the validation of the model. It is concluded that if the model behaves as expected, TRL 3 is achieved.

Chapter 2 is a study on the micro-level of affective agent-based models, and Chapter 3 focuses on the macro-level.

2. SIMULATION OF HUMAN AFFECTIVE PROCESSES

This chapter aims to perform a comparative analysis of the studies that model individual human and human affective behaviour. The chapter also defines the capabilities and properties a model of human affective behaviour must possess. Human simulation is impossible without psychology research; for this reason, this chapter is interdisciplinary and reviews relevant psychology concepts and computer science developments.

2.1. The role of emotions and emotion theories

The Thesis defines emotions as short-term affective states (Hudlicka, 2011; Gebhard, 2005). Affective states also include mood and personality. Mood is an intermediate-length affective state (Hudlicka, 2011; Gebhard, 2005), and personality is a set of characteristics that impacts the affective state in the long term (Hudlicka, 2011; Gebhard, 2005).

Emotion theories research how emotions and related concepts (mood, personality) occur, are expressed, and impact rational thinking. The Thesis reviews only the sufficiently formalised theories, thus having the most significant impact on affective computing (Marsella et al., 2010; Scherer, 2009).

Ekman's theory is based on emotion categories and distinguishes among six basic emotions (joy, sadness, disgust, anger, and surprise) (Ekman, 1992). However, this theory is insufficient to model emotional processes and emotion elicitation, as Ekman's theory does not explain emotion elicitation and the transition between various emotions. At the same time, using this model allows the agents to identify each other's or the user's emotions.

PAD (pleasure arousal dominance) space allows modelling mood and emotions using the same theory (Mehrabian, 1996; Russell & Mehrabian, 1977) by describing the affective state in three dimensions. Pleasure determines how pleasant an emotion is, arousal refers to arousal level, and dominance relates to control over the situation (Russell & Mehrabian, 1977). PAD emotion theory authors have experimentally found PAD space values for more than 160 emotions (for example, joy is $\langle 0.76; 0.48; 0.35 \rangle$) (Russell & Mehrabian, 1977).

Ekman's theory and PAD space allow modelling emotions, but not their elicitation; for that purpose, the *OCC model* can be used. OCC is used in multiple computer science applications since it can be easily formalised and algorithmised (Ortony et al., 1988; Steunebrink et al., 2009). The OCC model was later appended, developing a complete cognitive processing framework that contains three information processing layers: reactive, routine, and reflexive (Ortony et al., 2005).

Personality modelling is done by *the BigFive model* (also known as the OCEAN model); it defines personality as a set of five trait values: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (McCrae & Costa, 2003).

It is necessary to define the functions that emotions fulfil in a human as they are required for the human emotion simulation model. In general, functions of emotions in a human are defined as emotion roles and can be classified into intrapsychic or interpersonal roles (summary in Hudlicka, 2011). Multiple sources have concluded that an agent must possess all these roles

to behave like a human (Broekens et al., 2008; Hudlicka, 2011; Sloman, 2000). Within the context of the agent group, the interpersonal roles have crucial importance; these roles are (Hudlicka, 2011): communication of internal state, communication of status information, mediation of attachment, communicate acknowledgement of wrongdoing.

2.2. The models of affective agents

Emotion modelling in computer systems can be classified into interaction modelling and affective reasoning modelling. Interaction modelling mainly focuses on human–computer interaction, while affective reasoning modelling focuses on how emotions impact reasoning and decision-making, thus attempting to make these processes more similar to how humans think (Hudlicka, 2004; Marsella et al., 2010). When developing an affective human group simulation model, regardless of the number of agents, it is necessary to focus on the second group's models; the Thesis author has concluded that such affective agents are used in three domains:

1. For decision-making and interaction simulation. In this group, the Thesis reviews and analyses the following studies: H-Cog-Aff (Sloman, 2000), EMA/Emile (Gratch, 2000; Marsella & Gratch, 2009), FLAME (Seif El-Nasr et al., 2000), MAMID (Hudlicka, 2008), and PECS (Urban, 2001).
2. For serious games and virtual environments. In this group, the Thesis reviews and analyses the following studies: a simulation model for firefighter training (Korecko et al., 2014), an ALMA agent (Gebhard, 2005), and a WASABI agent (Becker–Asano, 2008).
3. To improve the system's performance. In this group, the Thesis reviews and analyses the following studies: GEmA CME and its extensions (Kazemifard et al., 2012) and Robocode implemented agent teams (Rebelo et al., 2015).

The reviewed studies overall lead to two conclusions: (1) believable behaviour of agents is necessary for multiple applications and (2) there are many affective models but there are no current reviews of those models and related good practices.

2.3. The aspects of affective agent model analysis

A variety of aspects must be considered when developing an affective agent. These aspects are analysed in the models referred to in Section 2.2 and general affective computing literature; here, only the main conclusions are listed.

The general structure of CME is closely related to the agent's architecture. After reviewing the models, one can conclude that most models contain vertically layered emotion processing since the support for the layered structure of emotions can be found in multiple psychology studies. In existing models, the layers tend to have similar functions: (1) the primary layer performs the initial emotion processing, (2) the secondary layer serves cognitive processing and elicits emotions related to cognitive processing, and (3) the tertiary layer allows an agent to make conclusions about social processes or higher-level cognitive processes and elicit corresponding emotions.

CME must perform multiple **functions** that are taken from existing research (Hudlicka, 2011; Marsella et al., 2010). For this reason, for analysis purposes, the functions defined by Hudlicka are used (Hudlicka, 2011); these functions also correspond to the aforementioned emotion roles. Hudlicka defines two main functions with six subtasks: **(a) emotion generation** (with subtasks: stimuli-to-emotion mapping, combining multiple emotions, intensity calculation) and **(b) emotion effects on cognition and behaviour** (with subtasks: effect-to-emotions mapping, combining multiple emotions effects, calculating effect magnitude).

In the **emotion generation**, **(a) stimuli-to-emotion mapping** is usually implemented by the OCC model; then, emotion is transformed into PAD space. *Combining multiple emotions* includes integrating both – similar and dissimilar emotions. In the case of similar emotions, the integration is the same as re-calculating the intensity of emotion; in the case of different emotions, the state is stored either as a tuple or integrated into the PAD space as an affective state. Two mathematical functions must be defined for *intensity calculation*: emotion activation and decay functions. Based on the trigger, the activation function determines how intensive the emotions will be; based on the literature review, the most corresponding function is sigmoid (Hudlicka, 2011; Picard, 1997) – which is also used in the Thesis. The decay function allows for determining how quickly and in what way emotion will pass and an agent will return to an initial state – it is modelled as an exponent (Codispoti et al., 2009; Reisenzein, 1994). The decay function's parameter values are based on physiology (Codispoti et al., 2009) and research in psychology (Verduyn et al., 2009).

In **emotion effects (b)**, the *effect-to-emotions mapping* is a function that describes how emotions are mapped upon the corresponding internal and external effects. In affective agents, emotion effects are coded either as IF-THEN rules (more useful in the primary architecture layer) or indirect (e.g., through choosing a particular strategy). For *combining multiple emotions effects*, the weighted approach is used. However, if emotions in an agent are stored as a single state (e.g., in PAD space), it can be used directly for effect calculation. *Calculating effect magnitude* is similar to the emotion magnitude calculation; it determines how strong and lingering emotion effects are. The expression function describes how strongly emotions are expressed; it can be modelled as a sigmoid, similar to the activation function.

Modelling individual traits ensures a variation within agents that is similar to humans (Bosse et al., 2009; Kelly & Barsade, 2001). In the existing models, the personality is first defined in OCEAN model traits and then transformed to the PAD space (Mehrabian, 1996) as a core state – point in the PAD space towards which the agent's emotions decay. Albeit the OCEAN model in these models is seemingly unnecessary, there is no psychology research that allows determining what the personality impact on emotions is directly in the PAD space. However, there is research on the OCEAN model, including Ekman's basic emotion dynamics dependency on personality traits. The highest correlations between emotions and personality traits are for Expression and Neuroticism traits (Rusting, 1998). The relation between OCEAN personality traits and discrete emotions is linear (Pease & Lewis, 2015; Rusting, 1998). In practice, the personality determines the activation, decay, and expression function parameter values.

For **emotion formalisation**, mathematical and simulation models are used. In the Thesis, the main focus is on the computer models since there are no formal mathematical models that would allow describing emotion dynamics; there is also no proof that such a model would have benefits compared to algorithmic models. Computer models and formal systems (such as fuzzy sets, probability theory, and Bayesian networks) are combined in practice.

Reasoning and knowledge base are components of an agent located outside CME. Emotions are usually related to the reasoning and planning processes of an agent. Reasoning of agents is closely related to how emotions are formalised. In most models, the affective and rational components cannot be separated, which leads to the conclusion that integrated CME is used and CME functions are only distinguishable when abstracting from implementation details. Albeit some affective agents are reactive, usually, it is a more complex architecture, such as BDI architecture, that includes the agent's goals and environment analysis.

2.4. Affective agent model comparison and analysis

A believable simulation of an individual human is related to a model that simulates all the emotion roles and individual traits. That can be done by ensuring that (1) the model implements all the general processes defined by Hudlicka; (2) a multi-layered architecture is developed based on the layers of Sloman (Sloman, 2000): in the reactive layer, fast, primitive processing is done, in the routine layer, cognitive processing is done, and in reflexive level, social processing and self-reflection is done; and (3) the personality is modelled horizontally – i.e., across all functions. Based on the analysis of the models listed in Section 2.2, the author has made the following conclusions regarding aspects discussed in Section 2.3.

The largest number of roles are either fully or partially implemented in the MAMID model and the model of Kazemifard and colleagues (more than 70 %); most models implement less than half of the roles. This difference arises because most models are created for a specific use case without the need to implement all the roles. In the models that implement many roles, it is often done by the structure of the agent.

The distribution of implemented intrapsychic or interpersonal roles shows that interpersonal roles are neglected – these roles are either wholly left out or just mentioned. The relative implementation of intrapsychic and interpersonal roles shows that intrapsychic roles are implemented twice as often – this leads to the conclusion that these models, in particular, lack the roles necessary for group modelling.

Personality impact, which should be modelled as a horizontal function, is the most present in the model of Kazemifard and colleagues. The models that do not use a comprehensive personality description model (WASABI, Emile) use personality only in some roles. A single theory – personality transformed to core state in PAD space – is used in the ALMA agent and Rebelo and colleagues' model.

The importance of the full implementation of emotion roles varies depending on the task. If the use case is narrow and specific, not all roles may be equally essential, and the model can achieve sufficient results without all the roles. That, however, only applies to simplified use cases or non-human models.

When considering a fully believable individual or small group model, it is crucial that it fulfils all the emotion roles. One drawback is that in such a model, traceability can be difficult due to many parameters. The need for models that create an illusion of life is well-established, but currently, no models implement all the roles. In the Thesis, the author aims to simulate human groups; however, the interpersonal roles that are particularly important for this purpose are neglected.

2.5. Summary and conclusions

Chapter 2 of the Thesis reviews individual affective models from psychology and computer science perspectives. The chapter contains emotion roles in human modelling, emotion theories, and related aspects. Based on these aspects, the existing affective models are compared with a focus on implemented emotion roles.

The **main result** of the chapter is the comparative analysis of the affective models and design decisions for the affective human behaviour model based on this analysis.

Based on the existing models, the **main conclusions** are as follows:

- Affect-based reasoning allows to improve agents' performance and functioning ability in specific environments and can model complex reasoning.
- Using affects in the reasoning of a rational agent or agents' communication allows modelling a more believable system.
- Despite the benefits of emotion modelling, none of the existing affective models implement all the emotion roles. In particular, no models fully implement interpersonal roles that are especially important for this Thesis.

