12th Higher Education Institutions Conference

20 – 21 September, 2024

CHALLENGE OF LEARNING, TEACHING AND INNOVATION
– ARTIFICIAL INTELLIGENCE AND HIGHER EDUCATION

PROCEEDINGS

Double-Blind Peer Reviewed

Edited by: Karmela Aleksić-Maslać and Mateja Kovačić

ZSEM Zagreb School of Economics and Management

LSB Luxembourg School of Business

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Publisher MATE Ltd., Zagreb

For Publisher Vesna Njavro

Chief Editor PhD Mato Njavro

Editors Karmela Aleksić-Maslać and Mateja Kovačić

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Welcome Note

Dear guests and friends,

On behalf of Zagreb School of Economics and Management, Croatia's first AACSB accredited business school which is among the top 5 % best business schools in the world since, I'm proud to wish you all a warm welcome to our twelfth consecutive Higher Education Institutions Conference – HEIC 2024. This conference has been a beacon of inspiration for the academic community over the past eleven years, symbolizing excellence, educational trends, and growth. Our theme for this year, "Challenge of Learning, Teaching and Innovation – Artificial Intelligence and Higher Education," aims to delve into the transformative landscape shaped by emerging technologies and disruptive innovations.

Building on the success of HEIC2023, which set new standards for discourse within the educational industry, we aspire to continue fostering discussions on the latest trends. In the relentless pursuit of the future, HEIC2024 focuses on the rapid evolution of technologies and innovations that are not only reshaping the education sector but also the world at an unprecedented pace. As a pioneering force among Croatian higher education institutions, the Zagreb School of Economics and Management has been shaping future leaders for over two decades, navigating through challenges with resilience. It is imperative to equip students for the imminent changes ushered in by the latest technological advancements, particularly the dynamic landscape of artificial intelligence. Recognizing that the current developments in artificial intelligence are advancing at an astonishing rate, we acknowledge the necessity of integrating them into the realm of education. Despite the challenges, we believe that embracing these innovations is crucial for enhancing higher education standards. We, as members of the academic society, bear the responsibility of spearheading the development of artificial intelligence in our respective countries.

Our collective task is to collaborate, engage in meaningful discussions, learn from one another, and contribute to the improvement of higher education by seamlessly integrating artificial intelligence. Through sharing our experiences and knowledge, our goal is to showcase how higher education can harness the benefits of AI implementation, pioneering intelligent trends that will guide the next generations towards a brighter future.

To solidify the said, ZSEM has become a part of the European University alliance titled EUonAIR – The European University on AI in Curricula, Smart UniverCity and (Return)Mobility. EUonAIR is an ambitious alliance of 10 business and technical universities dedicated to creating a new responsible and collaborative AI model in education. This alliance aims to reshape learning, research, and working methods, aligning them with the current and future requirements of our educational systems and wider ecosystems. EUonAIR recognizes the transformative potential of Artificial Intelligence (AI) in addressing complex issues like mobility and migration.

The alliance is committed to leveraging AI responsibly and innovatively to develop inclusive, sustainable, and innovative solutions to some of the world's most pressing challenges. This proposal outlines a comprehensive vision and foundation for the next four years and beyond, positioning EUonAIR as a lighthouse European University Initiative (EUI) Alliance. The alliance aims to contribute significantly to the overarching goals of the European Universities Initiative call and the enhancement of both European society and its European Education and Research Area.

Our mission in the EUonAIR is to transform the educational system to successfully use and leverage the power of AI in education, research, and mobility for lasting and positive social change. The alliance is determined to elevate international collaboration and exchange at partner institutions, advancing the education, research, and mobility offer for students, faculty, staff, and communities.

Best regards,

Mato Njavro, PhD
Dean, Zagreb School of Economics
and Management

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KEYNOTE SPEAKERS / 2024

Mato Njavro, PhD

Zagreb School of Economics and Management

SOURCE:
https://zsem.hr/en/dr-sc-mato-njavro/

Dr. Mato Njavro serves as the Dean of Zagreb School of Economics and Management (ZSEM) in Croatia. He also teaches at the Luxembourg School of Business and the University of St. Gallen in Switzerland. With a diverse academic and professional background, Dr. Njavro has worked at the St. Gallen Institute of Management in Asia, in Singapore, where he served as a senior research fellow.

He was also a lecturer at the Singapore Management University, where he taught a course on China's economic development. Prior to joining the University of St. Gallen and Singapore Management University, Dr. Njavro was a visiting research fellow at Harvard University's Institute for Quantitative Social Sciences (IQSS). Dr. Njavroauthored and co-authored several papers and case studies published by the Harvard Business School publishing. Dr. Njavro has earned his bachelor's and master's degree in economics and finance from Bocconi University in Milan, Italy. He earned his PhD in finance from the University of St. Gallen in Switzerland. His professional experience includes working in the investment banking divisions of Lehman Brothers and Nomura in London.

Micael Dahlen, PhD

Stockholm School of Economics

SOURCE:
www.micaeldahlen.com

Micael Dahlen is a professor at the Stockholm School of Economics, in Economics and in Wellbeing, Welfare and Happiness (first professorship of its kind!). In his academic career, he rose rapidly to take up a leading position in the intersecting areas of consumer behavior, human happiness, welfare, marketing, and creativity. Dahlen is ranked number 2 in the world among researchers in his field (The Journal of Business Research, September 2021), and was nominated for the Business Professor of the Year Award by The Economist's Intelligence Unit. Professor Dahlen has written books on diverse topics such as marketing, happiness, serial killers (it's true), sex, the numbers that make us tick, long-term well-being and social media. His books are published in Europe, in Asia and in the United States. Micael is an internationally acclaimed speaker and has given keynote presentations in cities that include Istanbul, New York, Lisbon, and Shanghai, for clients such as Google, Ericsson, Samsung, Deloitte, Volkswagen, Fujitsu, and Oriflame.

Prof. Dr. Izabela Grabowska, PhD

Kozminski University

SOURCE:
www.izabelagrabowska.com

Izabela Grabowska is a sociologist and economist, holding the title of Full Professor of Social Sciences. She earned her PhD from the Department of Economics at the University of Warsaw, along with Master's Degrees in Economic Sciences from University College Dublin and in Sociology from the University of Wroclaw. In 2021, Professor Grabowska joined the Department of Economics at Kozminski University, where she founded the CRASH Center for Research on Social Change and Human Mobility and serves as its director. From 2016 to 2021, she led the Interdisciplinary Doctoral School at SWPS University, Warsaw. Her work for the Centre of Migration Research in Warsaw spanned from 2002 to 2019, and she remains an active member of its Scientific Board. Professor Grabowska has also contributed significantly to the IMISCOE network, serving on its Executive Board and Board of Directors from 2008 to 2019.

University of Cambridge

Assoc. Prof. Steven Watson

Steven Watson's research is transdisciplinary and focuses on practical and real issues in and around education, involving a level of abstraction to understand and explain these issues in a broader scientific context. Transdisciplinarity, the approach he employs, transcends traditional disciplinary boundaries. It integrates knowledge from various academic fields and non-academic sources, fostering collaboration among scholars, practitioners, and stakeholders to tackle complex, real-world problems. This holistic approach seeks to develop new frameworks and solutions that are comprehensive and applicable across diverse contexts. This holistic approach aligns with his background in engineering, teaching, and social sciences, as well as his interests in philosophy, sociology, and psychology, enabling him to create solutions that are applicable and relevant in varied settings. While a central focus of his research is generative AI, prof. Watson also researches educational and societal inclusion, political and cultural systems, the nature of learning, the history, sociology and philosophy of technology, from this holistic and transdisciplinary standpoint.

University of St.Gallen

Prof. Dr. Thomas Bieger

Prof. Thomas Bieger is the former President of the University of St.Gallen (2011-2020) a full-time Professor of Business Administration with a special emphasis on the tourist industry. During his time in office, the University of St.Gallen moved up from 16th to 4th place among the best European business schools in the international ranking of the "Financial Times". Bieger was committed to the idea of the university being more embedded in the region as a strong and consistent contributor to both the economy and communities, but he considered the university's further global expansion just as important. Bieger is a member of various boards of directors for companies such as Appenzeller Bahnen, Roland Berger International Consultants, Alpine Classic Hotels, and Migros Ostschweiz. He is married and a father of two children. Bieger is a passionate sailor and enjoys going on ski tours. His preferred way of getting around St.Gallen is by bicycle.

PANELISTS / 2024

PANEL 1

Introducing AI in HEIs – Ethical and implementation challenges

Moderator: **Ivan David Dogan**

Ivan David Dogan finished his major in philosophy at University of Zagreb, specialising in the field of philosophy of technology and management. He is an MBA candidate in Supply Chain Management at Zagreb School of Economics and Management (ZSEM). Ivan David is working as an assistant at ZSEM, under the Department for Management, Entrepreneurship and Digital Transformation. He delivers seminars and professional education on leveraging AI for productivity and innovation to the business community. His research activities are shifted towards sociological and managerial aspects of new technologies.

Zagreb School of Economics and Management

Panelists: **Prof. Dr. Michael Jaensch**

Prof. Dr. Michael Jaensch is a distinguished professor at HTW Berlin, specializing in European, corporate, international, and comparative law. He leads research and teaching in areas such as private law, commercial law, and civil law. Prof. Jaensch is also the chair of multiple examination committees across various programs, including Project Management and Data Science, Real Estate Management, and Business Law. His extensive research includes 20 projects, 112 publications, and 88 presentations. He is based at the Treskowallee campus in Berlin.

HTW Berlin

Panelists: Prof. Dr. Susanne Wilpers

Heilbronn University of Applied Sciences

Professor Susanne Wilpers has been teaching and researching human resource management at Heilbronn University since 2005. She is currently working on issues relating to the change in international human resource management in the context of opportunities offered by digitization. Before that, she was an HR manager at a multimedia agency and an HR developer at a company in the steel industry. As a doctor of personality psychology from the Humboldt University of Berlin (Advisor: Prof. Dr. Jens Asendorpf) and a keen traveler, she sets impulses in the internationalization of the faculty. Since March 2021 and February 2024, Prof. Dr. Wilpers has been an elected and reelected member of the advisory board of Heilbronn University. Since August 2021 Prof. Dr. Wilpers has been a tutor at the German Academic Scholarship Foundation.

Panelists: Adam Wierzbicki, PhD

Polish-Japanese Academy of Information Technology

Prof. Adam Wierzbicki is a Full Professor of Informatics; a researcher with interdisciplinary knowledge and experience in informatics, psychology, and sociology. He is employed at the Polish-Japanese Academy of Information Technology, where he is Vice-President, Head of the Ph.D programme (since 2010, this interdisciplinary program involved several hundred students), and leader of a research group in Social Informatics. His research interests lie in Social Informatics, an area of informatics that aims to design information systems and algorithms while taking into account their social and psychological impact, as well as the reciprocal impact of human behavior on information systems. Prof. Wierzbicki has been a pioneer of research on Web content credibility. In 2013-2016, he led the Reconcile project that researched methods of Web content credibility evaluation, pioneering research in this area before the term “fake news” was coined. He is the author of the monograph “Web Content Credibility” (Springer, 2018). Prof. Wierzbicki is the Steering Committee Chair of the International Conference on Social Informatics (SocInfo) and a Senior Member of ACM.

Panelists:

Boris Debić, MSc Physics.

Zagreb School of Economics and Management

Boris Debić, Google's Chief History Officer emeritus, is a renowned technologist who spent 15 years with the company from its earliest days through its most accelerated growth phase ($3B to $161B revenue/year, 3500 to 210k workforce). During his tenure at Google, he held several significant roles, including Release Engineering, G+Privacy, Global Infrastructure, Data Center Site Location, AI-Driven Decision Making, Ads Serving and Machine Learning Infrastructure, and Developer Relations. He collaborated with Google.org on the analysis and exchange of global climate modeling data sets and agricultural data to provide food security forecasts, and in providing access to education to Syrian refugees in Jordan and across the Arab world. Additionally, with support from NASA Ames, Debić directs Mars Society's NorCal Rover project. He is also a board member of several high-tech startup companies in both the US and Croatia, including Production.Pro, which was featured as a top three at Launch Fest in San Francisco. Before joining Google, he held positions in Silicon Valley startups, most notably E.piphany, the United Nations, the Croatian Ministry of Foreign Affairs, and the University of Zagreb. Boris Debić will participate this year in the prestigious IJCAI (International Joint Conference on Artificial Intelligence) 2024 conference.

PANEL 2

What we've learnd so far from the European Alliances

Moderator: **Dubravka Kovačević, PhD**

Zagreb School of Economics and Management

Dubravka Kovačević, Ph.D., joined the International Co-operation Office of ZŠEM. She received her doctorate in the field of the world economy – international business with a special focus on the European Union at the University of Economics in Bratislava where she also gained her master's after already having one in Marketing from the University of Zagreb, Faculty of Business and Economics. She knows the topics and institutions related to the European Union very well. She has significant teaching experience and experience in business administration in international relations. She worked for some time in the banking industry. Over the course of time spent at the ZSEM Dubravka has gained substantial experience in running/co-running several EU projects. Besides that, she teaches courses Business Communication and Business Communication-Applied Research Project. Due to her international experiences gained by living in the UK, Slovakia and Lebanon, Dubravka speaks English and Slovak fluently and has a good command of Czech, German, and Italian.

Panelists: Prof. Dr. Enita Nakaš

University of Sarajevo

Dr. Enita Nakaš is a highly accomplished Professor of Orthodontics at the University of Sarajevo's School of Dental Medicine, where she has been a faculty member since 2002. Over her career, she has held various leadership positions, including Vice-Rector for International Relations and Head of the Orthodontic Department. She earned her Ph.D. from the University of Sarajevo and completed specialized training at Harvard. Dr. Nakaš has been actively involved in numerous research projects and has published extensively. She also serves on editorial boards and organizes international scientific meetings.

Panelists: Prof. Dr. Izabela Grabowska

Kozminski University

SOURCE:
www.izabelagrabowska.com

Prof. Dr. Izabela Grabowska is a sociologist and economist, holding the title of Full Professor of Social Sciences. She earned her PhD from the Department of Economics at the University of Warsaw, along with Master's Degrees in Economic Sciences from University College Dublin and in Sociology from the University of Wroclaw. In 2021, Professor Grabowska joined the Department of Economics at Kozminski University, where she founded the CRASH Center for Research on Social Change and Human Mobility and serves as its director. From 2016 to 2021, she led the Interdisciplinary Doctoral School at SWPS University, Warsaw. Her work for the Centre of Migration Research in Warsaw spanned from 2002 to 2019, and she remains an active member of its Scientific Board. Professor Grabowska has also contributed significantly to the IMISCOE network, serving on its Executive Board and Board of Directors from 2008 to 2019.

Panelists: Nick Andersson

Nick Andersson serves as Senior Advisor to the Stockholm School of Economics, working closely with the President and Senior Faculty to conceive, develop, and implement strategic initiatives. His role extends to the House of Innovation, where he is involved in overall funding and supports strategic interactions for the Center for Family Enterprise and the Jacob and Marcus Wallenberg Center for Innovation and Sustainable Business Development.

Stockholm School of Economics

SOURCE:
https://www.hhs.se/en/research/research-houses/house-of-innovation/our-people-3/-/nick-andersson/

Panelists: Prof. Dr. Darko Lazarov

Dr. Darko Lazarov is an Associate Professor and Head of the Department of Economics at Goce Delchev University, North Macedonia. He earned his Ph.D. in Economics from Ss. Cyril and Methodius University, Skopje. With expertise in economic growth strategies, trade, and industrial policy, Dr. Lazarov has led numerous high-impact projects, focusing on regional economic development, export competitiveness, and industry analysis. He has also organized and participated in various international courses and seminars. He is the President of the IIBA in Skopje and actively contributes to economic research and policy development in the region.

Goce Delčev University Štip

Panelists: **Prof. Dr. Metka Tekavčič**

University of Ljubljana

Prof. Metka Tekavčič was named Dean of the Faculty of Economics, University of Ljubljana (FELU) in 2013. From 2001 to 2007 professor Tekavčič was Vice-Dean at the FELU. From 1999 to 2001 she was also the Head of the Academic Unit of Management and Organization. Her research interest lies in the fields of cost and performance management, as well as non-profit and especially education management. Prof. Tekavčič has attended many international conferences, where she has presented papers from her research areas. She has published several research articles in Slovene, other European, and US peer-reviewed journals. She is a member of editorial boards in several prominent journals from her research field. Prof. Tekavčič is president of the FELU's Senate and the Head of the Institute for Management and Organization. In 2014 she was awarded the Artemida award for Women's Excellence in Management. From 1992 to 2013 she was a member of the City Council of Ljubljana, Slovenia. She has long been and remains a member of the supervisory boards of many important Slovenian companies and other institutions. In 2016, Dean Tekavčič was appointed as a member of the EQUIS Accreditation Board, run by the European Foundation for Management Development (EFMD), the leading international network for management development. Since 2017, prof. Tekavčič has also served as a member of the AACSB International – The Association to Advance Collegiate Schools of Business (AACSB) Initial Accreditation Committee and a member of the European Advisory Council (EAC). In addition to her work, she is a vice-dean of Challenge: Future, a global youth and a global think-DO-tank.

PANEL 3

Strategic Challenge of Higher Education System

Moderator: **Mato Njavro, PhD**

Zagreb School of Economics and Management

SOURCE: https://zsem.hr/en/dr-sc-mato-njavro/

Dr. Mato Njavro serves as the Dean of Zagreb School of Economics and Management (ZSEM) in Croatia. He also teaches at the Luxembourg School of Business and the University of St. Gallen in Switzerland. With a diverse academic and professional background, Dr. Njavro has worked at the St. Gallen Institute of Management in Asia, in Singapore, where he served as a senior research fellow. He was also a lecturer at the Singapore Management University, where he taught a course on China's economic development. Prior to joining the University of St. Gallen and Singapore Management University, Dr. Njavro was a visiting research fellow at Harvard University's Institute for Quantitative Social Sciences (IQSS). Dr. Njavroauthored and co-authored several papers and case studies published by the Harvard Business School publishing. Dr. Njavro has earned his bachelor's and master's degree in economics and finance from Bocconi University in Milan, Italy. He earned his PhD in finance from the University of St. Gallen in Switzerland. His professional experience includes working in the investment banking divisions of Lehman Brothers and Nomura in London.

Panelists: **Prof. dr. hab. Grzegorz Mazurek**

Kozminski University

Professor Grzegorz Mazurek is a graduate of the Poznań University of Economics and Business (PUEB). During his time at the PUEB, he received a scholarship for two years of study at the University of Tilburg, one of the best European business schools. Among other things, Mazurek worked there as an Assistant and received his third master's degree (in Organization and Marketing). After returning to Poland in 2005, he defended his dissertation and obtained a doctoral degree from the SGH Warsaw School of Economics. The thesis concerned the adaptation of companies listed on the Warsaw Stock Exchange to the conditions of Poland's "new economy" after the country's transition from Communism. Prof. Mazurek has worked at Kozminski University since September 2005 in the Department of Marketing; first as Senior Assistant, then as Assistant Professor, Associate Professor, and since May 2020, as Full Professor. In 2017, he completed the development program at the IESE Business School in Barcelona.

Panelists: Assoc. Prof. Dr. Dalius Misiūnas

ISM University of Management and Economics

Associate Professor Dr. Dalius Misiūnas is the President of ISM University of Management and Economics in Lithuania. He has more than 10 years of experience in different business organizations – he has worked at SWECO, Ernst & Young, Lietuvos Energija, and Maxima Grupė. He also holds the positions of Independent member and chairman of the management board at Auga Group. Associate Professor Dr. D. Misiūnas has a Bachelor's degree from Kaunas University of Technology (KTU). Upon graduating, he studied at Lund University in Sweden, where he later obtained his PhD. Additionally, he has completed the Baltic Institute of Corporate Governance's Executive program for Professional Board members.ISM's President has also been involved in various educational activities as a member of the Council of Higher Education of Lithuania, as Chairman of the Council of KTU, and as a member of the Board at ISM. Associate Professor Dr. D. Misiūnas is a member of The Lithuanian University Rectors' Conference. In 2017, he was a Member of the Working Group on Network Optimisation of Public Higher Education Institutions, which was created by Lithuania's Ministry of Education, Science and Sports; currently, he advises the Government of the Republic of Lithuania on issues of planning the future of the state and its progress as a member of the governmental commission – State progress council, and he is also a member of the Advisory council to the Prime Minister of the Republic of Lithuania on economic revitalization and resilience enhancement. Associate Professor Dr. D. Misiūnas also conducts research at ISM University. He and his colleagues wrote a study titled „Designing business insolvency model and its application for assessing implications of COVID-19 in Lithuania".Associate Professor Dr. D. Misiūnas actively shares his knowledge with ISM's community. His teaching areas include leadership, strategy and business management. The President of ISM also shares his insights, expert opinion, and experience during some of the largest conferences in Lithuania, such as Login or EBIT.

Panelists: Marin Njavro

Luxembourg School of Business

Marin Njavro is the co-founder of Luxembourg School of Business, the first and leading business school in Luxembourg accredited by the Ministry of Higher Education and Research of Luxembourg. Marin is responsible for the School's overall strategy, operations, and relations with the School's main stakeholders. Marin, a graduate of Sciences Po Paris, has previously worked for Barclays Capital in London and the corporate law department of Loyens & Loeff in Luxembourg. A lifelong enthusiast about education and technology, Marin has also co-founded an Edtech startup 'Cogent' in 2022 with a mission to empower educators by helping them scale what they do using next-gen instructional materials.

Panelists: Prof. Dr. Ralf Dillerup

Heilbronn University of Applied Sciences

Dr. Ralf Dillerup is a distinguished professor and expert in business management and controlling. He currently serves as the head of the Institute for Strategy & Controlling at Heilbronn University and is also a professor of Financial Management in the European MBA program at the University of Louisville, Kentucky. Additionally, he is a guest lecturer at the St. Gallen Business School. Dr. Dillerup leads both the Steinbeis Transfer Center for Strategy & Controlling and the Controlling Dialogue initiative. His extensive professional experience includes senior roles in controlling at Robert Bosch GmbH, particularly within the Thermotechnology division, and roles in corporate planning, procurement, and logistics at Mercedes-Benz AG. Early in his career, he worked in production planning at ASB Greenworld Ltd. Academically, Dr. Dillerup earned his Ph.D. and served as a research associate at the University of Stuttgart, where he also taught. His teaching experience further extends to Stuttgart's Cooperative State University and the University of Wales, Swansea. He holds a degree in technically-oriented business administration from the University of Stuttgart.

Panelists: Swen Seebach, PhD

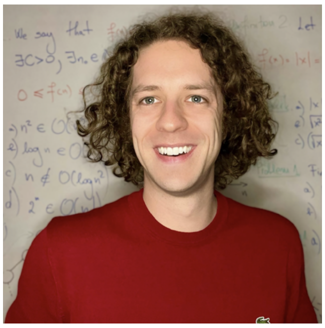
Abat Oliba CEU University

The scholar Swen Seebach (PhD) has achieved his Diplom (BA+MA) in Political Sciences from the University of Leipzig. He has studied as part of his ERASMUS at the University of Sussex. Seebach did his doctoral degree in the Study of the Information and Knowledge Society at the Open University of Catalonia (Internet Interdisciplinary Institute) in collaboration with the University of Halle and gained his International Doctoral Degree (excellent cum laude and with special honors in 2013). He achieved the Special Award for the best doctoral thesis of his year in 2014. In 2014 Seebach achieved a postdoc researcher position at the IN3. In 2014 and 2015 Seebach worked as a junior associate professor at the UAO CEU and the UOC. In 2015 he gained the Juan de la Cierva formación scholarship from the Spanish Ministry of Economy, Industry and Competition which allowed him to work as a researcher at the Autonomous University of Barcelona. Swen Seebach forms part of the research group PROTCIS (former GRECS). Seebach has been contracted as a researcher in two European Research projects in which he played the role of a field observer and mediator for interdisciplinarity. Seebach has published in various journals and books. He has published a book with the prestigious editorial Routledge. He has published two articles with JCR 1 Quartil, and 5 articles with JCR 3 Quartil. He has also published articles with Scopus and has various other publications of which some are with important scholars in the field of social research.

PANEL 4

Innovating with AI: The Next Frontier in Science & Research

Moderator: **Andrej Novak, PhD**



University of Vienna

Dr. Andrej Novak is a research fellow at the Faculty of Mathematics and Economy, University of Vienna, and a professor at the Faculty of Science, University of Zagreb. He holds a Master's and Ph.D. in Applied Mathematics, as well as a Medical Degree from the School of Medicine at the University of Zagreb, where he graduated with a thesis on cellular models in neuroscience. Dr. Novak's research focuses on applied mathematics and computer science, with a special interest in partial differential equations, optimization theory, medical image processing, and utilizing interpretable predictive analytics in managing heart pathologies. In his teaching career, he has overseen and coordinated more than ten university-level courses in mathematics, quantitative methods, and computer science at both undergraduate and graduate levels. He has contributed to developing curricula for several university computer science programs and has taught courses on quantitative methods at various institutions. Dr. Novak has participated in numerous national and international projects, serving both as a researcher and a member of management committees. He has been the principal investigator for scientific projects and has collaborated with international firms specializing in algorithmic solutions for imaging and computationally intensive problems. Dr. Novak is also an internationally acclaimed speaker, having delivered over 20 international talks in Europe and worldwide, including in the USA, Brazil, Taiwan, and Indonesia.

