Loreta Juškaite

E-LEARNING TECHNOLOGIES FOR INTENSIVE BRIDGING EDUCATION

Summary of the Doctoral Thesis

RTU Press
Riga 2026

RIGA TECHNICAL UNIVERSITY
Faculty of Computer Science, Information Technology and Energy
Institute of Digital Humanities

RTU LIEPĀJA ACADEMY

Loreta Juškaite

Doctoral Student of the Study Programme "E-learning Technologies and Management"

E-LEARNING TECHNOLOGIES FOR INTENSIVE BRIDGING EDUCATION

Summary of the Doctoral Thesis

Scientific supervisors:

Associate Professor Dr. phys. ATIS KAPENIEKS

Professor Dr. paed. ALĪDA ZIGMUNDE

RTU Press

Riga 2026

Juškaite, L. E-Learning Technologies for Intensive Bridging Education. Summary of the Doctoral Thesis. – Riga: RTU Press, 2026. 55 p.

Published in accordance with the decision of RTU Promotion Council “P15” of 10 April 2026, Minutes No. 04030-9.17.1.2.

Cover image from www.shutterstock.com.

https://doi.org/10.7250/9789934373312

ISBN 978-9934-37-331-2 (pdf)

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

To be granted the scientific degree of Doctor of Science (PhD), the present Doctoral Thesis has been submitted for defence at the open meeting of the RTU Promotion Council on 11 September 2026 at 11:00 at RTU Liepaja Academy, 14 Liela Street, Room 227, Liepaja, Latvia.

OFFICIAL REVIEWERS

Professor Dr. phys. Pāvels Jurs,
RTU Liepāja Academy, Latvia

Professor Dr. phys. Mārcis Auziņš,
University of Latvia, Latvia

Researcher Dr. math. Aija Cunska,
Vidzeme University of Applied Sciences, Latvia

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 (PhD) is my own. I confirm that this Doctoral Thesis has not been submitted to any other university for promotion to a scientific degree.

Loreta Juškaite ……………………………. (signature)

Date: ………………………

The Doctoral Thesis has been written in Latvian. It consists of an introduction, three chapters, research conclusions, 58 figures and 22 tables, a bibliography containing 374 entries, and 10 appendices. The volume of the Doctoral Thesis is 214 pages including appendices.

ACKNOWLEDGEMENTS

I would like to express my deep gratitude to the scientific supervisors of the Doctoral Thesis, Associate Professor Dr. phys. Atis Kapenieks and Professor Dr. paed. Alīda Zigmunde, for your ideas, suggestions, and pieces of advice. Thank you for the opportunity to learn from you.

My sincere gratitude to Dr Airisa Šteinberga (Dr. psych.), Dr Jānis Kapenieks (Dr. paed.) and Dr Sarma Cakula (Dr. paed.) for their valuable advice, insightful recommendations, and support throughout the development of this doctoral research.

I am grateful to my colleagues and supporters for your warm hearts and encouragement. Thank you for taking the time to speak with me, for the experience gained together, adventures, suggestions and pieces of advice (in no particular order): Aleksandrs Gorbunovs, Žanis Timšāns, Bruno Žuga, Iveta Daugule, Marina Platonova, Viktors Zagorskis, Līga Mangusa, Mērija Jirgensons, Inete Ielīte, Lāsma Ulmane-Ozoliņa, Evija Mirķe, Oksana Ivanova, Mārīte Treijere, Ieva Vitoliņa, Dace Ratniece, Guna Jākobsone-Šnepste, Anita Vēciņa, Rūta Lapsa, Vita Pētersone, Ieva Grada, Anita Jansone, Mārcis Greiselis.

My sincere thanks to all experts, consultants, cooperation partners for your deep insight (in no particular order): Enrique Martin, Anastasiya Boiko, Jelena Milenkovic, and Evita Tasiopoulou (European Schoolnet), Stella Magid-Podolsky (Israel), Piedade Rebelo (Portugal), Jelena Mamčenko and Romualda Lazauskaitė (Lithuania), Suzana Filipecki Martin (the Netherlands), Filiz Şentürk (Turkey), Dulce Vaz and Raquel Santos (Portugal), Panagiotis Angelopoulos and Panagiotis Kanychis (Greece), Ivo Jokin (Bulgaria), Karīna Brikmane, Kaspars Špūle, Inga Lande, and Irina Nizivaja (Latvia), Rosa Doran and Maria Luísa Teixeira de Almeida (Portugal), Daniel Tysman (Great Britain), Šárka Kvasničková (the Czech Republic), David Marti (Spain), Anna Mičurina (Ukraine).

Thanks to Beata Lebionkaitė, Jokūbas Lebionka, Sandra Trinkūniene, Laura Dzelzkalēja, Aleksandrs Ipatovs, and Dmitrijs Riazanovs for excellent collaboration on joint publications, for the ideas, and knowledge co-creation.

Many thanks to the Latvian physics teachers for your involvement, patience in completing the questionnaires, and approval of the tasks!

Thanks to the i-Zvaigzne team for your willingness to take on challenges and experiment! Special thanks to Sintija Buhanovska, Linda Zemīte and Sabīne Trēde for your co-operation.

I would like to express my sincere gratitude to my family and friends for giving me time to conduct research. Thank you for your support and selfless love. Special thanks to Austris Cābelis for your generosity, creativity, suggestions and recommendations!

TERMS AND ABBREVIATIONS USED IN THE DOCTORAL THESIS

Terms	
Approbation research	Research in which knowledge is acquired through practical observations and experience gained through experiments; the suitability of materials for the set aims is tested in practice.
Diagnostic evaluation	Assessing the learner's strengths and weaknesses to identify the support needed.
Digitalisation	The process of converting information from a traditional format into a digital one.
Digital ecosystem	Technology-based ecosystem for intensive bridging education.
Efficiency	The ability to achieve the intended results using the resources and means available.
Feedback	The process of information exchange, which is the most important part of formative evaluation.
Formative assessment	Assessment that serves a diagnostic purpose – all activities carried out by learners and the teacher to collect information about teaching and learning.
Information and communication technologies (ICT)	Technologies that are used to create, access, store, transfer and transform information (telecommunications, computers, sensors, data storage devices, audio-visual systems, software).
Intensive bridging education (IBE)	A pedagogical approach used to support learners' individual development and mastery in a relatively short time. It focuses on each learner, their individual needs, requirements and abilities, striving to provide equal opportunities for all learners.
Interactive learning material	Material (various simulations, tasks, etc.) that gives instant feedback; it can be used through computers and different types of interactive whiteboards.
Learner	A person who is trying to gain knowledge or skill in something by studying, practicing, or being taught.
Meta-competences	"Generic" competences that cover a wide range of working conditions and promote adaptability and flexibility. They include learning, adapting, anticipating and creating change.
Model	A manifestation of the essential properties of a real system that reflects (simulates) the functioning (behaviour) of the system in a certain way and is used to study it.
Module	A relatively self-contained part of the learning process, a highly structured set of subjects and lessons designed to promote a particular specialisation or orientation.
System	A part of objective reality consisting of separate elements that interact with each other.

Summative assessment	Aggregate assessment of learners' performance.

Abbreviations

AI	Artificial Intelligence
CE	Centralised Examination
DT	Diagnostic Test
IoT	Internet of Things
EC	European Commission
EICT	Electronic and Optical Equipment Manufacturing, Information and Communication Technology
EU	European Union
EUA	European University Association
IDD	Introductory Diagnostic Test
ICT	Information and Communication Technologies
IBE	Intensive Bridging Education
MES	Ministry of Education and Science
CM	Cabinet of Ministers
NDD	Final Diagnostic Test
NEF	New Economics Foundation
NIST	National Institute of Standards and Technology
OECD	Organisation for Economic Co-operation and Development
PISA test	Programme for International Student Assessment (tests the skills and knowledge of pupils in reading, mathematics and science)
RTU	Riga Technical University
SOLO	Structure of Observed Learning Outcomes – a taxonomy for measuring the depth of a learner's understanding
STEM	Science, Technology, Engineering and Mathematics
UNESCO	United Nations Educational, Scientific and Cultural Organisation
NDT	National Diagnostic Test
NCE	National Centre for Education
VLE	Virtual Learning Environment
VL	Virtual Laboratory

TABLE OF CONTENTS

1. GENERAL DESCRIPTION OF THE DOCTORAL THESIS 9
   1.1. Topicality and Relevance of the Research 9
   1.2. Research Questions, Object and Subject of the Research 9
   1.3. Research Goal and Objectives. Empirical Basis of the Research 10
   1.4. Research Methods 11
   1.5. Research Implementation Process 13
   1.6. Scientific Contribution and Practical Significance of the Research 13
   1.7. Thesis Statements to be Defended 15
   1.8. Research Limitations 16
   1.9. Dissemination and Validation of Research Results 17
   1.10. Structure of the The Doctoral Thesis 18
2. OVERVIEW OF THE DOCTORAL THESIS CHAPTERS 19
   2.1. The Interrelation of Pedagogical Theories and E-Learning Technologies for Intensive Bridging Education Support 19
   2.2. Digital Ecosystem Approach – Efficient Pedagogical Process Support and Improvement for Intensive Bridging Education in Physics 25
   2.3. Research Process and Findings 32
3. SUMMARY AND CONCLUSIONS 47
   3.1. Summary of Findings and Validation of the Research Propositions 47
   3.2. Answers to the Research Questions 49

LIST OF REFERENCES USED IN THE SUMMARY OF THE DOCTORAL THESIS 51

1. GENERAL DESCRIPTION OF THE DOCTORAL THESIS

1.1. Topicality and Relevance of the Research

The ongoing digital transformation of education has altered the requirements for curriculum design, teaching approaches, and learner competencies. Contemporary educational systems are expected to support the development of digital literacy, self-regulated learning skills, and the ability to adapt to rapidly changing technological and social environments (European Commission, 2021; OECD, 2022).

Within this context, STEM education has gained increasing importance due to its contribution to scientific and technological development and its role in preparing a qualified workforce. However, studies indicate that many students entering higher education demonstrate substantial differences in their prior knowledge of physics and other STEM subjects, creating challenges during the transition from secondary to higher education (Birziņa & Cēdere, 2019).

To address these disparities, intensive bridging courses are widely used to support the consolidation of knowledge and skills prior to the commencement of higher education studies (Gorbunovs et al., 2016). Nevertheless, there remains a limited body of research addressing how digital learning technologies, learning analytics, personalised learning, and diagnostic assessment can be integrated into a coherent pedagogical framework for intensive bridging education in STEM.

Therefore, this Doctoral Thesis focuses on the development and empirical evaluation of an e-ecosystem model for the pedagogical process of intensive bridging education (IBE). The proposed model provides a structured framework for organising technology-enhanced and personalised learning in physics during the transition from secondary to higher education.

1.2. Research questions, object and subject of the research

Research questions

1. How can the pedagogical process e-ecosystem for intensive bridging education (IBE) in physics be characterised within the context of educational paradigm shifts

and technological development during the transition from secondary to higher education?

2. How can the use of technology contribute to the effectiveness of the pedagogical process and the improvement of learners' academic achievement in intensive bridging education (IBE) during the transition from secondary to higher education?
3. What are the characteristics of the pedagogical process e-ecosystem that is most appropriate for this educational context?

The object of research

The pedagogical process e-ecosystem for intensive bridging education (IBE) in physics during the transition from secondary to higher education.

The subject of research

Intensive bridging education (IBE) in physics during the transition from secondary to higher education.

1.3. Research Goal and Objectives. Empirical Basis of the Research

The goal of the Doctoral Thesis is to investigate the pedagogical process e-ecosystem for intensive bridging education (IBE) in physics, analyse cognitive learning achievements, and develop an e-learning technology-based e-ecosystem model of the pedagogical process to support learning during the transition from secondary to higher education.

Research objectives

1. To investigate the social need for intensive bridging education (IBE) in physics during the transition from secondary to higher education within the context of sustainability, drawing upon findings from previous research and regulatory documents governing the Latvian education system.
2. To develop criteria for an effective pedagogical process e-ecosystem for intensive bridging education (IBE) in physics during the transition from secondary to higher education, taking into account the requirements of twenty-first-century physics education at the upper-secondary level.
3. To analyse the technological infrastructure required to support the pedagogical process e-ecosystem for intensive bridging education (IBE) in physics during the

transition from secondary to higher education and to develop an e-technology-based pedagogical process e-ecosystem model.