The chapter contains **other conclusions**:

- Based on the emotion roles, it is possible to compare affective models and define the requirements of such models.
- A few psychology models are used to develop affective agents, and these models are often combined. Each emotion theory has its benefits; however, the psychology studies and affective model analysis show that PAD space has several advantages: it allows modelling emotions, mood, and personality in one space, as well as describes the transitions among emotions.
- Not all emotions have the same parameter values for dynamics modelling, even within the same agent, so a different set of parameter values is necessary for each of the emotions modelled.
- Architectures used in the models that implement more emotion roles contain more than one component and more than one layer; for this reason, a vertical multi-layered architecture is needed to reflect primary, secondary, and tertiary emotion processing.
- Agents must possess the ability to perceive and interpret the emotions of other agents.

The next chapter reviews emotions in a group, how those emotions are passed from agent to agent, and how they impact the group as a whole.

3. THE SIMULATION OF AFFECTIVE INTERACTIONS

The chapter aims to review and compare interaction mechanisms upon which the social group's affective communication is based and the possibility of modelling those mechanisms in the simulation model. The chapter is interdisciplinary and includes the underlying social theories, a concept review, and a comparison of existing simulation models. In the Thesis, a human group is a social system with boundaries, relationships, and specific roles that enable achieving a common goal (Kelly & Barsade, 2001).

3.1. Emotions as social information

The Thesis reviews the research direction that looks at emotions as a social paradigm within the group; it is based on the idea that emotions have developed as a social information carrier (van Kleef, 2016). Similarly, based on the emotion roles described by Hudlicka (2011), one can conclude that regulating human interaction is one of the main tasks of emotions.

EASI (*Emotions as Social Information*) theory is based upon two primary considerations: (a) humans, by expressing emotions not necessarily show their internal affective state, and (b) all emotional expressions allow the observer to get some information, but at the same time not all emotional expressions are functional and allow the observer to achieve their goal (van Kleef, 2016). A fundamental assumption of the EASI is that emotions are the primary aid to decision-making in otherwise vague situations (van Kleef, 2016; Manstead & Fischer, 2001); it is related to the information processing layers described in the previous chapter and means that the processing of incomplete information can happen (van Kleef, 2016) (a) in the secondary layer if the unclarity is about the others' motifs or goals, or the internal state of self, or (b) in the tertiary layer if the unclarity is about group status and structure, on social intentions and relationship type (cooperation or competition).

According to EASI theory, emotional expressions have a dual impact on the emotion observer: affective and rational (van Kleef, 2016). The affective effects include the affective state or emotional intensity change based on the affective states of the expresser; rational effects include making conclusions based on the affective states of the expresser (van Kleef, 2016). These effects then lead to changes in the behaviour and interaction; as a result, emotion-expressing and observing mechanisms are recursive and tend to create a cycle (Collins et al., 2016; van Kleef et al., 2017).

3.2. Emotional contagion mechanisms

In the abovementioned theories and the literature, multiple emotional contagion mechanisms are viewed as processes according to which there are changes in the group's affective state. Van Kleef (2016) identified three parts for each communication: encoding, decoding, and emotion effects.

Each communication has several properties. Emotions can work as a piece of social information because expressions are universally recognisable (van Kleef, 2016), but based on

the goals of the emotion expresser, they can be *truthful* or *manipulated* (Kelly & Barsade, 2001). Decoding can be *explicit* (conscious) or *implicit* (subconscious) (Kelly & Barsade, 2001). Implicit decoding is mimicry, i.e., repeating others' emotions and automatic conditioning, while the conscious mechanisms include the intentional taking of somebody's perspective, embodiment, or social appraisal (van Kleef, 2016). The latter two allow appraising others' emotions, thus impacting rational reasoning. If the emotions of the emotion expresser and observer as a result of communication do not differ, then the affective states are *reciprocal*; if they differ, the affective states are *complementary* (van Kleef, 2016; van Kleef et al., 2017).

Based on (Collins et al., 2016; Hareli & Rafaeli, 2008; Kelly & Barsade, 2001; van Kleef, 2016), five mechanisms are identified, which are listed further.

Primitive emotional contagion is identified in all the abovementioned studies – in this case, the observer's emotion processing is implicit, and a reciprocal affective state is activated. Personality impacts primitive emotional contagion as it is directly dependent on two parameters: (1) how easily and intensely a person expresses emotions and (2) how quickly the observer changes the emotional state based on others' emotions (Barsade, 2002). The expression function, defined in the previous chapter, and the susceptibility function describe the first parameter. Similarly to the expression function, the susceptibility function can be obtained from the personality models (Santos et al., 2011). Typically, the susceptibility function is a threshold function that directly correlates with the OCEAN model Neuroticism (e.g., in (Bosse et al., 2015)).

Secondary emotional contagion means that the reciprocal affective state is achieved, but it is done explicitly; it is a process where humans use cognition, social values, and social models to feel and express emotion (Barsade, 2002). Van Kleef (2016) identifies two mechanisms: social and reverse appraisal. The reverse appraisal corresponds to the secondary emotion processing layer, and social appraisal – to the tertiary emotion processing layer.

Emotional contagion patterns can be implicit or explicit but always elicit a complementary affective state. These mechanisms can either be modelled with the help of appraisal theories in the secondary layer, e.g., the OCC model, or subconsciously with IF-THEN rules in the primary layer. Emotional contagion patterns are also related to the tertiary layer if emotion elicitation depends on social relationships.

Direct communication is a conscious and cognitive mechanism where the expresser intentionally attempts to elicit a specific reaction to change someone's actions or beliefs and achieve the expresser's goals (Kelly & Barsade, 2001). Direct communication can refer to social or other strategies – thus, be in the secondary or tertiary layer.

Manipulation is similar to direct communication; however, in this case, the expresser is not expressing an emotion they are feeling, instead adapting the expression purely based on social and emotional norms (Kelly & Barsade, 2001). From the perspective of the observer, it is irrelevant if the expression is truthful or manipulated. Manipulation can be done either to fit within the social environment (Kelly & Barsade, 2001) or to get benefits (Austin et al., 2007); in the first case, it fits interaction in the secondary layer; in the latter – interaction in the second layer.

3.3. Emotion effects on the group level

Inferential (rational) and affective (emotional) emotion effects on the group level are crucial as they describe macro-templates – i.e., the model's behaviour upon which the validation will be based.

Affective homogeneity is a macro-level phenomenon based on empirical observations that the mood of the group participants tends to converge over time. Similarly, *affective diversity* studies the groups where the affective state develops into opposite states for various group participants (Barsade & Gibson, 2012). By combining these macro-templates, the affective dynamics of the group are obtained in the long term. The Thesis considers three bottom-up factor groups: participants' personalities, social status, and relationships.

For the development of macro-patterns, there are two conditions of which at least one must be met (Hareli & Rafaeli, 2008; Kelly & Barsade, 2001; Sy & Choi, 2013): (a) group participants must interact all the time, and (b) an affective state of particularly high-status group member must change. In the Thesis, further validation is done based on the characteristics of these macro-patterns.

The affective homogeneity characteristics are gathered from multiple sources (Barsade, 2002; Felps et al., 2006; Hareli & Rafaeli, 2008; Sy & Choi, 2013; van Kleef, 2016):

- (1) *Emotions are elicited by observing other group members' emotions.*
- (2) *If there are no additional parameters, the average intensity of emotions will reach maximum and will not come down.*
- (3) *The stronger participants' emotional expression and susceptibility, the faster the average intensity of emotions will reach the maximum.*
- (4) *The higher the social status of the person expressing emotions, the more impact it has on the group's affective state.*
- (5) *The more positive the social relationships of people, the faster emotions converge and the higher the maximum average intensity of emotions.*

Affective diversity characteristics are as follows (Barsade, 2002; Hareli & Rafaeli, 2008; van Kleef, 2016):

- (6) *If social relationships are negative, the emotional state of group participants diverges.*
- (7) *If social relationships are negative and there are no other parameters, participants reach opposite emotional states and remain there.*

Regarding the rational consequences of emotions, the EASI theory specifically distinguishes rational effects: the impact on behaviour and inferences about the expresser (van Kleef, 2016). Based on the classification of the consequences defined by van Kleef (2016), other agents' emotions at the tertiary level should form changes in observers' beliefs about others' personalities and social strategies. On the secondary level, an observer should be able to change its strategy. This leads to two more group-level characteristics:

- (8) *Others' emotions change the behaviour of participants.*
- (9) *Others' emotions change the beliefs of group member status and social relationships.*

3.4. Comparative analysis of existing affective group models

Existing solutions can be split into two groups: (a) models explicitly made for emotional contagion modelling and (b) models in which group simulation is possible; however, it is not the primary goal.

Models for emotional contagion currently can be either (a) analytical models that study existing networks (usually social) and (2) simulation models that are used for human group behaviour prognosis and influencing factor analysis; the latter of the groups is within the scope of the Thesis. In the Thesis, only the models that met the following requirements were analysed: (1) there must be a possibility to implement the parameters for possible interactions, which would allow the implementation of a variety of social structures; (2) the model should not be specific to one emotion type without the possibility of extension. Based on these criteria, ASCRIBE framework (Bosse et al., 2015), Bispo and Paiva's model (Bispo & Paiva, 2009), and Rincon and colleagues' model (Rincon et al., 2018) were selected.

Models with emotional contagion mechanisms, albeit not explicitly intended for group modelling, are those models from Chapter 2 that implement at least one interpersonal role: ALMA, Emile/EMA and Kazemifard and colleagues' model. The comparison of these models based on contagion mechanism implementation is shown in Table 3.1.

Table 3.1

Summary of Emotional Contagion Mechanism Implementation

	Bosse et al.	Bispo et al.	Rincon et al.	ALMA	Emile/EMA	Kazemifard et al.
Primary emotional contagion	+	+	+	-	-	-
Secondary emotional contagion	+ sec. - tert.	- sec. + tert.	- sec. +/- tert.	-	-	-
Emotional contagion patterns	-	-	+/-	+	+/-	-
Direct communication	-	-	-	+/-	+	R
Manipulation	-	-	-	+/-	-	-

Table legend:

“+” – mechanism is implemented;

“-” – mechanism is disregarded completely;

+/-” – there is a possibility to design and implement this mechanism;

“R” – only rational effects of emotions modelled;

“sec.” and “tert.” if necessary, describe which emotion processing layer is in question.

As a result of the analysis, the author has concluded that neither of the existing models implements all the contagion mechanisms; such a method is necessary to develop a fully believable human group simulation model.

3.5. Using MAS and ABM mechanisms to model human affective interaction

Emotional propagation simulation models (e.g., (Bosse et al., 2015)) are always agent-based; however, as soon as it is necessary to differentiate among various emotional contagion

mechanisms, simple interactions that characterise agent-based models communication, cannot be used since varying types of interaction are needed. Such a variety can be ensured by using MAS agent communications. The analysis of MAS mechanism usability for affective interaction modelling is crucial to examine how current standards are usable to implement the five mechanisms identified earlier. From the perspective of MAS, the interaction among agents happens on multiple levels (Martin et al., 2000); the Thesis is focused on (a) intention and conversation and (b) content levels.

The abovementioned FIPA ACL is used to implement the messages' **intentions** (as performatives); the basis for **conversation** implementation are protocols: agent interaction sequence specifications on a high abstraction level (Chopra & Singh, 2013; Poslad, 2007). There are five performatives of FIPA ACL messages: information passing, requesting information, negotiation, action performing, and error handling (The Foundation for Intelligent Physical Agents, 2002), that are used as message types in the protocols.

In the case of emotional propagation mechanisms, all protocols are defined among two roles of the agents: expresser and observer. It is concluded that the unconscious emotional contagion mechanisms can be treated as information (van Kleef, 2016). However, a specific protocol is needed in mechanisms where the emotion communication is goal-driven, i.e., direct contact and manipulation. For protocol design FIPA standard AUML or UML sequence diagrams are used in general (Chopra & Singh, 2013; Pudāne & Lavendelis, 2017) and in the Thesis.

The rational and affective effects of emotions and the choice of the protocol largely depend not only on the emotional contagion mechanism but also on agents' internal parameters and relationships. In distributed systems, such as MAS, parameters related to information processing are in computing nodes, in this case – agents. At the same time, an agent-based model can be described as a graph on a macro-level. Thus, communication modelling is related to transformation between two models: (a) overview model – graph, where the possibility that the agents will ever communicate is denoted with an edge (Diestel, 2017), and (b) distributed model with all the parameters stored within agents.