Panelists: **Alimshan Faizulayev, PhD**

KIMEP University

SOURCE:
https://www.kimep.kz/faculty/en/2022/10/05/alimshan-faizulayev-ph-d

Alimshan Faizulayev serves as Research Director and Associate Professor of Accounting and Finance at Bang College of Business, Kimep University. Faizulayev holds a Ph.D. in Finance from the Eastern Mediterranean University in Cyprus and is esteemed as a distinguished academic and researcher. He has authored or co-authored over 25 research papers, many of which are listed by ABDC (Australian Business Deans Council) and ABS (Association of Business Schools) rankings. Prior to his current role, Dr. Faizulayev worked as a Financial Analyst and Accountant at BGFS Capital in Cyprus. At Kimep University, he received both the Teaching Excellence Award for 2022-2023 and the Research Excellence Award for 2023-2024, underscoring his dedication to impactful education and research in finance. Before joining Kimep, he served as a Senior Lecturer at the Eastern Mediterranean University and as a Guest Lecturer at the American Hotel & Lodging Educational Institute in the USA. His professional experience includes roles as an Investment Advisor at the Dovec Group of Companies in Cyprus and as a Project Manager at Dogus Yol Tourism in Turkey. Dr. Faizulayev enriched his global perspective through the Erasmus Exchange Program at the Zagreb School of Economics and Management in Croatia, and he currently co-owns and directs research activities at the London Center for Development in the UK since April 2021.

Panelists: **Prof. Dr. Aleksandra Przegalińska**

Kozminski University

SOURCE:
https://www.kozminski.edu.pl/en/community/card/prof-aleksandra-przegalinska-skierkowska

Professor Aleksandra Przegalińska is a philosopher and researcher of new technologies development, especially green and sustainable technology, humanoid artificial intelligence, social robots, and wearable technologies. She received a Ph.D. in 2014 from the Institute of Philosophy at the University of Warsaw. She graduated from The New School for Social Research in New York, where she researched identities in virtual reality, with a particular focus on Second Life. Przegalińska-Skierkowska has on many occasions popularized her research and knowledge in international media such as The Atlantic, Frankfurter Allgemeine Zeitung, and Harvard Business Review.

Panelists: **Alberto Termine, PhD**

SUPSI

Dr. Alberto Termine is a researcher in the Department of Innovative Technology at the University of Applied Sciences and Arts of Southern Switzerland, and a member of the Dalle Molle Institute for Artificial Intelligence in Lugano, Switzerland. He also holds an appointment as an Adjunct Research Fellow within the Ethics of AI Chair at the IGEM, Munich University of Technology. Dr. Termine obtained his PhD at the Logic, Uncertainty, Computation and Information Lab in the Department of Philosophy at the University of Milan, with a thesis focused on Probabilistic Model Checking with Markov Models Semantics. His research spans a variety of technical and philosophical topics, including causal and counterfactual methods in explainable AI, probabilistic model checking for trustworthy AI systems, metaphysics and epistemology of machine learning, and the ethical and social dimensions of artificial intelligence.

Innovative Approaches in AI and Data-Driven Education

SESSION CHAIR:

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Imagining the Use of Artificial Intelligence at HEI: A Constructive Approach to the Integration of New Technologies into Teaching, Management and Research

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Abstract

Whilst AI is perceived by some as potential risk to higher education, others see it as a set of powerful tools with the potential to enhance classroom teaching, students' independent work, research and administration tasks [1] that will reshape the higher education landscape and future professions inside and outside the HEI sector. This potential can only be realized if AI is integrated with a clear and critical strategy that adapts to the different needs of different HEIs' stakeholders and promotes a AI media literacy, that builds bridges between them. This paper will show that it is especially crucial to understand how people within HEI, perceive and imagine AI. Perceptions, or better to say imaginaries of AI, frame and shape the current and future reality of AI and its uses. A small sample study in a private HEI in Barcelona based on the analysis of 4 focus groups discussions (2 Teaching staff, 2 students) points at the differences between AI imaginaries of different stakeholders in HEI and consequent challenges when dealing with them inside and outside the classroom. The paper closes with a suggestion of different fields for strategic actions so that HEI continue to be leaders for the potential replies to the changes and opportunities resulting from AI.

Keywords: *Higher Education Institutions, Media Imaginaries, Artificial Intelligence, AI, Future of AI, Media Literacy.*

1. Introduction

Higher Education Institutions (HEIs) are deeply committed to academic excellence, the holistic development of its students, and educational innovation. In this context, Artificial Intelligence (AI) presents both a significant challenge and an opportunity [2]. Rather than a single technology, AI is a conceptual umbrella that encompasses a variety of technologies designed to replicate or surpass human processes that are typically considered hallmarks of human intelligence [3].

Initially, AI was associated with tasks such as language recognition, automated translation, decision-making, and problem-solving. However, the term has since evolved into a collective descriptor for technologies that enable machines to automate, either partially or fully, all kind of processes traditionally carried out by humans.

Without doubt, technological advancement is inevitable and consequent changes will be integrated into society, whether or not we take the initiative to guide potential uses. Some view AI as a potential disruptor to higher education, while others see it as a powerful tool with the potential to enhance classroom teaching, students' independent work and to reshape teaching and administration [1]. In the last decades universities have increasingly changed their role in society, from being centers of pure knowledge refinement to institutions focusing on preparing students for being future professionals. The capabilities of machines to create, write, and distribute written, spoken, and visual narratives have reshaped all kinds of professions. Knowledge, skills and competencies (KSC) for a meaningful usage of AI is going to be essential to all kinds of different professions, and are therefore a relevant dimension to the preparation of students for their future workplaces. However, AIs' potential for HEI and its stakeholders can only be realized if AIs are integrated with a clear and critical strategy. Recent developments of AI tools have sparked debates and concerns about their potential consequences within HEIs. We believe within this debate it is especially crucial to understand how different stakeholders involved in HEIs, perceive and imagine AI—what AI is currently doing, might do, and will do in the future. Perceptions, or better to say imaginaries of AI, frame and shape AI's current and future reality [4]–[5], the potential strategies of dealing with AI [6] and the potential communities created along with AI [7]-[9]. If AI is to be central in the professions of the future, universities must engage with AI actively to remain relevant to all their stakeholders. It must also understand what different stakeholders imagine AI is doing and will do in the future and communicate meaningfully and critically with these different imaginaries. In order to benefit and lead the changes resulting from AI, it is essential for educators and HEI to move beyond certain preconceived notions about these technologies, to overcome hurdles and obstacles of technologies from the past and to understand and deal with AI imaginaries of all kind of different stakeholders and so to explore their full potential.

A part of the current debate around AI mirrors the discussions Umberto Eco described as those between the "apocalyptic and integrated" [10] and parallels the anxieties that accompanied the birth of mass media and later of digital media. Historically, the advent of mass media prompted concerns about its effects on work, education, sociability, and creativity [11]-[12]. This concerns were raised mainly because new infrastructures introduced social change and contributed so to the reorganization of social structures. Similarly, the rise of digitalization led to fears about the future of education and a possible decline of culture. Scholars like Manuel Castells [13], as well as Anderson, Bell, and Shirky [14], have effectively argued against these pessimistic views and thereby helped to establish digitalization at the core of education. Drawing on Walter Benjamin's [15] insights from the early 20th century, HEI are once again called upon to equip stakeholders with the knowledge, skills and competencies necessary to become the masters of AI, as powerful means of production. This involves understanding potential uses but also fostering a critical media literacy that empowers individuals to navigate and utilize these technologies responsibly. In order to be able to engage successfully in the promotion of media literacy for different stakeholders it is essential to engage with and connect their imaginaries of these infrastructures and to truly built (imagined) communities of AI.

2. Context of Changes with AI and Its Influence on the Academic Sphere

The revolution of artificial intelligence (AI) is rapidly transforming sectors and dimensions of society [16], including higher education, presenting both significant opportunities and formidable challenges. The integration of AI into academic environments offers the potential to revolutionize pedagogical approaches, streamline administrative processes, and enhance professional and research capabilities of teaching staff and of students as future professionals, opening a pathway to a future where education could become more efficient and return to lead the construction of communities and imagined futures. However, advancements also introduce new complexities that require careful consideration and an ethical approach to ensure that AI infrastructures serve as an enriching tool rather than a source of inequity or depersonalization.

It is to expect that AI will influence HEI learning experiences. Adaptive learning tools leverage algorithms to customize educational content according to each student's needs and progress, image AIs can contribute to a better visualization of ideas and concepts, text-based AIs can help in revising and improving texts or provide narratives for meaningful conversations. While AIs different uses can help to deepen knowledge and enhance student outcomes, it also raises concerns about uneven learning standards and ethical consequences. Disparities, although beneficial in some contexts, may present challenges that need to be addressed to maintain educational equity.

AIs can also offer customized tutoring by responding to frequently asked questions and providing additional explanations, thereby freeing up educators to focus on more critical aspects of the educational process. However, this could further undermine the personal connection of students and teachers that is essential for effective teaching and learning. It might also lead to a stronger dependency of students on AI technologies rather than personal advice, especially when educators over-delegate relevant tasks. AIs have also the potential to greatly reduce the workload associated with routine tasks such as grading and management. By automating these functions, AI allows educators to dedicate more time to direct student interaction and activities requiring human critical judgment. However, in an increasingly bureaucratic educational environment, time saved by AI easily can lead to increased management responsibilities for staff, additional other administrative tasks, or new not yet imaginable tasks that rather than decrease accelerate the work of educators and students, a phenomenon described as social acceleration by Hartmut Rosa [17]. The balance between automation and human oversight is as crucial for a smooth integration of AI as a careful analysis of tasks carried out by teaching staff and a critical engagement with potential overestimation of AIs capabilities.

The integration of AI underscores the need for the development of critical and ethical thinking among students. While AI facilitates unprecedented access to information, it also necessitates a robust framework for evaluating the accuracy and reliability of AI-generated content. To prepare students for a future where technology and ethical decision-making are closely intertwined, it is essential to incorporate courses on AI ethics and digital competencies into the curriculum. This training is vital for developing professionals who can navigate the complexities of an advanced technological environment while upholding high standards of academic integrity.

Finally, AI's impact on research is profound, offering tools that can assist in information retrieval, data analysis, and review processes. However, there is a significant risk of over-reliance on AI, which could lead to unnoticed biases, a loss of originality, and a diminishment of the critical thinking that is essential for scholarly work. This concern is particularly relevant when dealing with students (e.g. in their Bachelor's theses) and their temptation to delegate too much of the research process to AI which could undermine the value of the thesis experience.

While AI holds great promise for transforming higher education, its integration must be approached with a nuanced understanding of both its potential benefits and its challenges and the understanding of both by different stakeholders in HEIs. By fostering an environment that emphasizes ethical use, critical thinking, and the responsible application of AI, HEIs can harness the power of AI to enrich the educational experience while safeguarding the core values of learning and scholarship but only if they understand their stakeholders' imaginaries of AI's capabilities, risks and potentials.

3. A small empirical prelude to AI and AI imaginaries

To explore imaginaries and perceptions of AI, I conducted a small-scale, qualitative empirical study at a private HEI in Spain. Although the study's scope is limited and its findings cannot be broadly generalized, it offers valuable insights into the potential challenges and opportunities AI presents in the academic environment. The study consisted of 4 focus groups discussions, which were directed by a set of questions. Focus groups are excellent means to explore new fields of study and to compare the narratives of different collectives about the same topic. The study involved four focus groups: two with students (one composed of first-year students and the other of final-year students in a Communication Studies Bachelor's program) and two with teaching staff from the same institution. The teaching staff focus groups were diverse, including professors from various disciplines, at different stages of their academic careers, and of varying ages. The idea of the focus group discussions was to understand underling conceptions and perceptions when discussing AIs and to understand better what different stakeholders imagine AI can and will. By exploring these imaginaries of AI, I hoped to understand also what myths and narratives imaginaries of AI were building upon and to identify potential similarities and differences. The results revealed a significant divergence in the imaginaries of AI between students and teaching staff.

3.1. Teaching Staff Imaginaries

Among the teaching staff, AI was predominantly perceived as a risk. Often AI imaginaries drew on existing cultural narratives (from films, series, academic and non-academic literature) about the threatening effects of technology and on preconceived ideas from other media introduced into HEI. One professor expressed concern that "like social media, AI reduce the depth of critical thinking in students, making education more about speed and easy replies rather than intellectual thought and exploration." Another voiced the fear that "we might end up with a generation of students who rely on AI for answers rather than developing their own analytical skills." To which many agreed verbally and non-verbally. This resulted in both focus groups in a debate about the ideological consequences of prefiltered knowledge and prewritten scripts. A professor expressed concern about the future of education, "if students consult AIs for answers rather than to search for themselves." In relation a concern about job security surfaced, with several faculty members noting, "If AI takes over certain teaching tasks, what will happen to the value of human educators? What can we bring to the table?" Nevertheless, participants insisted also in the opportunities of AI, potentially speeding up of substituting the performance of unnecessary task, reducing bureaucracy and fostering an education culture that allows educators to return to the most relevant deal: critical empowering knowledge transfer.

3.2. Student Imaginaries

Within our focus group discussions students generally viewed AI as an opportunity. Imaginaries drew usually on already existing everyday uses and experimentation with AI and related technologies. One first-year student shared their excitement, saying, "AI could make learning more about what is relevant to me and more engaging, allowing me to be more creative." In the other focus group a final-year student echoed this sentiment, adding, "With AI, I can focus on the more innovative aspects of my projects, letting the technology handle the repetitive tasks." However, there are also concerns about originality, as one student pointed out, "I worry that using AI might make my work less authentic or unique, even if it helps me generate ideas faster." Another student expressed apprehension about the future job market: "AI could change the potential areas for work. It might create new opportunities, but it might also mean fewer jobs are available." None of the students of the first year was concerned about AI's influence in perceptions and potential uncritical usage. However, some of the last year students referred to the importance of a critical use and remembered "a university class where we have discussed potential risks". This demonstrates the importance and the influence of HEI in learning about critical media literacy.

The divergent imaginaries reflect the broader tensions surrounding AI in HEIs. While teaching staff are more focused on the potential risks and disruptions AI might bring, students are generally more optimistic, viewing AI as a tool that can enhance their learning experience. Both groups draw on different resources that nourish their AI imaginaries. Whilst teachers build their imaginaries on the concerns of existing technological challenges and orient their views to the past, students focus on the opportunities of the future. It this sense student approach technologies from a similar viewpoint as other stakeholders that rather than employing a critical view look for opportunities in infrastructural change. This contrast highlights also the need for ongoing dialogue and collaboration between educators and students as AI continues to shape the future of higher education. It invites HEIs also to think about imaginaries of other stakeholders such as (future) employers or administrative staff.

4. Challenges

From the empirical work we deduce the forthcoming challenges that AI brings to the HEI that require careful attention and strategic responses. One of the foremost challenges is that HEI have to deal with a lack of tools for the critical use of AI. While AI technologies are rapidly advancing, there is a noticeable gap in the availability of educational tools and frameworks that help both educators and students critically assess the outputs generated by AI. This lack of critical tools can lead to a superficial engagement with AI technologies, where users may accept AI-generated information at face value without questioning its validity, its profundity or its ethical implications. Developing and implementing educational resources that promote critical thinking and ethical awareness in AI, that question expectations and imaginaries and that ensure that these technologies are used responsibly and effectively is needed. Educational resources and their implementation must allow stakeholders to connect and contrast their imaginaries of AI to those of others and actively create dialogues between them.

A similar challenge is the wrong estimation of AI's capabilities, which can lead to unrealistic expectations and reliance on these technologies beyond their current limitations. Involved stakeholders risk to falsely estimate the potential impact of AI. Wrong estimation can result in a dependency on AI for tasks that still require human judgment, such as complex decision-making or nuanced interpretation. When AI is expected to perform at levels beyond its actual capabilities, it can lead to errors, misjudgments, and a general mistrust in the technology. When AIs are judged as too influential and to risky, it might lead to a rejection of AI use in and outside the classroom, which can make HEI lose their role and credibility in leading technological change and in teaching the uses of and critical reflections about AI. Therefore, it is crucial for educational institutions to foster a balanced understanding of AI's strengths and limitations, ensuring that it is seen as a complementary tool rather than a complete replacement for human expertise, that challenges but also adds to the development of future processes. The dialogue between different imaginaries of teachers and students can help to limit respective debilities of the other.

Invisible biases within AI systems also pose a significant challenge, especially when not approached. AI algorithms are often trained on large datasets that may contain implicit biases, leading to outcomes that reflect and even perpetuate existing social inequalities. These biases can manifest in various ways, from skewed search results to unfair judgements, which can undermine the objectivity and fairness that educational institutions strive to uphold and that we need as a society. Addressing these invisible biases requires a concerted effort to ensure that AI systems are developed and implemented with a strong emphasis on fairness, transparency, and accountability. This includes ongoing monitoring and refinement of AI tools to minimize bias. HEI have to overtake a leading role in opening especially the minds of students (but also teaching and administrative staff and employers) for such potential risks, especially when they are not aware.

We already discussed that AI has the potential to reduce workloads by automating routine tasks, and it can lead to an increased workload, e.g. because institutions seek to cut costs by automating functions traditionally performed by human workers. While this may lead to short-term financial savings, it can also have long-term negative impacts on the quality of education

ISSN 2991-9371

and the well-being of remaining staff. The reduction of teams can lead to a loss of institutional knowledge and to an increase of work, especially of complex tasks in the long run. It is important for educational institutions to strike a balance between leveraging AI for efficiency and maintaining a robust, well-supported administrative workforce that can provide the personal touch and institutional continuity that technology cannot replicate. HEI should therefore revise critically their own imaginaries of AIs potential capabilities and risks. From our small study, we have seen that the concerns about those changes in the workplace are partially shared by students and teaching staff, which turns it into a good starting point for the creation of a productive debate.

The delegation of research tasks to AI tools, while offering efficiency, presents another significant challenge, particularly in the realm of academic rigor. AI can assist with data collection, analysis, and even writing, but overreliance on these tools can lead to a decline in critical thinking among students and researchers. When AI is used to generate content or guide research without sufficient human oversight, there is a risk that the work produced will lack the depth, originality, and critical insight that are hallmarks of quality academic research. To address this challenge, educational institutions must emphasize the importance of maintaining human oversight in the research process, ensuring that AIs serve as tools to enhance rather than replace human creativity and critical thought. This is especially important when engaging with students who lack awareness of the relevance of checking on AIs influence on reality through research.

Finally, the potential loss of originality is a significant concern as AI becomes more integrated into academic work. AI systems, by their nature, are designed to identify patterns and replicate existing data, which can result in outputs that are derivative rather than innovative. This reliance on AI-generated content risks stifling originality, as students and researchers may become more inclined to produce work that aligns with existing norms rather than pushing the boundaries of knowledge. To combat this, educators must create with students and other stakeholders a culture of innovation and originality, where AI is used to inspire and support creative endeavors rather than replace them. By fostering an environment that values original thought and critical engagement with AI, educational institutions can ensure that their graduates are prepared to contribute meaningfully to their fields in a way that is uniquely human.

5. HEI's responsibilities in the face of AI

In order to lead the teaching of KSC and potential uses and the discussion of ethical challenges of AI, higher education institutions (HEIs) must prioritize the protection of their own integrity in the face of rapid technological advancements but it must also turn towards AI media literacy as a part of their core strategy and integrate different stakeholders and their imaginaries in the process. Whilst it is important that AI uses do not affect HEIs' main values and compromise the quality of education or the institution's mission, including maintaining rigorous academic standards, preserving the autonomy of educational processes, and ensuring that the deployment of AI aligns with the institution's long-term goals and values, HEI must also establish robust governance structures, continuous oversight, and a flagship leadership vision, that allows HEIs to navigate the complexities of AI integration while upholding their institutional integrity and continuing to serve as pillars of knowledge and innovation.

The advancement of AI proposes new challenges and opportunities for research within HEIs. In the context of change, the personalization, quality, originality and critical engagement of academic work becomes increasingly important as AI tools are used to assist in everything from data analysis to teaching, to academic writing processes. HEI must enforce strict standards to prevent the over-delegation of tasks to AI, which can lead to a dilution of academic rigor and a loss of originality. They must also create meaningful debates about AIs between all stakeholders. Students, researchers but also employers should be encouraged to critically engage with AI tools, using them to enhance rather than replace their work and their productive contributions. By fostering an academic environment that emphasizes creativity, critical thinking, and ethical standards, HEIs can ensure that the research produced under their auspices remains of high quality and contributes meaningfully to the broader body of knowledge.

AI media literacy does not end with students it brings significant implications for faculty and staff. It is essential that institutions provide ongoing training and professional development to ensure that their staff are equipped to use AI responsibly and effectively. This includes not only technical training on how to use AI tools but also education on the ethical considerations and potential impacts of AI on teaching, research, and administration. Supporting staff in this way will help mitigate the risks of increased workloads and the potential depersonalization of student interactions. By investing in their faculty and staff, HEIs can create a culture of continuous learning and adaptation, ensuring that their educational offerings remain relevant and their academic community remains vibrant in an increasingly AI-driven world.

6. Strategic Actions for Effective Integration of AI and AI Imaginaries

As Artificial Intelligence (AI) becomes increasingly integrated into educational environments, it is crucial for Higher Education Institutions (HEIs) to approach its use in with careful planning and strategic actions. This section outlines various measures that can be taken to ensure that AI serves as a tool for enhancing, rather than undermining, the educational experience. The focus is on leveraging AI to support teaching and learning, while maintaining the essential human elements that are central to effective education and to align different AI imaginaries and the imagined communities resulting from them.

6.1. Teaching Assistance, Not Substitution

AI offers the potential to provide personalized tutoring, responding to students' frequent questions and offering additional explanations tailored to their needs. However, it is essential that the primary responsibility for tutoring, as well as emotional and academic support, remains with human teachers. AI should be viewed as a complement to traditional teaching methods, not a replacement. Teachers must continue to guide the educational journey, using AI tools to enhance their ability to address individual student needs while maintaining the personal connection that is vital for effective learning. Automated grading can save time, particularly for preliminary and low-risk tasks such as multiple-choice quizzes or initial drafts of assignments. However, to preserve academic integrity and human critical judgment, final assessments and qualitative feedback should always involve direct teacher involvement. Teachers must validate AI-generated grades, ensuring that the assessments are fair, accurate, and aligned with the course's learning objectives.

6.2. Adaptive Learning Platforms

Adaptive learning platforms that tailor educational content to individual students based on their progress and performance offer the promise of highly personalized education. However, it is crucial that these systems are transparent and auditable to ensure they do not perpetuate biases or limit access to diverse perspectives. Imaginaries about AIs capacities might overestimate real potentials. Educational institutions must implement ethical oversight mechanisms to regularly review and refine these platforms, ensuring they respect the diversity of students and provide equitable learning opportunities for everyone. AI systems can recommend study materials or suggest learning paths but these recommendations should complement, not replace, the academic guidance provided by teachers. HEI should bring together teaching staff with AI developers to ensure that the algorithms driving these recommendations are aligned with pedagogical goals and are informed by the latest educational research. This would further strengthen the role of HEIs as centers of debate and of uniting and leading imagined communities in times of AI.

6.3. Active Teaching of AI

To prepare students for a future where AI plays a central role in many professions, HEIs should actively integrate AI into their curricula. This includes not only teaching the knowledge, technical skills and competencies needed to use AI tools but also fostering a critical understanding of AI's broader societal implications. Students should be equipped to engage with AI as informed and critical thinkers, understanding both its potential and its limitations. By positioning students as "owners of the means of production" rather than passive users, HEIs can empower them to use AI ethically and effectively in their future careers.

6.4. Research Assistance

AI tools can significantly enhance researcher's and students' ability to retrieve and organize information, making research more efficient. However, it is essential that they are trained to critically evaluate their imaginaries of AI and to question the sources proposed by AIs and to verify their validity. Whilst AIs can assist in broadening the scope of research, researchers and students must remain responsible for the critical analysis of the information they gather. Implementing specific self-assessment protocols can help stakeholders to reflect on their use of AI, identify potential biases or problems, and take corrective measures where necessary. The same holds true to the analysis of large data sets in empirical research. The interpretation of these results and the drawing of conclusions must remain the researchers' and students' responsibility. HEIs should encourage researchers and students to use AI for data analysis while fostering a reflexive critical approach to the interpretion of results, integrating ethical considerations and real-world implications into their analyses.