4. To develop, pilot, and implement an e-technology-based system of online diagnostic tests and tasks for intensive bridging education (IBE) in physics during the transition from secondary to higher education.
5. To analyse and evaluate the interrelationships among the developed e-technology usage scenarios, methodology, and metrics in relation to the development of learners' competencies.
6. To develop a pedagogical process e-ecosystem model for intensive bridging education (IBE) in physics and evaluate its suitability for improving learners' academic achievement during the transition from secondary to higher education.

The empirical basis of the research was established at Riga Technical University through the implementation of intensive bridging education (IBE) courses in physics during the transition from secondary to higher education. The study was conducted between 2015 and 2021 and followed a design-based research approach, enabling the iterative design, implementation, refinement, and empirical evaluation of the proposed pedagogical process e-ecosystem model.

The research involved 620 learners participating in intensive bridging education courses in physics. Additional stages of instrument validation and piloting involved physics teachers, secondary school students, and participants in national diagnostic assessments. During the course of the study, a system of diagnostic tests and learning tasks was developed and validated, while learners' achievement was analysed using learning analytics and cognitive assessment approaches.

The pedagogical process e-ecosystem model for intensive bridging education was refined through multiple iterative cycles informed by empirical evidence and the analysis of research findings.

1.4. Research Methods

Questionnaires and focus group discussions were employed to investigate the need for intensive bridging education and to analyse learners' individual and group psychological well-being. During the development of diagnostic tests, learning materials, and the technological infrastructure, a review of scientific and educational literature was conducted to identify the most appropriate approaches to the integration of digital learning technologies within intensive bridging courses.

The validation study of the diagnostic tests involved the piloting of learning materials within the intensive bridging education process. Learners' academic achievement was assessed using the structure of observed learning outcomes (SOLO) taxonomy, which enables the analysis of learners' cognitive performance by identifying the complexity of knowledge structures and the depth of conceptual understanding demonstrated during the learning process (Biggs & Collis, 1982; Biggs, 1999; Biggs & Tang, 2011).

The methodological framework of the study was based on design thinking and the design-based research (DBR) approach, which is widely applied in educational research for the development, testing, and refinement of innovative learning solutions in authentic educational settings. Design thinking is characterised as both a methodology and a mindset for generating creative solutions grounded in the investigation of human needs and behaviour (Vaishnavi & Kuechler, 2015). In educational research, this approach is employed to iteratively design and empirically evaluate pedagogical solutions in real-world learning environments (McKenney & Reeves, 2019; Razzouk & Shute, 2015). Within the context of the intensive bridging education (IBE) model, this approach facilitates the examination of the learning process as a dynamic pedagogical system in which various instructional scenarios are designed, implemented, and refined with the aim of creating added value through the enhancement of learners' cognitive achievement. Design thinking is an iterative and flexible process that allows researchers to revisit earlier stages and improve proposed solutions on the basis of empirical evidence and experimental inquiry (Wrigley et al., 2018; Royalty, 2021). Such an approach enables the identification of shortcomings within the pedagogical process and supports the continuous improvement of learning solutions based on evidence obtained in authentic educational practice (Hess, 2020).

The e-ecosystem model of the pedagogical process for intensive bridging education was developed and refined through an iterative design-based research cycle comprising problem analysis, pedagogical solution design, implementation in an authentic learning environment, and empirical evaluation of outcomes (analysis → design → implementation → evaluation) (McKenney & Reeves, 2019; Vaishnavi & Kuechler, 2015). This approach ensures a systematic connection between theoretical inquiry and the development of practical pedagogical solutions.

To investigate factors influencing learners' motivation, willingness, and opportunities to acquire knowledge within the IBE model, an empirical investigation was conducted. Two data collection methods were used to evaluate the effectiveness of the IBE pedagogical process: document content analysis and learner surveys. Document content analysis was applied to evaluate the achievement of educational objectives, while learner surveys provided information regarding learning needs, the attainment of learning objectives, and the overall learning experience. A more detailed description of the research methods is provided in the respective sections describing each stage of the study.

1.5. Research Implementation Process

The research was conducted over the period from 2014 to 2026. During the preparatory phase, diagnostic instruments and learning materials were developed and validated. Subsequently, between 2015 and 2021, an empirical study was carried out, during which the e-ecosystem model of the pedagogical process for intensive bridging education (IBE) was designed, piloted, refined, and evaluated.

The research findings were systematically analysed, presented at international scientific conferences, and disseminated through peer-reviewed scientific publications. In the final phase of the study, the collected data were interpreted, synthesised, and integrated into the preparation of the Doctoral Thesis.

1.6. Scientific Contribution and Practical Significance of the Research

1. A pedagogical process e-ecosystem model for intensive bridging education (IBE) in physics during the transition from secondary to higher education has been developed. The model conceptualises the pedagogical process as an interconnected system integrating the learner, teacher, learning content, digital technologies, and learning environment within a unified functional framework. The proposed model extends the theoretical understanding of pedagogical process e-ecosystems in the context of intensive bridging education and provides a framework for organising technology-enhanced learning (Kapenieks et al., 2020).

2. An approach to the diagnosis and adaptive management of learning achievement has been developed and empirically substantiated by integrating diagnostic assessment, learning analytics, and cognitive achievement analysis based on the SOLO taxonomy (Biggs & Collis, 1982). The proposed approach enables the identification of learners' prior knowledge and skills, supports the personalisation of learning, and facilitates the monitoring of learners' progress throughout the IBE process.
3. The suitability and effectiveness of the developed pedagogical process e-ecosystem model for intensive bridging education in physics have been empirically validated within the transition from secondary to higher education. The findings demonstrate that a personalised approach supported by diagnostic assessment and learning analytics contributes to the improvement of learners' cognitive achievement and supports the effective organisation of intensive bridging education.

The pedagogical process e-ecosystem model for intensive bridging education (IBE) developed within this research provides a practical framework for organising technology-enhanced and personalised learning during the transition from secondary to higher education. The model supports curriculum planning, diagnostic assessment, learning process management, and the evaluation of learners' academic achievement within a unified pedagogical framework.

The proposed model and its methodological support have been implemented and evaluated in intensive bridging education courses in physics at Riga Technical University, involving 620 learners. The findings demonstrate the suitability of the model for organising learning in heterogeneous groups characterised by diverse levels of prior knowledge and skills.

The diagnostic assessment system, task bank, and learning analytics solutions developed within the research can be applied to the identification of learners' prior knowledge and skills, the design of personalised learning pathways, and the monitoring of learning progress in both secondary and higher education settings.

The proposed approach is transferable to other STEM disciplines. Its applicability has been demonstrated in mathematics bridging courses, indicating its potential for broader use in intensive bridging education across STEM fields.

The findings and methodological solutions developed within this research are currently being utilised in the Latvian National Research Programme project AI4EDULAB: Advancing AI-Driven, Ethical and Labour Market-Aligned Personalised Learning Content (No. VPP-IZGLĪTĪBA-2025/1-0007). Within the project, the research outcomes contribute to the development of adaptive learning technologies, the design of personalised learning content, and the piloting of technology-enhanced learning solutions in higher education courses.

The results of the research may be applied in higher education institutions, secondary schools, professional development programmes, and other educational contexts, where personalised, data-informed, and technology-supported learning processes are required.

1.7. Thesis Statements to be Defended

Thesis 1

The developed and empirically validated pedagogical process e-ecosystem model facilitates the implementation of intensive bridging education (IBE) in physics during the transition from secondary to higher education. The model incorporates pedagogical scenarios specifically designed for intensive bridging education and contributes to the improvement of learners' cognitive achievement.

Thesis 2

The developed and validated model provides a set of tools for the diagnostic assessment of learners' knowledge, level of understanding, and depth of cognition. The model supports effective planning and implementation of the pedagogical process and enables personalised learning within intensive bridging education in physics.

Thesis 3

The developed metric characterises learning content across three cognitive levels and provides a framework for evaluating learners' cognitive achievement in intensive bridging education in physics during the transition from secondary to higher education. The metric reveals learners' development in the following areas:

- the use of physics concepts, relationships, symbols, and units;
- understanding of physical phenomena and processes;
- understanding and application of models;
- understanding and application of functional relationships in problem-solving;
- inquiry-based and investigative activities.

Thesis 4

The application of the developed metric to learning process data analysis demonstrates that the effectiveness of the pedagogical process is determined by the interaction between the learner and the learning environment, including:

- alignment with intended learning outcomes;
- the suitability of learning content and pedagogical processes for achieving learning outcomes;
- the effectiveness of support measures;
- the implementation of individual learning needs;
- monitoring of learners' activities and adherence to individual learning pathways.

1.8. Research Limitations

The study was conducted within the context of intensive bridging education (IBE) in physics during the transition from secondary to higher education. Consequently, the findings are primarily applicable to STEM education and comparable forms of bridging education. Although the proposed model may be adapted to other subject areas, its effectiveness beyond physics was not systematically investigated within the scope of this research.

The empirical study was carried out at Riga Technical University. Therefore, the findings are influenced by the specific institutional and educational context in which the model was implemented. Further research is required to examine the transferability of the proposed model to other higher education institutions and educational systems.

The research focused primarily on the analysis of cognitive learning achievement through diagnostic assessment and learning analytics. Social, emotional, and motivational factors that may influence learning outcomes were not examined in depth.

The findings reflect the effectiveness of the proposed model within the technological context in which the study was conducted. Continued developments in digital technologies, artificial intelligence, and learning analytics may necessitate further refinement of individual model components and their implementation strategies.

1.9. Dissemination and Validation of Research Results

The research results have been validated both in scholarly environments and in authentic educational practice. The development, refinement, and evaluation of the pedagogical process e-ecosystem model for intensive bridging education (IBE) were carried out over an extended period through research conducted at Riga Technical University between 2015 and 2021.

The empirical validation of the model involved 620 learners participating in intensive bridging education courses in physics. Additional stages of instrument validation and piloting involved physics teachers, secondary school students, and participants in national diagnostic assessments.

The findings of the research have been disseminated through 22 scientific publications addressing the theoretical foundations of the IBE model, digital learning technologies, diagnostic assessment, learning analytics, and the empirical validation of the proposed model (Juškaite & Cābelis, 2017, 2021; Juškaite, 2018a, 2018b; Juškaite, 2019a).

The research outcomes have been presented at international scientific conferences, including INTED, ICERI, EDULEARN, CSEDU, SIE, and other conferences dedicated to educational technologies, STEM education, and the digital transformation of education (Juškaite, 2019a; Juškaite, 2019c).

Individual components of the research and the developed solutions have also been validated through international collaboration involving educational institutions and researchers from Lithuania, the Czech Republic, Ukraine, and Israel, as well as through the application of internationally recognised digital learning technologies and virtual laboratories.

The outcomes of the research continue to be utilised in subsequent research and educational innovation initiatives, including the Latvian National Research Programme project *AI4EDULAB: Advancing AI-Driven, Ethical and Labour Market-Aligned Personalised Learning Content* (No. VPP-IZGLĪTĪBA-2025/1-0007).

1.10. Structure of the Doctoral Thesis

The Doctoral Thesis consists of an introduction, three chapters, research conclusions, bibliography, and 10 appendices. The introduction of the Doctoral Thesis discusses the topicality of the research, justifies scientific novelty, and sets out the goal and objectives of the Doctoral Thesis. Chapter 1 is devoted to the review of scientific literature. Chapter 2 presents the digital ecosystem model of the pedagogical process for intensive bridging education in physics developed within the framework of the Doctoral Thesis. Chapter 3 describes the stages of research and the results obtained.

The Conclusions of the Doctoral Thesis summarise the findings and present conclusions drawn during the elaboration of the Doctoral Thesis, propose recommendations for further research, as well as describe the practical application of the research results. The volume of the Doctoral Thesis is 214 pages, including 58 figures and 22 tables. The bibliography includes the following sources of information used in the elaboration of the Doctoral Thesis: scientific literature, educational materials, and Internet sources (a total of 374 units).

2. OVERVIEW OF THE DOCTORAL THESIS CHAPTERS

The Doctoral Thesis consists of three interconnected chapters, which sequentially present the theoretical framework of the study, the development of the e-ecosystem model of the pedagogical process for intensive bridging education (IBE), and its empirical validation. The content and organisation of the chapters are aligned with the research aim, research objectives, and the methodological principles of design-based research (DBR).

2.1. The Interrelation of Pedagogical Theories and E-Learning Technologies for Intensive Bridging Education Support

The first chapter examines the social necessity of intensive bridging education (IBE), the implications of educational paradigm shifts, and the role of e-learning technologies in supporting effective pedagogical processes. The chapter aims to establish the theoretical foundations of intensive bridging education during the transition from secondary to higher education and to identify the prerequisites for the development of a pedagogical process e-ecosystem model.