One can conclude that there is no need for specific tools to implement emotional contagion mechanisms on a MAS level; however, a formal classification and formalisation are needed to model those mechanisms semantically.

On the **content** level, FIPA ACL performatives also describe the message's intention – thus passing part of the semantics – i.e., why an agent is communicating. At the same time, agent communication languages alone are not enough to describe the semantic level; to interpret the content of the message, FIPA ACL uses ontologies. To create the content of the message, a designer should use formal language. In the context of the Thesis, the formal language choice does not have a significant impact, so FIPA SL is chosen as it is compatible with FIPA ACL. There are no standards for interpreting emotional messages with the aid of ontologies. By reviewing the ontologies, the author of the Thesis has concluded that there is no unified ontology that would allow describing affective states; moreover, it is doubtful that such an ontology can ever exist due to use-case-dependent requirements. Another complication is the loose definition of affective states in psychology, making it hard to create one unified content

description structure. For these reasons, existing ontologies cannot be used in the Thesis. When creating a new ontology, two issues must be considered: (1) the receiver must recognise emotion, so the ontology must contain emotion type, and (2) since emotional contagion mechanisms do depend on the intensity of the emotion, ontology must contain emotion intensity.

3.6. Summary and conclusions

In the chapter, the affective interactions are reviewed based on psychology, existing solutions are compared based on implemented affective interactions, and implementation possibilities are examined.

The **main results** of the chapter are the classification of communication mechanisms from the perspective of formalisation, as well as the macro-pattern characteristics definition. The author of the Thesis does not aim to develop a new classification in sociology; the review in the chapter is done purely based on the information found in studies and by consulting with an expert, without making general conclusions or interpretations. In the chapter, an agent-based model comparison based on the emotional contagion mechanisms is done. A minor result is the content of the ontology.

The **conclusions** in the chapter are as follows:

- Various emotional contagion mechanisms are used in crowd and group modelling. No models implement all these mechanisms; however, they are necessary so that the human interaction modelling would be complete.
- The model must implement five affective interaction mechanisms for group interaction simulation: primary and secondary emotional contagion, emotional contagion patterns, direct communication, and manipulation. Mechanisms depend upon three factors: agents' personalities, social status, and relationships.
- To validate interactions, the model must comply with the behaviour according to the affective macro-pattern and rational macro-pattern characteristics. Affective mechanisms are mainly located within agents, that is, in the interpretation and MAS micro level. On the other hand, rational and emotional effects form a cycle, so for macro-pattern emergence, the interaction must contain primitives as opposed to implementation as a complex MAS protocol.
- Existing MAS mechanisms and standards are sufficient to implement affective interaction.
- In Chapter 2, it was concluded that the architecture must consist of three layers; the analysis in this chapter leads to the following conclusions regarding those layers. In the primary layer, primitive emotional contagion must be implemented if the affective state is positive or negative (i.e., without listing a specific emotion) or if agents do not implement a strategy. The secondary layer must implement mechanisms related to strategies and primitive emotional contagion if specific emotions are involved and agents have a strategy. The tertiary layer must contain beliefs about other agents' social states and relationships based on which affective mechanisms work.

4. HUMAN GROUP MODELLING APPROACH

Based on the conclusions made in the previous chapters, a framework is developed for designing and developing the affective MAS. Within the framework, artefacts have been created: methods, guidelines, and algorithms that enable affective system design and development in domain-independent and domain-dependent designs. The components of the approach and their relationships are shown in Fig. 4.1.; design, in general, is based on the affective agent requirements from the literature analysis.

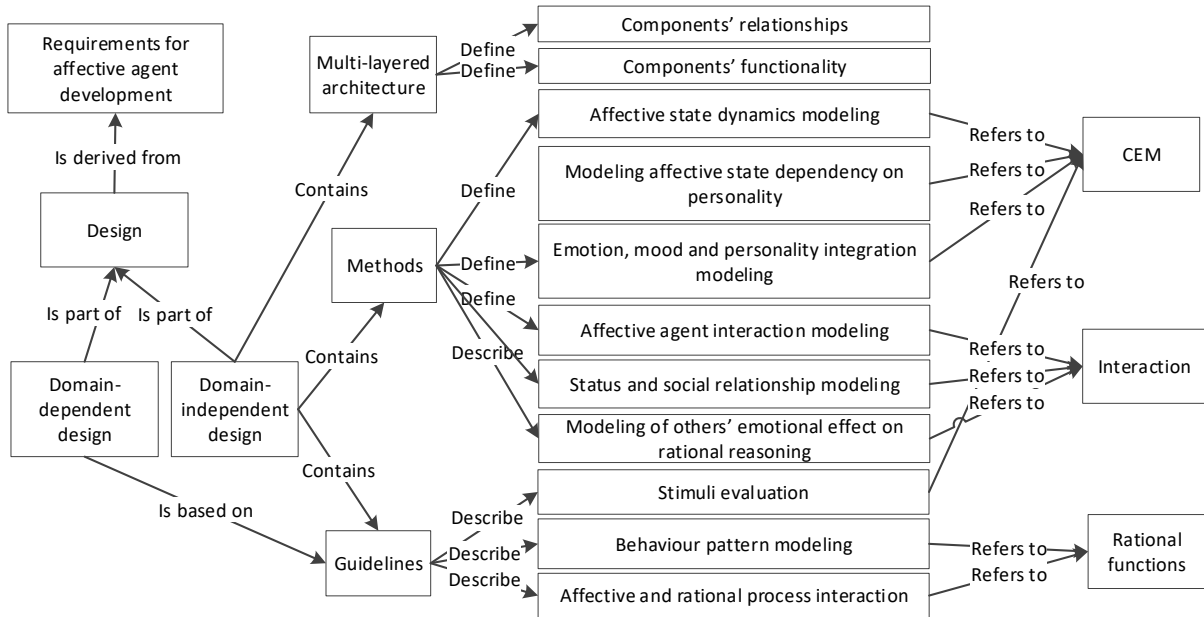


Figure 4.1. Components, context, and relationships of design components.

4.1. Affective agent requirements, architecture, and algorithms

To develop an affective agent, it must implement functions based on the emotion roles in Chapter 2. It was concluded that the implementation of agent communication and interpretation of messages depends on individual agents, so attention is directed towards the design of individual agent. The requirements defined are based on the role implementation and micro-level qualities necessary for affective agent communication.

Based on these considerations, requirements for affective agents were formulated, which are related to (a) agents' architecture, (b) the components of the architecture that enable reasoning, (c) the CME, (d) agent affective state integration into reasoning processes, (e) agent communication (for summary, see Table 4.1). Following the requirements, two design levels were created: domain-independent design, where the implementation of the requirements is done by the methods developed in the Thesis, and domain-dependent design, which includes design decisions specific to the use case. Some requirements are partially modelled in the domain-independent design but must be supplemented in the domain-specific design.

Table 4.1

Requirement Implementation

No.	Requirement	Supported in domain-independent design with...	Must be specified in the domain-dependent design
1.	Multi-layer emotion processing	Architecture layers and their properties	-
2.	Simple behaviour and emotions in the primary layer	Design of the primary layer	High and low pleasure events
3.	Reactivity of an agent	Design of the architecture	IF...THEN rules
4.	Switching between layers of emotional processing	Design of the architecture	-
5.	Physical restriction of capabilities	Design of the architecture	What capabilities will be restricted
6.	Impact of affective state on the behaviour	Guidelines for behaviour pattern modelling (in various PAD space octants)	Domain-specific behaviours in each of the PAD space octants
7.	Different behaviours in various emotion-processing layers	Guidelines for behaviour pattern modelling (in the architecture layers)	Domain-specific behaviours in each of the architecture layers
8.	Impact of the affective state on planning	Using BDI architecture and guidelines to connect affective and rational processes	Planning (strategy)
9.a	Determining the frequency of the learning	Guidelines for affective and rational process interaction	Learning frequency
9.b	Emotions serve as a reward or punishment	Using BDI architecture and guidelines for affective and rational process interaction	Learning method
10.	Multi-level affective state	Method for emotion, mood and personality integration modelling	-
11.	Personality impacts the affective state of an agent	Method for modelling affective state dependency on personality	-
12.a	Activation function	Method for affective state dynamics modelling	-
12.b	Decay function		-
12.c	Expression function		-
13.	Emotion elicitation	Guidelines for stimuli evaluation	Evaluation function
14.a	Reasoning about one's own status	Method for status and social relationship modelling	Status measure and status update function
14.b	Reasoning about the status of others	Method for status and social relationship modelling	Status measure and status update function
14.c	Adjusting communication mechanism to the internal state	Method for affective agent interaction modelling	-
15.a	Maintaining social relationships	Method for status and social relationship modelling	Social relationship update function
15.b	Adjusting communication mechanism to social relationships	Method for affective agent interaction modelling	-
16.	Subconscious emotional expression and susception	Method for affective agent interaction modelling	-
17.	Conscious emotional expression and susception	Method for affective agent interaction modelling	Cases in which conscious emotion expression and susception happen
18.a	Emotion susceptibility	Susceptibility and expression functions	-
18.b	The affective state depends on the status and social relationships	Method for status and social relationship modelling	-

The architecture of the affective agent is comprised of three layers (Pudāne et al., 2017), shown in Fig. 4.2: (a) primary or reactive behaviour layer, which is implemented as a reactive architecture; (b) secondary layer where an agent reasons and gets emotions related to reasoning – implemented as BDI architecture; (c) tertiary layer where an agent reasons about social beliefs and gets emotions related to it – implemented as BDI architecture. In addition, the personality and mood module were separated – as personality impacts all reasoning layers.

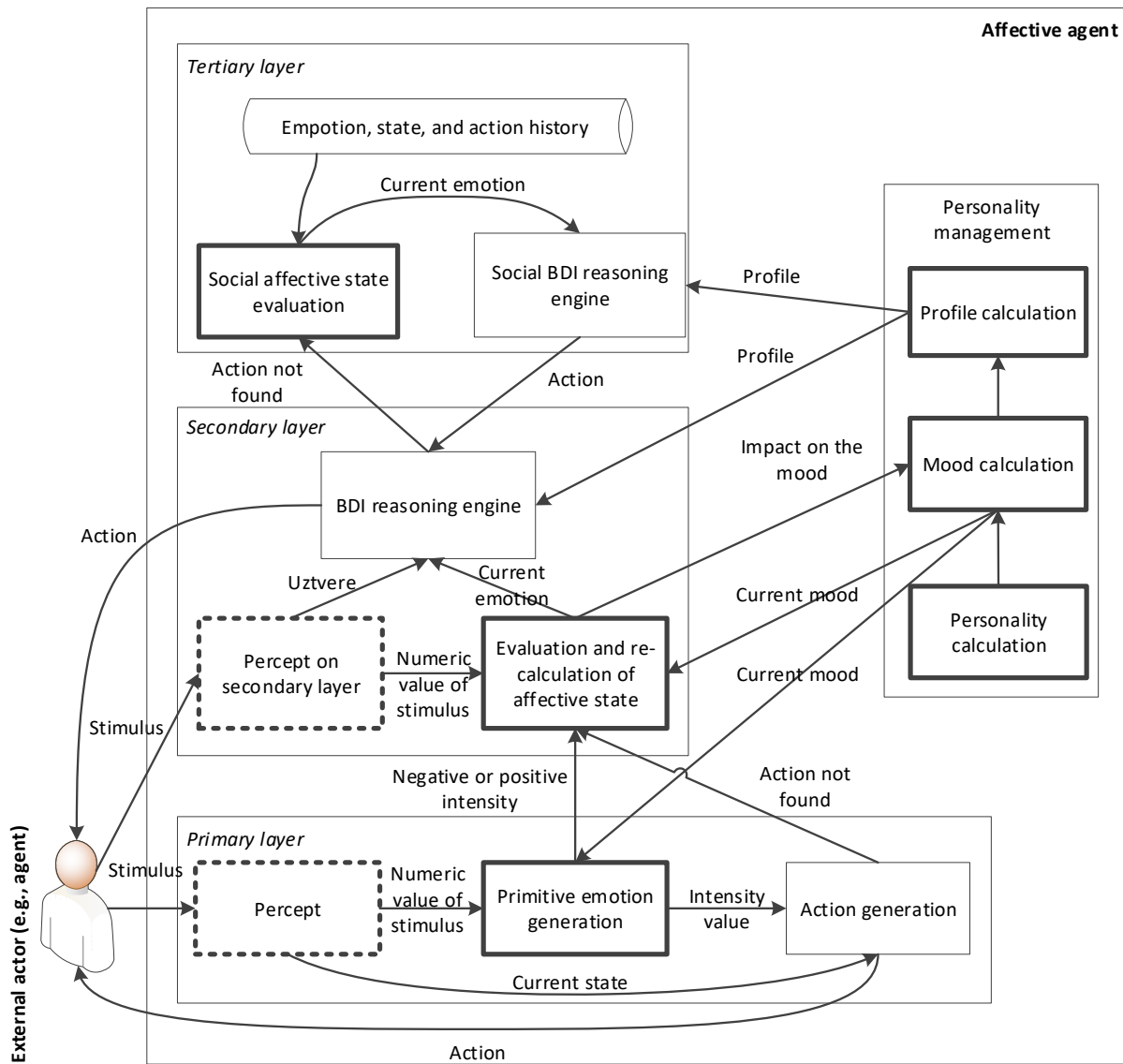


Fig. 4.2. Architecture of an affective agent.