6.5. Support in Writing and Text Revision

AI-based writing assistants can offer valuable feedback on style and grammar, helping students refine their written work. However, it is crucial that students develop their writing skills independently and do not become overly reliant on AI tools. Educators should encourage students to use these tools as a supplement to their writing process, promoting autonomy in crafting and revising their work. This balance helps students build the necessary skills to communicate effectively without becoming dependent on AI-generated corrections.

6.6. Plagiarism Ethics

Students should understand that originality in their work is not only a requirement but a reflection of their intellectual development. Institutions should integrate discussions about academic honesty into the curriculum, helping students see plagiarism detection as part of a broader commitment to ethical scholarship rather than a punitive measure. AI tools that detect plagiarism might be useful to emphasize the important role AIs can play in in maintaining academic integrity, rather than erasing it.

6.7. Development of Critical Thinking

AI can assist in identifying relevant sources and provide meaningful information. Educators should emphasize the importance of evaluating the credibility of AI-created information and AI-recommended sources and teach students to apply critical thinking skills when incorporating them into their work. This approach ensures that AI supports rather than diminishes the development of critical judgment in future professional work and academic research. AI-driven simulations can provide students with valuable opportunities to engage in decision-making processes in a controlled environment. However, these simulations should complement, not replace, critical discussions and analyses led by teachers. Educators should use AI-generated models as a starting point for deeper exploration of complex issues, encouraging students to question assumptions, explore alternative scenarios, and develop their problem-solving skills. This approach fosters a more profound understanding of the material and prepares students to apply their knowledge in real-world situations.

6.8. Continuous Training

To ensure the effective and ethical use of AI, HEIs must provide continuous training for faculty and administrative staff. This training should cover not only the technical aspects of AI tools but also the ethical considerations involved in their use and engage with the imaginaries that drive or create obstacles to the uses of AI By equipping educators with the knowledge and skills needed to navigate the complexities of AI, institutions can foster a teaching environment that integrates technology without compromising the human elements that are essential to education.

6.9. Ethics and Privacy

HEIs must establish clear policies that govern the ethical use of AI in the classroom, with a particular focus on protecting students' privacy and rights. These policies should be developed in consultation with legal and ethical experts and should be communicated clearly to both staff and students. By creating a framework that prioritizes ethics and privacy, institutions can build trust in AI technologies and ensure that their implementation respects the dignity and autonomy of all individuals.

6.10. Collaborative Innovation

To stay at the forefront of educational technologies, HEIs should actively seek collaboration with other institutions, employers, students, technology companies, and research organizations. These partnerships can facilitate the exchange of knowledge, best practices, and innovative ideas, helping institutions to continually improve their use of AI in education. By fostering a culture of collaborative innovation, HEIs can ensure that they remain leaders in the field, providing students with cutting-edge educational experiences while contributing to the broader development of AI technologies. This might help to HEIs in creating and leading new imagined communities that result from the changes brought by AIs.

7. Final Considerations

The rise of Artificial Intelligence (AI) presents a unique and transformative opportunity for Higher Education Institutions (HEIs). AIs have the potential to revolutionize teaching, research, administration and they will influence the future of a diversity of professions. HEIs can not only lead AI related changes within their structures but can forefront debates about, shape the specific focus on and unite different imaginaries of AI. They can create new imagined communities in times of AI. However, such an endeavour requires a careful balancing act between leveraging the technological advantages of AI and maintaining the humanistic values that are at the core of education. It requires also a deeper understanding of different stakeholders directly and indirectly involved in HEIs and the different modes, myths, narratives and imaginaries when approaching AI. A central objective of HEIs seeking to lead AI integration is to navigate the fine line between critical engagement and practical application that we have seen in the diverging imaginaries of AI of students and teaching staff. A successful strategy should be deeply embedded in the institution's mission, ensuring that AI is not merely adopted for its novelty but is thoughtfully applied in ways that genuinely enhance educational outcomes. HEI must strive to become "owners" and "masters" of AI—not merely users—by fostering a deep understanding of its capabilities, limitations, and ethical implications and so by creating a meaningful AI media literacy. This owner or mastership involves not just the technical proficiency to use AI tools but also the critical capacity to question and shape how these tools are developed and deployed and must permeate all stakeholders so that they themselves turn into masters of AIs, able to question their viewpoints and imaginaries of AIs. This can be only achieved by creating debate, by bringing different stakeholders and their views, preconceived ideas and imaginaries of AI together to build together the imagined communities that we want to have.

The goals of professionalization, high-quality academic knowledge, and fruitful debate are key to this strategic approach. HEIs have a responsibility to prepare students for a rapidly evolving job market where AI plays an increasingly central role. This involves equipping students with both the technical skills to use AI effectively and the soft skills—such as critical thinking, creativity, and ethical reasoning—that will enable them to navigate complex professional landscapes. HEIs must continue to uphold the highest standards of academic teaching and research, ensuring that AI is used to enhance, rather than replace, the rigorous intellectual inquiry that is the hallmark of scholarly work. This requires ongoing investment in faculty development, research support, and the cultivation of a research culture that values originality and critical engagement with AI technologies. Ethical oversight is another critical component of a university's AI strategy, that can be achieved addressing ethical challenges such as data privacy, algorithmic bias, and the potential for depersonalization in education and by inviting stakeholders to question their ideas about and uses of AIs. Universities must develop clear policies, curricula and frameworks that guide the responsible use of AI, ensuring that these technologies are used fairly and transparently. Continuous training for all members of the academic community—students, educators, researchers, administrative staff alike, even employers is a must. By fostering a culture of ethical awareness and ongoing education, HEIs can ensure that AI is used in ways that align with their values and mission and those of relevant stakeholders.

In conclusion, the integration of AI into higher education offers a powerful means to improve and personalize learning, advance research, and streamline administrative processes. However, realizing this potential requires a deliberate and strategic approach that balances the innovative possibilities of AI with a steadfast commitment to ethical integrity and academic excellence. It requires also the necessary imagination for a better integration of AI. These uses of AI should not be conditioned by experiences with technologies of the past, HEI must be ready to keep open for new opportunities of using and teaching AI. By embracing this approach, universities can not only enhance their educational offerings but also play a leading role in shaping the future of AI in society. Through critical engagement, professionalization, and a commitment to high-quality academic activities, universities can ensure that they remain at the forefront of educational innovation, equipping the next generation of leaders to navigate the challenges and opportunities of an AI-driven world.

ISSN 2991-9371

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Aligning Instructional Design and AI with Future Needs in Higher Education

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Abstract

This paper explores modern instructional design (ID) components and their application in business schools, focusing on how AI can enhance learning and teaching processes. The study examined 41 MBA courses in management and administration at ZSEM, focusing on various teaching methods. The study also presents examples of teaching approaches and discusses how AI could enhance learning in business education. The most frequently used teaching approaches were action/active learning, experiential learning, research-led learning, and real-world perspective. AI can enhance these approaches by personalizing, engaging, and making learning more interactive. The findings suggest that business schools should integrate ID theories and models with modern teaching methods, while AI can improve engagement and personalization. However, in-person interaction is still crucial for students to expand their networks and seek advice for corporate problems. A balanced approach between virtual and in-person teaching is recommended.

Keywords: *instructional design, artificial intelligence, higher education, business schools, management education.*

1. Introduction

Tusriyanto et al. [1]. research highlights that human resource development, industry collaboration, communication, and technology are key strategies for enhancing the quality of higher education management in response to its increasingly complex dynamics. This paper explores the crucial role of instructional design in creating educational materials and experiences that help people learn more effectively. Instructional Design (ID) involves analyzing learners' needs, setting goals, and creating instructional materials and activities that truly engage learners, followed by evaluating the instruction and learner performance. Today, there is a lot of discussion about incorporating new trends into ID, particularly the use of artificial intelligence (AI) in teaching, learning, instructional processes, and assessment.

Therefore, this paper aims to address the following research questions:

RQ1: What components are involved in modern ID,
and to what extent are they used in business schools?

RQ2: How can AI, in general, significantly enhance ID, i.e.,
learning and teaching processes in higher education?

The first part of the paper presents a comprehensive Literature review, exploring various perspectives on ID and the key components of modern ID in business schools. It also delves into the practical application of ID components in business schools worldwide and the integration of AI in ID. The second part of the paper outlines the research Methodology, followed by the results and discussion. The Discussion highlights the key findings of the research. At the same time, the Conclusion answers the research questions, summarizes the findings, discusses the study's implications, acknowledges its limitations, and offers recommendations for future research.

2. Literature review

Some authors view ID as a science [2], while others consider it a discipline [3]. Moore et al. [4] argue that ID can be seen as both a science and an art: a science grounded in learning theories derived from psychology, sociology, philosophy, and education, and an art because designing educational materials is a highly creative process. Alzand [5] describes ID as a new approach that emphasizes thinking as an aim of education, as well as a contract between learners, teachers, time, subject matter, and the learning environment. Moore et al. [4] emphasize that ID involves solving instructional challenges by systematically analyzing learning conditions and creating practical learning experiences based on this analysis. It translates principles of learning and instruction into plans for educational materials or activities. These plans rely on established learning theories to be functional and engaging for users. Instructional designers apply proven learning theories and models to guide their decision-making processes. Moore et al. [4] also concluded that despite the variety of ID models, most share key elements: identifying learners' needs and learning context, defining learning outcomes and objectives, developing meaningful assessment criteria, determining the most effective instructional delivery methods, evaluating the system's effectiveness (both instruction and learner performance), and implementing, adjusting, and maintaining the instructional system.

In his research paper, Blackburne [6] presented a conceptual ID model for executive education based on best practices and educational theory. He emphasized the importance of real-world relevance, experiential learning, and technology integration. He used the ADDIE (Analysis, Design, Development, Implementation, and Evaluation) framework and principles of authenticity, reflection, and collaboration to create an effective learning environment informed by learner needs and context. Radović et al. [7] concluded that ID models point to educational strategies that support more authentic, reflective, and collaborative instructional elements. Radović et al. [8] researched the use of their instructional model, which better supports the re- and decontextualization of knowledge in experiential learning environments, offering practical guidelines for linking learning experiences to academic knowledge. The study by Karthik et al. [9] focuses on studying the expectations of those attending e-learning courses and how they can better create more effective strategies to address those expectations. The research is based on six key elements: technical assistance, problem-based learning, aesthetics, gaming, storytelling, and social support.

2.1. Integrating AI in Instructional Design for Higher Education

In recent years, new technologies have become highly prominent in ID. As a result, many authors are studying various aspects of online learning, virtual campuses, and, more broadly, AI's digital transformation and use in higher education. Stoyanova & Stoyanov [10] argue that digital alternatives and technology are crucial for expanding online learning and improving administrative processes at institutions, enabling their sustainability and relevance in the future. Traditional models of education today face significant challenges, but there are also opportunities due to digital transformation. Over the past two decades, virtual universities and campuses have allowed all teaching and learning to occur online, from registration to certification. Goel [11] explored how these institutions utilize the Internet, email, video/audio conferencing, and other tools to offer competency-based programs based on work and life experiences. Students access materials, communicate via email, and participate in video-conferences with tutors, while online libraries, telephone counseling, and local centers support interaction and skill assessments, including e-assessments. Radović et al. [7] also emphasized that the relationship between experience (practice) and knowledge (theory) is becoming increasingly important in the formal learning process.

Rawas [12] claims that AI technologies today have the potential to transform how we teach and learn in higher education completely. Essa [13], in his research, explores how AI could reshape higher education by transforming institutional practices, pedagogy, and learning trends, focusing on enhancing personalized and flexible solutions. He also emphasizes a significant shift in the cost-value equation of education to support workforce development and lifelong learning.

Online learning leverages the Internet and digital technologies to facilitate education and has gained popularity, especially during the COVID-19 pandemic, which prompted many institutions to transition to online instruction [14]. While it offers benefits like flexibility, cost-effectiveness, and access to diverse resources, online learning also presents challenges for both educators and learners. Key difficulties include technical issues, lack of interaction, low motivation, limited personalization, time management struggles, and accessibility barriers. These challenges can negatively impact student engagement, which is crucial for the success of online courses. Engaged students are more likely to persist and succeed, highlighting the importance of strategies to enhance engagement. Singh et al. [14] study aims to explore the challenges of online learning from the perspectives of students and instructors in higher education and to propose strategies for improving student engagement in online courses.

Hampton & Bartram [15] suggest that online learning may not be as dominant as once believed, as it is not always the most suitable approach. They argue that a blended learning model may be more effective due to the limitations of e-learning, such as issues with streaming media, inadequate infrastructure, and slower computers, which often reduce content to basic text. Additionally, learners read 25 % slower on screens than from printed materials, making text on screen less effective, and the costs of printing or Internet access can be restrictive. As a result, a blended approach is increasingly accepted. Reengineering educational delivery requires considering the availability of materials, infrastructure, and trained staff and providing professors with professional development to implement new strategies. Birkinshaw [16] concluded in his research that despite all the advantages brought by the application of AI in higher education, students still need in-person interaction and activities to expand their network, meet interesting people, and seek advice for corporate problems. Blackburne [6] also concludes that it is not advisable to excessively focus on technological solutions for teaching delivery. The right balance between virtual and in-person instruction is recommended.

3. Methodology

In this paper, we developed a methodology to evaluate and extract meaningful information from qualitative text through coding and categorization. Specifically, a thematic analysis [17] was conducted on syllabi organized according to predefined categories. A clear description of each category preceded the coding. The research sample included 41 MBA program courses in management and administration, which are part of various concentrations at the Zagreb School of Economics and Management (ZSEM). The research was carried out in August and September 2024. The study involved two coders, professors in the MBA program who are familiar with the working methods and learning outcomes. The research method was adapted based on a study [6] that examined the nine most commonly used approaches to teaching and learning (Figure 1). Blackburne's [6] study was conducted on the websites of 14 of the world's top business schools, as ranked by the Financial Times.

FIGURE 1: Teaching Approaches as Part of Instructional Design in Higher Education
Source: [6]

Following is a description of each of the categories (various teaching approaches) taken from Blackburne's [6] study, outlined to code the syllabi in which they are found:

Action/active learning:

- It involves students' engagement in various discussions, debates, activities, and exercises that enable them to participate actively in the learning process.
- This approach actively applies skills like problem-solving, real-time application of theories, and critical thinking to the learning process. Illustrative methods include case studies, simulations, or project-oriented assignments that require students to make decisions and react to the results.

Experiential learning:

- Students acquire knowledge through active engagement, reflecting on their experiences, and utilizing their insights in novel contexts. This process may involve internships, practical projects, field studies, or simulations that mimic real-life scenarios. The emphasis is placed on obtaining practical experience connected to theoretical principles.
- Three pillars of learning environments foster experiential learning: Authenticity, Reflection, and Collaboration, along with the learning processes within each pillar [7].

Peer-to-peer learning:

- The core of this learning method is students learning with and from each other. That learning includes the absence of immediate teacher intervention because the focus is on student interactions to share their knowledge and experiences, develop collaboration, discussion, and collective problem-solving skills, and provide feedback.

Research-led learning:

- Students enrolled in this type of learning, which is driven by research, must engage in activities including gathering, evaluating, and applying research findings. Such activities may include literature reviews, data analysis, or hands-on research projects. The objective is to enhance students' understanding by linking them to the most recent advancements in their discipline and fostering scholarly investigation.

Collaborative learning:

- The key element of this learning method is teamwork, emphasizing problem-solving, completing projects, or engaging in discussion. Cooperation, shared responsibilities, and leveraging the strengths of group members to achieve a common goal are very important elements of this method. Skills like teamwork, communication, and group problem-solving (often via group presentations, joint projects, and collaborative discussions) are also important. Collaboration can be in pairs or groups.

Immersive learning:

- This learning method involves putting students into environments that aim to simulate real-world conditions. This can be achieved using simulations, role-playing, or other interactive methods that allow students to experience challenges. This method aims to help students apply skills and knowledge in a realistic and controlled environment.

Real-world perspective:

- A real-world perspective learning method connects knowledge gained from theory with real-world applications. Students then engage with real-world scenarios from businesses, market trends, or industry practices to understand how many academic concepts apply in a real professional setting. Case studies, industry collaborations, and current event analysis are a few ways to incorporate a real-world viewpoint into education.

Technology-enabled learning:

- Technology-enabled learning involves using digital tools and platforms to improve learning. Examples include online simulations, the use of R, Python, and Excel applications, digital communication tools, learning management systems, and any other technology that helps achieve learning objectives. The goal is to improve learning by utilizing contemporary technology tools.

Case study learning:

- This learning approach involves analyzing specific, relevant, and real-time hypothetical scenarios to apply concepts derived from theory and solve problems. Students use critical thinking and problem-solving to understand the complexity of the case they are working on, which is very common in social sciences. Those studies require students to gather information and present solutions.

Other studies [5,9] show that some categories (teaching approaches) can mix and overlap.

4. Discussion

The results showed that in the 41 courses considered, the most frequently used approaches, with equal frequency (33), were action/active learning, experiential learning, research-led learning, and real-world perspective (Table 1). This was followed by case study learning (31), collaborative learning (30), technology-enabled learning (23), peer-to-peer learning (21), and immersive learning (8).

MBA Syllabus	Action / Active learning	Experiential Learning	Peer-to-peer learning	Research-led learning	Collaborative Learning	Immersive Learning	Real world perspective	Technology enabled learning	Case study learning
Business Ethics, Corporate Social Responsibility, and Sustainability	x	x	x	x	x		x		x
Maximization and Measurement of Company Value	x	x	x	x	x	x	x	x	x
Leading in Organisations	x	x	x	x	x	x	x		x
Management of Change and Human Resources	x	x	x	x	x		x		x
Project Management	x	x	x	x	x	x	x	x	x
Quantitative Methods for Managers	x	x	x	x	x		x	x	x
Strategy	x	x	x	x	x		x		x
⋮									
Financial Fraud Detection	x	x		x			x	x	x
Financial Reporting and Analysis	x	x		x			x	x	x
Financial Statement Audit	x	x		x	x		x	x	x
Internal Audit	x	x		x	x		x	x	x
Managerial Techniques	x	x	x	x	x		x	x	x
Quantitative Methods and Econometrics	x	x		x			x	x	x
Quantitative Methods for Managers	x	x		x			x	x	x
Financial Derivates	x	x		x	x		x	x	x
Financial Institutions and Markets	x	x		x			x	x	x
Financial Management	x	x	x	x	x		x	x	x
TOTAL	33	33	21	33	30	8	33	23	31

TABLE 1: Excerpt from the research results on approaches to teaching and learning in the MBA program at ZSEM

By examining the syllabi of individual MBA courses at ZSEM, specific examples of teaching approaches and outcomes that describe these approaches were identified. Table 2 provides examples for each of the approaches to teaching and learning in the MBA program at ZSEM. The examples were selected as suggestions intended to help practitioners successfully facilitate more ID methods based on the practical guidelines for a course featuring more experiential learning developed by Radovic [18].

Teaching Approach	Course	Outcome description
Action/active learning	*Business Ethics, Corporate Social Responsibility, and Sustainability (SC 600; ECTS 5)*	"Students will **engage in problem-solving exercises** during in-class activities, such as the 'stakeholder distribution' task where students allocate resources to stakeholders and justify their decisions."
Experiential learning	*Managerial Techniques (MN 570E; ECTS 6)*	"Classes are designed to allow students a concrete application of acquired theoretical knowledge **using various software solutions in the computer room**."
Peer-to-peer learning	*Maximization and Measurement of Company Value (FN 547; ECTS 5)*	"Each student will have the opportunity to simulate organizational life within their Capstone Team, **consulting with colleagues/Board Members** on strategic decisions."
Research-led learning	*Design Thinking (ECTS 4)*	"Students will analyze and apply the design thinking methodology from **various research sources, including articles** by Tim Brown and Jeanne Liedtka."
Collaborative learning	*Leading in Organisations (MN 567; ECTS 4)*	"Students will participate in **leadership role-plays and interactive exercises that require teamwork**."
Immersive learning	*Project Management (ECTS 5)*	"Students will participate in the Harvard project management simulation, which provides an **immersive experience simulating real-world project** management challenges."
Case study learning	*Recruitment and selection (MN 572; ECTS 5)*	"The course will involve **analyzing case studies of recruitment and selection processes**, allowing students to apply the knowledge and skills learned."
Technology enabled learning	*Marketing Strategy – Simulation (MK 593; ECTS 5)*	"Students will use the Markstrat simulation, which is a **technology-based marketing strategy simulation**, to apply theoretical concepts in a digital environment."
Real-world perspective	*Applied Digital Marketing (MK 593; ECTS 4)*	"The course is conducted in collaboration with OMD (Omnicom Media Group), a global leader in marketing communication, allowing students to see marketing strategy and **tactics from the perspective of a real-world** digital marketing environment."

TABLE 2: Example of each teaching approach in a course with outcome description

ISSN 2991-9371

5. Conclusion

To answer the first research question (RQ1) about what components are involved in modern instructional design (ID) and to what extent they are used in business schools, a study was conducted that included 41 MBA program courses in the fields of management and administration, which are part of various concentrations at ZSEM. The results showed that the most frequently used approaches were action/active learning (33), experiential learning (33), research-led learning (33), and real-world perspective (33). These were followed by case study learning (31), collaborative learning (30), technology-enabled learning (23), peer-to-peer learning (21), and immersive learning (8). The approaches to teaching and learning at ZSEM slightly differ in frequency from those found in a study by Blackburn [6]. In his research on approaches to teaching and learning in executive education at 14 of the world's top business schools, the most commonly used methods were experiential learning (11), collaborative learning (11), and technology-enabled learning (11). They were followed by real-world perspective and peer-to-peer learning (10), case study learning (8), research-led learning (6), immersive learning (6), and action/active learning (5). Despite the differences in the frequency of teaching and learning approaches, which may depend on the type of course and its learning outcomes, the study showed that the same methods are used. The difference might also be that our study focused on MBA courses, whereas Blackburn's [6] study explored executive education.

To answer the second research question (RQ2) about how AI can significantly enhance instructional design, i.e., learning and teaching processes in higher education, examples of teaching approaches in a course with outcome descriptions related to business education were presented. It was shown that students use interactive exercises, case studies, software, and simulations, achieving diversity in teaching. With AI, various learning methods in business education can be upgraded, enabling a more personalized, interactive, engaging, and effective educational experience. In their study, Ruiz-Rojas et al. [19] claim that generative AI tools have significant educational potential and propose innovative ways to engage students, adapt content, and promote personalized learning. They suggest their ID matrix, which can enhance the effectiveness and coherence of educational activities. They conclude that by embracing these technological advancements, education can stay relevant and effectively meet the challenges of the digital world.

Mårtensson & Mullins [20] argue that AI has emerged in business education and will remain, and it is up to us, the professors, to adapt our roles accordingly. They identify six roles: in addition to being an expert and a skilled facilitator, we often play another role as supervisor/tutor, mentor/coach, designer/curator, bridge-builder, and gatekeeper – roles with different names in different contexts. Professors add value by helping the individual learner, or a small group of learners, to advance their thinking, projects, or theses. Tusriyanto et al. [1] highlight that human resource development, industry collaboration, communication, and technology are key strategies for enhancing the quality of higher education management in response to its increasingly complex dynamics. In this dynamic, the use of various modern work methods and the integration of digitization and AI in instructional design can significantly enhance the quality and efficiency of teaching and learning in higher education and lifelong learning [10,13]. Today, these methods also enable open and distance learning (ODL), which provides learner autonomy, meaning flexibility in the time and place of learning and the speed or pacing of learning [21]. There is also hybrid learning, which combines in-person and online teaching methods within a single course, offering students a mix of traditional and digital learning experiences. AI can significantly improve instructional design by adapting content to specific needs, automating many repetitive tasks, providing students with more straightforward and more timely feedback, and increasing their interest and engagement. Despite all this, students still need in-person interaction and activities to expand their network, meet interesting people, and seek advice for corporate problems [16]. For this reason, it is not advisable to excessively focus on technological solutions for teaching delivery. As Blackburne [6] emphasized, the right balance between virtual and in-person instruction is recommended.

The findings of this study can help program developers in business schools and other higher education institutions by allowing professors to focus more on the creative and strategic aspects of teaching through various teaching methods. The recommendation would be to reorganize educational curricula to consider ID theories and models. This study has shown that there are teaching and learning approaches that prove to be a good way to adapt ID to the needs of participants in contemporary business education programs. The limitation of the study is that it was conducted only on MBA courses at a business school, so future research could examine which teaching and learning approaches can enhance ID in other higher education programs. Another limitation is that the study was conducted within a single institution in Croatia to serve as a foundation for research on this topic in other countries.

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GenAI for Operational Efficiency or Value Innovation? Implications for Stakeholders in Academia, Business, and Regulation

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Abstract

This paper examines the dual impact of Generative AI on operational efficiency and business model innovation, providing an industry overview, a rapid review of the literature, and stakeholder-specific recommendations. Gen AI is transforming industries by enabling automation, enhancing decision-making, and driving personalization at scale across sectors such as finance, healthcare, manufacturing, and services. Leading consultancy firms underscore Gen AI's potential to streamline operations, reduce costs, but also to revolutionize business models through innovative approaches like AI-as-a-Service (AIaaS) and platform-based ecosystems. A rapid review of the literature highlights how Gen AI lowers market entry barriers, creates new value propositions, and fosters competitive advantages for new entrants and SME's. The paper concludes with strategic recommendations for various stakeholders—academia, AI providing businesses, policymakers, and consultants—emphasizing the need for collaborative frameworks, ethical guidelines, and adaptive business strategies to fully leverage Gen AI's disruptive potential in reshaping the future of business.