In the international literature, intensive bridging education is commonly associated with bridging courses, foundation programmes, and remedial education initiatives designed to reduce disparities in learners' prior knowledge and facilitate successful progression to subsequent stages of education (Hodara, 2013; Bickerstaff et al., 2017). Their significance has increased in response to the growing diversity of educational pathways, differences in curriculum content, and rising expectations regarding STEM competencies (OECD, 2020; European Commission, 2021).

Table 1 summarises the principal factors contributing to the demand for intensive bridging education in Latvia. The analysis indicates that disparities in learners' preparation in physics and mathematics arise from differences in educational programmes, variations in the extent of physics instruction, the specific characteristics of vocational education pathways, migration processes, and the optional nature of the national physics examination. These factors create a need for structured bridging education aimed at consolidating prior knowledge and supporting successful participation in STEM studies.

Table 1

Factors Contributing to the Need for Intensive Bridging Courses in Latvia

Factor	**Description**	**Consequences for the education system**
Differences in general secondary education programmes	The extent of science and mathematics subject provision varies across different educational programmes	Graduates demonstrate uneven levels of knowledge and skills in physics
Limited number of physics lessons	The number of physics lessons may range from one to six lessons per week	Insufficient preparation for the national examination and STEM studies
Prospective students returning to education after an interruption	Higher education is also entered by individuals who completed secondary education several years earlier	Revision and consolidation of previously acquired knowledge are required before commencing studies
Specific characteristics of vocational education	Physics is often taught within vocational education programmes to a limited extent	Insufficient prior knowledge for successful participation in higher education studies
Migration and mobility	Some young people spend part of their education abroad and subsequently return to Latvia	Knowledge consolidation and adaptation to the Latvian education system are required

Note. *Compiled by the author based on OECD (2019), Cabinet of Ministers Regulation No. 416, and Cabinet of Ministers Regulation No. 281.*

Intensive bridging education is conceptualised as a structured pedagogical process based on diagnostic assessment, individualisation, continuous feedback, and the integration of digital technologies. Particular importance is assigned to the identification of learners' prior knowledge and skills, as this enables the design of personalised learning pathways and enhances the effectiveness of the learning process (Graham, 2013; Hrastinski, 2019).

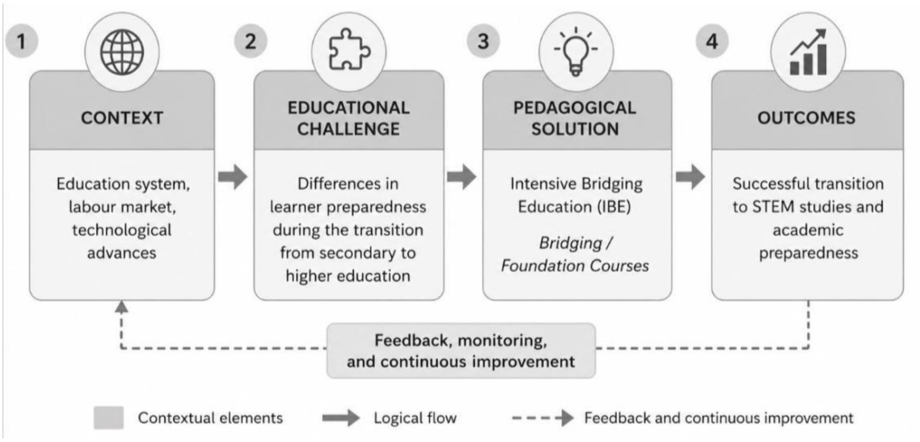

Fig. 1. Educational pathway flow diagram illustrating the conceptual model of the social need for intensive bridging education. *Source: Developed by the author based on the analysis of the scientific literature.*

Figure 1 illustrates the position of intensive bridging education within the educational system. The conceptual model depicts the transition from secondary to higher education, identifying uneven learner preparedness as a significant educational challenge and intensive bridging education as a potential solution. The model highlights the relationship between systemic educational challenges, pedagogical interventions, and the intended outcome of successful progression into STEM-related higher education studies.

The chapter further analyses changes in educational paradigms within the context of digital transformation. Contemporary education increasingly emphasises competency development, information literacy, inquiry-based learning, and higher-order thinking skills (European Commission, 2021; OECD, 2023). In physics education, particular importance is attributed to the integration of theoretical knowledge, mathematical reasoning, and experimental practice within a coherent learning process (Lederman, 1999; Broks, 2007; Vedins, 2008).

The digital transformation of education has generated a growing need for learning approaches that extend beyond the reproduction of knowledge towards conceptual understanding, problem-solving, and the application of knowledge in unfamiliar contexts. In this regard, the development of cognitive processes and the organisation of learning activities that support progression from reproductive to productive learning are of particular importance (Zoller, 2000).

The pedagogical process within intensive bridging education is viewed as a system of interconnected components whose effectiveness depends not on individual elements but on their interaction and coordination.

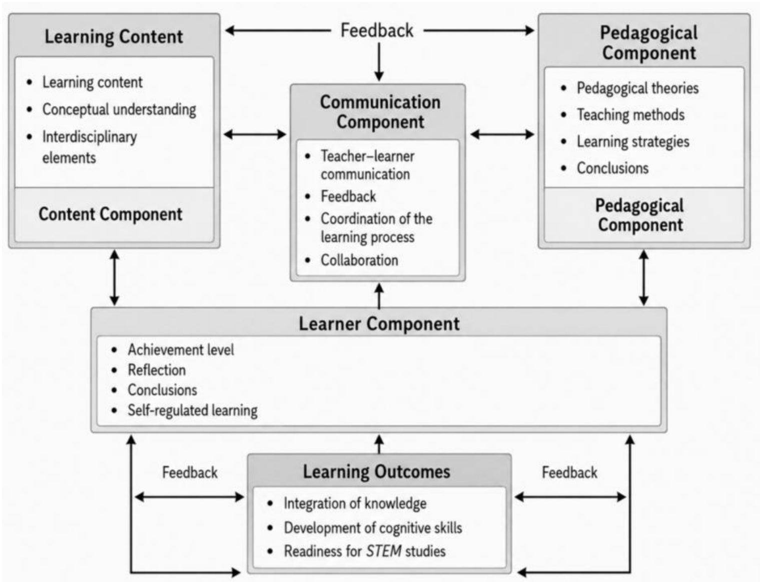

Fig. 2. Structural model of the pedagogical process for intensive bridging education (IBE).
Source: Developed by the author based on the analysis and synthesis of the theoretical concepts proposed by Mishra and Koehler (2006), Lederman (1999), Zoller (2000), Broks (2007), and Vedins (2008).

Figure 2 presents the structural model of the pedagogical process in intensive bridging education, comprising four interrelated components: content, pedagogy, learner, and communication. Within the model, the communication component occupies a central role, ensuring coordination, interaction, and feedback among the remaining components. This systemic perspective enables the pedagogical process to be analysed as an integrated whole and provides the theoretical foundation for the pedagogical process e-ecosystem model developed in the subsequent chapter.

To evaluate learning effectiveness, the Thesis analyses several cognitive taxonomies, including Bloom’s taxonomy (Bloom et al., 1956), the SOLO taxonomy (Biggs & Collis, 1982), and the revised taxonomy proposed by Anderson and Krathwohl (2001). These frameworks provide a theoretical basis for analysing learners’ cognitive development and for establishing criteria for evaluating learning effectiveness.

Table 2

Learning Effectiveness Criteria and Their Relationship to the Components of the IBE Model

Learning effectiveness criterion	Cognitive level	Assessment indicators	Assessment instrument	Relationship to the components of the IBE model
Advancement of cognitive performance	From knowledge reproduction to analysis and problem-solving	The learner can explain physics concepts, analyse situations, and formulate conclusions	Diagnostic assessments, conceptual tasks	Pedagogical component; learner component
Development of conceptual understanding in physics	Understanding and analysis	The learner identifies physical principles and understands relationships among concepts	Conceptual tasks, discussions	Content component; pedagogical component
Application of knowledge in non-routine situations	Analysis and evaluation	The learner applies physics knowledge in novel situations and solves problem-based tasks	Problem-oriented tasks, experimental activities	Content component; learner component
Learning progression within an intensive learning process	Transition between cognitive levels	Observable improvement in learner performance and increasing depth of cognitive engagement	Diagnostic and final assessments	Communication component; pedagogical component; learner component

Note. *The criteria were developed based on cognitive taxonomy approaches (Bloom et al., 1956; Anderson & Krathwohl, 2001) and international approaches to the assessment of learner achievement in science education (OECD, 2019).*

Table 2 summarises the criteria used to evaluate learning effectiveness within intensive bridging education. These criteria include progression in cognitive performance, conceptual understanding, the application of knowledge in non-routine situations, and learning development throughout the intensive learning process. Each criterion is linked to specific components of the IBE model and corresponding assessment instruments.

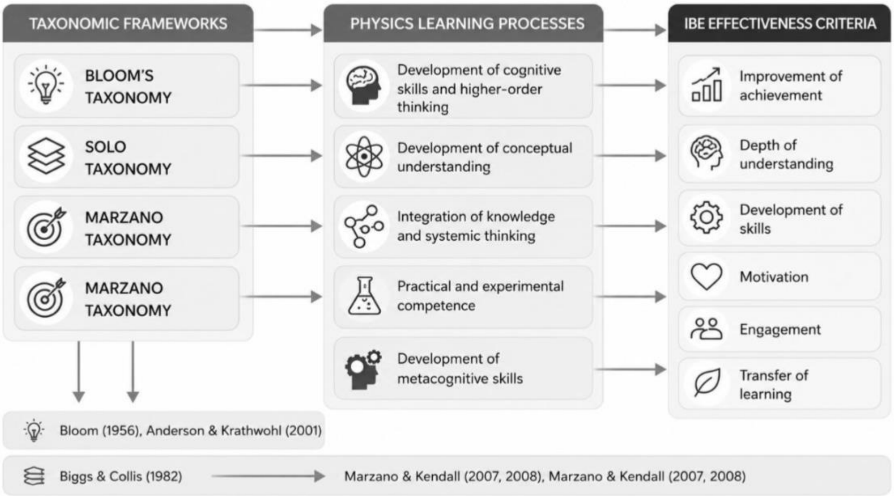

Fig. 3. Relationship between cognitive taxonomy frameworks, physics learning processes, and the effectiveness criteria of intensive bridging education (IBE). *Source: Author's synthesis based on Bloom et al. (1956), Anderson and Krathwohl (2001), Biggs and Collis (1982), Biggs (1999).*

Figure 3 illustrates the integration of different cognitive taxonomies within a unified theoretical framework. The figure demonstrates the relationships between cognitive and metacognitive processes, physics learning activities, and learning effectiveness criteria.

This integration forms the theoretical basis for evaluating the effectiveness of intensive bridging education and underpins the methodology subsequently applied to the analysis of learning achievement.

The theoretical analysis presented in Chapter 1 demonstrates that the effectiveness of intensive bridging education depends on a systematically organised pedagogical process that integrates contemporary pedagogical approaches, cognitive taxonomies, and digital technologies. These findings provide the theoretical foundation for the development of the pedagogical process e-ecosystem model for intensive bridging education presented in Chapter 2.

2.2. Digital Ecosystem Approach – Efficient Pedagogical Process Support and Improvement for Intensive Bridging Education in Physics

Chapter 2 presents the development of the pedagogical process e-ecosystem model for intensive bridging education (IBE), which constitutes the principal scientific outcome of this doctoral research. The model is grounded in systems theory, digital ecosystem approaches, personalised learning, and data-informed pedagogy, viewing the educational process as an integrated system of interrelated components (Briscoe et al., 2011; Jamaludin et al., 2020; World Economic Forum, 2019, 2023). The e-ecosystem approach enables the transition from fragmented use of educational technologies towards a coordinated interaction between learners, educators, learning content, digital technologies, and assessment processes.

Within the context of contemporary educational transformation, an educational ecosystem is understood as an adaptive and dynamic environment in which human resources, digital tools, learning content, and social factors interact to support competency development and the achievement of learning outcomes (Barron & Bell, 2015; ISTE, 2016; Jamaludin et al., 2020). Such an approach is particularly relevant to intensive bridging education, where learners with diverse educational backgrounds must acquire the knowledge and competencies required for successful participation in STEM-related higher education programmes within a limited timeframe.