Previously in the Thesis, it was concluded that the functions of the CME are usually distributed among various architectural components. In the general case, the state of an affective agent consists of rational state \mathcal{R} and affective state \mathcal{E} . For this reason, in the agent, there are two types of functions: the ones that return action (\mathcal{R} -type functions) and the ones that return affective state (\mathcal{E} -type functions). In Chapter 1, it was concluded that in the case of an affective

agent, emotions are integrated into the decision-making process; for this reason, affective functions do not return action.

As a result, all the algorithms and functions necessary for architecture implementation are defined. Some of the requirements are non-trivial, and corresponding functions require separate designs; they are described further. The author of the Thesis stresses that rational function modelling is not the Thesis's focus; these functions may require a distinct, more elaborate design. At the same time, to entirely ignore these functions would mean missing some of the affective agent requirements.

Based on the requirements and literature review, it was concluded that the affective state must impact three main rational functions: planning, behaviour choice, and learning. In the **behaviour choice**, an agent must implement two restrictions: firstly, it must restrict behaviours based on the architecture layers, and secondly, it must restrict behaviours based on the mood in the PAD space. As the author of the Thesis has not found relevant research that would strictly limit what type of actions can be done in which PAD mood, it remains a domain-dependent design issue. The architecture allows **planning** and **learning** based on the BDI architecture, so the basis for these functions exists on the architecture level.

4.2. The domain-independent design of CME

The domain-independent design of the CME includes: (a) affective dynamics modelling method based on the functions described in Chapter 2; (b) modelling affective state dependency on personality that determines how personality impacts affective state intensity and characteristics based on psychology literature; (c) the method for integrating personality, mood, and emotions into PAD space which is similar to the method used in the ALMA agent (Gebhard, 2005); (d) guidelines for evaluating stimuli from the external environment.

Affective state dynamics modelling. As concluded in Chapter 2, a separate parameter value set is necessary for each emotion that the agent models. Parameter values are defined for a four-function set (Eq. (4.1)); these functions transform the objective evaluation intensity I_{obj} to a subjective emotion intensity I_{subj} which depends on the personality and past and current emotional dynamics.

$$\Omega = \begin{cases} act(I_{obj}) = \frac{g}{1 + e^{\frac{I_{obj0} - I_{obj}}{s}}} + I_{subj0} \\ dec(t) = e^{-\lambda t}, \\ expr(I_{subj}) = \frac{g}{1 + e^{\frac{I_{subj0} - I_{subj}}{s}}} + E_{subj0}, \\ susc(I_{subj}) = \begin{cases} 1, & \text{if } (I_{subj} \geq tr) \\ 0, & \text{if } (I_{subj} < tr) \end{cases} \end{cases} \quad (4.1)$$

where

$act()$ – activation function, dependency of subjective intensity I_{subj} on objective intensity I_{obj} in the case of new incoming stimulus;

$dec()$ – decay function, agent emotional intensity I_{subj} dependency on time t ;
 $expr()$ – expression function; agent expression intensity E_{subj} dependency on internal emotional state I_{subj} ;
 $susc()$ – susceptibility threshold that models if an agent perceives affective stimuli from other agents based on I_{subj} .

Affective state dependency on personality. Although affective dynamic functions and their characteristics are similar for all the agents, it is necessary to model different personalities – which means differences in affective dynamics function values. With the proposed method, it is possible to obtain dynamics of separate emotions and positive and negative affective states (Pudāne et al., 2017). In this case, each emotion will have a set of functions from Eq. (4.1) with different parameter values. The method consists of two parts (Fig. 4.3): (1) to determine the dependency of the emotion emo impact imp on personality trait values and (2) to calculate function parameters, i.e., using relation $imp_{emo}(dim)$ to calculate function parameter values.

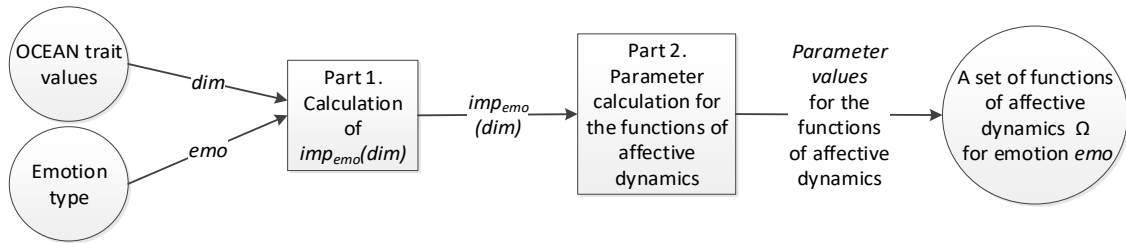


Figure 4.3. Method for calculating personality impact on affective dynamics.

Method for integrating personality, mood, and emotions. One of the requirements for an affective agent is multi-level affective state calculation. The PAD-space-based method allows (a) to calculate all the emotions in the 3D space without a clear semantic definition of the interim states among emotions, (b) to model various intensities and various emotions and transitions to different emotions, and (c) without using additional mechanisms, integrate various behaviour profiles. The impact of emotions, mood, and personality can be modelled as a single coordinate E_{curr} in a PAD space at each moment.

For each agent, the core state based on the personality C_0 and current mood M_{curr} is defined. For all agents in the model, the maximum coordinates of specific emotions (e.g., anger: E_{Angmax}), as well as maximum coordinates for all 8 PAD space moods (corresponding to the octants of PAD space), are defined. Mood maximum coordinates are located in the furthest point from the (0,0,0) in corresponding octants.

Guidelines for evaluating stimuli from the external environment. Although this topic is not the focus of the Thesis, assessing the stimuli is a significant component of an affective agent. Emotions can be evaluated in various ways, and the assessment method is domain-dependent. In any case, it should determine (a) what kind of emotion is felt – usually done by the OCC model and (b) the intensity of the emotion by using some measure. The author of the Thesis in various applications has used various measures, e.g., the difference between task complexity and student's knowledge level (Petroviča & Pudāne, 2016) or the points obtained in the game (Pudāne, 2017a). The measures are then normalised to scale [0,1] and become I_{obj} .

4.3. Emotional contagion among agents

Chapter 3 defines five mechanisms for emotional contagion. A proper formalisation is needed to implement these mechanisms in the MAS (Pudāne, 2017a). Since the type of the mechanisms is distinguished by how the message is sent (subconsciously or consciously, truthfully or through manipulation) and how the message is received (i.e., the interpretation of the message), the mechanisms must be modelled at the micro level. Based on the conclusion of Chapter 3, an approach that uses component combinations for mechanism implementation is used. Further in the design, the observer is called the receiver, and the message expresser is called the sender, a terminology closer to the MAS domain.

The interpretation of the message depends on the receiver. Here are two types of mechanisms: emotion is elicited automatically (i.e., subconsciously) or through strategy or social analysis. For this reason, emotions that are elicited by other agents' emotions are processed by using social relationships and status as parameters, causing either reciprocal or complementary emotions. As a result, agent affective state dynamics, as an effect of other agents' emotions, are described by Eq. (4.2).

$$I_{subj} = \mathfrak{R} \times \mathcal{E} \times Soc \times Sta, \quad \text{where } Soc, Sta \subset SocB, \quad (4.2)$$

where

- \mathfrak{R} – rational state;
- \mathcal{E} – affective state;
- Soc – social relationship value;
- Sta – status value;
- SocB – social beliefs.

In the case of the receiver, it is important to design the message interpretation, in the case of the sender – the choice of the emotion type. **The receiver** has four options for emotion integration into the reasoning mechanism: (1) re-calculating emotions based on the set Ω ; (2) including emotions into the affective state considering the status and social relationships; (3) rational reaction; and (4) social belief update. After processing the message, the agent's role switches from the receiver to **the sender**. The sender can express emotion with intensity E_{subj} , which becomes objective stimulus intensity I_{obj} in the content of the message; this is how the receiver obtains emotion. Direct communication and manipulation mechanisms to the sender are available on the secondary and tertiary levels. These mechanisms are triggered when activating a strategy and can be related to an agent's rational or social strategy.

In general, there are three types of messages that can initiate an interaction mechanism: (1) a type that is used to start the first three interaction mechanisms (primitive and secondary emotional contagion and emotional patterns); the content of this type is described by predicate *Emotional_reaction* (*emotion_intensity*, *emotion_type*); (2) message type that is used to start direct communication; and (3) message type that includes choosing a proper emotion for manipulation. In the case of the (1) type message, agents do not receive a reply; that is the only message sent. However, in the cases of direct communication and manipulation, a protocol is necessary.

This protocol consists of four types of messages: (a) *Emotional_request* (*emotion intensity, emotion type, requested action*): agent sends a specific emotion and the intensity of that emotion to another agent; the requested action is not mandatory; (b) *Emotional_response* (*emotion intensity, emotion type*): the agent's emotional response to another agent; (c) *Rational_response()*: a message that confirms or denies the sender's request; (d) *Emotional_reaction* (*emotion intensity, emotion type*) is a simple emotional message that ensures the emotion is passed to observers and is non-specific to direct communication and manipulation mechanisms.

The protocol for direct communication specifically includes an observer to distinguish between the agent to whom the message was intended and the others in the group (Fig. 4.4)

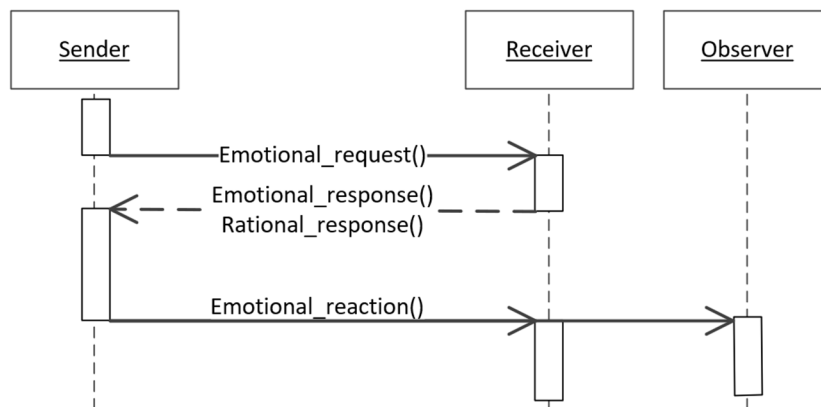


Fig. 4.4. Interaction among the agents in direct communication and manipulation.

According to the knowledge of the author of the Thesis, emotional contagion based on pleasure or arousal has not been studied; for this reason, for emotional contagion, specific emotions must be used – e.g., emotion types from Ekman's theory.