Keywords: *Generative AI, disruption, value creation, business modeling, AIaaS*

1. Introduction: The State of the Industry in the Era of Generative AI

Generative AI (Gen AI) represents a transformative technological advancement that is redefining the rules of various industries, fundamentally altering business models, operations, and value creation strategies [1]-[2]-[9]-[18]. The impact of Gen AI spans across sectors, from finance and healthcare to education, manufacturing and services, enabling unprecedented levels of automation, personalization, and innovation. Recent reports from leading consultancy firms such as McKinsey, BCG, PwC, Deloitte, and Accenture provide a multi-perspective overview of how organizations are navigating the era of AI disruption [1]-[2], revealing the opportunities and challenges associated with integrating Gen AI into their core strategies. For example, Gen AI can significantly reduce costs through automation of complex tasks, such as content creation, data analysis, and customer service, while simultaneously increasing speed and accuracy, resulting in a new quality-price paradigm [3].

PwC distills six common use-case patterns for Generative AI (Gen AI) and their respective shares of value creation. The largest share of value creation, at 33 %, is attributed to "Net-new creation," where AI generates entirely new content based on prompts. This is followed by "Augmentation" (21 %), which involves expanding existing content, and "Transformation" (19 %), which includes tasks like data conversion and personalization. "Dialogue" (14 %) and "Info retrieval" (12 %) focus on providing information and searching for specific data. The smallest share, "Summarization" (2 %), involves producing concise versions of content. These use cases highlight Gen AI's versatility in creating and enhancing content, transforming data, and supporting information retrieval and summarization tasks, showing its broad impact across different domains [4].

McKinsey emphasizes that generative AI is starting to deliver real results across service industries, particularly in sectors like customer service, marketing, consulting, and industries such as tech, banking, and healthcare [5]. According to McKinsey, this shift from potential to achieved productivity is driven by the ability of Gen AI to automate complex processes, enhance decision-making, and enable rapid innovation cycles. Gen AI solutions can aid new entrants in scaling operations efficiently by automating repetitive tasks such as inventory management, financial reporting, and customer support. According to a PwC report, this automation enables startups to redirect resources towards strategic growth initiatives and innovation while keeping operational costs low [6]. For example, AI-driven chatbots and virtual assistants are revolutionizing customer interaction by providing hyper-personalized experiences at scale, which improves customer satisfaction while significantly reducing operational costs.

Enhanced customer insights and personalization capabilities are surely one of the key benefits. Gen AI enables new entrants to collect and analyze vast amounts of data (through chatbots or tracking) to gain deep insights into customer behaviors and preferences. Deloitte's research points out that companies leveraging AI for customer insights can achieve up to a 20 % increase in customer satisfaction and retention by delivering hyper-personalized experiences or shorten the worker's average time spent on resolving customer issues [7]. This ability to customize offerings at scale allows new entrants to build strong relationships with customers and gain loyalty much more quickly. In synergy with traditional automation, Gen AI has a significant disruption potential which might cause trouble for the high market share companies among all industries and markets. But even more interesting is the fact that potential of Gen AI extends beyond operational efficiency; it has become a catalyst for reinventing business models. According to McKinsey's insights on managing in the era of Gen AI, organizations are leveraging AI to break traditional silos and create integrated ecosystems that drive collaborative growth and innovation. They also discussed how Gen AI can drive innovative business models, such as AI-as-a-Service (AIaaS), where companies offer AI-driven capabilities on demand, creating new revenue streams and enabling small and medium-sized enterprises to leverage advanced technologies without significant capital investment. Another important observation is that Gen AI is catalyzing the emergence of new entrants by lowering costs and democratizing access to sophisticated AI tools and data.

Generative AI value chain presents significant opportunities for new market entrants to disrupt or join in the established industries and rapidly gain a competitive edge [9]. With huge emphasis on applications and services, McKinsey implies that in the next 3 to 5 years we could witness a whole new ecosystem of market players (Figure 1). They also suggest that niche players might enjoy significantly less entry barriers.

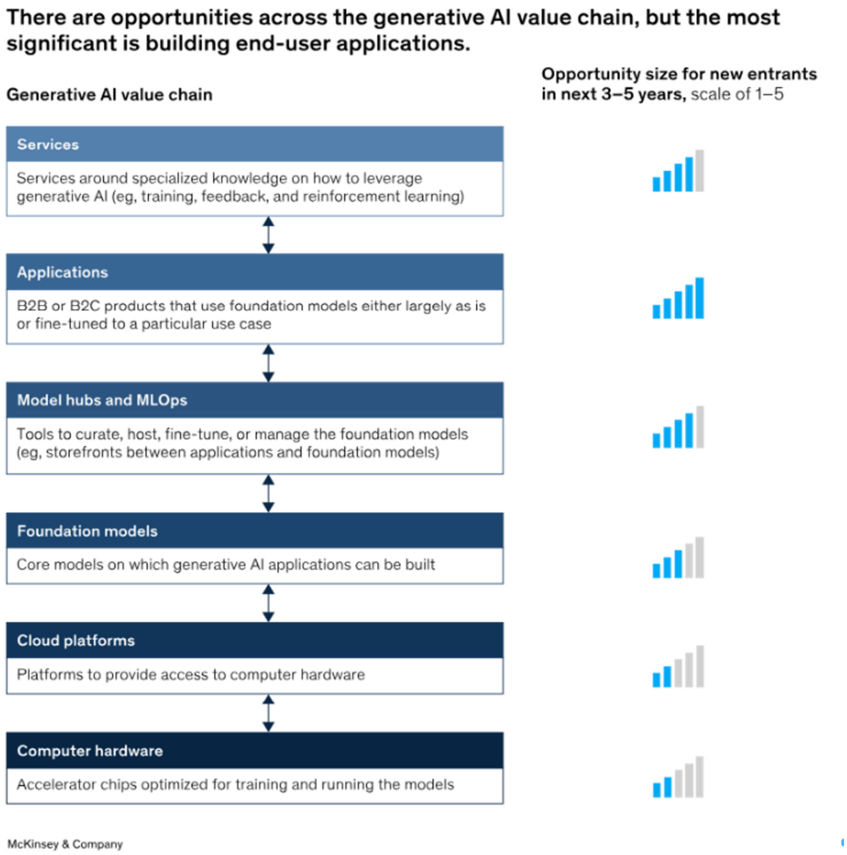

FIGURE 1. Gen AI value chain opportunities.
Source: McKinsey [9].

Industry-specific Impacts and Applications

Generative AI's impact varies across industries, tailoring its benefits to the unique needs and challenges of each sector. In the financial services industry, for instance, AI is being utilized to automate risk assessments, enhance fraud detection, and personalize financial products to meet individual customer needs. Meanwhile, in healthcare, Gen AI is facilitating more accurate diagnostics, personalized treatment plans, and advanced drug discovery processes, all of which are enhancing patient outcomes and operational efficiencies [10]. Manufacturers are also improving product quality and accelerating time-to-market for new innovations.

Pär Mårtensson and John Mullins, in their editorial article [34] „Generative AI and the Roles of Business School Teachers" disscuses whether ChatGPT and Gen AI poses threats to the world of teaching and learning; or do they offer opportunities? They identify the six key evolving roles of business school teachers in the context of generative AI technologies like ChatGPT: expert, facilitator, supervisor/tutor/mentor/coach, designer/curator, bridge-builder, and gatekeeper. Each role is examined in relation to how AI presents both opportunities and challenges. The primary takeaway is that AI can enhance roles that involve critical thinking, active learning, and practical application, but it also poses challenges, especially in roles focused on assessment and gatekeeping. The need for continuous development and adaptation among teachers is emphasized, with a call for HEI governance and their awareness of the need for strategic approach to AI both in quality of HEI core services and operational efficiency [35]-[36]-[37].

From 2020, the industry's journey with AI has transitioned from exploration to execution, with companies now focusing on scaling AI deployments to realize tangible business benefits. However, the move from promising AI to productive AI requires overcoming several challenges, including data integration, talent acquisition, and ethical concerns. According to PwC, a critical factor for success is the alignment of AI strategies with business objectives, ensuring that AI initiatives are not just isolated technical projects but integral components of broader business strategies [11]. This calls for a deep understanding of both AI technologies and the specific business contexts in which they are applied. The best predictor of successful AI adoption is the ability of organizations to foster a culture of experimentation, agility, and continuous learning [9]. This cultural shift is vital to navigating the fast pace brought about by AI and maintaining a competitive edge in an increasingly AI-driven marketplace. In a recent report Accenture suggested that organizations must embrace a reinvention mindset, where the focus is not just on enhancing existing processes but on fundamentally reimagining how value is created and delivered [12]. This is a central observation for approaching business modeling and value innovation driven by solutions possible with generative AI technologies.

2. A Rapid Review of the Literature

Leo S. Lo's editorial article [13] challenges the common perception of Gen AI as merely a tool to enhance efficiency, akin to a scientific calculator in mathematics. Instead, Lo argues that Gen AI is a foundational technology with transformative potential across sectors. Lo highlights Gen AI's capability to enable entirely new activities and interactions rather than just improve existing processes. The article discusses the current "AI adjustment period," which is characterized by experimentation, infrastructural development, and societal adaptation, and parallels this with the early stages of electricity and Internet adoption. Jerry Kaplan, a computer scientist, joins this comparison, saying „What jobs involve or benefit from the use of electricity? Obviously, an awful lot of them do. I think we're going to see the same thing [with AI]" [14]. Furthermore, Lo emphasizes the importance of understanding AI as a foundational technology that requires strategic planning, long-term investment, and ethical guidelines to leverage its full potential. This perspective is necessary for driving radical innovation and fostering new ways of engagement.

A recent article „AI-enabled business models for competitive advantage" [15] proposes a novel framework for how firms can leverage artificial intelligence (AI) to create and sustain competitive advantages. The paper integrates existing business model theory, data network effects, and the situated use of AI into a comprehensive framework. Authors argue that firms must evolve their business models through iterative cycles of novelty, efficiency, complementarity, and lock-in themes to maintain a competitive edge. AI can enhance these business model themes in various ways, such as using AI for personalization (novelty), automation (efficiency), bundling of services (complementarity), and customer retention (lock-in). Data network effects, where the value of a service increases as more people use it, are critical for new entrants in technology-driven industries. AI's unique learning capabilities from large datasets allow firms to create more personalized and valuable services, which can attract more customers and strengthen network effects. This insight suggests that generative AI can help new entrants build strong, data-driven competitive positions. Authors also discuss the concepts of grounding (tailoring AI to specific tasks), bounding (protecting AI capabilities from imitation), and recasting (continuously adapting AI to changing conditions). This approach is crucial for new entrants looking to differentiate themselves in the market and protect their AI-driven innovations from competitors.

On the same track, Joerg von Garrel and Carlos Jahn [16], highlighted the need for SMEs to not only focus on efficiency but also develop business models that leverage AI to create new value propositions and enhance competitiveness. Authors presented a socio-technical framework aimed at small and medium-sized enterprises (SMEs) in the manufacturing sector for implementing AI-based (service) business models, emphasizing that AI has the potential to significantly alter markets, industries, and business activities by enabling innovative service-oriented business models, especially in the context of "Industry 4.0."

Generative AI offers numerous opportunities for educational sector as well, including personalized learning, new content creation, rapid summarization of content, automation, and interactive environments [27]-[28]-[29]-[30]. Furthermore, Gen AI has a potential to revolutionize education and the entire educational experience through scalable and hyperengaging solutions [31]-[32]. Nevertheless, potential harmful externalities, like data privacy breaches and digital divide in education should be addressed by universities and policy makers, to ensure effective tools and methods are being developed [30]-[33].

The article "AI-driven business model innovation: A systematic review and research agenda" [17] explores how AI facilitates innovation in business models by enabling new forms of value creation and appropriation. It identifies that generative AI particularly is transforming industries and paving the way for novel business models. One key insight is that AI allows for the formation of new business model configurations, such as platform-based models, subscription services, and data-driven ecosystems. This supports the argument that generative AI can unlock new possibilities for value creation by enabling innovative approaches, such as direct-to-consumer models that personalize marketing and product recommendations.While the article highlights numerous opportunities for new entrants, it also notes significant challenges, including the necessity for substantial data, advanced analytics capabilities, and strategic alignment of AI with business objectives. Firms are encouraged to adopt flexible and adaptive business models to fully leverage AI's potential. This aspect can inform discussions about the specific hurdles new entrants may face when innovating with generative AI and strategies to navigate these challenges. Additionally, the concept of "situated AI" is introduced, emphasizing the importance of tailoring AI solutions to fit specific organizational contexts to achieve competitive advantages. This notion can illustrate how new entrants can utilize generative AI to customize their operations and strategies according to market needs, thereby differentiating themselves from established competitors.

The Forbes article titled "AI Is Going to Transform Business Models Across Every Industry" points out that AI can help companies reimagine traditional business models by shifting from a product-centric approach to one that is more service-oriented [18]. For example, AI allows businesses to use data-driven insights to offer customized services or to implement aforementioned AI-as-a-Service (AIaaS) models, where AI capabilities are sold on demand. This transformation allows companies to adapt quickly to changing market conditions, reduce costs, and scale operations efficiently. By providing these capabilities, generative AI opens opportunities for new market entrants to innovate and compete with established players. It levels the playing field by lowering entry barriers and enabling smaller firms to leverage advanced AI tools that were previously only accessible to larger organizations with significant resources.

In their paper „A value-oriented Artificial Intelligence-as-a-Service business plan using integrated tools and services", Funk and Li [19] build on the same concept of AIaaS and its potential to transform industries by providing scalable on-demand AI capabilities. Authors argue that AIaaS offers a flexible model, similar to cloud services, where businesses can subscribe to or pay on demand for AI services tailored to their specific needs, through solutions reliant on machine learning, natural language processing, or image processing. They outline the strategic benefits of AIaaS, including cost savings, scalability, and ease of access to sophisticated AI tools. The paper includes a business roadmap and heuristic pricing model that can serve as a benchmark for AIaaS providers, highlighting the importance of offering an integrated package of AI products and services appropriate for diverse industry needs. Authores underscore several advantages of adopting AIaaS, such as reducing the need for specialized AI skills, providing high-speed and reliable infrastructure, and offering transparent and flexible payment models. It presents a case study demonstrating a successful AIaaS business plan, which includes developing an integrated bundle of AI services using advanced technologies tailored to customer needs, such as data-driven systems, machine vision, and natural language processing that also may be employed for diverse set of use cases across industries. This approach ensures AIaaS providers can compete within a set of large market segments. More importantly, this approach allows client companies or institutions to leverage AI capabilities effectively while minimizing costs and maximizing return on investment (ROI). These findings suggest that businesses can enhance their market position and operational efficiency by integrating AIaaS into their strategic plans, ultimately leading to more innovative and customer-focused outcomes.

3. Discussion: Stakeholder Implications and Recommendations

The literature review on Gen AI and its transformative impact across industries reveals the vast potential of this technology to reshape business models, drive innovation, and lower barriers to entry for new market players. Consultancies like Deloitte, McKinsey, PwC, and BCG underscore that Gen AI is not merely a tool for operational efficiency but a catalyst for innovation, creating new avenues for hyper-personalization, cost reduction through automation, and the emergence of innovative business models such as AI-as-a-Service (AIaaS). The industry's transition is further illustrated by the emphasis on new business models, including platform-based models, subscription services, and data-driven ecosystems, which redefine value creation and appropriation [20]. However, realizing the potential of Gen AI is contingent upon the alignment of technological advancements with strategic, ethical, and societal considerations. This alignment necessitates a comprehensive understanding of the diverse stakeholder landscape and the implications for each group.

To move from the state of industry and literature review to a more stakeholder-focused discussion, it is crucial to identify and analyze the roles and interests of various stakeholders involved in or impacted by the integration of generative AI into business ecosystems. Each stakeholder cluster—academic and research, business and industry, policy, consultancy and advisory, end-user, and ethical—holds unique perspectives and expectations concerning the deployment of generative AI, requiring a nuanced approach to innovation governance. These recommendations are identified and designed to help stakeholders—from academia to business and policy clusters—effectively integrate Gen AI into their strategic plans and operations, focusing on maximizing business value.

3.1. Academic and Research Cluster

Within the academic and research cluster, stakeholders such as university researchers, AI scholars, and research labs play a pivotal role in advancing the foundational knowledge and frameworks necessary for understanding AI's impact on business models and societal norms. Scholars like Lo [13] emphasize that generative AI should be viewed as a foundational technology akin to electricity or the internet, capable of enabling entirely new forms of activity and interaction rather than merely enhancing existing processes. This perspective calls for robust collaboration between academia and industry to co-create ethical guidelines and frameworks that ensure AI innovations are socially responsible and beneficial.

Recommendations:

To the extent that HEI's are endangered by competition, they should also consider reinventing their business models towards integrating AI for automation and value innovation [21]. Despite this, in short term they should probably rely on AIaaS solutions much more than other market players. Simultaneously, it's desirible for them to endeavor to invest in long term industry collaboration on some large-scale innovation research projects. Both academic institutions and HEI's should focus on creating strong partnerships with industry to align AI research with real-world business challenges. Collaborative research centers or labs dedicated to AI for specific sectors (e.g., healthcare, finance, manufacturing) can drive targeted innovation and application [16]. Encourage the development of new business models that leverage Gen AI, such as AI-as-a-Service (AIaaS), platform-based ecosystems, or subscription services. Research should explore the scalability and adaptability of these models across different markets and industries [15]. Academic institutions should also establish frameworks that facilitate the translation of AI research into practical business applications. This can include creating "AI Innovation Hubs" within universities that focus on incubating AI startups, providing seed funding, and fostering collaborations between researchers, entrepreneurs, and venture capitalists [19]. One of possibly useful frameworks for this is „Triple helix model" that emphasizes collaboration among academia, industry, and government to foster innovation ecosystems where AI advancements can directly impact business strategies and practices.

3.2. Business and Industry Cluster – AI Service Providers, Startups & SME's Cluster

The business and industry cluster, encompassing SMEs, large corporations, startups, and AI technology vendors, is at the forefront of AI adoption and integration. As highlighted by McKinsey [5] and BCG [10]-[22], generative AI offers significant opportunities for these entities to innovate, reduce costs, and scale operations efficiently. Operations in marketing, content creation, compliance, reporting, customer relations and social media management already experienced decent savings and optimization in the early Gen AI phase across all industries. However, the transition to integrating AI to company business models presents multi-dimensional challenges.

Recommendations:

Firstly, it seems that adopting a hybrid AI integration strategy could be beneficial for most startups and SME's. Companies should blend internal AI development with AIaaS to optimize costs and flexibility. For core, strategic processes that require customization, businesses should build AI capabilities in-house. For more standardized needs, subscribing to some sort of AIaaS can provide cost-effective, scalable solutions [19]. Businesses should deploy Gen AI services for automating repetitive tasks, predictive maintenance, and supply chain optimization. Concurrently, leveraging AI for advanced data analytics can provide deep customer insights, enabling hyper-personalization and customization and improved customer engagement.

Developers of apps and services based on Gen AI technologies should implement user-centric AI design principles. Organizations should prioritize user-centric design in AI systems, ensuring ease of use, transparency, and alignment with user expectations. This involves incorporating user feedback loops throughout the AI development lifecycle [7]. Providers of AIaaS services together with consultancy firms should take responsibility for educating and empowering end-users for their specific needs and use cases while helping them customize and leverage AI tools for their specific needs, thereby enhancing user satisfaction and driving AI adoption [10]. There's already a lot of frameworks that showed themselfs useful for assessing readiness for AI integration. These frameworks typically evaluate dimensions such as data management capabilities, technology infrastructure, talent, and AI governance, providing a roadmap for gradual AI adoption and scaling [23]. Applying frameworks like this can help decide whether to go for self-developing or outsourcing AI services and solutions.

3.3. Policy and Governance Cluster

Policy makers and regulatory bodies are key stakeholders in creating an environment that supports responsible AI innovation while safeguarding public trust and safety. The literature suggests a growing need for regulatory frameworks that promote ethical AI research and application, as well as adaptability to keep pace with technological advancements [19]. In line with RRI 2.0, policy makers should prioritize anticipatory governance, which involves foresight and proactive measures to address potential risks and societal impacts of AI. This cluster must also foster public consultation processes and engage diverse stakeholder groups to ensure that AI policies are inclusive and responsive to societal concerns [24].

End-users, ranging from consumers to employees and community members, are directly impacted by the deployment of AI technologies. Their acceptance and trust in AI depend on how well these technologies align with their values, privacy concerns, and expectations for fairness and transparency. The literature emphasizes the importance of designing AI systems with a user-centric approach, incorporating continuous feedback loops to adapt to evolving needs and concerns.

Recommendations:

Policymakers should establish regulatory sandboxes that allow companies to experiment with AI technologies in a controlled environment. This fosters innovation while ensuring compliance with safety, privacy, and ethical standards [11]. Encouraging public-private partnerships for AI infrastructure might also be benefitial for national economies. Government bodies should collaborate with private enterprises to build robust AI infrastructure, including data-sharing frameworks, cloud computing capabilities, and AI research hubs. Such partnerships can accelerate AI adoption across sectors, especially for SMEs that lack resources [7]. Policies should be adaptable to keep pace with the rapid evolution of AI technologies. This involves setting up an AI governance body that regularly reviews and updates AI regulations in consultation with industry experts and academic scholars.

ISSN 2991-9371

Implementing the concept of Responsible Research & Innovation (RRI 2.0), which focuses on reflexivity, inclusiveness, anticipation, and responsiveness in research and innovation processes. As AI technologies advance, there is an increasing need for ethical oversight and governance to prevent unintended consequences such as data privacy violations, algorithmic bias, and social inequality [24]. Organizations must establish ethical review boards and develop guidelines that reflect these principles to ensure that AI development is ethically sound and socially responsible. Public engagement in ethical discussions is also crucial for building trust and ensuring that AI innovations align with societal values and expectations. AI governance framework could aid in ensurin that AI deployment aligns with national economic goals while safeguarding public interests [25].

3.4. Consultancy and Advisory Cluster

The consultancy and advisory cluster, including management consultants and AI-focused advisors, serves as an intermediary between AI developers, businesses, and policy makers. Consultants are crucial for translating complex AI concepts into actionable strategies that align with ethical standards and societal needs. CroAI is a good example of advisory association aiming to mediate between AI developers, businesses, governments and regulatory bodies [26].

Recommendations:

Consultants should create detailed AI playbooks that provide sector-specific guidelines for AI adoption. These playbooks should cover key areas such as use-case identification, ROI assessment, risk management, and scaling strategies [10]. They should also provide AI readiness, roadmap workshops and training sessions that help organizations understand their AI readiness levels, identify strategic AI opportunities, and develop detailed plans for AI integration [12].

4. Conclusion

Generative AI (Gen AI) is not just a technological advancement; it is a foundational technology with the potential to fundamentally disrupt industries by creating a new quality-price paradigm. By significantly reducing costs through automation and enhancing precision and speed, Gen AI allows companies to deliver higher-quality products and services at competitive prices. This shift challenges traditional cost structures and compels organizations to rethink their value propositions. Through innovative approaches such as AI-as-a-Service (AIaaS), companies are moving beyond product-centric models to more flexible, service-oriented and platform-based ecosystems. This transformation is lowering entry barriers for new market players and enabling small and medium-sized enterprises (SMEs) to leverage sophisticated AI capabilities without substantial capital investment. Gen AI's ability to accelerate the time-to-market for new innovations—by optimizing processes such as predictive maintenance, supply chain management, and rapid prototyping—empowers businesses to remain agile and competitive in fast-evolving markets. To fully harness the disruptive potential of Gen AI, organizations must adopt a "reinvention mindset," by rethinking opportunities that were neglected in times before GenAI, and by fundamentally reimagining how they create and deliver value.

As industries continue to evolve in the era of generative AI, the path forward will require a delicate balance between harnessing the technology's transformative potential and addressing its inherent challenges. Organizations that successfully integrate Gen AI into their strategic frameworks will be well-positioned to lead in their respective markets, driving both growth and innovation. However, achieving this requires not only technological expertise but also a commitment to ethical practices, stakeholder engagement, and continuous adaptation to the changing landscape of AI.