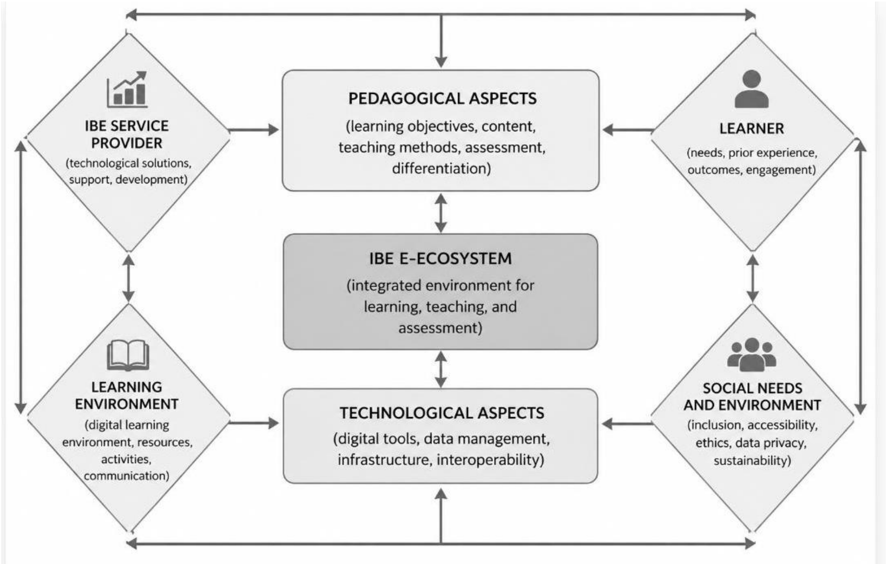

Fig. 4. Conceptual model of the intensive bridging education (IBE) e-ecosystem. *Source: Developed by the author based on Briscoe et al. (2011), Jamaludin et al. (2020), and World Economic Forum (2019, 2023).*

The developed IBE e-ecosystem model conceptualises the pedagogical process as an integrated system centred on the learner and the learning process. The model incorporates pedagogical dimensions, including learning objectives, content, teaching methods, and assessment, together with technological infrastructure, digital learning tools, social requirements, and learner characteristics. The coordinated interaction of these components enables a personalised, flexible, and data-informed learning environment that supports effective learning and progression (Briscoe et al., 2011; Jamaludin et al., 2020; World Economic Forum, 2019, 2023).

The model was developed using a design-based research (DBR) approach and Klafki's perspective planning model, allowing pedagogical, organisational, and technological dimensions to be analysed simultaneously (Klafki, 1995, 2006; Vaishnavi & Kuechler, 2015). This approach supports iterative model refinement based on theoretical insights, expert evaluation, and empirical evidence.

The practical implementation of the IBE e-ecosystem is based on a modular structure designed to support flexible and personalised learning pathways. Three interconnected modules were developed: (1) general knowledge and skills, (2) experimental and inquiry-based activities, and (3) transformation of information between different forms of representation. Each module includes clearly defined learning objectives, learning activities, assessment procedures, and feedback mechanisms, thereby supporting learners' progression across different cognitive levels.

To evaluate the effectiveness of the proposed model, a set of learning effectiveness criteria was developed based on cognitive taxonomy frameworks and the specific characteristics of physics learning.

The proposed e-ecosystem incorporates continuous feedback and systematic improvement of the pedagogical process. Its operation is based on a structured sequence consisting of input data, the pedagogical process itself, and output data. Such an approach enables timely identification of learning difficulties and supports the adaptation of instructional strategies to individual learner needs.

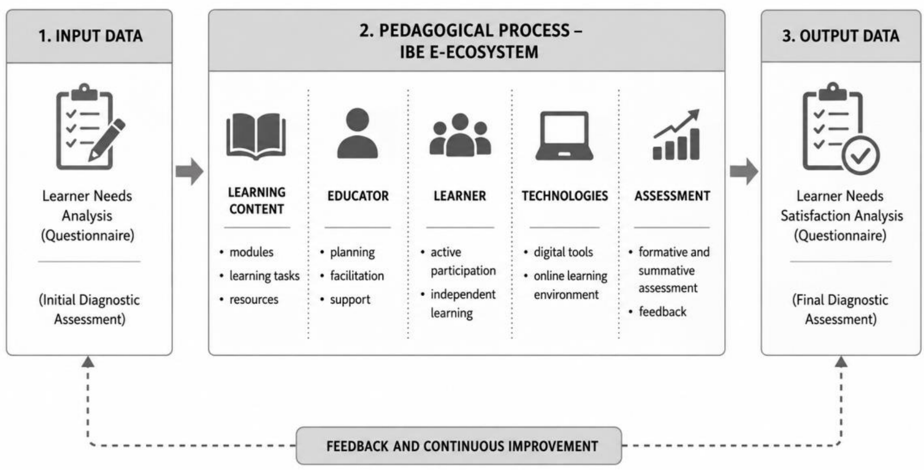

Fig. 5. Process structure of intensive bridging education.

The process structure of intensive bridging education consists of three interconnected stages: input data, the pedagogical process, and output data. Before the commencement of instruction, learners' needs and prior knowledge are assessed through an initial diagnostic assessment. Following the completion of the course, learning outcomes are evaluated through final diagnostic assessment. The comparison of input and output data serves as the principal indicator of pedagogical effectiveness and enables the evaluation of the suitability of the selected technologies, instructional methods, and learning scenarios for achieving the objectives of intensive bridging education (Verhagen, 2006; Watters, 2010; Trinkūniene & Juškaite, 2021).

The principal outcome of Chapter 2 is the development of an e-ecosystem model for intensive bridging education that integrates learning content, pedagogical strategies, digital technologies, learning analytics, and assessment mechanisms within a unified adaptive system. The model provides the theoretical and methodological foundation for the empirical validation and effectiveness evaluation presented in Chapter 3.

The developed IBE e-ecosystem encompasses not only the organisation of learning content and technological infrastructure but also a systematic approach to managing the learning process through diagnostic assessment, feedback, and continuous improvement. To support personalised learning and facilitate the timely identification of learners' difficulties, an implementation strategy and assessment framework for intensive bridging education were developed. The framework is based on a sequential process that begins with needs analysis and initial diagnostic assessment, continues through the implementation of learning activities, and concludes with the evaluation of learning outcomes and the introduction of corrective measures where necessary. This approach is consistent with the principles of data-informed pedagogy and supports the adaptation of the learning process to individual learner needs (Verhagen, 2006; Watters, 2010; Wagino et al., 2024).

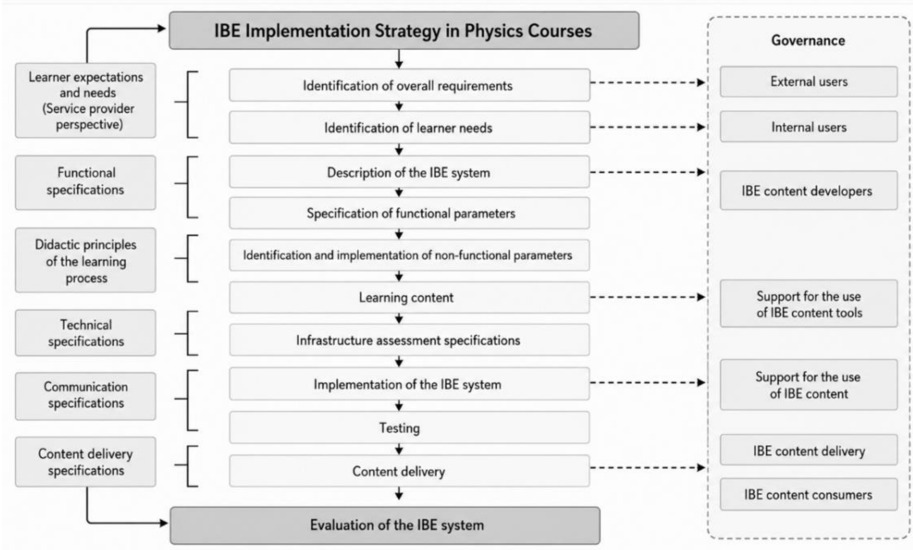

Fig. 6. Application of the assessment framework in the development of the intensive bridging education (IBE) system**.** *Source: Adapted and modified by the author for the IBE context from the product and service competitiveness system proposed by Briscoe et al. (2011).*

The framework presented in Fig. 6 demonstrates that the effectiveness of the learning process is enhanced through the integration of diagnostic assessment, learning analytics, formative assessment, and feedback within a unified system. Continuous monitoring of learner achievement enables the identification of both individual learning needs and content areas requiring additional support. Consequently, assessment serves not only as a mechanism for measuring learning outcomes but also as a tool for managing and improving the pedagogical process. Such an approach supports adaptive and personalised learning, facilitates learners' progression towards higher levels of cognitive performance, and contributes to improved preparedness for STEM-related higher education studies (Anderson & Krathwohl, 2001; Biggs & Collis, 1982; Verhagen, 2006).

To facilitate the practical implementation of the proposed IBE e-ecosystem model, a modular approach was adopted. The modular structure enables learning content to be organised according to learners' needs, prior knowledge, and learning objectives. Such an approach supports flexible curriculum design, personalised learning pathways, and the adaptation of learning activities to diverse learner profiles. It is consistent with contemporary principles of digital education and personalised learning, emphasising continuous diagnostic assessment, feedback, and individual learning progression (Bridges, 2000; Brockmann et al., 2008; Mulder, 2020).

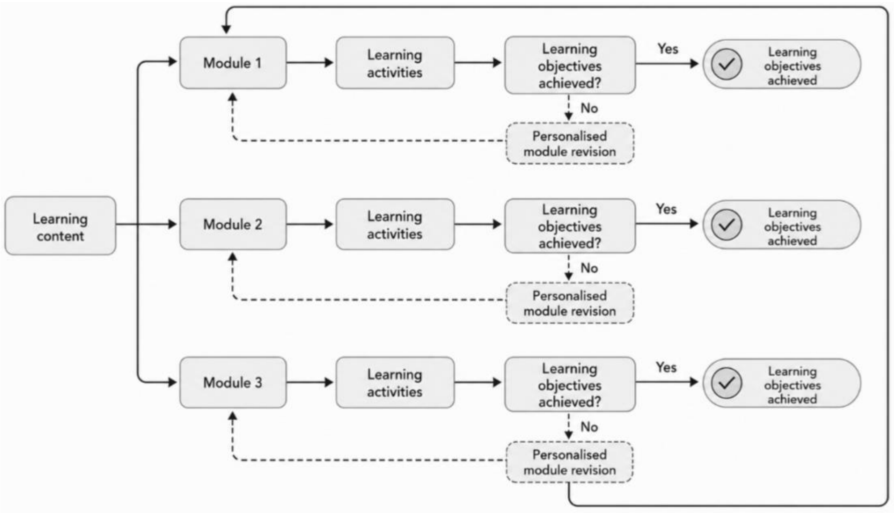

Fig. 7. Conceptual framework of the modular approach in the intensive bridging education (IBE) process. *Source: Developed by the author.*

The modular structure presented in Fig. 7 comprises three interconnected modules: general knowledge and skills, inquiry-based and experimental activities, and the transformation of information between different forms of representation. Each module addresses a specific aspect of physics learning while simultaneously supporting learners' cognitive development. Progression through the modules is informed by diagnostic assessment results and allows for the repeated study of particular content elements when the required level of achievement has not yet been attained. Consequently, the model provides a personalised and adaptive learning environment in which learners progress according to their individual needs and learning pace.

The proposed modular approach serves as the operational foundation of the IBE pedagogical process and enables the practical integration of the components defined within the theoretical e-ecosystem model. This approach is further elaborated through the process structure of intensive bridging education, which defines the relationships between input data, the pedagogical process, and learning outcomes.

To operationalise the proposed IBE e-ecosystem model, a structured framework was developed to align intended learning outcomes, physics content, and cognitive development levels. The framework is based on a modular organisation of learning content and establishes explicit relationships between learning objectives, subject content, and the progression of learners' cognitive performance. Such an approach supports systematic learning progression and provides a basis for personalised learning pathways within intensive bridging education.