Status and social relationships impact emotional contagion. However, there is no research that would define the numeric impact of these concepts; for this reason, the ranking approach was chosen. According to van Kleef, the mechanisms related to message interpretation, according to the status and social relationships, are implemented in the message receiver.

Modelling the macro-level of a MAS, status value s and relationship value r are modelled as the weight of the graph edges with not-reciprocal values. At the micro level, status and social relationships are additional factors that allow amplifying, weakening, or completely changing affective behaviour; the impact of r and s is modelled as coefficients q_r and q_s . In general, there is little research on the effect of social factors, and the author has found no research that would allow quantifying this impact; in the Thesis, general rules are used to model this impact.

Social beliefs about other agents and self must include information about the perceived status and social relationships; social beliefs are dynamic. A relevant measure is necessary for **social status modelling**. In the studies, there is no numerical measure for status definition; for this reason, social status update function dependency on the criterion k_s must be defined in the domain-dependent design based on the principle: social status and the update function of the social status are closely related to the agent's impact on other agents, i.e., semantically and

functionally agents with a higher status should have a stronger influence on others' affective state. **Social relationship modelling** can be implemented in various ways; the development of the social relationship depends on mutually performed beneficial actions. Like status modelling, relationship modelling is done in the domain-dependent design and depends on criterion k_r . In the case of the design of status and social relationships, there is a need for a change rate; a coefficient ρ determines how easily social relationships and status structures can be changed.

The social relationship and status update functions are shown in Eqs. (4.2) and (4.3).

$$r_{\text{new}} \leftarrow r_{\text{old}} + \rho_r \times \text{soc_rel_change}(k_r), \quad (4.2)$$

$$s_{\text{new}} \leftarrow s_{\text{old}} + \rho_s \times \text{status_change}(k_s), \quad (4.3)$$

where

$r_{\text{new}}, s_{\text{new}}$ – new values of relationship r and status s ;

$r_{\text{old}}, s_{\text{old}}$ – old values of relationship r and status s ;

ρ_r, ρ_s – change rate – determines how stable are existing structures;

$\text{soc_rel_change}(k_r), \text{status_change}(k_s)$ – relationship and status update functions based on criteria k_r and k_s .

4.4. Summary and conclusions

The **main result** of the chapter is an approach comprised of methods, architecture, and guidelines necessary for modelling the affective state of a human group. The domain-independent design includes the agent's general architecture, the agent CME's design, guidelines for modelling rational functions, and necessary formalisations and models for agent communication. Domain-independent design can be further used to develop use-case-specific models. In addition to that, some functions are domain-dependent and must be specified at the implementation level (Table 4.1). The results of the chapter are shown in Fig. 4.1.

In the development process, the author of the Thesis has **concluded** that the design of the believable simulation of human group affective state is possible using approaches employed in MAS. The author has also concluded that when designing an affective multi-agent system, it is essential to consider the micro level as emotion interpretation, and the choice of the appropriate mechanism lies within agents. The importance of the micro level, in turn, means that ABM is especially suitable to model this problem domain.

In the design process, conclusions were made regarding the validation of the work. Considering that the ranking approach was used in multiple design decisions, one must be cautious when interpreting simulation model results; that is, one cannot use the absolute values obtained from the model; the results can only be compared with those obtained from the same model. In the real-life scenario, the model must be calibrated; additional research is needed in psychology and sociology for this purpose.

The next and last chapter of the Thesis summary demonstrates how the results of this chapter can be used, mainly focusing on group affective state dynamics.

5. THE IMPLEMENTATION AND VALIDATION OF THE SOLUTION

Based on the design, three applications have been developed: (1) the demonstration of an individual affective agent, (2) a crowd modelling scenario, and (3) a board game scenario. An experiment set is defined to test if the system works correctly; this set must (1) test the behaviour of a single agent and (2) test the model's behaviour of the system regarding macro-patterns and effects defined in Chapter 3.

5.1. The validation of the design and experiment plan

The applications developed in the Thesis are based on the requirements defined in the previous chapter. The author of the Thesis consciously has developed applications that pay more attention to some requirements than others, as the Thesis goal is related to emotional contagion in a human group; all affective agent components and functions do not impact it. As a result of the analysis, it has been found that the following requirements influence emotional contagion: *multi-layer emotion processing; switching between layers of emotional processing; multi-level affective state; adjusting communication mechanism to internal state; emotion susceptibility; reactivity of an agent*. Some of the requirements necessary for affective agent implementation do not directly impact the macro-pattern development, or the impact is not defined, and there are no studies upon which to base the model; it is out of the scope of the Thesis. These requirements are as follows: *simple behaviour and emotions in the primary layer; impact of the affective state on planning; determining the frequency of the learning; emotions serve as a reward or punishment*.

Initially, a single agent was created to test the individual agents' behaviour; it interacts only with the user interface. This agent aims to demonstrate how the affective dynamics described in the previous chapter work and verify that the software functions according to the model defined in Chapter 4. This application was developed because the simulation model contains many elements, and by creating a group simulation model, it is not possible to verify just the micro level. The remaining two applications aim to demonstrate the affective MAS in action. The implementation of two different scenarios, namely, crowd modelling and board game modelling, indicate that the method developed in the Thesis generally can be used to implement MASs with various affective abilities. Considering the specifics of the Thesis, the functions not related to the emergence of macro-patterns are implemented in a simplified way from the affective agent perspective and the domain perspective.

In the Thesis, to ensure that the simulation model as a whole behaves correctly, it is enough to check that it works according to the macro-pattern characteristics found in the studies. Precise validation and calibration are possible only in close cooperation with psychologists and are outside the Thesis scope. The experiments in the Thesis aim to demonstrate how implementing all five mechanisms: primitive emotional contagion, secondary emotional contagion, emotional contagion patterns, direct communication, and manipulation, benefit the correspondence of the group's affective state to the expected behaviour.

Part of the experiments are done based on the crowd modelling scenario, and part – on the board game scenario. The reason for this distinction is that in the case of the crowd application, the crowd is characterised by weak structure and lack of cognitive factors, i.e., the humans involved in this group either do not know others or know others poorly. Due to the agent's simplicity, such a domain does not show all the model properties. Still, this domain enables demonstrating the simulation of the human group affective state dynamics' correspondence to macro-patterns. At the same time, the board game scenario is too complex and contains too many parameters that complicate validating some macro-pattern characteristics. Three types of experiments have been defined; the summary is in Table 5.1.

1. Agents interact and use primitive emotional contagion. This approach corresponds to Bosse's study; it does not allow verifying divergence or rational consequences. The first experiment is done in the crowd modelling scenario.
2. Secondary emotional contagion and patterns are added; results like Rincon and colleagues' work are obtained. The experiment is done in the UNO board game scenario.
3. Finally, direct communication and manipulation are added; they impact the changes in status and social relationships (i.e., facilitate rational effects). The experiment is done in the UNO board game scenario.

Table 5.1

The Summary of the Experiments

Macro-pattern characteristics and rational effects	Corr. exper.	Specifically impacted by	Demonstration in the summary
Emotions are elicited by observing other group members' emotions	1	Primitive emotional contagion	Text in Section 5.5
If there are no additional parameters, the average intensity of emotions will reach maximum and will not come down	1	Primitive emotional contagion	Fig. 5.2 (a)
The stronger participants' emotional expression and susceptibility, the faster the average intensity of emotions will reach the maximum	1	Agent micro level, primitive emotional contagion	Fig. 5.2 (b)
The higher the social status of the person expressing emotions, the more impact it has on the group's emotional state	2	Secondary emotional contagion, emotional contagion patterns	Fig. 5.2 (c)
The more positive the social relationships of people, the faster emotions converge and the higher the maximum average intensity of emotions	2	Secondary emotional contagion	Fig. 5.2 (c)
If social relationships are negative, the emotional state of group participants diverges	2	Secondary emotional contagion, emotional contagion patterns	Fig. 5.2 (d)
If social relationships are negative and there are no other parameters, participants reach opposite emotional states and remain there	2	Secondary emotional contagion, emotional contagion patterns	Text in Section 5.5
Others' emotions change the behaviour of participants	3	Direct communication or manipulation, agent micro level	Fig. 5.2 (e) and (f)
Others' emotions change the beliefs of group member status and social relationships	3	Direct communication or manipulation, agent micro level	Text in Section 5.5

5.2. Demonstration agent

The demonstration agent aims to show the functions of the CME that do not differ based on the application:

- core state transformation to PAD space;
- dynamics of the affective state in the case of negative and positive stimulus;
- dynamics of the affective state in the secondary and tertiary layers;
- the integration of personality, mood and emotions;
- affective state dependency on social status and relationships in the tertiary layer.

To illustrate how this agent works, in Fig. 5.1, one can see affective dynamics visualised from the demonstration agent using abstract stimuli.

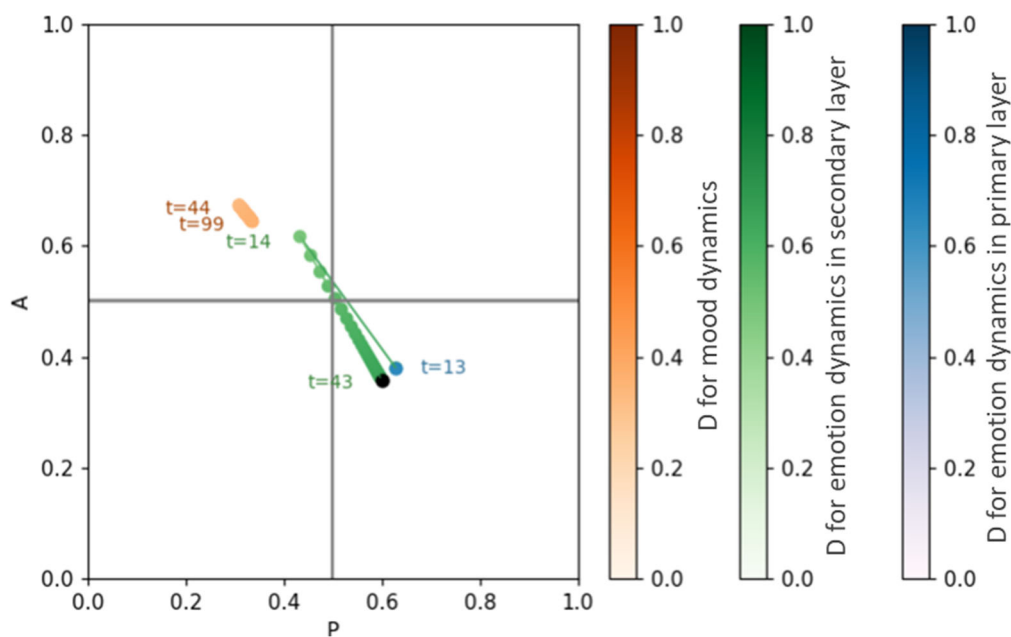


Fig. 5.1. Affective state integration, $t = [number]$ denotes the time moment (second) for an affective state. The third dimension of the PAD space, D , is depicted with the intensity of the colour (the higher the value, the more saturated the colour) – except for the black core personality point. Orange colour visualises mood dynamics; blue – the primary layer, and green – the secondary layer. The figure depicts seconds 13–99, initial state $t = 13$; at the moment $t = 14$, a new stimulus comes $\langle \text{anger}, 0.5 \rangle$. Emotions decay until $t = 43$; at $t = 44$, the decay of the mood begins. The simulation run ends at $t = 99$.

The demonstration agent shows that:

- emotions work as expected in each layer, in correspondence with the affective dynamics functions;
- in various architecture layers, CME works correctly, and an affective state, regardless of the architecture layer, is integrated into the PAD space's current emotion and mood point;
- the dynamics of the mood work according to the domain-independent design;
- on the micro level status and relationship impact on the affective state works according to the design.

5.3. Crowd modelling scenario

The crowd modelling scenario allows modelling weakly structured human groups where the relationship among agents can be interpreted not only as a relationship but also as reachability, physical distance, etc. The crowd model demonstrates the dependency of the affective state on parameters, such as the personality of the group members and interaction frequency. At the same time, there is an option to define different crowd interaction structures that make it useful for studying various systems on the macro level.