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Comparative study of the challenges and opportunities posed by Big Data and Machine Learning for social and managerial sciences

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Abstract

The emergence of AI and Big Data has sparked considerable enthusiasm and debate within both industry and academia. Major high-tech companies such as Google, Amazon, Microsoft, and Facebook have established successful data analytics teams, often staffed by individuals with advanced degrees in fields like IT and mathematics. This trend has led to concerns among social and management scientists about the potential encroachment of Big Data analysts from these disparate disciplines into their domains. The rise of atheoretical and inductive research methodologies, which prioritize pattern detection over causal relationships, has further fueled these apprehensions. This research seeks to empirically assess the impact of Big Data on social and managerial sciences by conducting a scientometric analysis of articles published in top-tier sociology and management journals over the past decade. The study aims to determine whether there has been an increase in the proportion of publications utilizing Big Data and to examine how this trend affects the use of theory in research. The analysis will compare citation patterns and the academic backgrounds of authors to evaluate the integration of Big Data within traditional theoretical frameworks. Drawing on the disruptive innovation theory and Thomas Kuhn's model of scientific revolutions, this study will explore whether Big Data constitutes a paradigm shift in social and management sciences. Additionally, insights from the Social Study of Science and Science and Technology Studies will be incorporated to contextualize these changes. The findings are expected to reveal whether Big Data is becoming prevalent in these academic fields and how it influences theoretical rigor and research methodologies. This investigation will provide a nuanced understanding of the evolving landscape of social and managerial sciences in the era of Big Data, offering valuable insights into the interplay between data-driven and theory-centric research approaches.

Keywords: *Big Data, Machine Learning, Future of Social and Managerial Sciences.*

1. Research puzzle

The proposed research aims to demonstrate that "insightful" scientific research valued by academic peers still needs to be theory-centric and hypothesis-driven. Possessing Big Data and being data-driven is not sufficient because data alone will never speak for itself. This implies that despite the "clear and present danger" posed by Big Data and Machine Learning to traditional empirical research in various scientific fields that have historically relied heavily on insights, concepts, and hypotheses derived from theory, it is unlikely that scientific research can do without these elements, abandon the search for causality, and become entirely inductive.

In 2008, Chris Anderson, editor of Wired Magazine, made a controversial claim in the article titled "The End of Theory: The Data Deluge Makes the Scientific Method Obsolete."[1] He argued that the abundance and rapid growth of data, which can be collected, stored, and analyzed without direct human guidance or reliance on prior theories or hypotheses, makes correlation sufficient and could render traditional social sciences redundant. This sentiment was echoed by Mayer-Schönberger and Cukier [2] in their book Big Data: A Revolution That Will Transform How We Live, Work, and Think, where they suggested that there might be good reasons to prefer these "fast and cheap" correlations. For example, one could simply aim to detect patterns in data instead of searching for hard-to-discover causal relationships. Furthermore, with the emergence of data mining and other efforts to make sense of Big Data, some voices suggest that academic research should abandon its traditional deductive approach, where research questions and hypotheses are derived from theory.

Such a shift would mean that research would not benefit from aspects derived from theory, such as better selection and operationalization of concepts, adoption or development of data collection instruments, selection of measurement scales, data analysis methods, and interpretation of results. Some support for these expectations can be found in the research practices of big tech companies. Enthusiastic reporters often illustrate this with examples from large high-tech companies, such as Google, Amazon, Microsoft, Walmart, eBay, Facebook, LinkedIn, and Twitter, which have established special teams of data analysts. Given that data scientists employed by these organizations often graduate in fields like informatics or mathematics, one may question how much social or management theory is necessary for practical data analysis. As Thomas H. Davenport and D.J. Patil pointed out in their article "Data Scientist: The Sexiest Job of the 21st Century," published in Harvard Business Review in 2012 [3], it is not uncommon for these data scientists to have advanced academic degrees in fields like ecology, systems biology, or astrophysics.

Although these fields are far removed from business or management sciences, it is not entirely unrealistic to expect, based on changes in business practice, that data science could come to dominate more academically oriented research and its scientific output. This is what Mishra et al. [4] detected in their paper "Big Data and Supply Chain Management: A Review and Bibliometric Analysis." While Big Data has not yet overtaken the entire field of management science, it is plausible that its impact has been greatest on sub-fields of business research whose parent disciplines are in engineering and exact sciences, and smaller in sub-fields of business studies with parent disciplines in social sciences. This corresponds to the sub-fields and parent disciplines presented in the left and right columns of the following figure.

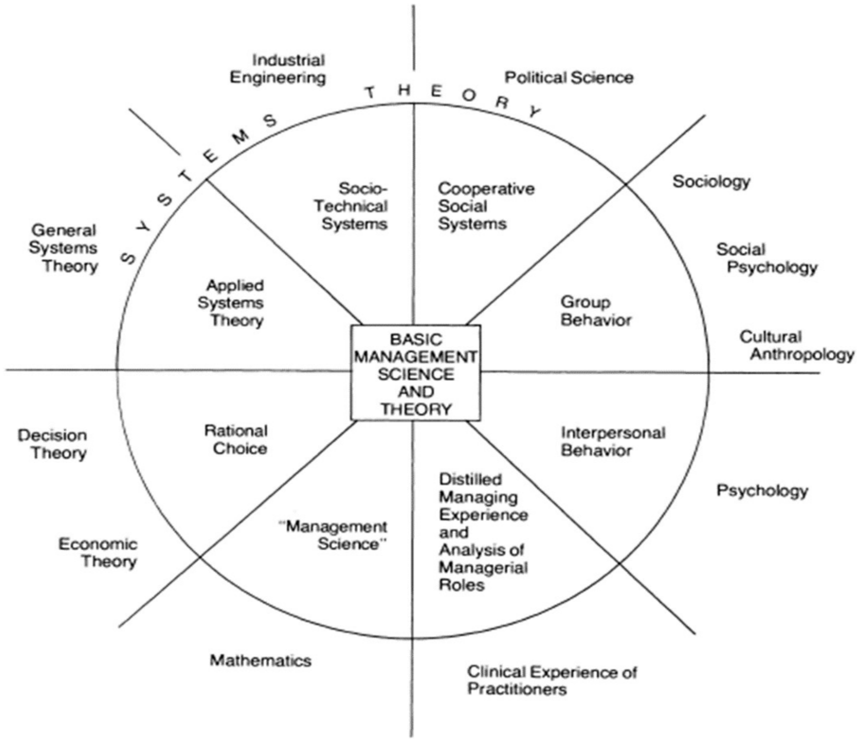

FIGURE 1. The Scope of Operational Science and Theory [5]

Nevertheless, even the parent disciplines of traditional social sciences, such as sociology, feel threatened by the emergence of Big Data. This is precisely how many have interpreted one of the most cited papers in sociology over the past decade by Savage and Burrows (2007), titled "The Coming Crisis of Empirical Sociology."[6] They suggest that "transactional data, which are now routinely collected, processed, and analyzed by a wide variety of private and public institutions," is rendering the typical methods used by sociologists obsolete. They argue that survey and in-depth interview methods do not offer an advantage to sociologists over corporate researchers working on the "transactional data" routinely collected by private institutions as a by-product of institutional transactions.

Szelényi [7], goes even further and suggests in his paper "The Triple Crisis of US Sociology" that sociology is simultaneously facing crises in theory, methods, and politics. He argues that because the subject matter studied by sociologists is not significantly different from that studied by other social scientists, and because neoclassical economists and rational choice political scientists are methodologically better equipped to handle (Big) Data, the discipline is in danger of losing its raison d'être. He asserts that sociology must redefine itself around a proposed agenda of neoclassical sociology that takes theory as seriously as the founding fathers of the discipline and becomes truly reflexive towards original/primary data collection and analysis.

Given the above, I intend to examine to what extent Big Data and Machine Learning are already affecting social and managerial sciences and their potential to disrupt the entire ecosystem. Specifically, can we detect a pattern indicating that the proportion of publications utilizing Big Data and Machine Learning have increased in the top 10 most prestigious journals in social and management sciences over the last decade? Additionally, are articles that utilize Big Data and Machine Learning and are published in top journals cited significantly more within 2 or 5 years after publication compared to other articles published in the same outlets? Furthermore, I would like to study the educational background of the authors to determine if they have been able to publish atheoretical articles, which follow an inductive reasoning approach rather than the traditional hypothesis-driven approach, more common in the grounded theory tradition of social and managerial sciences.

I hypothesize that it is unlikely that analysts who utilize Big Data and Machine Learning in their research have been able to publish in top journals without theoretical knowledge of the analyzed field. To get published in these top-tier outlets, authors utilizing Big Data and Machine Learning still need to use strategies for gaining theoretical credibility, as suggested by Pääkkönen [8]. It is unlikely that atheoretical research would be published in top academic outlets, and even less likely that it would be highly regarded by fellow academics. If Big Data and Machine Learning have found its way into these outlets, the authors of these articles likely resemble conventional empirical researchers, where theory inspires them to ask interesting questions, formulate hypotheses, and engage with the generalizations of previous studies. It is improbable that data alone will provide the necessary insights. The insights, indicated in the third column of the following figure, would need to come from the theory of the field.

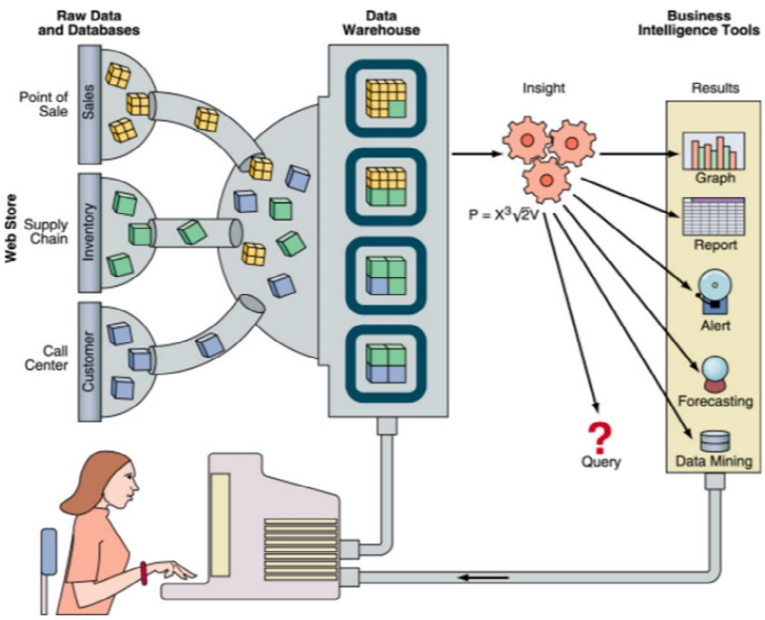

FIGURE 2. The Basic Understanding of BI [9]

ISSN 2991-9371

2. Theoretical framework

I shall make an attempt to extend the "theory of disruptive innovation" to the interruption that the emergence of Big Data is expected to make on such ecosystems as social sciences in general and management sciences in particular. Although the "theory of disruptive innovation", first put forward by Bower and Christensen [10], has gone over a major development cycle over the decades, one can still expect that the Schumpeterian [11] logic would hold. That is, one would expect to be able to observe that the process brought about the digitalization of much of the modern business conduct and administrative affairs in advanced economies and societies – reflected in the emergence of Big Data and Artificial Intelligence – can be detected also in the published research in the top journals of social and managerial sciences as well as in the corresponding decrease of the importance of the role of theory in research publications. Given the nature of disruptive innovations where the users of a mainstream "product" or "service" turn to a different offering, often provided by a less established provider of the innovation not all at once but in accordance with their ability to spend and tolerate the uncertainties related to it, on the one hand, and the reasonable expectation that there is a resistance to change in any ecosystem, on the other, it seems plausible that the process by which Big Data and Machine Learning could potentially be disrupting social and managerial sciences.

The ongoing process of digitalization and the mass generation of administrative data is expected to cause a major disruption in research methodologies, as noted by commentators like Mayer-Schönberger and Cukier [2]. This shift may follow a pattern similar to the adoption of Big Data and Machine Learning in social and managerial research, characterized by the following groups of users: (1) innovators, (2) early adopters, (3) early majority, (4) late majority, and (5) laggards. Consequently, it is important to assess which stage of this change can be detected based on the top journals in social and managerial sciences.

The second theoretical inspiration for this research comes from Thomas Kuhn's ideas in The Structure of Scientific Revolutions regarding the evolution of science through stages: preparadigmatic, normal, and revolutionary science. Although this narrative is well-known, it is worth noting that industry commentators have reported not only the emergence of a paradigm shift but also that "The Fourth Paradigm," leading to "data-intensive scientific discoveries," has already arrived [12]. These ideas provide a valuable perspective for the analysis.

I will counterbalance these insights with perspectives from scholars in the Social Study of Science and Science and Technology Studies, who focus on the use of methods in (social) sciences. While some commentators refer to this research interest and related investigations as "methodography" [13]-[15], others, like Timans et al. [16], suggest that the growing interest in the sociological study of methods is leading us toward a consistent research program known as the "social life of methods" [17], as the foundational elements are already in place.

ISSN 2991-9371

2.1. Research Approach and Implementation

To address the research problem outlined in the first section, I will conduct a scientific analysis of articles published in top sociology and management journals. I will determine whether the proportion of articles utilizing Big Data and Machine Learning have increased over the past decade in these fields. In addition to frequency counts and changes in proportion, I aim to explore the implications for the use of theory in research: Is research in selected disciplines becoming more atheoretical and inductive, essentially adopting a "computational grounded theory" approach where data precedes theory, as suggested by Berente and Seidel [18]? Finally, to assess whether applied sciences are more affected by Big Data and Machine Learning compared to disciplines with stronger self-identity and institutionalized professional protections, I will compare publication and citation patterns in the top 10 management science journals with those in the top 10 sociology journals over the past decade.

For details see the literature reviews put forward by Christensen et al. [19] and Martiınez-Vergara and Valls-Pasola [20].

2.2. Sampling, Data Collection, and Analysis

Sampling will involve selecting the top 10 sociology and top 10 management journals based on the Web of Science Journal Citation Index. The list of articles published in these top journals over the last decade will form the sample frame for this research. Similar to Mishra et al. [4], I will identify original research articles (excluding editorials and book reviews) using the criteria of "Big Data" or "Machine Learning" mentioned in titles, abstracts, and keywords. Articles meeting these criteria will constitute the sample of sociology and management articles for this study.

Given the expected stability in the number of articles published in top journals, I will observe whether the proportion of those utilizing Big Data and Machine Learning have increased over the last decade. I will also examine the structure of these articles and the role of theory within them. Citation data for articles using Big Data and Machie Learning in the top 10 sociology and management journals will be compared to the most cited papers in these journals and to the average citations of these journals (Journal Citation Index) to determine if Big Data and Machine Learning papers are among the most cited and how they compare to the average.

For data analysis, I will use Mishra et al. [4] as a model, following their bibliometric and PageRank analysis methods. I will also consider whether cluster analysis and network analysis could add value to the study. Finally, by including both a more "fundamental" social science field (sociology) and a more applied field (management), this study will facilitate comparisons and contrasts between these two disciplines.

3. Summary

On the one hand, there is considerable excitement and enthusiasm about Big Data and Machine Learning. Enthusiastic reporters often highlight examples from major high-tech companies such as Google, Amazon, Microsoft, Walmart, eBay, Facebook, LinkedIn, and Twitter, showcasing how these organizations have successfully established data analytics teams. Given that many data scientists in these companies have advanced degrees in fields like IT and mathematics, social and management scientists often feel their disciplines are under threat from these Big Data and Machine Learning experts. As Thomas H. Davenport and D.J. Patil [3] noted in their widely discussed Harvard Business Review article, "Data Scientist: The Sexiest Job of the 21st Century," it is not uncommon for these data scientists to have advanced degrees in "esoteric" fields such as ecology, systems biology, or even astrophysics.

On the other hand, social sciences, particularly management sciences, are facing challenges from the rise of Big Data and its analysts, whose training and conceptual frameworks originate from disciplines quite distinct from those they now apply their skills to. Traditional scholars in social and management sciences feel threatened and question the value of atheoretical and inductive research based on Big Data, which often does not aim to uncover causal relationships [21]-[23].

Despite these concerns, it remains unclear to what extent the threats posed by Big Data and Machine Learning to social and management sciences have materialized. Are these disciplines genuinely undergoing or about to undergo fundamental changes due to the emergence of routinely collected, processed, and analyzed data by various private and public institutions? This research plan aims to answer these questions empirically by conducting a scientometric analysis of articles published in top sociology and management journals. While the theory of disruptive innovation is complex and was not originally designed to address changes in academic ecosystems, it may still offer valuable insights into the potential disruptions caused by the digitalization of administrative and business affairs. With an open-minded approach and a willingness to extend this theory to academia, we might observe similar processes in scholarly fields as those experienced in industry.

One might argue that examining top journals in social and management sciences could be unfair, as they might be more conservative. However, if Big Data represents superior data, as suggested by Cukier [24], and if a "paradigm shift" is underway, as argued by Wilbanks [12], it could be argued that even the most conservative editors and reviewers in these fields cannot ignore it. Furthermore, while it is possible that editors and reviewers of top journals have pressured authors to incorporate theory into manuscripts that initially lacked it, my experience as a member of the editorial board of Prometheus: Critical Studies in Innovation suggests otherwise. There are very few authors willing to make such fundamental changes. Manuscripts that leverage Big Data and Machine Learning while remaining theory-centered are likely to be co-authored by individuals from diverse academic backgrounds. My analysis aims to identify these cases by examining the academic backgrounds of authors utilizing Big Data and Machine Learning in articles published in top journals in social and management sciences.

4. Acknowledgements

The acknowledgement for funding organizations etc. should be placed in a separate section at the end of the text.

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Integrating Generative AI in Marketing Curriculum: The case of Marketing Management Classroom

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Abstract

This paper explores the possibilities of integrating Generative Artificial Intelligence (GenAI) within the marketing curriculum through the case of the marketing management classroom. It does so by reviewing the potential of various GenAI tools, highlighting their key features and capabilities. Here, emphasis is placed on the practical applications of GenAI in educational settings of marketing management classroom, specifically focusing on assessment of producing strategic marketing plans through tasks such as information provision, data extraction and analysis, content generation as well as creative outputs. The case study of Zagreb School of Economics and Management's Marketing Management course is presented, demonstrating how GenAI can be integrated into the curriculum to enhance the quality of strategic marketing plans produced by students, especially due to the recorded decline in quality of submitted assessments by generations 2022/2023 and 2023/2024. Despite these generations of students having had GenAI tools available and free to use, they nevertheless underperformed in producing their assessments in comparison to the pre-GenAI generations of students. Therefore, this paper advocates for strategic adoption of GenAI as an essential tool in the marketing management course, offering recommendations for curriculum design and teaching methods that are aiming to equip students with the competencies needed to adapt to the rapidly transforming labour market.

Keywords: *Generative AI (GenAI), AI in higher education, Marketing education, Curriculum design, Marketing Management*

ISSN 2991-9371

1. Introduction

"A.I. will force us humans to double down on those talents and skills that only humans possess. The most important thing about A.I. may be that it shows us what it can't do, and so reveals who we are and what we have to offer." [1]

Generative AI (GenAI) tools have significantly impacted approaches to marketing strategies in the digital age [2], consequently impacting approaches to teaching marketing in higher education. In this paper we explore general concepts of GenAI and offer an overview of selected GenAI providers, products and tools. We then in detail provide a clear understanding of the selected range of GenAI tools, placing them in the context of their usefulness for approaching marketing strategies in the digital age.

We then focus on practical applications of GenAI in marketing, specifically their use in the marketing management classroom. We are doing so by reflecting on the evident decrease of quality of submitted assessments by generations 2022/2023 and 2023/2024. From an average score of 17.0 points (out of 25) in generation 2019/2020 to average score of 15.7 and 15.1 for generations 2022/2023 and 2023/2024. Interestingy, despite the availability of the GenAI tools for new generations, students' performance is decreasing (see figure 1 below). This could be, apart from other factors, due to the inappropriate use, or the lack of knowledge as to how to properly use the GenAI tools for writing assessments.

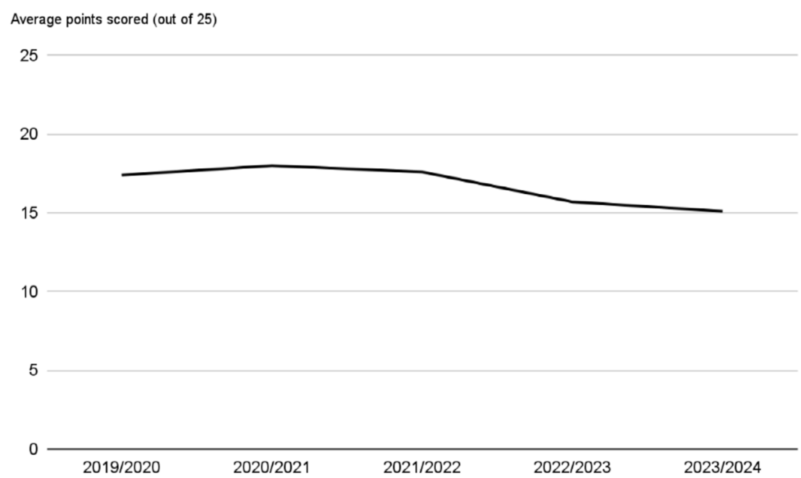

FIGURE 1. Average points for marketing management assessment 2019-2024.
Source: Authors

Therefore, in order to explore the possibilities of integration of GenAI into the marketing management curriculum and consequently enhancing the quality of strategic marketing plans produced by students, we reference one of the main components of the grading marketing management course, production of strategic marketing plans. We test different GenAI tools to approach the R-STP-MM-IC formula (research – segmentation, targeting, positioning –

marketing mix – implementation and control) analysing effectiveness of selected tools. Such exploration sheds light into how these can be used as pedagogical approaches aiming at increasing the quality of assessments through strategically teaching how to use tools in the marketing landscape. Finally, we suggest a framework for effective use of GenAI tools in the marketing management classroom for the assessment of producing strategic marketing plans. The proposed framework offers insights for higher education lecturers with regards to approaches to teaching methods that are aimed to better equip students with the competences needed for a rapidly transforming marketing labour market.

2. Generative AI: An overview

This part of the paper is divided into three sections. First section discusses the history of Gen AI. The second section looks at the use of the AI tools in higher education. Finally, the third section discusses the selected generative AI and their usefulness in the context of this research.

2.1. History of Gen AI

"Between June 2022 and March 2023, the traffic volume for the keyword "AI" has tripled, going from around 7.9 million monthly searches to more than 30.4 million during the last month of the measured period" [3]. This growing interest aligns with the emerging relevance and impact that GenAI has today. Despite the multiple concerns regarding its usage, AI is present and already integrated on some level in all aspects of our everyday lives. Therefore, there is a need for the GenAI to be examined and used in a beneficial way to highly perform in tasks that it has been designed for. The term *artificial intelligence* was used for the first time in 1955 by John McCarthy when he described it as science and engineering of making intelligent machines [4].

AI can be defined as a "broad field encompassing various techniques and approaches to create intelligent machines that perceive their environment and take actions" [5], and it presents the crucial technology for the digital transformation of society [6]. New paradigms of machine processing have been made possible by recent advancements in AI, which have allowed activities to move from data-driven, discriminative AI to complex, creative tasks [7]. Aim of those activities is to offer undistinguished content from human craftsmanship [8]. All the mentioned activities are possible with GenAI, a special field within AI that "focuses on developing algorithms and models capable of generating synthetic data that closely resemble real-world data" [9], making creativity as its unique feature. These outputs include data like code, text, image, audio, video and other data that is labelled. However, it can also achieve significant success in some complex domains that can be clearly modelled [10].

Therefore, GenAI refers to AI systems whose main goal is new data creation. Farrelly and Baker argue that "these systems use machine learning techniques, particularly deep learning, to identify and mimic patterns, styles, and structures found in the input data they are trained on" [11]. The model, data processing, and user interface components are all included in a generative

AI system. The model functions as the system's central component, enabling application and interaction in a wider environment [8]. Moreover, these models excel through their training on extensive datasets, allowing them to recognize patterns and structures in input data and generate new, similar data. Neural networks enable this pattern recognition, using methods like unsupervised and semi-supervised learning [2].

GenAI gained traction in 2014, when Ian Goodfellow and his team introduced Generative Adversarial Networks (GANs) [12]. The field made major progress with the publication of OpenAI's Generative Pre-Trained Transformer (GPT) models, particularly GPT-2 in 2019 and GPT-3 in 2020, which displayed exceptional ability in generating human-like language [5]. Today, some of the most popular GenAI tools are for example GPT-3 and GPT-4 by OpenAI, DALL-E 2 by OpenAI, ChatGPT by OpenAI, and Copilot by GitHub. These progress in publications of a variety of GenAI tools consequently triggered interest in GenAI in academic research since 2019. Recent findings are highlighting the growing importance and impact that GenAI has [2, 5]. Precedence Research estimated the global market for GenAI to be worth USD 10.79 billion in 2022 and is expected to increase to roughly USD 118.06 billion by 2032, growing at a compound annual growth rate (CAGR) of 27.02 % between 2023 and 2032 [13]. Another research has suggested that "it could potentially boost Europe's annual GDP growth by 0.4 % to 0.7 % by 2030, a substantial increase compared to the forecasted growth rate of around 1.4 % without AI effects" [14]. These all suggest the importance of understanding and incorporating Gen AI has, in the context of this research, in its practical application in higher educational settings of marketing management classroom.