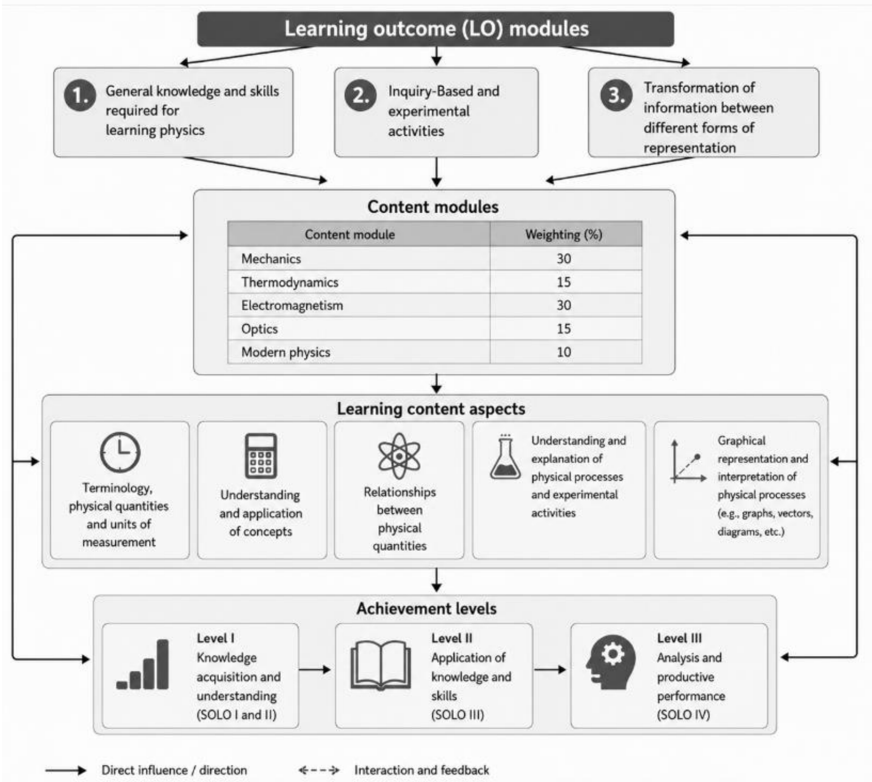

Fig. 8. Structure of learning outcome modules and cognitive development levels in the intensive bridging education (IBE) process. *Source: Developed by the author.*

Figure 8 demonstrates that the IBE model is organised around three interconnected learning outcome modules: general knowledge and skills, inquiry-based and experimental activities, and the transformation of information between different forms of representation. These modules encompass the principal areas of upper secondary physics and are linked to specific learning content aspects, including conceptual understanding, the application of physical quantities and relationships, interpretation of physical processes, and graphical representation of scientific information.

The framework further integrates cognitive development levels based on the SOLO taxonomy, enabling learners to progress from knowledge acquisition and understanding towards the application, analysis, and productive use of knowledge. Consequently, the model establishes a coherent relationship between learning outcomes, content organisation, and assessment, thereby providing the pedagogical foundation for the process structure and assessment framework presented in the following sections of the chapter. Chapter 2 is organised around the following conceptual sequence:

model → modules → learning process → assessment and adaptation.

2.3. Research Process and Findings

The third chapter presents the empirical validation of the proposed intensive bridging education (IBE) pedagogical process e-ecosystem model and evaluates its effectiveness in supporting the transition from secondary to higher education in physics. The chapter describes the research design, implementation of the diagnostic system, monitoring of learners' academic achievement, and evaluation of the effectiveness of the developed model. The empirical study was conducted within the framework of design-based research and involved 620 participants enrolled in IBE physics courses at Riga Technical University between 2015 and 2021. The study integrated diagnostic assessment, learning analytics, statistical analysis, and learner feedback to evaluate the effectiveness of the developed pedagogical solution.

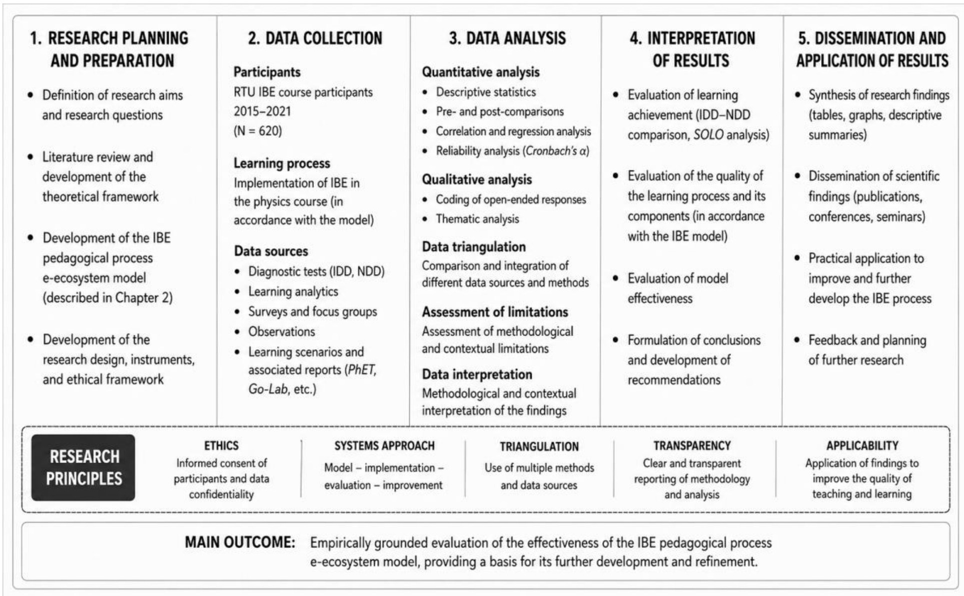

Fig. 9. Research design and evaluation framework of the IBE pedagogical process e-ecosystem model.

The research was organised as a multi-stage process comprising learner needs analysis, initial diagnostic assessment (IDD), implementation of the IBE learning process, continuous monitoring, final diagnostic assessment (NDD), and evaluation of learning outcomes. This design enabled the collection of both quantitative and qualitative evidence regarding the effectiveness of the developed model and its impact on learners' cognitive achievement.

A central component of the empirical study was the development and implementation of a diagnostic assessment system based on the integration of classical test theory, the SOLO taxonomy, and the revised Bloom taxonomy. Learners' performance was classified into three cognitive achievement levels: Level I – knowledge acquisition and understanding, Level II – application of knowledge and skills, and Level III – analysis and productive activity. This framework provided a practical instrument for monitoring cognitive development throughout the IBE process.

Table 3

Interpretation of Classical Test Theory (CTT), the SOLO Taxonomy, and Bloom's Taxonomy within the Intensive Bridging Education (IBE) Diagnostic Assessment System

Component	CTT (measurement)	SOLO level	Bloom's taxonomy level
Reproduction of knowledge	High difficulty not required; low discrimination	Unistructural	Remembering
Understanding of fundamental knowledge	Moderate difficulty; moderate discrimination	Multistructural	Understanding
Understanding of relationships	Optimal discrimination ($D > 0.40$)	Relational	Analysing
Higher-order thinking	High discrimination; greater difficulty	Extended abstract	Creating/evaluating

Note. *The table illustrates the integration of classical test theory (CTT), the SOLO taxonomy (Biggs & Collis, 1982), and the revised Bloom's taxonomy (Anderson & Krathwohl, 2001) within the diagnostic assessment framework developed for intensive bridging education (IBE).*

The developed diagnostic system enabled the identification of learners' initial level of preparedness, the monitoring of learning progress, and the evaluation of changes in cognitive achievement levels throughout the course. The integration of pedagogical and psychometric approaches provided an evidence-based foundation for personalised support and informed pedagogical decision-making. Analysis of the obtained results and comparison of learner performance dynamics between the initial diagnostic assessment (implemented in the proposed IBE model as the Initial Diagnostic Test, IDD) and the final diagnostic assessment (implemented in the proposed IBE model as the Final Diagnostic Test, NDD) indicate that the timely identification of learning difficulties significantly contributes to improvements in learner achievement.

Transition matrices and Sankey diagrams were employed to analyse learners' movement between cognitive achievement levels. Transition matrices provide a systematic representation of transitions between states (Chung, 1967) and have been successfully applied in educational research to examine learning progress using pre-test and post-test data (Morris et al., 2017).

The number of participants involved in the study was sufficient to support statistically valid and objective conclusions regarding learners' knowledge and skill levels, as well as to identify their strengths and weaknesses in the acquisition of physics content at the general secondary education level. Comparative analysis across multiple academic years, together with the evaluation of specific aspects of the curriculum, demonstrated a consistent improvement in learning achievement following participation in the intensive bridging education (IBE) course.

Although the results of the initial diagnostic assessment (IDD) and the final diagnostic assessment (NDD) varied slightly across academic years (for example, during the 2019/2020 academic year, the impact of the COVID-19 pandemic resulted in different transition dynamics from Cognitive Level I to Cognitive Level II, as well as a different proportion of learners remaining at Level II (see Table 4), no statistically significant differences were identified that would suggest substantially different outcomes across the years under investigation.

Table 4

Transitions Between Cognitive Achievement Levels Across Academic Years (IDD–NDD Comparison)

Achievement level transition	**2015/2016**	**2016/2017**	**2017/2018**	**2018/2019**	**2019/2020**	**2020/2021**
I → I	3.3	7.1	5.1	10.1	15.6	4.5
I → II	39.2	30.2	28.0	34.4	19.1	30.3
I → III	2.7	3.2	3.5	2.3	2.3	2.4
II → II	8.1	22.5	7.0	24.1	31.1	11.4
II → III	40.2	25.7	45.6	24.8	20.5	40.5
III → III	6.5	11.3	10.8	4.3	11.4	10.9

Note. *The table presents the percentage distribution of learners according to transitions between cognitive achievement levels from the initial diagnostic assessment (IDD) to the final diagnostic assessment (NDD) during the intensive bridging education (IBE) course for learners with available results in both assessments.*

The analysis of learning achievement revealed a substantial improvement between the initial diagnostic assessment (IDD) and the final diagnostic assessment (NDD). For instance, in the 2020/2021 academic year, the mean IDD score was 47.2 points, while the mean NDD score reached 75.4 points. Moreover, all learners who completed the final diagnostic assessment, providing evidence of considerable learning gains achieved during the intensive bridging education (IBE) course.

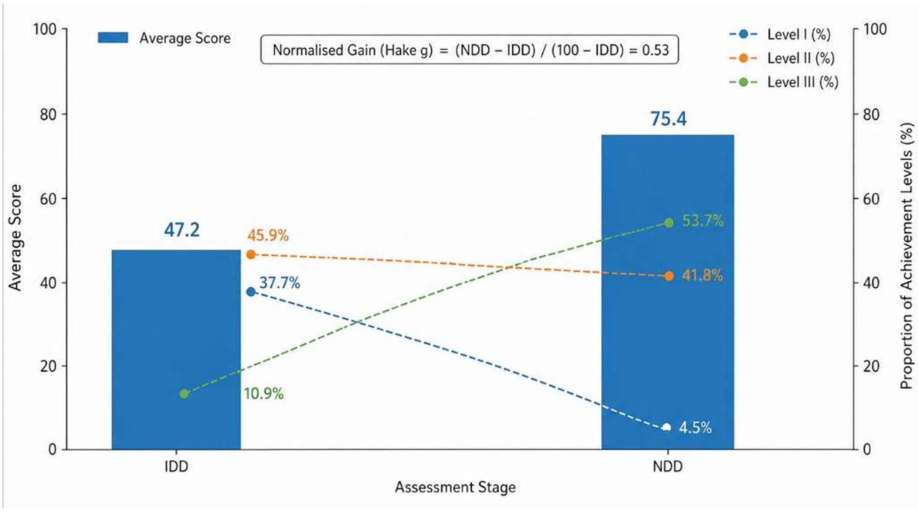

Fig. 10. Dynamics of IBE learning outcomes and cognitive progression (2020/2021 academic year).

Figure 10 illustrates both the quantitative growth in achievement and the qualitative progression across cognitive levels. To evaluate learning effectiveness, the normalised gain coefficient (Hake g) was calculated. The obtained value ($g = 0.53$) corresponds to a medium educational effect according to Hake's classification and indicates a pedagogically significant improvement in learners' achievement. The result confirms that the developed IBE pedagogical process contributes substantially to learners' academic development in physics.

While the increase in average scores is important, the most significant finding concerns the development of learners' cognitive performance. Before participating in the IBE course, the majority of learners were concentrated in Levels I and II, whereas after completing the course more than half of the participants achieved Level III performance. The proportion of learners at Level III increased from 10.9 % to 53.7 %, while the proportion at Level I decreased from 37.7 % to 4.5 %. These findings indicate substantial progression from knowledge reproduction towards analytical thinking and productive problem-solving.