In the domain-dependent design the following additions were made to the methods used in the domain-independent design:

- behaviour rules have been specified: agents have a rule according to which agents express emotions;
- pleasant and unpleasant events are modelled via the interface;
- the evaluation function is also simplified and implemented through an interface.

As a result of the Thesis, a tool for crowd modelling was developed; it can be used for generating various crowd structures and emotional contagion modelling. In the tool, the crowd structure is based on the input graph, where the edge between nodes denotes a relation between the corresponding agents. Referring to this structure, the MAS is generated, and emotional contagion modelling is performed. For the convenience of the user, dynamic visualisation of emotional contagion can be viewed.

In the tool, it is possible to model five basic emotions (as defined by Ekman) and the average intensity dynamics for these five emotions. Due to qualitative differences in the emotions and the volume of the studies, anger was examined. The author of the Thesis has published three papers that describe the design of the tool (Pudāne et al., 2017), analyse anger contagion based on interaction frequency and personality (Pudāne et al., 2018), and study emotional contagion in various graph structures (Pudāne et al., 2020).

This line of research concluded that the anger intensity rapidly grows when the Neuroticism of the agents is above average in the population (Pudāne et al., 2018). The experiments showed that one agent was usually left with a lasting affective state after the end of the simulation run. This observation led to the conclusion that anger contagion depends on agent communication structure; for this reason, the next set of experiments was related to the crowd structure research. In (Pudāne et al., 2020), various graph structures were examined, making conclusions about how average emotional intensity dynamics change depending on different graph parameters.

Concerning the Thesis, this application directly demonstrates that primitive emotional contagion mechanisms work as designed based on personality or a particular emotion.

5.4. Board game scenario

The board game scenario based on the game UNO was implemented to demonstrate affective agent group behaviours that cannot be shown in the crowd modelling scenario. Only part of the functions for board game simulation have been implemented to achieve Thesis results. A board game scenario is implemented based on the domain-independent design

described in the previous chapter. Affect-independent behaviour is making a move as it is essential for gameplay. The following additions to the methods used in the domain-independent design were made in the domain-dependent design.

- Based on the general guidelines, sets of different behaviours were defined in various architecture layers and PAD space octants.
- Simplified planning and learning were introduced; the learning is performed by updating beliefs; the beliefs are coded in tuple $\langle \text{Type}, \text{Object} \rangle$. The intention set of the agents is generated based on beliefs and mood. Each intention, like beliefs is coded in the form $\langle \text{Type}, \text{Object} \rangle$. In the tertiary layer, agent beliefs are coded in the form $\langle \text{Agent}, \text{Type}, \text{Value} \rangle$ where Agent is the identifier of an agent to which belief refers; Type is status or relationship value; Value is the numerical value of status or relationship.
- Emotion evaluation functions were defined as related to the OCC model, where each emotion has its intensity calculations; fear calculations were used to demonstrate Thesis results. Fear intensity is calculated as a proportion between (a) the cards that are not played and on which the agent cannot play a card and (b) cards that are not played.
- The status update function was defined based on emotional contagion. When an agent directly expresses or manipulates emotions, the status in the message receiver's social beliefs changes by 0.1 until it reaches 0.
- The social relationship update function was defined related to agents' actions and whether an agent helps another agent.
- The game-specific strategies for direct emotion communication and expression were defined; when the agent has received a message that he will have the next move, an agent can then try to impact the turn of the previous agent by expressing either anger or sadness depending on the D dimension in the PAD space.

5.5. Validation based on macro-pattern characteristics and rational consequences

The experiment summary is shown in Table 5.1 to demonstrate the result validation of the Thesis. It (1) states the macro-pattern characteristics and rational effects based on which the results of the Thesis have been validated, (2) demonstrates which experiment implements it as well as specific components that impact the emergence of these macro-pattern characteristics, and (3) for the traceability, it is stated which figure or section demonstrates proof of macro-pattern characteristics or rational effect.

In all the applications, **emotions are elicited by observing other agents**; even if emotions are not explicitly directed at the agent, the agent will change its affective state based on other agents' expression functions. In Fig. 5.2 (a), it is demonstrated that if agent communication does not stop, the emotional intensity reaches its maximum and does not decay. In the oriented graph, the average intensity of emotions gradually decays because emotion communication happens in one direction. Reaching the maximum emotional intensity depending on the personality is

shown in Fig. 5.2 (b) – when Neuroticism (N) grows, the steepness and maximum achievable emotional intensity grows. These macro-pattern characteristics in more detail are described in the publications (Pudāne et al., 2018) and (Pudāne et al., 2017).

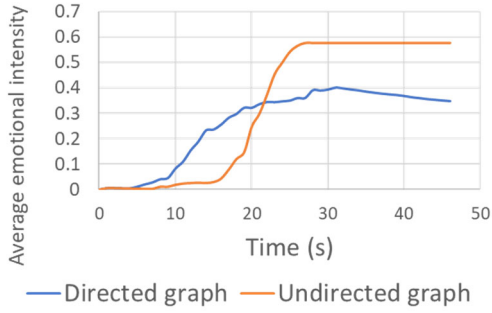
As a result of the second experiment, the macro-pattern validations are demonstrated in Fig. 5.2 (c) and (d), and described in the publication (Pudāne, 2017a). In Fig. 5.2 (c), it is shown how emotional intensity changes based on status and relationship values. In this case, the agent status values towards agent Ana vary from 0.2 to 1; agent Alex: 0.2; agent Greg: 0.4; agent Robert: 0.6; agent Maria: 0.8; and agent Gita: 1. Agent Ana was the only agent that obtained the emotions based on the elicitation functions. As a result, the affective state changed only as a secondary emotional contagion result for the rest of the agents. It can be observed that the belief of certain status value changes the affective intensity of the agent that holds that belief. Figure 5.2 (d) shows the affective dynamics when two agent groups with mutually competitive relationships are involved. The first group contains agents Ana, Gita, and Maria, and the second group: Greg, Robert and Alex. Emotions from the evaluation functions are elicited only in agent Ana. In Fig. 5.1 (d), time interval from 80 to 100 seconds, agent Ana develops a high enough fear value so the other agents would perceive it; one can see the divergence of emotional intensity, but since the model contains other parameters, the affective state gradually decays. **Emotions would not decay if there were no additional parameters.**

Finally, rational consequences are demonstrated in Fig. 5.2 (e) and (f) and are published in (Pudāne, 2023). The experiment tested agent Anas's behaviour changes if agent Ana did not have an elicitation function. In Fig. 5.1 (e), it is shown how the affective state of the agent Ana changes although the agent has no inputs. According to the gameplay in Fig. 5.2 (f), initially agent Ana will perform the behaviours characteristic of PAD octant where the core state is located, that is, will say "Uno!" when one card is left. When other agents feel fear, agent Ana's affective state is impacted; it moves to another PAD octant, and the agent stops performing the behaviour "Say UNO!". Participants change their beliefs **based on their status and social relationships**; they either ask for help from each other or choose to help (Pudāne, 2023).

5.6. Model restrictions and further research

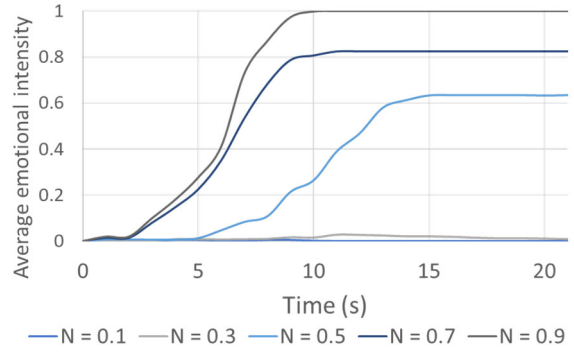
Although the author of the Thesis has developed the existing model and design as completely as possible, the model has several limitations that must be considered in the analysis of the data obtained and in the use of this model in subsequent studies and implementations.

The principal model limitation is related to the fact that it has yet to be calibrated and validated in a real scenario. Although it has yet to be done for objective reasons, the high degree of interdisciplinarity and complexity in other areas (psychology, sociology), it is necessary to do so in further studies to be fully operational. In its current version, the model is usable for comparing the affective states of different groups. The developed software modules can be supplemented for various applications. The crowd modelling tool can be used to study other crowd structures.



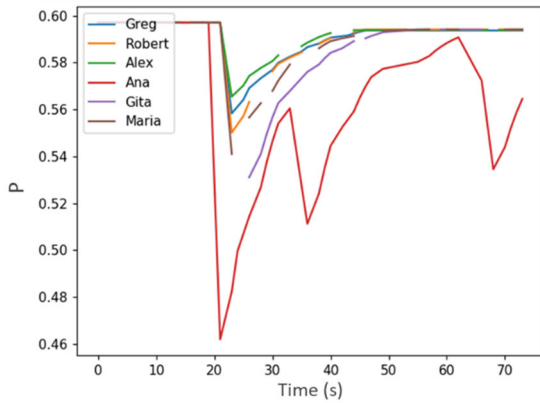
(a)

If the graph is not oriented and the model contains no other parameters, emotion intensity reaches the maximum and does not decay.



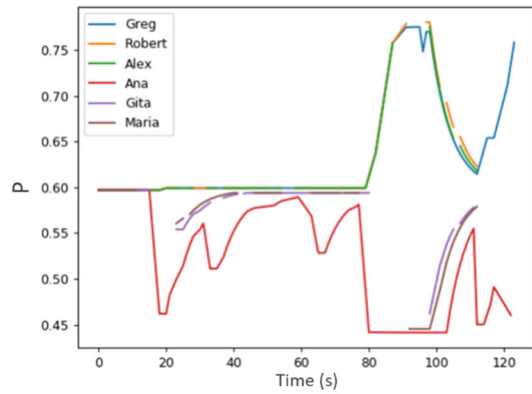
(b)

Emotion dynamics with varying Neuroticism (N).



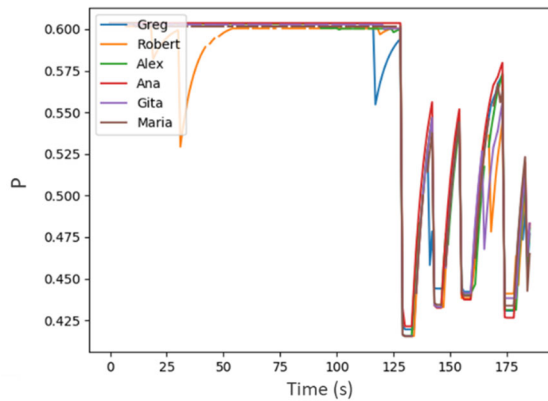
(c)

Affective dynamics of various agents based on their beliefs about Ana's status.



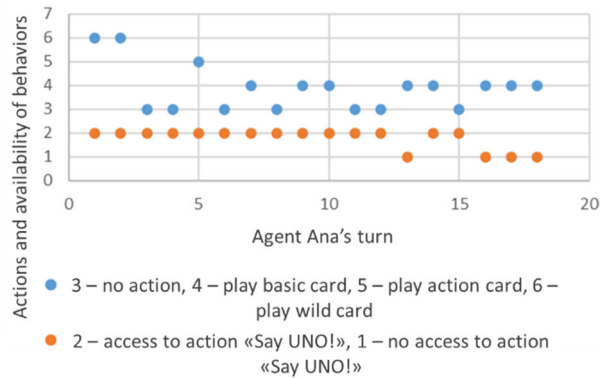
(d)

Affective dynamics of various agents based on their beliefs about the relationship with agent Ana.



(e)

Affective dynamics on the P-axis for various agents in the PAD model – agent Ana's affective dynamics follow other agents' affective dynamics.



(f)

Agent behaviour changes and accessibility to action "Say UNO!"

Fig. 5.2. The validation of various macropattern characteristics.

Existing scenarios, such as the board game application, also open the way for a variety of other interdisciplinary studies on various aspects, such as:

- unilateral impact of status and social relations on the affective state;
- PAD-model-based emotional contagion;
- the impact of emotion displays on the reasoning of others' emotions;
- simulation models of different levels of emotional intelligence.