2.1.1. Gen AI in higher education

As suggested in previous sections, it is evident that GenAI is recording extensive spread, both in its technological development, and in its usage [7, 11]. The mentioned examples, such as GPT-4, "are currently revolutionising the way we work and communicate with each other" [8]. This affects both educational institutions, particularly higher education institutions by reshaping and emerging the need to transform the existing infrastructure of education. Therefore, "universities currently face challenges in how to incorporate GenAI technologies into their curriculums and academic integrity policies" [15].

Therefore, implementing GenAI in higher education demands careful planning and patience to ensure its successful integration, along with recognition of the awareness of raising concerns regarding the implementation, academic integrity, detection of plagiarism, and the impact on students critical thinking skills [16]. Even though higher education is not the fastest-moving sector, it is being compelled to alter these underlying educational structures due to quick and widespread technological advancements [5] to better equip students with the skills and knowledge required to thrive in a rapidly evolving digital landscape. Farrelly and Baker (2023) discuss how the current shift in technological realities necessitates an update in the essential toolkit of competencies for modern individuals [11]. The shift is considered to have a successful outcome should it incorporate speed and agility, which have become crucial for success [17]. Therefore, higher education stakeholders are in need to remain current with emerging trends and effectively manage to adapt to them. More specifically, by adopting a careful strategy that fosters cooperation among educational institutions, AI specialists and students, we address challenges and leverage GenAI to enhance a variety of tasks such as exam administration or knowledge assessment. GenAI could therefore be seen as a tool that requires careful integration into the educational system, ensuring adherence to ethical and legal standards [4]. Furthermore, despite all the positive sides discussed above, there is, on the other hand, a need to reflect the concerns that GenAI might be bringing. Various authors have detected raising concerns regarding the usage of GenAI such as academic integrity, ethics and privacy, academic rigour and quality, constraint of resources, regulations, cheating in academic programming to disobey academic norms, academic work, less efficient and valuable education system, decrease in quality, long-term consequences on students' academic and professional careers, and decrease in quality among students [4, 11, 16]. Prompt (short-term) response to these concerns is offered by "a growing number of ed tech startups, as well as long-established technology companies, that have suddenly turned their attention to developing tools that claim to be able to detect text generated by AI models, using the language of "protecting academic integrity" [11]. On the other hand, there are also numerous GenAI's possibilities that can foster productivity and effectiveness of the educational system. Some of them are 24/7 support and accessibility, personalised approach to each student, language learning and communication skills, new learning experience, data analysis, learning and memorising assistance, learning new things related to digital work, and vivid learning partner [5,16].

Considering all the mentioned above, various higher education courses have the potential to redefine their pedagogical approaches and curriculums by incorporating the use of GenAI within their curriculum. The section below will explain selected GenAI tools in the context of a marketing management classroom used for the purposes of this research.

2.2. Generative AI tools in use today

This section explores some of the most popular and prominent GenAI tools. Those are Canva, Gemini, and ChatGPT which are currently influencing the development of AI-driven communication and content creation. With the application of cutting-edge AI technology, these tools have become indispensable in a variety of creative and professional domains, improving user experience and expanding the boundaries of design, communication, and automation. This is why they are also important in the context of their application in the marketing management classroom. Therefore, the following sections summarise their main functions and benefits.

2.2.1. Canva

Canva is primarily known as an online, graphic design and visual communication platform [18] that was introduced by Melanie Perkins, Cliff Obrecht and Cameron Adams in 2012. Company itself is the platform's provider which was launched in 2013. The motto of the platform is to empower the world to design [18]. Therefore, Canva platform offers various combinations of design tools with the purpose to create presentations, social media content (posts, stories, social media ads, profile pictures), logos, videos, brochures, posters, resumes, etc. These design tools can be used by everyone, and they can be published anywhere. Furthermore, for creation of these materials users have a wide range of templates, fonts, colours, images, stickers and other design elements that can be easily customised for content to be appealing. With GenAI gaining more and more popularity and its extensive usage, Canva has also incorporated some AI-powered features. Those features include Magic Design and Magic Write. The first one offers the possibility of generating design templates that are based on inputs like text while the second one is a tool on the platform for creating material and copy. Because of all features highlighted, Canva platform is an invaluable tool for professional, marketing, and educational settings.

2.2.2. Google

In December 2023 Google introduced Gemini (ex Bard). Gemini is GenAI cutting-edge platform that was in the moment of its release the most advanced AI model. It was developed by Google DeepMind to be able to process and integrate various inputs like text, images, audio, video, and code with multimodality being its most important feature. It has become an important AI tool for content creation and AI-driven communication, just like GPT-4 (discussed below). Gemini provides benefits like extensive interaction with the Google ecosystem, making it a desirable and agile tool in the GenAI landscape. The platform is currently available in two versions, including the free Gemini Pro and more advanced Gemini Ultra, with each being optimised for different levels of complexity and tasks [19].

2.2.3. OpenAI

ChatGPT, introduced in 2022, has quickly established itself as the most popular GenAI tool available on the market. This AI platform was developed by OpenAI, and it positioned itself as a valuable conversational agent tool [20]. The main purpose of its existence and usage is generating AI-driven communication, and content creation possibilities. With a wide range of features, compared with user-friendliness, that can be applied in various contexts, like generating text, answering questions, summarising content, assisting and creative writing, ChatGPT became one of the most widely utilised and prominent generative AI tools today [21]. Currently, ChatGPT is offered in two versions: a free version using GPT-3.5 and a paid version, ChatGPT Plus, which includes GPT-4 and DALL-E 3 for text and image generation. Sora, a new feature, has been introduced to generate videos from text input. GPT-4, especially the enhanced GPT-4 Turbo, is recognized as a benchmark in the GenAI space due to its advanced generative capabilities. Additionally, ChatGPT's functionality can be expanded with plugins, which extend its capabilities beyond the original training data [2].

GenAI models	Provider	Tools	Open source
Canva	Canva	Design tools	No
Gemini	Google	Gemini, API	No
GPT-4	OpenAI	ChatGPT, API	No

FIGURE 2. Popular GenAI Models. Adapted from [1]

Above figure 2 summarises discussed GenAI models, where the following section takes this further by exploring applications of these tools in the context of a marketing management classroom.

3. Applications of Generative AI in Marketing Management Classroom

With the above explored foundation of understanding of GenAI tools, in this section we shift our attention to the practical applications of GenAI tools for the purposes of the marketing management classroom. We specifically focus on the assessment of producing strategic marketing plans through tasks such as information provision, data extraction and analysis, content generation as well as creative outputs. Here, by referencing one of the main components of the grading marketing management course, production of strategic marketing plans, we test different GenAI tools to approach the R-STP-MM-IC formula (research – segmentation, targeting, positioning – marketing mix – implementation and control) analysing effectiveness of selected tools. As discussed earlier, GenAI plays a significant role in marketing [22]. Marketing often relies on processing vast amounts of data to identify patterns, behaviours, and opportunities [23]. Furthermore, GenAI's impact can be described through a three-stage framework for strategic marketing planning: mechanical AI, which handles repetitive tasks; thinking AI, which processes data to support decision-making; and feeling AI, which evaluates human interactions and emotions [24].Therefore, figure 3 below is structured to correspond to the main components of writing strategic marketing plans, providing a comprehensive overview of how these tools can be utilised in teaching marketing management and producing higher quality marketing plans by students. Figure 3, apart from offering stages of marketing planning, also includes a rating system to assess the effectiveness and reliability of selected GenAI tools across various marketing management tasks while writing strategic marketing plans.

The performance strength of a GenAI tool is graded by "*" signs, where "***" indicates excellent performance, demonstrating that GenAI excels at this task; "**" signifies a strong performance where the tools are notably effective; and "*" indicates a supportive role, highlighting areas that require further development [2]. Additionally, the reliability of these tools is classified as either 'reliable', suggesting general dependability in performing the task; or 'caution', advising users to remain attentive due to potential challenges or limitations in the current capabilities of the explored GenAI tool for the purposes of writing strategic marketing plans. We categorise the utility of GenAI in marketing into four main components of production of strategic marketing plans: research; segmentation, targeting and positioning; marketing mix; and implementation and control. Each task type leverages the distinct strengths of GenAI tools, transforming how marketing management students and lecturers can approach their work. By incorporating these tools into their practices, it is believed they can achieve enhanced efficiency, accuracy, and creativity in their work.

	Research	**Segmentation, Targeting, Positioning**	**Marketing Mix**	**Implementation and Control**
Canva	▫ summarises data and insights ▫ gives ideas as to how to approach research	▫ generates proposed segmentation, targeting and positioning strategies	▫ generates personalised marketing messages ▫ generates images ▫ generates videos ▫ generates campaigns ▫ can offer pricing ideas	▫ provides some ideas for implementation and feedback
Performance	*	**	*** (for promotion)	*
Reliability	Cautious	Cautious	Cautious for product, place and price; Reliable for promotion	Cautious
Gemini	▫ offers general guidelines for approaching research ▫ gives valuable aspects to be aware of when doing research	▫ provides comprehensive explanations of segmentation, targeting and positioning ▫ offers guidance on selecting the most appropriate segment ▫ formulates effective positioning statement	▫ generates personalised marketing messages ▫ proposes relevant price and place strategies ▫ describes the content that should be used for social media	▫ provides specific strategies for implementation and control ▫ generates a basic structure of diagram for implementation and control
Performance	*	**	*	**
Reliability	Cautious	Cautious	Cautious	Cautious

ISSN 2991-9371

ChatGPT	▫ summarise facts from market reports ▫ summarises data and insights	▫ generates proposed segmentation, targeting and positioning strategies	▫ generates personalised marketing messages ▫ generates images ▫ generated creative marketing messages ▫ creating materials for social media and other forms of content	▫ provides ideas for implementation and feedback
Performance	**	**	*	**
Reliability	Cautious	Cautious	Cautious	Cautious

FIGURE 3. Popular GenAI Models and tasks that can be applied in Marketing Management Classroom.
Source: Authors, adapted from [2]

The figure 3 above compares Canva, Gemini, and ChatGPT across key marketing functions: Research, Segmentation Targeting and Positioning (STP), Marketing Mix, and Implementation and Control. Canva excels in generating personalised marketing materials and campaigns, with strong performance in the promotion part of the Marketing Mix. Gemini offers comprehensive guidance on segmentation, targeting, and positioning, along with specific strategies for implementation, but performs lower in Marketing Mix. ChatGPT provides balanced performance with strengths in Research and STP, focusing on summarising market insights and generating creative content for various platforms. Each tool has distinct advantages depending on the specific marketing task. Finally, GenAI tools are highly effective at offering access to extensive repositories of knowledge, which makes them crucial for distributing current information in marketing courses and practices [2]. These tools are instrumental in conveying well-established facts and concepts and in sourcing and summarising new knowledge, including the latest trends and data in the marketing field. Thus, above exploration sheds light into how these can be used as pedagogical approaches aiming at increasing the quality of assessments through strategically teaching how to use tools in the marketing landscape.

4. Conclusion

This paper explored integration of GenAI in the marketing curriculum: the case of marketing management classroom. Findings suggest that such GenAI tools may be used as an innovative teaching method within marketing management classroom. It showed (see figure 3 above) that explored GenAI tools have (to some extent) ability to generate information provision, data extraction and analysis, content generation as well as producing creative outputs. Despite their effectiveness and usefulness in various stages of producing strategic marketing decisions, they nevertheless remain tools that cannot be used properly should students have no knowledge of marketing theories that allow them to give GenAI appropriate prompts and avoid limitations when it comes to deep reasoning and original creative outputs. In the figure 4 below we propose possible integration of examined GenAI tools into the marketing management course curriculum which might positively impact the quality of strategic marketing plans produced by students.

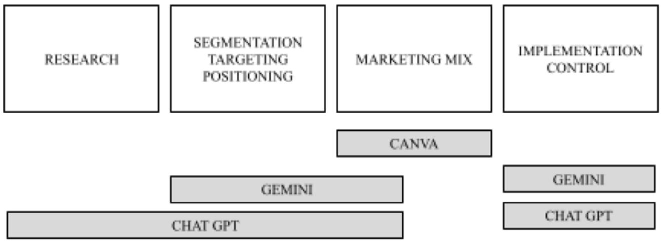

FIGURE 4. GenAI Models application for marketing management curriculum for production of strategic marketing plans

While being aware that usefulness of these tools might overlap (as also suggested in the figure 3 above), we highlight the potential of Gemini and ChatGPT to be more reliable in the stages of research and segmentation, targeting and positioning, while we highlight the usefulness of Canva in the marketing mix, especially in the context of promotion. For implementation and control it is also useful to use ChatGPT or Gemini as a tool for assisting strategy development. Furthermore, it is suggested that these tools are introduced as a part of the marketing management module, while covering related topics as per figure 4 above. While on the one hand it can positively impact advancements of teaching methods and save time and effort placed in producing strategic marketing plans, it on the other hand has many challenges such as limited understanding of processes, quality assurance through lack of deep reasoning as well as the risk of plagiarism. This calls for further exploration of how to effectively use GenAI within assessments by maintaining academic integrity. As literature review suggests, higher education institution lecturers are in need of staying updated with the developments of GenAI that impact approaches to teaching marketing strategies, to understand how and in what way these need to be used in teaching approaches.

Finally, incorporating GenAI in the marketing management classroom is no longer useful but rather essential as a tool in the contemporary digital era. While teaching marketing, we need to recognise and use the power that GenAI can provide, such as generate information provision, data extraction and analysis, content generation as well as producing creative outputs, however at the same time be aware of its many limitations while equipping students with the competencies needed for adapting to the rapidly transforming labour market.

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The Transformation of Data Literacy Education in Business Schools: An AI-Driven Paradigm Shift

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Abstract

This project, executed within ZSEM, explores the transformative impact of Artificial Intelligence (AI) tools and Large Language Models (LLMs) on business school education in the domains of data literacy, data analysis, statistics, and econometrics. It aims to outline and craft visions for a new generation of foundational courses in data analysis theory and practice, developing educational products that enhance learning experiences and outcomes.

The critical importance of teaching data analysis and data literacy in business schools is underscored by the prevalence of data-driven decision-making in today's business environment. The new paradigm of business communication implies data-driven argumentation and the ability to understand and critically acclaim statements made using data. However, teaching these subjects presents significant challenges due to their complexity, the diverse backgrounds of students entering business programs, and the rapid evolution of analytical tools and methodologies.

Students often struggle to connect theoretical concepts with practical applications, making engagement and retention difficult. Additionally, traditional approaches require extensive technical training in scripting and programming languages, which may not align directly with the interests of business school students. The volume and variety of data available for analysis have grown exponentially, requiring new approaches to data handling and interpretation.

AI and LLMs are revolutionizing data analytics workflows through natural language interfaces, AI-powered data cleaning and preprocessing tools, automated insight generation, enhanced interpretation of unstructured data, and AI-driven visualization tools. These advancements are making complex data more accessible to non-technical stakeholders and augmenting predictive analytics capabilities. LLMs are also facilitating more efficient literature reviews and market intelligence gathering for research-driven analysis.

ISSN 2991-9371

These developments necessitate a reevaluation of traditional teaching approaches. The shift towards natural language querying requires less emphasis on teaching complex query languages. The automation of many analytical tasks demands a greater focus on interpretation and strategic application of insights rather than calculation. New AI-powered tools enable seamless development of reproducible analytical outlines, facilitate data-driven storytelling and visualization. The increasing importance of unstructured data analysis calls for new approaches to teaching text and sentiment analysis in the domain of business studies (e.g. empowering qualitative and mixed methods research).

The project outlines key components of AI and LLM-augmented data analysis teaching, including:

1. Introduction to AI and LLM capabilities in data analysis, including their strengths and limitations.
2. Training in effective use cases and prompt engineering principles for interacting with LLMs in data analysis contexts.
3. Techniques for critically evaluating and validating AI-generated insights and recommendations.
4. Practical experience with AI-enhanced data visualization and interpretation tools.
5. Exploration of ethical considerations in AI-driven data analysis, including bias detection and mitigation.
6. Hands-on projects involving the use of domain-specific LLMs for various analytical tasks.
7. Instruction on integrating AI tools with traditional statistical methods for comprehensive analysis.
8. Development of skills in explaining AI-driven analyses to non-technical stakeholders.

The vision for next-generation data analysis education includes seamlessly integrating AI and LLM tools alongside traditional statistical methods, prioritizing curriculum flexibility and adaptability, emphasizing ethical AI and responsible data use, and fostering interdisciplinary collaboration. Practical, real-world applications will form the core of learning experiences, with AI tools enabling more complex and realistic case studies.

Ultimately, this educational transformation aims to produce not just data analysts, but strategic data leaders capable of driving AI-informed decision-making in organizations. The goal is to equip business professionals with the skills to leverage AI and data analysis to drive more effective, ethical, and innovative business solutions in an increasingly data-driven world.

Keywords: *Data analysis education, data literacy, data-driven decisions, AI for education, edtech, learning experience design, business education*

New Horizons and Challenges in Education and Business

SESSION CHAIR:

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Promoting social and sustainable business through entrepreneurship education

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Abstract

In the Master's degree programme in Entrepreneurship at Heilbronn University, Entrepreneurship Education enables students to start their own business during or shortly after their studies. Particular emphasis is placed on sustainable business start-ups. In various courses in the first semester, especially in the Social Entrepreneurship course, students deal intensively with the problems of the world such as climate change, biodiversity loss, social inequality, etc. and learn about sustainable business models such as the Triple-Layer Business Model Canvas. This study uses the Q-method to investigate whether the current curriculum encourages students to change their attitude and become active in the field of social or sustainable entrepreneurship. The results show that this is indeed the case. Students are rethinking and changing their opinions, attitudes and values in relation to social and sustainable enterprises and issues. They value the role of social enterprises and their potential economic power higher at the end of the semester than at the beginning. More than half of the students state that a social or sustainable start-up is now more likely to be an option for them.

Keywords: *Entrepreneurship Education, Social Entrepreneurship, Future Skills, Personal Development, Values*

1. Project presentation

As part of the project Induko (Innovation durch Kollaboration (Innovation through Collaboration), the Master's degree programme in Entrepreneurship at Hochschule Heilbronn has been revised and remodelled since the winter semester 2021/2022. The main focus of the programme is on setting up your own company responsibly. To this end, new teaching and learning strategies are being developed, tested and evaluated, e.g. elements of education for sustainable development have been taken into account in the design of the programme. Over the course of the programme, students are given the tools to recognise and address socially relevant problems and – if they wish – to tackle them by founding their own company. In order to consider founding a sustainable or social enterprise, students attend the Social Entrepreneurship module in the first semester. At the beginning of this module, students are confronted with the major problems of the world such as climate change, social

ISSN 2991-9371

inequality and biodiversity loss. They then get to know social start-ups and their business models, meet social entrepreneurs and social business angels. The other courses also integrate social and sustainable topics into their teaching. This study is used to determine the attitude towards the topics of sustainability and social entrepreneurship with which students start the Master's programme and whether or how this attitude has changed by the end of the first semester.

2. Entrepreneurship Education

Entrepreneurship education refers to all educational measures designed to help students start a business [1]. In addition to the obligatory economic and legal expertise, this also includes courses focussing on the development of values and attitudes of future founders as well as the development of start-up ideas [1]. It is assumed that people are not born with an "entrepreneurship gene", but can learn to act entrepreneurially and develop the necessary characteristics [2]. Accordingly, entrepreneurship is also regarded as teachable and is now considered a separate field of research [2].

In recent years, start-up activity in Germany has increased on average [3].

> "The increase in start-up activity was accompanied by a shift between age groups. Until 2017, 35 to 44-year-olds were the group with the highest start-up rate. Since then, start-up activity has continuously shifted towards the younger population groups of 18- to 24-year-olds and 25- to 34-year-olds." [3].

This statistic shows that the topic of start-ups is of particular interest to young adults who are typically at university age. Although support for this group is also conceivable through accelerator programmes, for example, learning the skills as part of a degree course has the advantage that a higher educational qualification is acquired in the same breath. This can be utilised in the event of a future career reorientation.

Today's entrepreneurship students will have the opportunity to help shape the economy in the near future. Depending on the content of the curriculum for these degree programmes, different focal points are set and introduced to the students. For this reason, it is essential to provide students with basic knowledge about alternative forms of entrepreneurship, such as social entrepreneurship or sustainable entrepreneurship, so that these can be taken into consideration when developing their business models. Social entrepreneurship refers to entrepreneurship that focuses on social issues [4] or that creates added social value [5] or social challenges [6] should overcome. In the spirit of social entrepreneurship education, students are encouraged to adopt a social entrepreneurial mindset so that they have the opportunity to tackle social problems in the future by setting up their own business [7].

In the Entrepreneurship degree programme at Hochschule Heilbronn (HHN), the aim is to support students as closely as possible through coaching units provided by lecturers, close supervision by the programme director and, if possible, direct work on the students' respective start-up ideas. Ideally, students should be enabled to set up their own company during or directly after their studies. The degree programme therefore corresponds to the principle of Entrepreneurship Education for Entrepreneurship [8].

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The Master's degree programme in Entrepreneurship at HHN focuses strongly on generating the students own start-up ideas and visions for the future, particularly at the beginning of the programme. In the first semester, students attend both the Future Value Creation module, Social Entrepreneurship module and the Innovation Management module. In these modules, participants learn what characterises a good, future-relevant start-up idea and apply methods such as design thinking to develop them. As the programme is taught in block format, it is possible to interlink the content of the modules and thus alternate between idea generation phases and units of the Social Entrepreneurship module. These units on social entrepreneurship take place at important times during the semester, for example before the idea generation phase and after the relevance test. In the course of the module, students are also informed about methods and myths in connection with social entrepreneurship. The design of the degree programme places a strong emphasis on social and sustainable entrepreneurship. Just as already [9] described in their publication, the programme aims to contribute to a deeper integration of entrepreneurship and sustainability in entrepreneurship education.

In order for students to successfully found a company, they also need to develop values and attitudes such as empathy and openness [1]. The framework of the non-profit initiative *Inner Development Goals* was therefore integrated into the curriculum of the degree programme [10]. Particular attention was paid to empathy and compassion because empathy can be a motivator for social entrepreneurs [11].

Since the above-mentioned interlinking of the modules on the topic of social entrepreneurship was carried out in this form for the first time in the winter semester 2023/2024, this study aims to determine how students' attitudes towards the topics of social entrepreneurship and sustainability change over the course of the first semester. The research question of this article is therefore: How do students' opinions, attitudes and values towards social entrepreneurship and sustainability change during the first semester?

3. Use of the Q method

As the research question explained in the previous chapter is intended to determine the opinion and attitude structure of students on the Master's degree programme in Entrepreneurship, the Q method was selected as the survey method. The method was developed in the 1930s at Oxford University by the psychologist William Stephenson [12]. Although the method was developed almost 100 years ago, it is hardly known in German-speaking countries [13]. In the field of environmental research, however, it is being used more and more frequently [12]. The Q method combines qualitative and quantitative research. It is used "particularly for recording opinion, attitude and value structures" [13]. The present study uses the Q method to analyse the attitudes of the test persons to the topics of social entrepreneurship and sustainability. It also examines whether founding a social enterprise is an option for them. Furthermore, their opinions on specific topics, such as the role of companies in solving social problems, are recorded. A Q-set of 33 statements was created for this purpose. These 33 statements are to be arranged on the grid (see Fig. 1) in such a way that each one lies on one of the 33 fields. The fields may only be filled once.

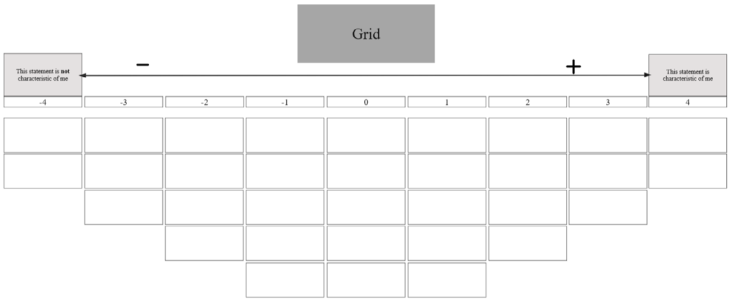

FIGURE. 1: Grid used for the allocation of the 33 statements

Twelve of the statements were adapted to the Q-set of Bhatt et al. (2019) who conducted a study on social entrepreneurship in China [14]. The statements that matched the content of the present study were selected, translated and slightly adapted where necessary. A further seven statements were modelled on the statements from the study on sustainability by Barry and Proops (1999) were used [15]. These statements were also translated and slightly modified. In order to cover all areas relevant to the study, a further 14 statements were developed in-house. These mainly cover the areas of *motivations for starting a business*, *monetary incentives*, *problems in the world*, *goals of starting a business* and *courage*. The assertions for these statements came from conversations the research team had with students from previous cohorts or from typical conversations that take place during classroom sessions. This resulted in a Q-set of 33 statements (see Tab. 1). As both academic sources and typical statements from the students' communication context were used for the sample, this study is referred to as a hybrid sample. The survey is exploratory and the representativeness of the statements was not the focus of the selection, which is why it is an unstructured sample [13].