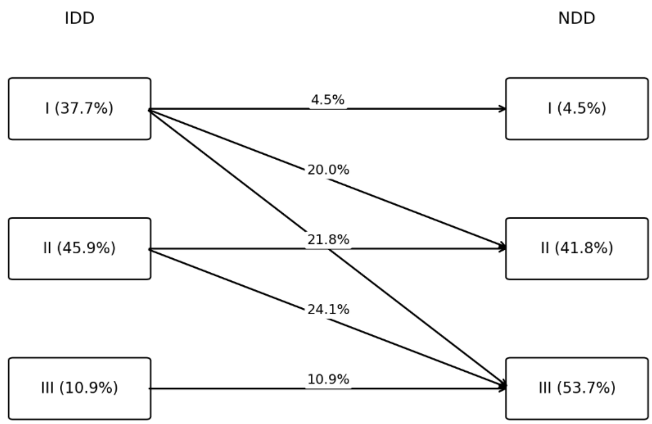

Fig. 11. Visualisation of cognitive progression transitions between IDD and NDD (2020/2021 academic year).

The transition matrix demonstrates the movement of learners between cognitive achievement levels during the learning process. Dominant transitions were observed from Level I to Level II and from Level II to Level III, while regression to lower levels was minimal. These results provide empirical evidence that the IBE model supports systematic progression towards higher-order cognitive skills.

To evaluate the long-term stability of the model, achievement data from six consecutive academic years were analysed. The results revealed consistent patterns across all cohorts. In every academic year, the proportion of learners achieving Level III increased substantially, whereas the proportion remaining at Level I decreased. These findings indicate that the observed effects are not limited to a single cohort but reflect stable characteristics of the developed pedagogical process.

The transition matrix illustrates learners' progression between cognitive performance levels throughout the learning process. The predominant transitions were observed from Level I to Level II and from Level II to Level III, while regression to lower levels was minimal. These findings provide empirical evidence that the intensive bridging education (IBE) model promotes systematic progression towards higher-order thinking skills.

The study developed an approach for the quantitative characterisation of learners' progression across cognitive performance levels through the use of transition matrices and learning analytics visualisations. In a general form, the identified relationships can be represented by a transition matrix that describes learners' movement between cognitive performance levels. The elements of the transition matrix were calculated as the relative frequency of learners transitioning from one achievement level to another.

This approach enables the quantitative analysis of learners' progression between cognitive performance levels and facilitates the comparison of progression patterns across different academic years (Puterman, 2014; Siemens & Baker, 2012; Romero & Ventura, 2020).

$$p_{ij} = \frac{n_{ij}}{\sum_{j=1}^{m} n_{ij}}$$

(p_{ij}) – the relative frequency of transitions from cognitive performance level *i* to cognitive performance level *j*;
(n_{ij}) – the number of learners who transitioned from level *i* to level *j*;
(m) – the total number of cognitive performance levels.

In this matrix, p_{ij} represents the relative proportion of learners who transition from cognitive performance level *i* to level *j*, for example, from knowledge reproduction to analytical thinking, in accordance with the hierarchical structure of the SOLO and Bloom's taxonomies (Biggs & Tang, 2011; Anderson & Krathwohl, 2001). This approach enables the quantitative analysis of learners' learning trajectories and the evaluation of the impact of the learning process on cognitive development (Romero & Ventura, 2020; Siemens & Baker, 2012).

Calculation example. In the 2020/2021 academic year, the proportion of learners who were classified at achievement Level I in the initial diagnostic assessment (IDD) and reached Level II in the final diagnostic assessment (NDD) was 30.3 %. The total proportion of learners at Level I in the initial diagnostic assessment was 37.2 % (I→I + I→II + I→III). Therefore, the transition probability from Level I to Level II was calculated as follows:

$$P_{I\to II} = \frac{30.3}{4.5 + 30.3 + 2.4} = \frac{30.3}{37.2} = 0.815$$

This indicates that 81.5 % of learners who were initially classified at achievement Level I progressed to Level II following completion of the intensive bridging education (IBE) course. The obtained result demonstrates a high transition rate from the lower to the intermediate achievement level and provides evidence that the IBE pedagogical process facilitates learners' progression from knowledge reproduction to the application of knowledge and skills.

From the perspective of the SOLO taxonomy, this transition represents movement from the unistructural to the multistructural level of understanding. Within the framework of Bloom's taxonomy, it corresponds to progression from remembering and understanding to applying knowledge (Biggs & Tang, 2011; Anderson & Krathwohl, 2001).

$$p_{II \to III} = \frac{40.5}{11.4 + 40.5} = 0.780$$

This indicates that 78.0 % of learners who were classified at Level II in the initial diagnostic assessment (IDD) progressed to Level III following completion of the course. The transition probability from Level II to Level III reached 78.0 %, demonstrating that the majority of learners who had already acquired the ability to apply knowledge and skills subsequently attained the highest achievement level, characterised by analysis and productive performance. This finding is particularly significant, as it reflects not only an increase in the volume of knowledge acquired but also a qualitative advancement in cognitive functioning.

As a result of the study, a metric was developed for the quantitative evaluation of learners' progression across cognitive performance levels. In a general form, the identified relationships can be represented by a transition matrix describing learners' movement between cognitive performance levels. In the ideal case, the matrix represents a situation in which all learners achieve the highest cognitive performance level (Level III). Conversely, in the case of an insufficiently effective learning process, the matrix demonstrates minimal or no progression between levels (see Fig. 12).

Ideal Matrix	Completely Ineffective Matrix
$\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \times \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} \mathrm{I} \\ \mathrm{II} \\ \mathrm{III} \end{bmatrix}$	$\begin{bmatrix} \mathrm{I} \\ \mathrm{II} \\ \mathrm{III} \end{bmatrix} \times \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} \mathrm{I} \\ \mathrm{II} \\ \mathrm{III} \end{bmatrix}$

Fig. 12. Theoretical achievement assessment matrices representing ideal and completely ineffective learning outcomes. *Source: Developed by the author.*

The transition matrix (Chung, 1967; Morris et al., 2017) serves as a conceptual and analytical instrument for evaluating the effectiveness of the intensive bridging education (IBE) pedagogical process, enabling the quantitative analysis of learners' cognitive development dynamics.

Learners' progression across achievement levels over successive academic years is presented in Fig. 13. The metric developed in this study enables the quantitative analysis of long-term trends in learners' academic achievement and provides a basis for evaluating the effectiveness of the pedagogical process. The figure summarises the results obtained over six academic years from the intensive bridging education courses in physics implemented at Riga Technical University (RTU).

Academic Year	Progression Between Cognitive Performance Levels
2015/2016 Academic Year	$\begin{bmatrix} 0.033 & 0 & 0 \\ 0.392 & 0.081 & 0 \\ 0.027 & 0.402 & 0.065 \end{bmatrix} \times \begin{bmatrix} 0.459 \\ 0.476 \\ 0.065 \end{bmatrix}$
2016/2017 Academic Year	$\begin{bmatrix} 0.071 & 0 & 0 \\ 0.302 & 0.225 & 0 \\ 0.032 & 0.257 & 0.113 \end{bmatrix} \times \begin{bmatrix} 0.404 \\ 0.483 \\ 0.113 \end{bmatrix}$
2017/2018 Academic Year	$\begin{bmatrix} 0.051 & 0 & 0 \\ 0.280 & 0.070 & 0 \\ 0.035 & 0.456 & 0.108 \end{bmatrix} \times \begin{bmatrix} 0.397 \\ 0.495 \\ 0.108 \end{bmatrix}$
2018/2019 Academic Year	$\begin{bmatrix} 0.101 & 0 & 0 \\ 0.344 & 0.241 & 0 \\ 0.023 & 0.248 & 0.043 \end{bmatrix} \times \begin{bmatrix} 0.463 \\ 0.494 \\ 0.043 \end{bmatrix}$
2019/2020 Academic Year	$\begin{bmatrix} 0.156 & 0 & 0 \\ 0.191 & 0.311 & 0 \\ 0.023 & 0.205 & 0.114 \end{bmatrix} \times \begin{bmatrix} 0.395 \\ 0.491 \\ 0.114 \end{bmatrix}$
2020/2021 Academic Year	$\begin{bmatrix} 0.045 & 0 & 0 \\ 0.303 & 0.114 & 0 \\ 0.024 & 0.405 & 0.109 \end{bmatrix} \times \begin{bmatrix} 0.393 \\ 0.498 \\ 0.109 \end{bmatrix}$

Fig. 13. Transition matrices of learner achievement levels across academic years in intensive bridging education.

The data summarised in Fig. 13 describe changes in learners' achievement levels and can be analysed using the transition matrix approach. The developed metric provides a means of quantitatively characterising learners' movement between cognitive performance levels (Levels I, II, and III) and evaluating the intensity of this progression as an indicator of the effectiveness of the intensive bridging education (IBE) pedagogical process.

A transition matrix is employed to analyse learners' transitions between achievement levels at different stages of the learning process. The figure combines quantitative changes in learner achievement with transitions between performance levels. The normalised gain coefficient (Hake's *g*) included in the figure characterises the effectiveness of the learning process by comparing the actual increase in achievement with the maximum possible increase attainable by a particular group of learners (Hake, 1998; Nissen et al., 2018).

As the study focuses on physics learning, the normalised gain coefficient (Hake's *g*) was used to characterise improvements in learning achievement. This measure is one of the most widely applied indicators of instructional effectiveness in physics education research and enables comparisons of achievement gains across different samples regardless of learners' initial level of knowledge (Hake, 1998). Compared with a simple difference between mean scores, this indicator provides a more objective assessment of the effectiveness of the learning process.

The calculated value of Hake's g indicates a pedagogically meaningful improvement in achievement within the analysed sample. The normalised gain coefficient (Hake's g) was calculated using the following formula (Hake, 1998):

$$g = \frac{\bar{X}_{NDD} - \bar{X}_{IDD}}{100 - \bar{X}_{IDD}}$$

where:

- g – normalised gain coefficient;
- $\bar{X}_{IDD}$ – mean initial diagnostic assessment score (%);
- $\bar{X}_{NDD}$ – mean final diagnostic assessment score (%);
- 100 – maximum possible score.

The normalised gain coefficient represents the achieved increase in learning outcomes relative to the maximum possible increase attainable within a particular group of learners and enables comparisons of instructional effectiveness across different samples regardless of their initial level of knowledge (Hake, 1998). For example, the following calculation was obtained using the 2020/2021 data:

$$g = \frac{75.4 - 47.2}{100 - 47.2} = \frac{28.2}{52.8} = 0.53$$

The calculated normalised gain coefficient was $g = 0.53$, which corresponds to a medium learning gain according to Hake's classification ($0.30 \leq g < 0.70$) (Hake, 1998).

To provide a more detailed analysis of changes in achievement levels, a visualisation based on the principles of transition matrices was employed. This approach enables the representation of learners' transitions between achievement Levels I, II, and III from the initial diagnostic assessment (IDD) to the final diagnostic assessment (NDD) and facilitates the identification of dominant learning trajectories.

To evaluate the long-term stability of the model, data collected over six academic years were analysed. The results revealed similar patterns across all samples. In each academic year, the proportion of learners attaining achievement Level III increased, while the proportion of learners at achievement Level I decreased. These findings indicate that the observed effects are neither random nor specific to a single cohort of learners; rather, they reflect stable characteristics of the developed pedagogical process.

Table 5

Distribution of Learners Across Cognitive Performance Levels in the Initial Diagnostic Assessment (IDD) and Final Diagnostic Assessment (NDD)

Academic year	IDD Level I (%)	IDD Level II (%)	IDD Level III (%)	NDD Level I (%)	NDD Level II (%)	NDD Level III (%)
2015/2016	45.2	46.1	6.5	3.3	41.7	54.0
2016/2017	40.4	46.0	11.3	7.1	54.2	38.7
2017/2018	38.6	47.4	10.8	5.1	38.4	56.1
2018/2019	45.4	47.4	4.3	10.1	58.9	31.0
2019/2020	35.5	49.1	11.4	15.6	52.5	31.9
2020/2021	37.7	45.9	10.9	4.5	41.8	53.7

Note. *Percentages may not sum to 100% because some learners did not complete all stages of assessment.*

The long-term analysis of the data confirms the sustainability of the observed achievement gains. Across all six academic years, a consistent progression towards higher cognitive performance levels was observed. The increase in the proportion of learners attaining Level III, together with the corresponding decrease in the proportion of learners at Level I, provides compelling evidence of the effectiveness and stability of the developed intensive bridging education (IBE) model.

To obtain a more detailed understanding of learners' learning trajectories, transition matrices and Sankey diagrams were employed. These analytical and visualisation techniques enabled the representation of transitions between achievement levels and facilitated the identification of dominant patterns of learner progression.