5.7. Summary and conclusions

The **main result** of the chapter is the implementation of the approach developed in the Thesis in three different applications. The applications are then used to demonstrate and validate the behaviour against macro-pattern characteristics and rational effects.

The chapter also contains the following **results**:

- An application that demonstrates *affective agent on a micro level*.
- *A tool that allows modelling crowd behaviour* with different agent parameters and different crowd structures.
- *An application that shows more complex reasoning* in the case of an affective MAS using a board game scenario.

The author of the Thesis has made the following **conclusions**:

- The domain-independent design described in Chapter 4 allows the modelling of all the macro-patterns identified in Chapter 3.
- The domain-independent design described in Chapter 4 can be used to model affective agents with varying affective abilities, demonstrated by the three applications developed in the Thesis.
- Agents with different emotional abilities have been used to illustrate different macro-pattern characteristics, as otherwise, the model is becoming too complicated to make conclusions.

The results obtained in the chapter have allowed the validation of the developed approach, demonstrating how the developed design at the micro- and macro-levels implements the defined macro-patterns of group behaviour.

CONCLUSIONS

The Thesis has the following main **results**:

- Classification of agent-based simulation models from the perspective of MAS and the scope of the Thesis in the agent-based modelling domain, as well as class compatibility matrix.
- Affective agent architecture summary and comparative analysis based on the emotion roles.
- Affective multi-agent model comparative analysis, based on the amount of the interaction mechanisms implemented, and the classification and formalisation of affective interaction mechanisms.
- An approach for human group affective state modelling that consists of a domain-independent design and a set of functions that must be detailed in the domain-dependent design; the domain-independent design includes (a) the model of affective dynamics, including emotion, mood, and personality integration, (b) the architecture of an affective agent, and (c) the formalisation of affective interaction mechanisms.
- Three applications: single agent demonstration module, crowd modelling tool, and an affective MAS demonstration in a board game scenario; the results obtained with these applications demonstrate how the design can be used to develop various types of affective agents.
- Using developed applications demonstrates how the macro-patterns identified in the literature are achieved to validate the proposed approach.

Theoretical and practical **significance**:

- Agent-based model classification can be used as a tool or guideline to develop agent-based models and make design decisions, for example, to choose appropriate agent architecture and agent network structure.
- Affective architecture and affective interaction analysis are usable as overview material and can act as guidelines to complete the model when the model does not have full affective abilities or as a set of criteria to determine the affective abilities of a model.
- A new human group behaviour modelling approach has been developed to model all the affective interaction mechanisms identified in the psychology literature; this modelling approach is formulated as a design that can be used to develop various models.
- The developed applications can be used for multiple purposes:
 - demonstration agent can be included as a module in affective systems;
 - crowd modelling tool can be used to perform experiments on various crowd structures; potentially, relationships and status can be added;
 - the board game scenario is mainly used to demonstrate the Thesis results; it can potentially be made into the system that allows the user to learn emotional abilities.

The experiments described in Chapter 5 have confirmed the hypothesis. If "believable modelling" is considered to be the implementation of the macro-patterns found in the studies, then affective agents and affective interactions in a MAS allow modelling of the human group affective state and its dynamics. The same can be concluded about the rest of the Thesis statements, proven in the specific chapters.

- In Chapter 1, it is proven that the MAS are a suitable paradigm to model affective state dynamics and effects in human groups.
- In Chapter 2, it is proven that none of the existing affective agents implement all the functions necessary for ensuring affective behaviour.
- In Chapter 3, it is proven that none of the existing affective interaction modelling methods models all the interaction mechanisms necessary for the affective behaviour human group simulation.
- Chapters 4 and 5 prove that the approach developed allows to model all the functions related to emotions, including affective interactions.

The main **conclusions** of the Thesis are related to the interdisciplinary aspects.

Although many models allow modelling the affective abilities in a single agent and some of the affective interactions, there are no models that would employ the full affective spectrum. Such models would enable new applications for virtual environments, such as teaching emotional intelligence, and allow improvement of the current applications. Currently, there is a lack of such models mainly because affect and especially affective interaction modelling is a relatively new field. As with any interdisciplinary topic, it is characterised by the dependency on research in different areas, such as psychology and sociology. At the same time, while working with students in the post-pandemic age and seeing how technologies and their everyday use develop, the author of the Thesis believes there is a great potential for emotion modelling in improving social and technological aspects of everyday life.

Affective state modelling with computer systems can be used as an additional research method in psychology and sociology if the model allows for acquiring data similar to empirical data. This need for similar results leads to the conclusion that emotion modelling must develop in close interaction between computer science and social sciences. If social sciences overtake computer science, plenty of unformalisable models will emerge. The author of the Thesis believes that the vagueness of the models from the computer science perspective is why affective computing initially developed slowly. On the other hand, if computer science surpasses social sciences, there is a situation when models are not validated; avoiding this problem was the most challenging task in the development of the Thesis. The direction of the thesis, i.e., the affective interactions, is a relatively new research direction; for this reason, the approbation of the model is done by formalising and using macro-patterns found in the studies. The applications developed in the Thesis show that it is possible to create a method that simulates the human group's affective behaviour. To build such a system, it is not enough that there are separate laboratories in various research institutions in Latvia. Instead, an interdisciplinary laboratory or research centre that merges the necessary competencies is needed.

There are multiple potential research directions already mentioned in the Thesis:

- criteria definition to assess the affective abilities of a system;
- including a user in an affective agent group;
- modelling of various social structures;
- emotion effect modelling on different rational processes.

LIST OF REFERENCES

- Austin, E. J., Farrelly, D., Black, C., & Moore, H. (2007). Emotional intelligence, Machiavellianism and emotional manipulation: Does EI have a dark side? *Personality and Individual Differences*, 43(1), 179–189. <https://doi.org/10.1016/j.paid.2006.11.019>
- Barsade, S. G. (2002). The ripple effect: Emotional contagion and its influence on group behavior. *Administrative Science Quarterly*, 47(4), 644–675. <https://doi.org/10.2307/3094912>
- Barsade, S. G., & Gibson, D. E. (2012). Group Affect: Its Influence on Individual and Group Outcomes. *Current Directions in Psychological Science*, 21(2), 119–123. <https://doi.org/10.1177/0963721412438352>
- Becker-Asano, C. (2008). *WASABI: Affect Simulation for Agents with Believable Interactivity* [Dissertation zur Erlangung des Grades eines at Bielefeld] [Doctoral Thesis, Universitat Bielefeld]. https://becker-asano.de/Becker-Asano_WASABI_Thesis.pdf
- Bellifemine, F., Poggi, A., & Rimassa, G. (2001). JADE. *Telecom Lab Italia*, 216–217. <https://doi.org/10.1145/375735.376120>
- Bispo, J., & Paiva, A. (2009). A model for emotional contagion based on the emotional contagion scale. *Proceedings – 2009 3rd International Conference on Affective Computing and Intelligent Interaction and Workshops, ACII 2009*, 1–6. <https://doi.org/10.1109/ACII.2009.5349396>
- Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences of the United States of America*, 99(SUPPL. 3), 7280–7287. <https://doi.org/10.1073/pnas.082080899>
- Bosse, T., Duell, R., Memon, Z. A., Treur, J., & Van der Wal, C. N. (2015). Agent-Based Modeling of Emotion Contagion in Groups. *Cognitive Computation*, 7(1), 111–136. <https://doi.org/10.1007/s12559-014-9277-9>
- Bosse, T., Duell, R., Memon, Z. A., Treur, J., & Van Der Wal, C. N. (2009). A multi-agent model for emotion contagion spirals integrated within a supporting ambient agent model. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): Vol. 5925 LNAI* (pp. 48–67). https://doi.org/10.1007/978-3-642-11161-7_4
- Bristow, M., Fang, L., & Hipel, K. W. (2014). *Agent-Based Modeling of Competitive and Cooperative Behavior Under Conflict*. 44(7), 834–850.
- Broekens, J., DeGroot, D., & Kusters, W. A. (2008). Formal models of appraisal: Theory, specification, and computational model. *Cognitive Systems Research*, 9(3), 173–197. <https://doi.org/10.1016/j.cogsys.2007.06.007>
- Chopra, A. K., & Singh, M. P. (2013). Agent Communication. In G. Weiss (Ed.), *Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence* (2nd ed., p. 867). The MIT Press.
- Codispoti, M., Mazzetti, M., & Bradley, M. M. (2009). Unmasking emotion: Exposure duration and emotional engagement. *Psychophysiology*, 46(4), 731–738. <https://doi.org/10.1111/j.1469-8986.2009.00804.x>
- Collins, A. L., Jordan, P. J., Lawrence, S. A., & Troth, A. C. (2016). Positive affective tone and team performance: The moderating role of collective emotional skills. *Cognition and Emotion*, 30(1), 167–182. <https://doi.org/10.1080/02699931.2015.1043857>
- Dey, P., & Roberts, D. (2007). A conceptual framework for modelling crowd behaviour. *Proceedings - IEEE International Symposium on Distributed Simulation and Real-Time Applications, DS-RT*, 193–200. <https://doi.org/10.1109/DS-RT.2007.5>
- Diestel, R. (2017). *Graph Theory* (5th ed.). Springer Berlin Heidelberg. <https://doi.org/10.1007/978-3-662-53622-3>
- Ekman, P. (1992). Are There Basic Emotions? *Psychological Review*, 99(3), 550–553. <https://doi.org/10.1037/0033-295X.99.3.550>
- Felps, W., Mitchell, T. R. R., & Byington, E. (2006). How, When, and Why Bad Apples Spoil the Barrel: Negative Group Members and Dysfunctional Groups. *Research in Organizational Behavior*, 27, 175–222. [https://doi.org/10.1016/S0191-3085\(06\)27005-9](https://doi.org/10.1016/S0191-3085(06)27005-9)
- Gebhard, P. (2005). ALMA. *Proceedings of the Fourth International Joint Conference on Autonomous Agents and Multiagent Systems*, 29–36. <https://doi.org/10.1145/1082473.1082478>