4. Carrying out the investigation

The study was carried out at the beginning and end of the first semester with students on the Master's in Entrepreneurship programme. The structure of the survey differed both times. Following the lessons, the aim of the survey was briefly explained to the students and it was made clear that participation in the survey was voluntary and would not affect their grades. The students who agreed to take part signed a declaration on data processing. Firstly, it was explained how the Q method works, then each test subject was directed to a Miroboard that had been prepared in advance. On the Miroboard, the test subject was then able to read through the statements without a time limit and assign them to the grid using drag and drop. The Miroboard also contained an area where the test subjects could make notes or leave comments for the experimenter. As soon as all the statements had been assigned, the participants were able to leave. In the second survey, which took place at the end of the semester, the students first assigned the statements on the grid again and were then asked to answer six questions (see Fig. 2). The field for notes was omitted in the second survey. Due to the poorer availability of the students, the second survey took place either in presence, in an online meeting or for independent processing of the Miroboard without a contact point.

1) Has your attitude towards social entrepreneurship changed over the course of the semester? Briefly explain what has changed and why.
2) Has your attitude towards sustainability changed over the course of the semester? Briefly explain what has changed and why.
3) Look at what you placed on -4 (this statement is not characteristic of me) in the last round. Does this still correspond to your opinion or have you placed something else there today? Briefly explain your decision.
4) Look at what you placed on 4 (this statement is characteristic of me) in the last round. Does this still correspond to your opinion or have you placed something else there today? Briefly explain your decision.
5) Is starting a social or sustainable business more or less of an option for you today than it was at the beginning of the semester? Why?
6) Is there anything else you would like to tell us?

FIGURE 2: Open questions at the end of the semester

Thirteen first-semester students on the Master's degree programme in Entrepreneurship took part in both surveys. Due to the incorrect handling of the grid, one person could not be included in the analysis for each of the two surveys. Accordingly, twelve students (n = 5 female, n = 7 male) were included in the analysis for the first survey. Twelve people were also included in the quantitative analysis of the second survey (n = 6 female, n = 6 male). As the answers to the open questions of the person who used the grid incorrectly were included, as well as those of another person who submitted their answers later, 14 people (n = 7 female, n = 7 male) were included in the qualitative analysis.

For the evaluation, a mean value was calculated for each statement. Statement No.1 "The government solves social problems." was placed 12 times in one field in the first round (-4, -2, 2, -1, -4, -2, -4, -3, 1, -2, 1, -3) These values were added together and divided by the number of participants. This produces a mean value of -1.75 for statement 1, meaning that a value was calculated for all 33 statements in both surveys. The statements were then ranked in ascending order for each round. The lowest rank thus corresponds to the statement with the lowest mean value and is therefore the statement most likely to be assigned to "-4 This statement is *not* characteristic of me". Accordingly, the highest rank reflects which statement was most likely to be categorised as "+4 This statement is characteristic of me". A higher value in the "Change in rank" column thus reflects a greater movement on the grid. The value 0 indicates that the statement was positioned the same on average in both surveys.

5. Results and discussion

The detailed analysis of the results shows that students' attitudes have changed as a result of the content taught in the first semester. The biggest change in the ranking of statements was in No. 26 "I would like to earn money with my first company so that I can then devote myself to more important social issues with another start-up". At the beginning of the semester, the statement was rated with an average of -1.08, at the end of the semester with 0.75 and has thus risen from rank 5 to rank 18. The students therefore rated this statement as more characteristic of themselves at the end of the semester. The second biggest change occurred in statement No. 30 "I want to create a better world with my foundation.". While the statement was ranked 12th at the beginning of the semester, it was ranked 21st at the end of the semester and is therefore categorised as more characteristic of the students. The third largest change occurred in statement No. 20 "Sustainability is an important aspect for me when founding a company".

Statements No. 6 "Social enterprises do not have enough power to bring about social change", No. 15 "Our society is wasteful and consumption-driven" and No. 16 "People only think in the short term. They don't think about the long-term impact of their actions." have all moved up 6 places. All three were rated as more characteristic of the students in the first round than at the end of the semester. Statement No. 10 "Young people find it more important to get a well-paid job than to use their talent to start a social enterprise.", statement No. 23 "I want to start a business because I want to take responsibility." And statement No. 28 "The social and ecological problems that currently exist in our world are being ignored." changed. No. 10 and No. 23 have moved further to the right on the grid and statement No. 28 further to the left.

TABLE 1: Mean values and ranks of the statements at both measurement times

No.	Statement	Mean value survey 1	Rank survey 1	Mean value survey 2	Rank survey 2	Amount change in rank
1	The government solves social problems.	-1,75	2	-2	1	1
2	Individuals can solve social problems better than the government.	-0,6	8	-0,33	11	3
3	The government would rather use resources to create privileges and promote companies than to solve social or ecological problems.	-0,1	11	-0,5	9	2
4	There is a lot of misinformation about social enterprises.	-0,1	11	-0,67	8	3
5	Social enterprises are not present enough in the media.	0,5	16	1,08	19	3
6	Social enterprises do not have enough power to bring about social change.	-0,4	9	-1,25	3	6
7	Social enterprises have an important role to play in driving change around the world.	1,5	22	2,5	24	2
8	Social enterprises can play an important role alongside the government in solving social problems.	1,33	21	1,92	23	2
9	Most people are materialistic and are not interested in social or ecological problems.	0,3	15	-0,33	11	4
10	Young people are more interested in getting a well-paid job than using their talent to set up a social enterprise.	-0,2	10	0,25	15	5
11	It is necessary to forego financial benefits when setting up a social enterprise.	-0,8	6	-0,75	7	1
12	Founding a social enterprise is more bureaucratically complex than founding a conventional company.	-1,08	5	-1,17	4	1

13	The root of the ecological crisis is greed and therefore money.	0,8	18	0,08	14	4
14	I'm not too worried about the environment.	-1,25	3	-1,5	2	1
15	Our society is wasteful and consumption-driven.	1,667	23	0,67	17	6
16	People only think in the short term. They don't think about the long-term effects of their actions.	0,92	19	0	13	6
17	Technology means progress.	0,1	14	0,08	14	0
18	We all have to take responsibility for environmental problems.	1,17	20	1,42	22	2
19	Most (future) environmental problems will be solved by technology.	0	13	0	13	0
20	Sustainability is an important aspect for me when founding a company.	-0,1	11	0,75	18	7
21	For me, solving social and ecological problems is an important aspect of founding a company.	0,1	14	-0,5	10	4
22	For me, earning a lot of money is an important aspect of starting a business.	0,3	15	0,25	15	0
23	I want to start a company because I want to take on responsibility.	0,6	17	1,42	22	5
24	Doing something meaningful is more important to me than earning a lot.	0,92	19	0,42	16	3
25	Social entrepreneurship and financial success can be combined.	0,1	14	-0,25	12	2
26	I want to earn money with my first company so that I can then devote myself to more important social issues with another start-up.	-1,08	5	0,75	18	13
27	There are many social and ecological problems in our society.	1,75	24	1,17	20	4
28	The social and ecological problems that currently exist in our world are being ignored.	-0,7	7	-1,5	2	5
29	Everyone must take responsibility for the social and ecological problems in our world.	0,1	14	0	13	1
30	With my foundation, I want to create a better world.	0	12	1,25	21	9
31	I found a company so that I can sell my business quickly.	-2,42	1	-1,5	2	1
32	I found a company because I want to combat social and ecological problems in the long term.	-0,4	9	-1,17	6	3
33	Founding a social or sustainable company requires more courage than founding a traditional company.	-1,17	4	-0,92	5	1

A closer look at the statements positioned at both ends of the grid reveals that there is hardly any difference between the statements positioned at the extremes at the beginning and end of the semester. On the left-hand side of the grid (This statement is *not* characteristic of me) and in first and second place at both points in time are statements No. 31 (I start a business so that I can sell my company quickly) and No. 1 (The government solves social problems), closely followed by No. 14 (I am not very concerned about the environment). Statement No. 28 (The social and ecological problems that currently exist in our world are ignored) was also ranked second at the second survey date. This statement was previously ranked seventh. In terms of content, it covers similar areas to statement one. On the right-hand side of the grid (this statement is characteristic of me) there are major changes between the two survey dates. At the beginning of the semester, statement No. 27 (There are many social and ecological problems in our society) was ranked furthest to the right on average. In the second survey, this statement was still in 20th place, and the statement that was in 23rd place in the first survey (No. 15: Our society is wasteful and consumption-driven) was only in 17th place in the second survey. On the other hand, statement No. 7 (Social enterprises have an important role to play in bringing about change throughout the world) has slipped from 22nd to 24th place. Statement No. 8 (Social enterprises can play an important role alongside the government in solving social problems.) is ranked 23rd at the end of the semester. Consequently, statement No. 23 (I want to start a business because I want to take responsibility.) and No. 30 (I want to create a better world with my start-up.) have also moved further to the right.

The results described above show that the teaching of the first semester has resulted in some changes in students' attitudes. The fact that statement No. 26 rose from rank 5 to rank 18 can be interpreted in various ways. One interpretation could be that the students were already planning to found a company dedicated to social challenges at the beginning of the semester and now want to postpone this. However, it could also indicate that the students did not even consider founding such a company at the beginning and that it is now a possibility for them, at least in the more distant future. In the open questions, two students comment on this and clearly state that they "(...) would like to set up a social enterprise as a 'follow-up company' if there is enough capital available." (P8, question 5) and "In the long term, I would start a social enterprise, but not at the beginning, as I don't currently have a social idea that I am passionate about." (P13, question 5). Person 13 goes on to say: "At the beginning I was a bit more open to it (note: starting a social or sustainable business), where you didn't have a concrete idea yet, but I think earning more money at the start is easier to start a social business afterwards." (P13, question 5). Accordingly, a lack of an idea can also prevent a person from directly founding a social or sustainability-oriented company.

The rise of statements No. 30 and No. 20 indicate that the students after the semester are more likely to pursue idealistic goals with their start-up and that their values have therefore changed (possibly in addition to monetary goals). In response to the open question: "Is starting a social or sustainable business more or less of an option for you now than at the beginning of the semester? Why?", eight students (P1, P2, P3, P5, P7, P10, P14, P15) stated that starting a social or sustainable business is more of an option for them now than at the beginning of the semester. The reasons given for this include: "I think I would be sad if I didn't start something that makes sense and helps other people. That's what fulfils me and that's what the world needs." (P15, question 5) and "(...) at the beginning of the semester I wasn't as well informed as I am now" (P14, question 5) or "Dealing with the topics has increased my interest and motivation to become active and make a contribution." (P3, question 5).

A closer look at the statements No. 6, No. 15 and No. 16 reveals that all three use very pessimistic wording. Considering that all three statements were categorised further to the left at the end of the semester, it is therefore reasonable to assume that the students have distanced themselves somewhat from this pessimistic view and have developed a more positive attitude. For four of the students, their answers to the open questions directly reveal what has improved their mood or motivation. For example, available funding (P1, question 1) and getting to know other, already successful social entrepreneurs (P5, question 1; P12, question 1), for example by attending the Entrepreneurship Summit in Berlin at the beginning of the semester (P12, question 1), are mentioned. P10 also writes in response to question 1: "I have realised that you can 'quickly' add a social aspect to a company. That makes me happy and gives me courage. I definitely have another focus/incentive for the future".

Although the previous observations have shown that the students can certainly imagine a socially or sustainably motivated start-up, they rated statement No. 10 at the end of the semester as more characteristic than before. This could indicate an internal bias, as their own group has certainly developed more into an ideologically motivated start-up (see also the change in statement No. 23), but this is not perceived as being the case for the external group of other "young people". The change in the categorisation of statement No. 28 again clearly shows that the students, as already mentioned above, have a less pessimistic view of the world than at the beginning of the semester. They are now also more positive about starting a social enterprise: "I no longer find it surreal and particularly difficult to start a social enterprise, it doesn't require that much more effort" (P6, question 1).

The fact that there is hardly any change at the extreme left end of the grid shows that starting a business for purely monetary reasons seems to be rather absurd for the students. This could be due to the fact that students are very concerned about the environment and do not see the government solving social problems. This all suggests that a social or sustainable incentive is at least part of the students' motivation for starting a business. The major changes on the right end of the grid again indicates that the students have acquired a more positive attitude over the course of the first semester and see their own role in the economy as more important or potentially more effective. The influence of social enterprises is now also considered to be greater (P2, question 4; P8, question 3; P10, question 4) and existing social enterprises are perceived more consciously (P5, question 1).

In conclusion, it can be noted that five students explicitly cite the courses in the first semester as the reason for their more positive attitude towards the topics of social entrepreneurship or sustainability. Four of them attribute this to the Social Entrepreneurship module (P2, question 1; P7, question 1; P12, question 1 and P14, question 1), one person does not name a single module, but only "(...) the discussions and studies in the course" (P3, question 2).

6. Conclusion and outlook

In summary, it can be said that the majority of students have changed their opinions, attitudes and values towards social entrepreneurship and sustainability during the first semester. Eight of the 14 students who answered the questions in the second survey stated that starting a social or sustainable business is now more of an option for them than at the beginning of the semester. Based on the placement of the statements on the grid, it can be seen that the students rated the role of social enterprises and their potential economic power as greater at the end of the semester. Moreover, at the beginning of the semester, statements with a pessimistic wording, for example with a focus on problems, were classified as very characteristic of the students, whereas at the end of the semester, statements with a positive wording focussed on possible changes and solutions.

The open questions make it clear that the students find the first semester modules very helpful and that these are responsible for the change in their values, opinions and attitudes. Dealing with the world's major problems has shown them the urgency of solving them. Studying social business models and getting to know social entrepreneurs and social business angels has broken down barriers to setting up a social enterprise.

Although the results of the study are very encouraging, it must be mentioned that their significance is limited. In particular, the small sample size weakens the results, as individual influences can distort the results in small groups and results are not representative. In order to obtain more reliable results, the survey will be repeated with a larger number of students in the winter semester 24/25.

It remains to be seen whether the students will push ahead with their current plans to set up their own business and actually establish more socially and sustainably oriented companies. The plan for the coming semester is to continue supporting students with individual coaching sessions, learning agreements and courses in which they can work specifically on their own business idea.

7. Acknowledgements

This project was funded by Stiftung für Innovationen in der Hochschullehre

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Stock Prices Reaction to Earnings Announcement: A Case Study on Kazakhstan Stock Exchange

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Abstract

This study explores the dynamics of the Kazakhstan Stock Exchange (KASE), a developing market, in the context of efficient stock markets, where stock prices swiftly and properly reflect new information. Here, we carry out a thorough event study analysis with a particular focus on the stock price responses to publicly traded companies' quarterly earnings that were being announced. With the use of a chosen sample consisting of 12 financial and non-financial enterprises over a two-year post-COVID period (January 2022 to December 2023), our research provides some fascinating findings. Furthermore, the study provides evidence for a higher degree of volatility in growth companies relative to value stocks, given the market's noticeably more robust reaction to changes in growth stocks.

Keywords: *KASE, COVID-19, Event Study, Earnings Announcements.*

1. Introduction

Analysts evaluate a company's earnings report by comparing it to the prior quarter's estimated numbers. There is no denying the importance of earnings information to investors. These projections account for the company's historical performance, current occurrences, both favorable and unfavorable, and outside variables like the state of the economy that may have an impact on the company's success. An earnings surprise is any difference between actual results and these projections. Stock values might be greatly impacted by these revelations. Positive surprises usually result in an increase in the stock price of the firm since they give investors hope for the future profitability of the company. On the other hand, unfavorable shocks lower the stock price since they are interpreted by investors as a bad omen for the company's prospects.

The objective of this study is to determine in practice if the information contained in earnings reports affects the market price of stocks traded on the Kazakhstan Stock Exchange (KASE) depending on the type of stock (growth stock or value stock) and the industry they are related to. By examining the price movements of common stocks in the days preceding the announcement date, the research specifically focuses on how investors react to earnings releases.

2. Data collection and methodology

Initially, in this study, a sample of all financial and non-financial companies that are listed on the Kazakhstani Stock Exchange was chosen for analysis covering the post-COVID periods of 2022-2023. However, due to limited amount of information about earnings announcements and daily share price from lack of liquidity in the market, only 12 companies were included in the sample for further investigation.

To investigate the effect of quarterly earnings reports on companies listed in Kazakhstani Stock Exchange the event study was implemented with estimation period of 180 days followed by a post-estimation period of 100 days. The event window span consisted of 41 days, which included the event day and 20 surrounding days. The event period was excluded from the estimating period to prevent its impact on parameter estimations.

To estimate the parameters of the market model daily data on KASE index returns and on stock's daily returns were used, which serve as the foundation for calculating abnormal returns. Historical data about the daily returns on KASE index was collected from KASE's official website (kase.kz) while the data on historical daily returns of companies' stocks were taken from Refinitiv Eikon database for the analysis period of 2022-2023.

Implication of regression analysis using ordinary least squares was the first step to quantify the return of a stock under typical conditions. To determine the companies' abnormal returns, the difference between the company's actual returns and their estimated returns for the same year was implied:

$$AR_{it} = R_{it} - E\left(R{<<}y_{it}\right)$$

In this context, R represents the actual return, whereas E(R) reflects the expected return for stock i at time t. The term AR refers to an abnormal return.

To calculate the projected return estimated market model was implemented with the KASE daily index for the relevant time serving as a substitute for the market portfolio:

$$E\left(R_{it}\right) = \alpha_i + \beta_i\left(R_{mt}\right) + \varepsilon_{it}$$

Here, R(E) is the estimated return on stock i at time t, αi is the intercept of the straight line for stock i, βi is the slope coefficient of stock i, Rmt is the actual return on the market portfolio at time t, and εit is the error term.

Calculated as follows for n given events, the average deviation of expected returns from their expected values is assessed by AAR:

$$AAR_{it} = \frac{1}{n}\sum_{i=1}^{n} AR_{it}$$

The abnormal return is computed throughout the duration of the event, whereas the expected return is assessed for each and every data point.

The total AAR throughout the course of the event window is used to compute the Cumulative Abnormal Return, or CAAR:

$$CAAR_k = \sum_k AAR_{it}$$

Here, the k values range from -20 to +20 days.

3. Literature review

The link between earnings releases and stock price reactions has long been a topic of financial study, with multiple studies showing that stock prices respond considerably to unexpected earnings reports, sometimes known as earnings surprises. These reactions are sometimes classified by the kind of stock, such as growth or value stocks, which have different characteristics that influence their sensitivity to earnings announcements. Growth stocks are distinguished by high Price-to-Book (P/B) ratios, lower dividend yields, and significant previous price performance, whereas value companies have lower P/B ratios, greater dividend payments, and more consistent historical returns. Fama and French [1] made major additions to our knowledge of stock characteristics by establishing the three-factor model, which combines market risk, size, and the value component, so supporting the assumption that value companies outperform growth firms in the long term. However, their model implies that growth companies may respond more strongly to earnings shocks, especially in the short term, due to their greater valuation and market expectations.

Lakonishok, Shleifer, and Vishny [2] questioned the efficient market hypothesis, claiming that value equities beat growth companies due to behavioral biases in investor expectations. Their findings show that growth companies are frequently overpriced due to overly optimistic predictions, making them more volatile and susceptible to events such as earnings releases. Value stocks, on the other hand, are frequently undervalued and provide more consistent long-term returns.

Empirical investigations reinforce these theoretical foundations by demonstrating that earnings shocks result in considerable anomalous returns. For example, Dichev and Tang [3] discovered that growth stocks have larger responses to favorable earnings releases, owing to their higher growth expectations. Similarly, Barth and Kallapur [4] found that growth stocks had more stock price volatility in reaction to earnings announcements than value equities, which respond less significantly. This increased sensitivity might be linked to the market's expectation of future growth potential, which is inherent in growth company prices.

Market reactions to earnings releases in developing nations, such as Kazakhstan, may vary due to distinct economic considerations, market structures, and liquidity situations. Emerging markets are frequently less efficient and more volatile, resulting in larger market reactions to fresh information, such as profit announcements [5]. Studies on post-COVID financial market behavior have found that industries, particularly those that underwent significant changes during the pandemic, respond differently to earnings announcements, with telecommunications and retail showing more pronounced reactions [6].This setting is especially pertinent to the Kazakhstani market, where enterprises in various industries operate.

Overall, the extant literature consistently supports the hypothesis that growth equities respond more strongly to earnings releases than value stocks. The current study expands on these findings by applying them to the Kazakhstani Stock Exchange (KASE) and includes post-COVID data. It emphasizes the distinct reactions of growth and value equities to earnings reports, which supports previous studies on established and emerging markets.

4. Findings

The information under the scope of study events in post-COVID period of 2022-2023 includes twelve companies that represent several industries in Kazakhstani market: confectioneries, mining of uranium, utilities, telecommunications, oil & gas and banking sectors. A brief overview of the sample that is being studied is given in Table 1 below:

TABLE 1. Summary table of sample analysis

Year	Min	Median	Max	Standard deviation	Positive events	Negative events	Observations
2022	-4,41 %	-0,02 %	8,83 %	1,31 %	1	1	560
2023	-1,40 %	0,02 %	3,84 %	0,68 %	9	1	2800
Total	-2,91 %	0,00 %	6,34 %	0,99 %	10	2	3360

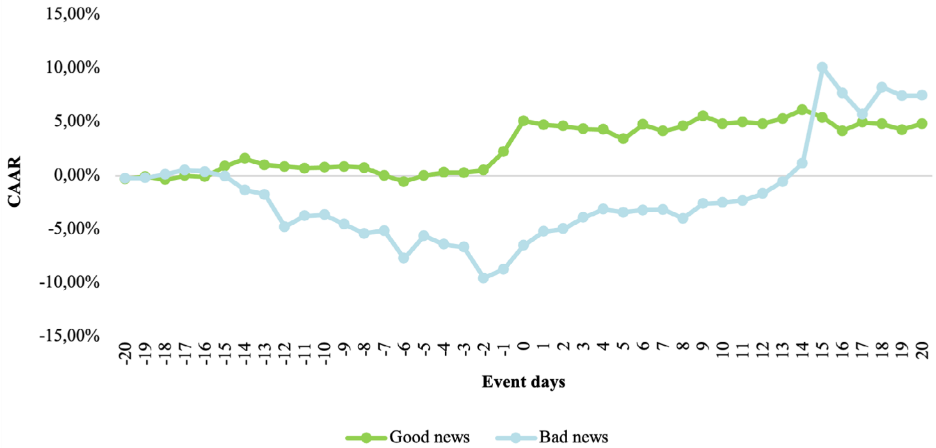
Source: Refinitiv Eikon, KASE

Table 1 summarizes the minimum, median and maximum values derived from daily average returns of stocks by year and provides the calculated standard deviation of the study sample. The research study encompasses 12 earnings announcement events spanning the years 2022 to 2023. Based on the direction of quarterly profits growth relative to the same time in the prior year, these events were classified as either positive or negative. In particular, a rise or fall in profits was considered good or bad news, accordingly.

4.1. Reactions of stock prices to announcement of good and bad news

Figure 1 presents the behavior of discrete cumulative average abnormal returns in response to the good and bad news for all firms under the scope of event study. According to Figure 1, cumulative average abnormal returns for good news are presented at the stable level prior to event date, while coming closer to the event date, average CARs started moving upward – upward movement of AAR at 1 day before earnings announcement was observed with 5 % significance level. At the day of earnings announcements, the market reacts positively to the good news which is observed by upward drive with 1 % level of statistical significance. Initially for negative news, the average CAR exhibited a decline, however, from the event date onward, it demonstrated an upward trend, eventually stabilizing and recovering towards the end of the event window. As depicted in the Figure 1, the reactions to the bad news were stronger causing higher volatility in the abnormal returns under the event study.