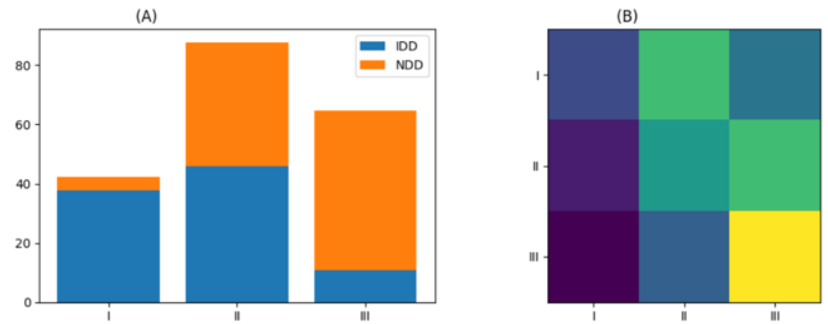

Fig. 14. Distribution of achievement levels and transition matrix for IBE physics courses (2015–2021).

Figure 14 demonstrates a consistent redistribution of learners from lower to higher achievement levels following participation in the IBE courses. The combined analysis of achievement distributions and transition matrices reveals both quantitative improvement and qualitative cognitive development. The majority of learners progressed from Levels I and II towards Level III, while regression remained negligible.

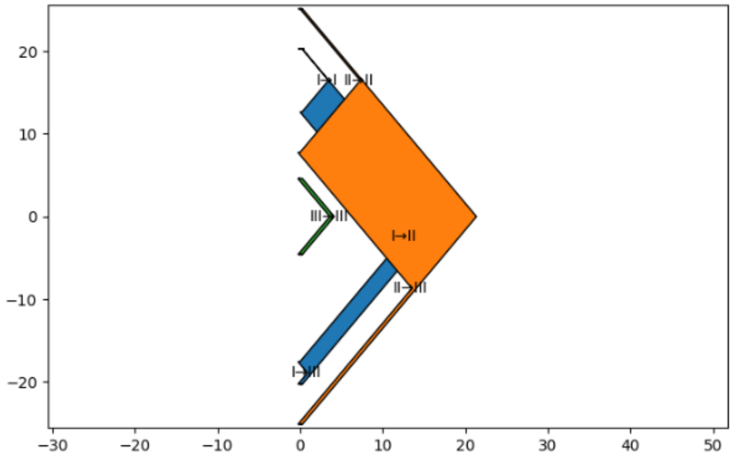

Fig. 15. Learner transitions between achievement levels (Sankey diagram).

The Sankey diagram provides a visual representation of learners' cognitive development trajectories (Askinadze et al., 2019; Oran et al., 2021). The dominant flows correspond to transitions from Level I to Level II and from Level II to Level III, confirming a structured and progressive learning process. The analysis further revealed that approximately 81.5 % of learners initially classified at Level I progressed to Level II, while approximately 78 % of learners at Level II advanced to Level III. These findings demonstrate that the IBE model effectively supports learners in moving towards higher-order cognitive functioning.

In addition to achievement monitoring, the study examined relationships between the use of digital learning technologies and learning outcomes. Correlation analysis revealed statistically significant positive relationships between the use of virtual laboratories, e-learning environments, and learners' self-reported achievement of learning objectives (r = 0.31–0.44, $p < 0.05$). Although the observed relationships do not imply causality, they indicate that active engagement with digital learning tools is associated with more positive learning experiences and outcomes.

The effectiveness of the IBE pedagogical process was also evaluated from the perspective of learner satisfaction and goal attainment. Since IBE participants represent a heterogeneous population with diverse educational backgrounds and learning objectives, the model emphasises learner-centredness, personalised learning pathways, and self-regulated learning. Evaluation of learner expectations and experiences demonstrated a strong correspondence between learners' identified needs and the educational opportunities provided by the model.

Table 6

Comparison of Learners' Identified Learning Conceptions and Their Realisation within the Intensive Bridging Education (IBE) Process. *Source: Compiled by the author based on the analysis of learner responses*

Most important learning conceptions prior to participation in the learning process	**%**	**Learning conceptions identified as most important during the IBE process**	**%**	**Realisation of learning conceptions within the learning process**	**%**
1. Personal growth	72 %	1. Acquisition of new knowledge	62 %	1. Personal growth	76 %
2. Acquisition of knowledge and skills for practical application	59 %	2. Personal growth	64 %	2. Acquisition of new knowledge	72 %
3. Transformation of received information into personal knowledge	47 %	3. Acquisition of knowledge and skills for practical application	56 %	3. Acquisition of knowledge and skills for practical application	61 %
4. Acquisition of new knowledge	49 %	4. Construction of personal knowledge	49 %	4. Transformation of practical experience into knowledge	53 %
5. Construction of personal knowledge	42 %	5. Transformation of received information into personal knowledge	48 %	5. Transformation of received information into personal knowledge	49 %

Note. *Respondents were allowed to select more than one learning conception. Therefore, the percentages within each column do not sum up to 100 %.*

The results indicate that the most highly valued learning concepts – including personal growth, acquisition of new knowledge, and practical application of knowledge and skills – were successfully realised within the learning process. The strong alignment between learners' expectations and their evaluation of the implemented learning experience provides additional evidence of the suitability and effectiveness of the developed pedagogical process.

Overall, the empirical findings demonstrate that the developed IBE pedagogical process e-ecosystem model effectively supports learners' cognitive development, promotes progression towards higher levels of achievement, and provides a sustainable framework for personalised learning in the transition from secondary to higher education. The integration of diagnostic assessment, learning analytics, digital technologies, and adaptive pedagogical support contributes to substantial and pedagogically significant improvements in learners' achievement and validates the applicability of the proposed model in authentic educational settings.

3. SUMMARY AND CONCLUSIONS

3.1. Summary of Findings and Validation of the Research Propositions

1. The analysis of the scientific literature demonstrates that, despite the widespread use of e-learning technologies in STEM education, no unified, theoretically and empirically grounded model has been identified that integrates pedagogical scenarios, digital technologies, learning analytics, and the assessment of learners' cognitive achievement within the context of intensive bridging education (IBE). This theoretical and methodological gap justifies the need for the development of an e-ecosystem model of the IBE pedagogical process.
2. Drawing upon the theoretical foundations of constructivism, connectivism, personalised learning, and learning analytics, an e-ecosystem model of the IBE pedagogical process was developed. The model integrates learners, educators, learning content, digital technologies, and learning analytics into a unified pedagogical system. The proposed model extends the theoretical understanding of the use of e-learning technologies in STEM education by conceptualising technology not as a collection of isolated instructional tools but as interconnected elements of a pedagogical process whose effectiveness depends on their integration within a coherent e-ecosystem.
3. **(Validation of Proposition 1).** The results of the empirical study confirm that the developed and pedagogically validated e-ecosystem model of the IBE pedagogical process provides an effective framework for the implementation of intensive bridging education in physics during the transition from secondary education to higher education. Within the empirical study involving 620 learners, the comparison of the available initial diagnostic assessment (IDD) and final diagnostic assessment (NDD) results demonstrates a systematic increase in learners' achievement across all analysed academic years, while the analysis of transition matrices and Sankey diagrams confirms a dominant progression from lower to higher cognitive performance levels. These findings indicate that the effectiveness of intensive bridging education is determined not only by the intensity of content delivery but also by systematic diagnostics, personalised feedback, and adaptive organisation of the learning process.
4. **(Validation of Proposition 2).** The diagnostic system and validated item bank developed during the study provide a means of diagnostic assessment of learners' knowledge, level of understanding, and depth of cognition. Of the 2400 tasks developed,

2006 were recognised as statistically valid and included in the diagnostic system. The diagnostic results were utilised for learning process planning, individualisation, and learner progress monitoring. The validation of the diagnostic system demonstrates that a statistically validated item bank structured according to cognitive performance levels provides a reliable foundation for personalised learning design, learner progress monitoring, and pedagogical decision-making.

5. **(Validation of Proposition 3).** The developed metric, grounded in the SOLO taxonomy, Bloom's taxonomy, and classical test theory, enables the assessment of learner achievement across three cognitive performance levels. The application of the metric facilitated the identification of progress in the use of physics concepts, relationships, symbols, and measurement units, the understanding of physical processes, the use of models, the interpretation of functional relationships, and inquiry-based activities. The proposed metric demonstrates the feasibility of integrating different approaches to learner assessment within a unified framework, thereby enabling multidimensional analysis of learning achievement and the evaluation of cognitive development over time.

6. **(Validation of Proposition 4).** Analysis of learning process data confirms that the effectiveness of the IBE pedagogical process is closely associated with the interaction between the learner and the learning environment. Particular importance is attributed to the identification of learners' needs, the alignment of learning content with educational objectives, the provision of personalised support, learner activity monitoring, and the adaptive adjustment of the learning process. The findings confirm that personalised learning constitutes a fundamental prerequisite for the effective teaching of heterogeneous learner groups during the transition from secondary to higher education.

7. Statistically significant positive relationships were identified between learners' self-assessment of learning objective attainment and participation in inquiry-based activities within virtual laboratories ($r = 0.44$, $p < 0.01$), engagement in e-learning environments ($r = 0.40$, $p < 0.01$), and the use of e-ecosystems ($r = 0.31$, $p = 0.02$). These findings indicate a positive relationship between the use of digital learning solutions and learners' perceptions of their learning outcomes. The identified relationships suggest that the effectiveness of digital technologies is determined not by their use per se, but by their purposeful and pedagogically grounded integration into the learning process.

8. Learners' evaluations of the organisation of the IBE process, the structure of the learning content, and the use of digital solutions indicate a high level of alignment with learners' needs. The structure, clarity, feedback mechanisms, and opportunities for

personalised learning were particularly positively evaluated. These favourable evaluations demonstrate the alignment of the developed model with the requirements of contemporary education and confirm its potential applicability within other STEM educational programmes.

9. The findings of the study lead to the conclusion that the e-ecosystem model of the IBE pedagogical process constitutes a theoretically and empirically grounded framework for organising intensive bridging education in physics. The model integrates a diagnostic-driven approach, personalised learning, digital technology integration, and learning analytics within a unified pedagogical system. The effectiveness of the model is evidenced by improvements in learner achievement, progression to higher cognitive performance levels, positive learner evaluations, and the results of long-term implementation and validation. Collectively, these findings confirm the suitability of the model for supporting learners during the transition from secondary education to higher education.

3.2. Answers to the Research Questions

In response to the first research question, it was concluded that the e-ecosystem of the pedagogical process for intensive bridging education (IBE) in physics constitutes a multi-component system integrating learner, content, pedagogical, and communication components. The developed model conceptualises the interactions among these components as a unified pedagogical system in which digital technologies, learning analytics, and personalised learning strategies support the achievement of educational objectives. The structure of the model and the relationships among its components are presented in the e-ecosystem model of the IBE pedagogical process and are empirically substantiated by the findings reported in Chapter 3.

In response to the second research question, it was established that the use of technology contributes to the effectiveness of the pedagogical process when it is pedagogically justified and purposefully integrated into learning activities. Statistically significant relationships were identified between the self-reported achievement of learning objectives and the use of virtual laboratories, e-learning environments, and other e-ecosystem elements. The findings demonstrate that the educational value of digital technologies is determined not by their mere presence, but by their systematic integration into pedagogically meaningful learning scenarios that support learner engagement, feedback, and self-regulated learning.

In response to the third research question, an e-ecosystem model of the IBE pedagogical process was developed, implemented, and empirically validated. The model integrates diagnostic assessment, personalised learning, digital technologies, and learning analytics within a unified pedagogical framework. The effectiveness of the model is evidenced by improvements in learners' achievement as measured through the initial diagnostic assessment (IDD) and the final diagnostic assessment (NDD), progression to higher cognitive performance levels, and the consistency of results observed across multiple academic years. The findings confirm that the proposed model provides a theoretically and empirically grounded framework for organising intensive bridging education in physics during the transition from secondary education to higher education.

LIST OF REFERENCES USED IN THE SUMMARY OF THE DOCTORAL THESIS

Anderson, L. W., & Krathwohl, D. R. (Eds.). (2001). A taxonomy for learning, teaching, and assessing: A revision of Bloom's taxonomy of educational objectives. Longman.

Askinadze, A., Liebeck, M., & Conrad, S. (2019). Using Venn, Sankey, and UpSet diagrams to visualize students' study progress based on exam combinations. In Proceedings of the Visualization in Learning Analytics Workshop (ViLA 2019). Heinrich Heine University Düsseldorf.

Barron, B., & Bell, P. (2015). Learning environments in and out of school. In R. K. Sawyer (Ed.), The Cambridge handbook of the learning sciences (2nd ed., pp. 495–516). Cambridge University Press.