- Gratch, J. (2000). Émile. *Proceedings of the Fourth International Conference on Autonomous Agents - AGENTS '00*, 325–332. <https://doi.org/10.1145/336595.337516>
- Gratch, J., & Marsella, S. (2004). A domain-independent framework for modeling emotion. *Cognitive Systems Research*, 5(4), 269–306. <https://doi.org/10.1016/j.cogsys.2004.02.002>
- Hareli, S., & Rafaeli, A. (2008). Emotion cycles: On the social influence of emotion in organizations. *Research in Organizational Behavior*, 28, 35–59. <https://doi.org/10.1016/j.riob.2008.04.007>
- Helbing, D., & Baliotti, S. (2013). How to Do Agent-Based Simulations in the Future : From Modeling Social Mechanisms to Emergent Phenomena and Interactive Systems Design Why Develop and Use Agent-Based Models ? In *Social Self-Organization* (pp. 25–70). <https://doi.org/10.1007/978-3-642-24004-1>
- Hudlicka, E. (2004). Beyond Cognition: Modeling Emotion in Cognitive Architectures. *Sixth International Conference on Cognitive Modeling*, 3, 118–123.
- Hudlicka, E. (2008). Modeling the mechanisms of emotion effects on cognition. *Papers from the 2008 AAAI Fall Symposium*, 1–5.
- Hudlicka, E. (2011). Guidelines for Designing Computational Models of Emotions. *International Journal of Synthetic Emotions*, 2(1), 26–79. <https://doi.org/10.4018/jse.2011010103>
- Kazemifard, M., Ghasem-Aghaee, N., & Ören, T. I. (2012). Emotive and cognitive simulations by agents: Roles of three levels of information processing. *Cognitive Systems Research*, 13(1), 24–38. <https://doi.org/10.1016/j.cogsys.2010.10.002>
- Kelly, J. R., & Barsade, S. G. (2001). Mood and emotions in small groups and work teams. *Organizational Behavior and Human Decision Processes*, 86(1), 99–130. <https://doi.org/10.1006/obhd.2001.2974>
- Kennedy, W. G. (2012). Modelling Human Behaviour in Agent-Based Models. In *Agent-Based Models of Geographical Systems* (Issue January 2012, pp. 167–179). Springer Netherlands. https://doi.org/10.1007/978-90-481-8927-4_9
- Korecko, Š., Sobota, B., & Curilla, P. (2014). Emotional agents as non-playable characters in games: Experience with Jadex and JBdiEmo. *CINTI 2014 – 15th IEEE International Symposium on Computational Intelligence and Informatics, Proceedings*, 471–476. <https://doi.org/10.1109/CINTI.2014.7028721>
- Lavendelis, E. (2009). *Atvērta daudzāģentu arhitektūra un metodoloģija intelektuālu mācību sistēmu izstrādei*. [Doctoral thesis, Riga Technical University].
- Lee, Y. S., & Malkawi, A. (2013). Simulating human behavior: An agent-based modeling approach. In E. Wurtz (Ed.), *Proceedings of BS 2013: 13th Conference of the International Building Performance Simulation Association* (pp. 3184–3191).
- Luck, M., McBurney, P., Shehory, O., & Willmott, S. (2005). *Agent technology: Computing as interaction*. <http://www.agentlink.org/roadmap/al3rm.pdf>
- Macal, C. (2016). Everything you need to know about agent-based modelling and simulation. *Journal of Simulation*, 10(2), 144–156. <https://doi.org/10.1057/jos.2016.7>
- Macal, C., & North, M. (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation*, 4(3), 151–162. <https://doi.org/10.1057/jos.2010.3>
- Macal, C., & North, M. (2014). Introductory Tutorial: Agent-Based Modeling and Simulation. *Proceedings of the 2014 Winter Simulation Conference A.*, 6–20.
- Manstead, A. S. R., & Fischer, A. H. (2001). Social appraisal: The social world as object of and influence on appraisal processes. In K. R. Scherer, A. Schorr, & T. Johnstone (Eds.), *Appraisal processes in emotion: Theory, methods, research* (pp. 221–232). Oxford University Press.
- Marsella, S., & Gratch, J. (2009). EMA: A process model of appraisal dynamics. *Cognitive Systems Research*, 10(1), 70–90. <https://doi.org/10.1016/j.cogsys.2008.03.005>
- Marsella, S., Gratch, J., & Petta, P. (2010). Computational Models of Emotion. In K. R. Scherer, T. Bänziger, & E. Roesch (Eds.), *A Blueprint for Affective Computing* (pp. 21–46). <https://doi.org/10.1109/IJCNN.2005.1556117>
- Martin, F. J., Plaza, E., & Rodríguez-Aguilar, J. A. (2000). Conversation Protocols: Modeling and Implementing Conversations in Agent-Based Systems. In *Issues in Agent Communication*. https://doi.org/10.1007/10722777_17
- McCrae, R., & Costa, P. (2003). Personality in Adulthood. In *Personality in Adulthood* (2nd ed.). The

- Guilford Press. <https://doi.org/10.4324/9780203428412>
- Mehrabian, A. (1996). Pleasure-Arousal-Dominance: A General Framework for Describing and Measuring Individual Differences in Temperament. *Current Psychology*, 14(4), 261–292. <https://doi.org/10.1007/BF02686918>
- Nikolic, I., & Ghorbani, A. (2011). A method for developing agent-based models of socio-technical systems. *2011 International Conference on Networking, Sensing and Control, ICNSC 2011*, 44–49. <https://doi.org/10.1109/ICNSC.2011.5874914>
- North, M. J., Howe, T. R., Collier, N. T., & Vos, J. R. (2008). A Declarative Model Assembly Infrastructure for Verification and Validation. In S. Takahashi, D. Sallach, & J. Rouchier (Eds.), *Advancing Social Simulation: The First World Congress* (pp. 129–140). Springer. https://doi.org/10.1007/978-4-431-73167-2_13
- On Chin, K., Gan, K. S., Alfred, R., Anthony, P., & Lukose, D. (2014). Agent Architecture: An Overview. *Transactions on Science and Technology*, 1(1), 18–35.
- Ortony, A., Clore, G. L., & Collins, A. (1988). Introduction. In *The Cognitive Structure of Emotions*. Cambridge University Press.
- Ortony, A., Norman, D. A., & Revelle, W. (2005). Affect and Proto-Affect in Effective Functioning. In J.-M. Fellous & M. A. Arbib (Eds.), *Who Needs Emotions?: The Brain Meets the Robot* (pp. 173–202). Oxford University Press. <https://doi.org/10.1093/acprof:oso/9780195166194.003.0007>
- Pease, C. R., & Lewis, G. J. (2015). Personality links to anger: Evidence for trait interaction and differentiation across expression style. *Personality and Individual Differences*, 74, 159–164. <https://doi.org/10.1016/j.paid.2014.10.018>
- Petroviča, S., & Pudāne, M. (2016). Emotion Modeling for Simulation of Affective Student-Tutor Interaction: Personality Matching. *International Journal of Education and Information Technologies*, 10, 159–167.
- Picard, R. W. (1997). Affective Computing. In *Affective Computing*. The MIT Press. <https://doi.org/10.1007/BF01238028>
- Poslad, S. (2007). Specifying protocols for multi-agent systems interaction. *ACM Transactions on Autonomous and Adaptive Systems*, 2(4), 15–es. <https://doi.org/10.1145/1293731.1293735>
- Pudāne, M. (2017a). Affective Multi-Agent System for Simulating Mechanisms of Social Effects of Emotions. *2017 Seventh International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW 2017): Proceedings*, 129–134.
- Pudāne, M. (2017b). Classification of agent-based models from the perspective of multi-agent systems. *2017 5th IEEE Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE)*, 1–6. <https://doi.org/10.1109/AIEEE.2017.8270547>
- Pudāne, M. (2023). Affective multi-agent system: modelling and simulation of social and rational effects of emotions. *Proceedings of 64th International Scientific Conference on Information Technology and Management Science* (submitted).
- Pudāne, M., Brooks, B., Houston, R., & Radin, M. (2018). Agent Based Model of Anger Contagion and Its Correlations with Personality and Interaction Frequency. *International Journal of Education and Information Technologies*, 12(1), 7–12.
- Pudāne, M., Brooks, B., & Radin, M. A. (2020). The Spread of Supply Chain’s Consumers’ Emotions as Function of Their Social Network Structure. In E. Ginters, M. Ruiz Estrada, & M. Piera Eroles (Eds.), *ICTE in Transportation and Logistics 2019. ICTE ToL 2019. Lecture Notes in Intelligent Transportation and Infrastructure* (pp. 61–68). Springer, Cham. https://doi.org/10.1007/978-3-030-39688-6_9
- Pudāne, M., & Lavendelis, E. (2017). General Guidelines for Design of Affective Multi-Agent Systems. *Applied Computer Systems*, 22(1), 5–12. <https://doi.org/10.1515/acss-2017-0012>
- Pudāne, M., Radin, M., & Brooks, B. (2017). Emotion Contagion among Affective Agents - Issues and Discussion. *Proceedings of 9th International Conference on Intelligent Systems and Agents (ICAART 2017)*, 328–334. <https://doi.org/10.5220/0006252603280334>
- Rebelo, A., Catalão, F., Alves, J., Marreiros, G., Analide, C., Novais, P., & Neves, J. (2015). Prototyping Teams of Affective Agents in Robocode. *International Journal of Imaging and Robotics*, 15(1), 102–112.
- Reisenzein, R. (1994). Pleasure-Arousal Theory and the Intensity of Emotions. *Journal of Personality*

- and Social Psychology*, 67(3), 525–539. <https://doi.org/10.1037/0022-3514.67.3.525>
- Rincon, J. A., Costa, A., Villarrubia, G., Julian, V., & Carrascosa, C. (2018). Introducing dynamism in emotional agent societies. *Neurocomputing*, 272, 27–39. <https://doi.org/10.1016/j.neucom.2017.03.091>
- Russel, S., & Norvig, P. (2010). *Artificial Intelligence: A Modern Approach* (3rd ed.). Prentice Hall.
- Russell, J. A., & Mehrabian, A. (1977). Evidence for a three-factor theory of emotions. *Journal of Research in Personality*, 11(3), 273–294. [https://doi.org/10.1016/0092-6566\(77\)90037-X](https://doi.org/10.1016/0092-6566(77)90037-X)
- Rusting, C. L. (1998). Personality, Mood, and Cognitive Processing of Emotional Information: Three Conceptual Frameworks. *Psychological Bulletin*, 124(2), 165–196. <https://doi.org/10.1037/0033-2909.124.2.165>
- Santos, R., Marreiros, G., Ramos, C., Neves, J., & Bulas-Cruz, J. (2011). Personality, emotion, and mood in agent-based group decision making. *IEEE Intelligent Systems*, 26(6), 58–66. <https://doi.org/10.1109/MIS.2011.92>
- Scherer, K. R. (2009). Emotions are emergent processes: They require a dynamic computational architecture. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1535), 3459–3474. <https://doi.org/10.1098/rstb.2009.0141>
- Seif El-Nasr, M., Yen, J., & Ioerger, T. R. (2000). FLAME - Fuzzy Logic Adaptive Model of Emotions. *Autonomous Agents and Multi-Agent Systems*, 3(3), 219–257. <https://doi.org/10.1023/A:1010030809960>
- Sloman, A. (2000). Architectural Requirements for Human-like Agents Both Natural and Artificial: What sorts of machines can love? In K. Dautenhahn (Ed.), *Human Cognition and Social Agent Technology* (pp. 163–195). John Benjamins Publishing Company.
- Steunebrink, B. R., Dastani, M., & Meyer, J.-J. C. (2009). The OCC Model Revisited. In D. Reichardt (Ed.), *Proceedings of 4th Workshop on Emotion and Computing - Current Research and Future Impact* (pp. 1–8).
- Sy, T., & Choi, J. N. N. (2013). Contagious leaders and followers: Exploring multi-stage mood contagion in a leader activation and member propagation (LAMP) model. *Organizational Behavior and Human Decision Processes*, 122(2), 127–140. <https://doi.org/10.1016/j.obhdp.2013.06.003>
- The Foundation for Intelligent Physical Agents. (2002). *FIPA Communicative Act Library Specification*. FIPA TC Communication. <http://www.fipa.org/specs/fipa00037/SC00037J.html>
- Urban, C. (2001). PECS: A reference model for human-like agents. *IFIP Advances in Information and Communication Technology*, 206–216. <https://doi.org/10.1007/978-0-306-47002-8>
- van Kleef, G. A. (2016). The Interpersonal Dynamics of Emotion. In *The Interpersonal Dynamics of Emotion: Toward an integrative theory of emotions as social information*. Cambridge University Press. <https://doi.org/10.1017/cbo9781107261396>
- van Kleef, G. A., Heerdink, M. W., & Homan, A. C. (2017). Emotional influence in groups: the dynamic nexus of affect, cognition, and behavior. *Current Opinion in Psychology*, 17, 156–161. <https://doi.org/10.1016/j.copsyc.2017.07.017>
- Verduyn, P., Delvaux, E., Van Coillie, H., Tuerlinckx, F., & Mechelen, I. Van. (2009). Predicting the Duration of Emotional Experience: Two Experience Sampling Studies. *Emotion*, 9(1), 83–91. <https://doi.org/10.1037/a0014610>
- Wilensky, U., & Rand, W. (2015). *An Introduction to Agent-Based Modeling*. The MIT Press.
- Wooldridge, M. (1999). Intelligent Agents. In G. Weiss (Ed.), *Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence* (pp. 27–78). Massachusetts Institute of Technology.
- Wooldridge, M. (2009). *An Introduction to MultiAgent Systems* (2nd ed.). John Wiley & Sons.



Māra Pudāne was born in 1990 in the town of Preiļi. After graduating from Riebiņi high school, she obtained a Bachelor of Engineering in Computer Science in 2011 and a Master of Engineering in Computer Science with distinction in 2013 from RTU. Since 2013, she has worked at RTU Department of Artificial Intelligence and Systems Engineering (formerly Department of Systems Theory and Engineering) as a researcher and lecturer. She completed a staff training program in 2020 and 2022 at the University of Buffalo, USA. Her scientific interests relate to agent-based modelling and affective computing.