Bickerstaff, S., Barragan, M., & Rucks-Ahidiana, Z. (2017). Experiences of earned success: Community college students' shifting thoughts about remedial education. Teachers College Record, 119(3), 1–44.

Biggs, J. B. (1999). Teaching for quality learning at university. Open University Press.

Biggs, J. B., & Collis, K. F. (1982). Evaluating the quality of learning: The SOLO taxonomy. Academic Press.

Biggs, J., & Tang, C. (2011). Teaching for quality learning at university (4th ed.). Open University Press.

Birziņa, R., & Cēdere, D. (2019). Students' preparedness for higher education in science subjects. Journal of Baltic Science Education, 18(2), 123–135.

Black, P., & Wiliam, D. (2009). Developing the theory of formative assessment. *Educational Assessment, Evaluation and Accountability,* 21(1), 5–31.

Bloom, B. S., Engelhart, M. D., Furst, E. J., Hill, W. H., & Krathwohl, D. R. (1956). Taxonomy of educational objectives: The classification of educational goals. Handbook I: Cognitive domain. David McKay.

Bridges, D. (2000). Back to the future: The higher education curriculum in the 21st century. Cambridge Journal of Education, 30(1), 37–55.

Briscoe, G., Sadedin, S., & De Wilde, P. (2011). Digital ecosystems: Evolving service-oriented architectures. Natural Computing, 10(3), 1143–1194.

Brockmann, M., Clarke, L., & Winch, C. (2008). Knowledge, skills, competence: European divergences in vocational education and training (VET) – The English, German and Dutch cases. Oxford Review of Education, 34(5), 547–567. https://doi.org/10.1080/03054980701782098

Broks, A. (2007). Ontodidactics within the development of modern natural science and technology education. In Proceedings of the 7th IOSTE Symposium for Central and Eastern Europe (pp. 26–30). Šiauliai University.

Carless, D., & Boud, D. (2018). The development of student feedback literacy: Enabling uptake of feedback. *Assessment & Evaluation in Higher Education,* 43 (8), 1315–1325.

Cābelis, A., & Juškaite, L. (2017). Tiešsaistes testi fizikā 12. klasei. Zvaigzne ABC.

Chung, K. L. (1967). Markov chains with stationary transition probabilities (2nd ed.). Springer-Verlag. https://doi.org/10.1007/978-3-642-62015-7

Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences (2nd ed.). Lawrence Erlbaum Associates.

Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). Sage.

Dawson, P., Yan, Z., Lipnevich, A., Tai, J., Boud, D., & Mahoney, P. (2024). Measuring what learners do in feedback: The feedback literacy behaviour scale. *Assessment & Evaluation in Higher Education,* 49(3), 348–362.

Embretson, S. E., & Reise, S. P. (2000). *Item Response Theory for Psychologists*. Lawrence Erlbaum Associates.

European Commission. (2021). Digital economy and society index (DESI) 2021: Latvia. https://digital-strategy.ec.europa.eu

Gorbunovs, A., Kapenieks, A., & Cakula, S. (2016). Self-discipline as a key indicator to improve learning outcomes in e-learning environment. Procedia - Social and Behavioral Sciences, 231, 256–262. https://doi.org/10.1016/j.sbspro.2016.09.100

Graham, C. R. (2013). Emerging practice and research in blended learning. In M. G. Moore (Ed.), Handbook of distance education (3rd ed., pp. 333–350). Routledge.

Hake, R. R. (1998). Interactive-engagement versus traditional methods: A six-thousand-student survey of mechanics test data for introductory physics courses. *American Journal of Physics, 66*(1), 64–74. https://doi.org/10.1119/1.18809

Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research,* 77(1), 81–112.

Hess, A. N. (2020). Modular learning design in STEM education: A systematic approach. Journal of STEM Education, 21 (3), 45–56.

Hodara, M. (2013). Improving students' college readiness: The role of remedial and developmental education. The Journal of Higher Education, 84(3), 324–350.

Hrastinski, S. (2019). What do we mean by blended learning? TechTrends, 63(5), 564–569.

ISTE. (2016). ISTE standards for students. International Society for Technology in Education. https://www.iste.org

Izglītības likums. (1998). https://likumi.lv

Jamaludin, R., McKay, E., & Ledger, S. (2020). *Are we ready for Education 4.0 within ASEAN higher education institutions? Thriving for knowledge, industry and humanity in a dynamic higher education ecosystem? Journal of Applied Research in Higher Education, 12*(5), 1161–1173.

Juškaite, L. (2018a). The gap between high school and university education in STEM subjects. In Abstracts of the 60th International Scientific Conference of Daugavpils University (pp. 130–131). Daugavpils University Academic Press "Saule".

Juškaite, L. (2018b). New challenges and opportunities for STEM education in the Latvian educational context. In Abstract book of the 2nd International Conference "Innovations and Creativity" (p. 24). Liepaja University.

Juškaite, L. (2019a). Analysis and comparison of national diagnostic paper-based and online tests. International Journal of Advanced Trends in Computer Science and Engineering, 8(1), 280–286. https://doi.org/10.30534/ijatcse/2019/4981.12019.

Juškaite, L. (2019b). The advantages of online testing in Latvian general education schools. In Proceedings of the 13th International Technology, Education and Development Conference (INTED2019) (pp. 3001–3008). IATED Academy. https://doi.org/10.21125/inted.2019.0791

Juškaite, L. (2019c). Data mining in education: Online testing in Latvian schools. In Proceedings of the 3rd International Baltic Symposium on Science and Technology Education (BalticSTE2019) (pp. 86–90). Scientia Socialis Press.

Juškaite, L., Ipatovs, A., & Kapenieks, A. (2019). Mobile technologies in physics education in Latvian secondary schools. *Periodicals of Engineering and Natural Sciences, 7*(1), 187–196.

Juškaite, L., & Cābelis, A. (2021). Tiešsaistes testi fizikā 10. klasei. Zvaigzne ABC.

Juškaite, L., Lebionkaitė, B., & Lebionka, J. (2023). E-learning technologies-based model for supporting bridge courses in physics. In *Proceedings of the 16th International Conference of Education, Research and Innovation (ICERI2023)* (pp. 4924–4931). IATED Academy. https://doi.org/10.21125/iceri.2023.1226

Juškaite, L., Šteinberga, A., & Kapenieks, A. (2020). Modern digital assessment systems & tools: The measurement of student ability & human factor exclusion. In INTED2020 Proceedings (pp. 4677–4683). IATED. https://doi.org/10.21125/inted.2020.1292

Kapenieks, A., Daugule, I., Kapenieks, K., Zagorskis, V., Kapenieks, J., Timsans, Z., & Vitolina, I. (2020). *TELECI Approach for e-Learning User Behavior Data Visualization and Learning Support Algorithm*. *Baltic Journal of Modern Computing, 8*(1), 129–142. https://doi.org/10.22364/BJMC.2020.8.1.06

Klafki, W. (1995). Neue Studien zur Bildungstheorie und Didaktik: Zeitgemäße Allgemeinbildung und kritisch-konstruktive Didaktik (5th ed.). Beltz.

Klafki, W. (2006). Didaktik und Bildungstheorie: Beiträge zur kritisch-konstruktiven Didaktik. Beltz.

Kraft, M. A. (2020). Interpreting effect sizes of education interventions. Educational Researcher, 49 (4), 241–253.

Lederman, N. G. (1999). Teachers' understanding of the nature of science. Journal of Research in Science Teaching, 36 (8), 916–929.

McKenney, S., & Reeves, T. C. (2019). *Conducting educational design research* (2nd ed.). Routledge. https://doi.org/10.4324/9781315105642

Ministru kabinets. (2017). *Pedagogu profesionālās darbības kvalitātes novērtēšanas organizēšanas kārtība* (Ministru kabineta noteikumi Nr. 501).

Ministru kabinets. (2018). *Noteikumi par valsts pamatizglītības standartu un pamatizglītības programmu paraugiem* (Ministru kabineta noteikumi Nr. 747).

Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. Teachers College Record, 108(6), 1017–1054

Morris, G. A., Walter, P. J., Skees, S., & Schwartz, S. (2017). Transition matrices: A tool to assess student learning and improve instruction. The Physics Teacher, 55(3), 166–169.

Mulder, M. (2020). Competence-based vocational and professional education: Bridging the worlds of work and education. Springer.

Nissen, J. M., Talbot, R. M., Thompson, A. N., & Van Dusen, B. (2018). A comparison of Hake's g and Cohen's d for analyzing gains on concept inventories. Physical Review Physics Education Research, 14(1), 010115.

OECD. (2019). OECD future of education and skills 2030. OECD Publishing.

OECD. (2020). Education at a glance 2020: OECD indicators. OECD Publishing.

OECD. (2022). Trends shaping education 2022. OECD Publishing. https://doi.org/10.1787/6ae8771a-en

OECD. (2023). Education at a glance 2023. OECD Publishing.

Oran, A., Martin, A., Klymkowsky, M., & Stubbs, R. (2021). Identifying students' progress and mobility patterns in higher education through open-source visualization. University of Colorado Boulder.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology,* 88(5), 879–903.

Puterman, M. L. (2014). Markov decision processes: Discrete stochastic dynamic programming. Wiley.

Razzouk, R., & Shute, V. (2015). What is design thinking and why is it important? Review of Educational Research, 85(3), 330–348. https://doi.org/10.3102/0034654315579467

Romero, C., & Ventura, S. (2020). Educational data mining and learning analytics: An updated survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10(3), e1355.

Royalty, A. (2021). Design thinking for educators: A practical guide. International Journal of Design Education, 15 (2), 45–60.

Schmidt, M. (2008). The Sankey diagram in energy and material flow management. Journal of Industrial Ecology, 12(1), 82–94.

Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Houghton Mifflin.

Siemens, G., & Baker, R. S. J. d. (2012). Learning analytics and educational data mining: Towards communication and collaboration. In Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (LAK ’12) (pp. 252–254). ACM.

Trinkūnienė, S., & Juskaite, L. (2021). COVID-19 and the digital transformation of education: The case of Latvia and Lithuania. *SOCIETY. INTEGRATION. EDUCATION. Proceedings of the International Scientific Conference, 5*, 221–231.

UNESCO. (2018). *UNESCO ICT competency framework for teachers: Version 3*. UNESCO.

Vaishnavi, V., & Kuechler, W. (2015). Design science research methods and patterns: Innovating information and communication technology (2nd ed.). CRC Press.

Vedins, I. (2008). Pedagoģijas pamati. RaKa.

Verhagen, P. (2006). Connectivism: A new learning theory? International Journal of Instructional Technology and Distance Learning, 3(11), 3–10.

Wagino, J., Suyanto, E., & Widodo, A. (2024). Development of data analysis and interpretation skills in digital learning environments. Journal of Science Education and Technology, 33(2), 210–225. https://doi.org/10.1007/s10956-024-10089-3

Watters, A. (2010). The role of technology in personalized learning. Educause Review, 45(4), 6–7.

World Economic Forum. (2019). Strategies for the new economy: Skills as the currency of the labour market. World Economic Forum.

World Economic Forum. (2023). The future of jobs report 2023. World Economic Forum. https://www.weforum.org/reports/the-future-of-jobs-report-2023

Wrigley, C., Straker, K., & Bucolo, S. (2018). Design thinking pedagogy: The educational design ladder. Innovations in Education and Teaching International, 55(3), 374–385.

Zoller, U. (2000). Teaching tomorrow’s college science courses. Journal of Research in Science Teaching, 37(2), 91–95.

Loreta Juškaite was born in 1964 in Molėtai, Lithuania. She obtained the qualifications of Physicist and Lecturer (1995), a Master's degree in Physics (1998), and the qualification of Secondary School Informatics Teacher (2005) from the University of Latvia.
She has been the Head of the Physics Teachers' Methodological Association of the Latgale District of Riga, Deputy Principal and Teacher of Physics and Informatics at the Riga Lithuanian Secondary School. She has participated in numerous national and international STEM education projects and is a co-author of several physics teaching and methodological resources designed for upper secondary education and for the transition from secondary to higher education. She has authored and co-authored a number of peer-reviewed scientific publications indexed in the Web of Science and Scopus databases.
Since 2021, she has been a member of the Advisory Board of the INTED (International Technology, Education and Development) Conference. Since 2011, she has been a Lecturer at Riga Technical University (RTU), where she also headed the RTU Preparatory Courses Division for more than ten years. She is currently a Lecturer at RTU and a Senior Expert and National Methodologist for General Education at the State Education Development Agency of Latvia.
Her research interests focus on the development and implementation of virtual laboratories, e-tools, and digital learning technologies in physics education.