FIGURE 1. Discrete CAAR for Earnings Announcement of All Firms



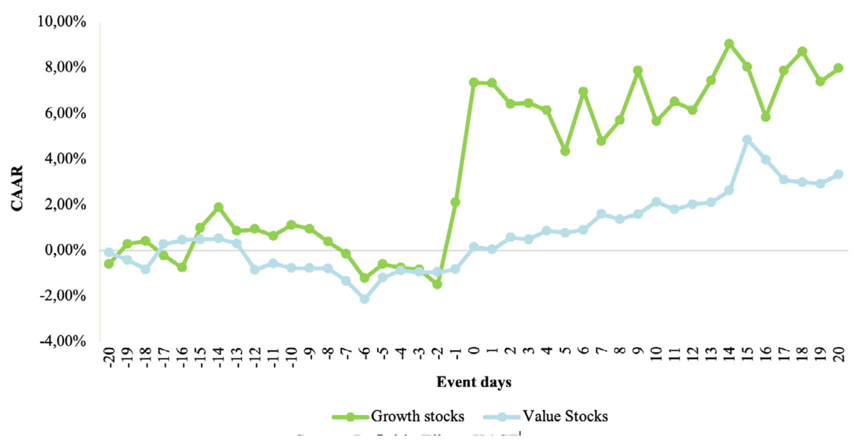
Source: Refinitiv Eikon, KASE

4.2. Reactions of stock prices to earnings announcement of growth and value stocks

Figure 2 illustrates the behavior of discrete cumulative average abnormal returns in response to earnings release separately on growth stocks and value stocks. Chosen sample of twelve companies under event study was classified to growth stocks and value stocks based on following factors: market capitalization, dividend payout, Price-to-Book ratio and historical performance of the stock prices. As a result, 5 companies were classified as growth stocks and other 7 companies as value stocks (please see Appendix 1). To support the classification of value and growth companies based on market capitalization, dividend payment, Price-to-Book ratio (P/B), and historical performance, research reveals that these measures are extensively used to discriminate between the two groups. Growth companies, which are often distinguished by low dividend yields, high P/B ratios, and substantial historical price gains, are likely to outperform during periods of big earnings surprises, according to research such as Fama and French [1]. On the other hand, value companies, which are generally recognized by lower P/B ratios, bigger dividend distributions, and slower historical growth, are less reactive to earnings releases but are seen as less volatile, offering long-term, consistent returns [2]. These contrasts are consistent with the observed behavior in the event research, which showed that growth equities respond more strongly to earnings releases than value stocks.

As shown in Figure 2, on the announcement day and the following days, firms' earnings releases cause both growth stocks and value stocks to react favorably. However, data shown that growth stocks were more sensitive to earnings releases over value stocks, with immediate increase in average cumulative abnormal returns at the event date and 1 day prior to announcement. Average abnormal returns on the event date and 1 day prior were observed for growth stocks with statistical significance level of 1 %.

FIGURE 2. Discrete CAAR for Earnings Announcement of Growth and Value Stocks



Source: Refinitiv Eikon, KASE

4.3. Reactions of stock prices to earnings announcement by industries

Figures 3-8 demonstrate the movements of discrete cumulative average abnormal returns in response to announcements of earnings by each industry. According to the Figures 3-8, the immediate reaction to the earnings release with highest volatility was observed in companies operating in confectionery and telecommunication industries based on the dynamics of their cumulative average abnormal returns under the event window. Such results could be the indicator of the recovery from COVID-19 for confectionery sector which operates in retail industry and a positive impact of lockdown leading to increased usage of traffic benefitting companies in telecommunication sector. For companies from other sectors the delayed reaction to earnings release was observed under the event study – closer to towards the end of the event window.

FIGURES 3-8. Discrete ARR and CAAR for Earnings Announcement by Industries

Source: Refinitiv Eikon, KASE

5. Conclusion

This research study investigated in post-COVID period of 2022-2023 how stock prices respond to release of companies' earnings listed in Kazakhstani Stock Exchange, where KASE index returns was retrieved from Kazakhstani Exchange website (kase.kz), quarterly earnings announcement data provided by the online source investing.com, as well as the associated stock prices downloaded from the Refinitiv Eikon database. Market model using OLS regression was applied to compute abnormal returns of each company after releasing their earnings. These abnormal returns, together with cumulative abnormal returns, were averaged across businesses for each date in the event window.

Examining aggregate returns over all 12 earnings events during the period of 2022-2023, a statistically significant positive price reaction was observed immediately on the day of the earnings announcement. Under the event study it was also found out that the companies releasing positive news generate, on average, 11 % more abnormal returns on the day of the occurrence than do companies announcing negative news regarding their earnings. Moreover, the companies releasing negative news experience faster and stronger reaction from the market than the companies with positive news about their earnings.

This research looked at how average abnormal returns of chosen sample of companies reacted to earnings announcements depending on the types of stock classified as: (1) growth stocks and (2) value stocks. The event study shown that both growth stocks and value stocks positively react to companies' earnings announcements at and after the event date. With increasing average cumulative abnormal returns and 1 % level of significance at the event date, however, the differential between growth stocks and value stocks made up 7 % premium in favor of growth stocks making them more sensitive to earnings announcements.

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Bootstrapping Approach to Teaching Confidence Intervals

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Abstract

The bootstrapping approach to teaching confidence intervals offers an intuitive and accessible alternative to traditional parametric methods. By employing resampling techniques, students can construct confidence intervals without extensive knowledge of specific distributions. This paper examines the mathematical basis of bootstrapping and its application in education through two student activities: a card game illustrating resampling variability and a computer simulation for hands-on coding experience. Our preliminary study involving first-year students shows that the bootstrapping method not only clarifies the concept of confidence intervals but also addresses common misconceptions about their interpretation and construction. This research highlights the benefits of integrating bootstrapping into statistics curricula to enhance conceptual understanding and practical skills.

Keywords: *Bootstrapping, Confidence Intervals, Statistical Education, Resampling Methods, Student Engagement, Teaching Methods.*

1. Introduction

Teaching confidence intervals in elementary statistics often involves traditional methods based on parametric assumptions and formulas. Students are frequently introduced to confidence intervals through methods that assume normality or other specific distributions. These methods, while mathematically rigorous, can often seem abstract and daunting to beginners, who may struggle to grasp the underlying concepts. However, the bootstrapping approach provides an intuitive alternative for students' first exposure to this concept. Bootstrapping, a resampling method, allows students to construct confidence intervals without relying on specific distributional assumptions, making it accessible and conceptually clear. This hands-on approach not only demystifies the concept of confidence intervals but also fosters a deeper understanding of variability and estimation. This article explores the implementation of bootstrapping to teach confidence intervals, detailing its mathematical foundation, presenting two student activities, and evaluating its effectiveness through an experimental study.

The origins of the bootstrapping method can be traced back to Bradley Efron's seminal work in 1979 [1, 2], which introduced the technique as a robust statistical tool. Since then, bootstrapping has gained widespread recognition and application in various fields of research due to its flexibility and minimal reliance on theoretical distributional assumptions. Several studies have highlighted the effectiveness of bootstrapping in teaching statistical concepts. For instance, [2] found that introducing bootstrap methods in introductory statistics courses using dynamic visualizations significantly improved students' conceptual understanding of confidence interval construction. The Visual Inference Tools (VIT) software used in their study provided students with a visual and interactive means to understand how bootstrap confidence intervals are formed and interpreted.

Similarly, Engel [1] emphasized that bootstrapping helps students gain intuition about sampling distributions and the variability of sample statistics, which are central to inferential statistics. Engel's study demonstrated that through computer simulations and resampling techniques, students could better grasp the process of constructing confidence intervals and the underlying statistical principles. This method reduces the reliance on formal mathematical derivations and allows students to explore statistical concepts through experimentation and observation.

Research conducted by Reaburn [3] indicated that students' comprehension of confidence intervals improved using computer simulations and interactive activities that incorporated bootstrapping methods. This study also revealed that traditional methods often lead to misconceptions among students, such as misunderstandings about the interpretation of confidence levels and the variability of sample means. By incorporating bootstrapping into the curriculum, educators can address these misconceptions and provide a more accurate and intuitive understanding of statistical inference.

It was found in [1] that the bootstrapping method's flexibility allows it to be applied to various types of data and statistical problems. It enables students to construct confidence intervals for parameters such as medians, quartiles, measures of spread, and correlations, which are often challenging to address with traditional methods. This versatility makes bootstrapping an invaluable tool in the statistical education toolkit, providing students with a comprehensive understanding of statistical inference beyond the constraints of parametric assumptions.

Recently, the use of advanced statistical methods, such as bootstrapping, has become increasingly common in fields like medicine. For example, in cardiovascular pharmacotherapy, statistical procedures based on machine learning, which rely on conceptually similar principles as bootstrapping, allow for more precise estimates and a better understanding of clinical outcomes [10]. Similarly, research on long-term survival following acute pulmonary embolism has shown that applying these advanced statistical methods can significantly improve patient prognoses, providing insights into the impact of various factors, such as body mass index, on survival [11].

1.1. Misconception: The Width of a Confidence Interval Decreases as the Confidence Level Increases

Many students mistakenly believe that a 90 % confidence interval is wider than a 95 % confidence interval for the same data [6]. This misconception arises from a misunderstanding of how confidence levels affect the width of confidence intervals. A higher confidence level means that we want to be more certain that the interval contains the true population parameter. To achieve this higher certainty, the interval must be wider to cover more potential values. Therefore, a 95 % confidence interval is indeed wider than a 90 % confidence interval because it needs to encompass more of the potential variability in the data to achieve higher confidence. This misconception was found in 75 % of undergraduate students and 23 % of postgraduate students [5] and is particularly relevant in fields such as psychology and physics [8, 9].

1.2. Misconception: Meaning of Confidence Intervals

According to [4], students often incorrectly think that confidence intervals provide plausible values for the sample mean rather than the population mean. This confusion indicates a fundamental misunderstanding of the purpose of confidence intervals. The correct interpretation is that a confidence interval estimates a range in which the true population parameter (such as the population mean) is likely to lie, based on the sample data. It does not pertain to the sample statistic itself. For example, a 95 % confidence interval for the population mean means that if we were to take many samples and construct a confidence interval from each sample, we would expect about 95 % of those intervals to contain the true population mean.

1.3. Misconception: The Effect of Sample Size on Interval Width

There are conflicting misconceptions among students regarding the relationship between sample size and the width of a confidence interval. Some students believe that the width of a confidence interval is not affected by sample size, while others think that the width increases with sample size [4]. The width of a confidence interval decreases as the sample size increases, assuming the confidence level remains constant. This is because larger sample sizes provide more information about the population parameter, reducing the margin of error. Consequently, with more data, the estimate becomes more precise, resulting in a narrower confidence interval.

Conversely, smaller sample sizes provide less information and thus result in wider intervals due to higher uncertainty.

2. Materials and Methods

2.1. Mathematical Foundation of Bootstrapping

Suppose we want to estimate the mean (denoted as μ) of a population. Observing every member of the population is impractical, so we take a random sample and calculate the sample mean (denoted as $\bar{x}$). While $\bar{x}$ is a good estimator of μ, it varies from sample to sample and will not be exactly equal to μ. Next, we need to understand how much $\bar{x}$ varies between samples to evaluate our data. For example, if is 6 ± 2, then we would expect the true population mean μ to lie within the interval 4 to 8. Values outside this range would be considered less likely.

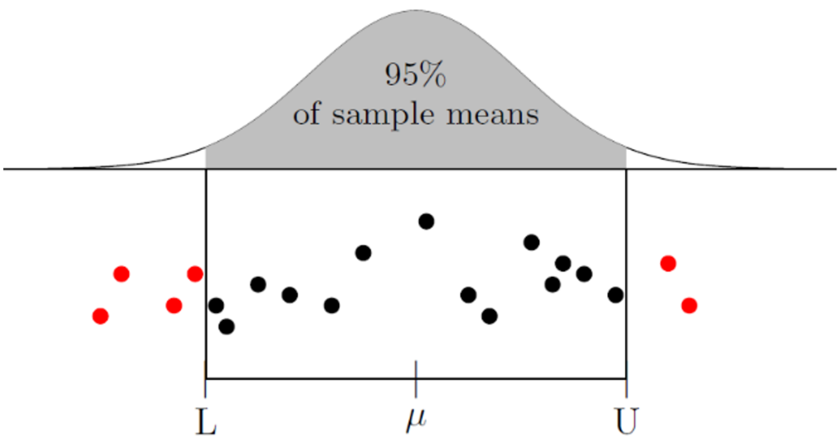

FIGURE 1. Sampling distribution of the sample mean ($\bar{x}$) showing the 95 % confidence interval (L, U) with sample means.

If we knew the exact distribution of, we would conclude from the above discussion that, with 95 % confidence, μ lies within this range by considering the central 95 % of the distribution. However, in practice, this is complex because we would need to make additional assumptions about the population or the sample size, which are often not feasible. What we can do instead is empirically derive the sampling distribution of by repeatedly taking samples from the population. This would involve taking many samples and calculating $\bar{x}$ for each one to understand its distribution. Unfortunately, this method is often too expensive and time-consuming to be practical.

As a more feasible alternative, we can use bootstrapping. This involves taking a single sample from the population and then generating many new samples by resampling with replacement from this original sample. This can be imagined as mixing the sample data in a bag, drawing a piece, recording it, returning it to the bag, and drawing again. Some data may be selected multiple times while others may not be chosen at all. By doing so, we can create an empirical estimation of the sampling distribution of. Using different initial samples, bootstrapping would provide different estimations of the sampling distribution of.

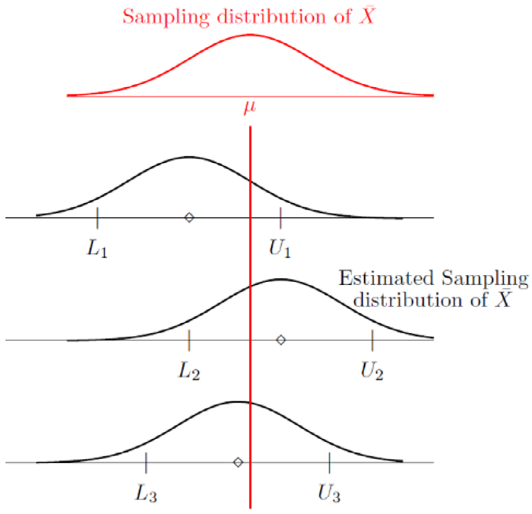

FIGURE 2. True sampling distribution (red) and bootstrapped sampling distributions (black) with empirical confidence intervals.

For each possible sample, we could create the estimated sampling distribution of and calculate the L and U values that capture the middle 95 % of this distribution. The intervals from twenty samples are shown below, most of which contain the true parameter μ. In practice, we take only one sample, calculate one sample mean, and one interval. The method ensures that 95 % of such intervals will contain the mean μ, hence it is called a 95 % confidence interval.

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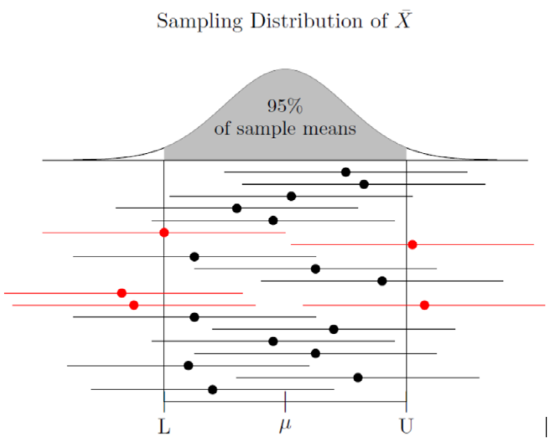

FIGURE 3. Distribution of sample means with 95 % confidence interval illustrating the variability of different sample means and the interval capturing the true population mean (μ).

Algorithm:

1. **Obtain a Sample**: Collect a sample of size from the population, denoted as.
2. **Resample with Replacement**: Generate bootstrap samples, each of size, by randomly sampling from X with replacement, denoted as.
3. **Calculate Statistic**: Compute the statistic of interest (e.g., mean) for each bootstrap sample, resulting in.
4. **Construct Confidence Interval**: Use the bootstrap samples to calculate the statistic of interest (e.g., mean). Sort these statistics and find the and percentiles of the sorted values to create a confidence interval.

2.2. Proposed Activities

Activity 1: Card Game (*duration: 30 minutes*)

Objective: Help students understand the concept of resampling, variability, and difference between 95 % and 90 % confidence interval.

Materials:

1. 10 small pieces of paper.
2. A pen.
3. A bag.

Preparation:

1. Write a random number between 1 and 100 on each of 10 small pieces of paper.
2. Place these papers into a bag.

Procedure:

1. Before the students start drawing papers from the bag, the professor will give each student a short introduction to the exercise: "Imagine we are researchers trying to understand how much people like a new chocolate bar. We surveyed 10 people and asked them to rate this chocolate bar on a scale from 1 to 100, where 1 means they don't like it at all, and 100 means they absolutely love it. We recorded their ratings on 10 pieces of paper that are now in this bag. Our goal is to estimate the average rating of this chocolate bar in the whole population based on this sample."
2. All 10 recorded numbers, along with the ones pulled from the bag, should be known to students.
3. The student will draw a paper from the bag, record the number, and return the paper to the bag. This process will be repeated 10 times.
4. The student will then calculate the mean of the recorded numbers.
5. The bag is passed to the next volunteer, and the process is repeated 10 times.

Final Steps:

1. Collect all the calculated means and arrange them in order.
2. Draw a histogram of the means.
3. Calculate the 2.5th and 97.5th percentiles.
4. Calculate the 5th and 95th percentiles.

Discussion:

1. What is the difference between the numbers in the bag and the numbers you pulled out? Are they all different or do some repeat?
2. Are the numbers you pulled out considered a sample? If not, elaborate why?
3. Does it make sense to keep "recycling" the same ten numbers?
4. Can you obtain any new information about the population by "recycling" the numbers?

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5. Is it better to calculate the mean of the original 10 numbers without resampling? Why might resampling be useful in this context?

6. Where on the histogram do you expect the population parameter to be most likely and least likely located, and why?

7. Shade the 95 % area of the histogram where you believe the population parameter is most likely to be located. Additionally, indicate the minimum and maximum values within this shaded area and explain how you determined them.

8. If you were to repeat this for a 90 % area, what would happen to the minimum and maximum values compared to the 95 % area?

9. What percentiles would you calculate to find a 99 % confidence level interval?

10. Without calculating the 99 % confidence level interval, compare the width of this confidence interval to others?

Activity 2: Computer Simulation I (*duration: 15 minutes*)

Objective: Deepen understanding of bootstrapping through coding and visualization.

Materials:

1. A device with internet access (e.g., laptop, desktop, or tablet).

2. Google account.

Preparation:

1. Go to https://colab.research.google.com/ and log in with your Google account.

2. Create a new notebook by clicking on “New Notebook”.

3. Copy and paste the following code into the first cell of your Colab notebook:

```
import numpy as np
import matplotlib.pyplot as plt
data = []
n = len(data)
B = 1000
bootstrap_means = []
for _ in range(B):
resample = np.random.choice(data, size=n, replace=True)
bootstrap_means.append(np.mean(resample))
lower_bound = np.percentile(bootstrap_means, 2.5)
upper_bound = np.percentile(bootstrap_means, 97.5)
print(f"95 % Confidence Interval: [{lower_bound}, {upper_bound}]")
#Plotting the histogram
plt.hist(bootstrap_means, bins=30, edgecolor='k', alpha=0.7)
plt.axvline(lower_bound, color='r', linestyle='dashed', linewidth=1, label='2.5 Percentile')
plt.axvline(upper_bound, color='b', linestyle='dashed', linewidth=1, label='97.5 Percentile')
plt.title('Histogram of Bootstrap Means')
plt.xlabel('Mean Values')
plt.ylabel('Frequency')
plt.legend()
plt.show()
```

Procedure:

1. Provide students with a dataset (e.g., sample heights of students).
2. In the third line, within [], enter your dataset separated by commas.
3. Students run the cell by clicking the "Run" button or pressing Shift + Enter.
4. Compare bootstrap intervals with traditional parametric intervals.

Discussion: Students analyse how the bootstrap intervals provide robust estimates regardless of the underlying data distribution.

Activity 3: Computer Simulation II (*duration: 10 minutes*)

Objective: Understand the impact of sample size on the width of confidence intervals, and learn why we use the term "confidence interval" rather than "probability interval."

Materials:

5. A device with internet access (e.g., laptop, desktop, or tablet).

Preparation:

1. Go to https://www.statcrunch.com/applets/type3&cimean.

Procedure:

1. Familiarize yourself with the applet interface, which allows you to adjust the sample size, confidence level, and standard deviation.

Discussion:

1. What happens to the width of the confidence interval when you increase the sample size?
2. Why does increasing the sample size affect the interval width?
3. Why are some intervals red? If you have 100 intervals and calculate 95 % confidence intervals, how many would you expect to be red?
4. What happens to the number of red intervals if you decrease the confidence level from 95 % to 90 %?
5. If, for a particular sample, we obtain a 95 % confidence interval, such as [50, 70], does $P(\mu \in [50,70])=0.95$? Explain why or why not.

Activity 4: Quiz (*duration: 15 minutes*)

Objective: Assess students' understanding of bootstrapping and confidence intervals, identifying misconceptions and ensuring accurate interpretation and application.

Materials:

1. A device with internet access (e.g., laptop, desktop, or tablet).
2. Google account.

Preparation:

1. Go to https://forms.google.com/ and log in with your Google account.
2. Click on the "Blank" form to create a new quiz.
3. Title your form, for example, "Bootstrapping and Confidence Intervals Quiz."
4. Add the multiple-choice questions as listed:

   What is the primary advantage of bootstrapping over traditional methods for constructing confidence intervals?

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A. It is faster to compute.

B. It does not require assumptions about the data distribution.

C. It always produces narrower intervals.

D. It uses fewer samples.

In bootstrapping, what does resampling with replacement mean?

A. Drawing samples without putting them back into the dataset.

B. Drawing samples and putting them back before drawing again.

C. Replacing missing values in the dataset.

D. Changing the values of the dataset before sampling.

How many bootstrap samples are typically recommended for constructing a reliable confidence interval?

A. 10

B. 50

C. 1000

D. 10,000

Which of the following best describes a confidence interval?

A. A single point estimate of a population parameter.

B. A range of values used to estimate the true value of a population parameter.

C. A method to adjust the sample data to fit the population data.

D. A technique to minimize the standard error of a sample statistic.

If a 95 % confidence interval for the mean of a sample is [10, 20], what can be inferred?

A. The true population mean is between 10 and 20.

B. There is a 95 % probability that the sample mean is between 10 and 20.

C. There is a 95 % confidence that the true population mean lies between 10 and 20.

D. The mean of the sample must be 15.

When constructing a 95 % bootstrap confidence interval, which percentiles of the bootstrap distribution are used?

A. 2.5th and 97.5th

B. 5th and 95th

C. 10th and 90th

D. 25th and 75th

What is the main reason bootstrapping can be applied to non-normally distributed data?

A. It uses the original data directly.

B. It modifies the data to fit a normal distribution.

C. It reduces the impact of outliers.

D. It estimates the sampling distribution empirically through resampling

5. Click on the "Send" button at the top right corner, then select "Link" to generate a shareable link for your Google Form.

Procedure:

1. Distribute the quiz link to the students via email, online learning platform, or by posting it in a group chat.
2. Instruct the students to complete the quiz within the allocated 15 minutes.

Discussion:

1. Review each question with the students and provide the correct answers.
2. Invite students who answered incorrectly to voluntarily share their reasoning and thought process behind their answers.
3. Point out where they made mistakes and explain the correct reasoning.

3. Results and Discussion

Preliminary research was conducted among 10 first-year students from Zagreb School of Economics and Management, consisting of 3 female and 7 male students, to explore the introduction of confidence intervals through the bootstrapping method. The students are currently enrolled in an experimental Statistics 2 course, where instead of teaching confidence intervals using the traditional approach, we employed bootstrapping. The subsequent discussion will analyse the outcomes of the card game and computer simulation, evaluate students' understanding and engagement, and reflect on how bootstrapping compares to traditional methods in the context of statistical education.

3.1. Outcomes of the Card Game Activity

The sample presented to the students consist of 10 numbers (31, 79, 51, 14, 67, 42, 50, 43, 97, 25). Table 1 shows resample of each student's draw and calculated mean for each resample.

Students	Draw Numbers	Mean
1	25, 67, 51, 97, 97, 97, 51, 43, 25, 50	60.3
2	25, 97, 51, 14, 31, 50, 67, 25, 50, 97	50.7
3	97, 25, 50, 67, 50, 67, 42, 97, 79, 67	64.1
4	43, 79, 31, 97, 97, 42, 67, 97, 25, 14	59.2
5	42, 43, 42, 42, 50, 31, 42, 79, 31, 79	48.1
6	14, 67, 42, 51, 97, 14, 42, 97, 97, 50	57.1
7	51, 43, 97, 51, 50, 51, 50, 42, 25, 67	52.7
8	67, 43, 51, 25, 79, 25, 79, 25, 42, 14	45.0
9	31, 42, 51, 43, 51, 43, 31, 50, 50, 50	44.2
10	25, 42, 50, 25, 67, 42, 43, 67, 50, 14	42.5

TABLE 1. Results of Each Student's Draws

The 2.5th and 97.5th percentiles of the resample means are 42.9 and 63.2, respectively. Additionally, the 5th and 95th percentiles are 43.3 and 62.4, respectively. Resample distribution is shown by histogram.

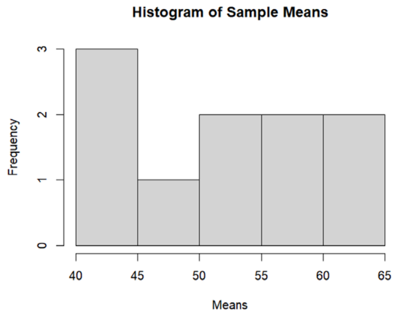

FIGURE 4. The histogram shows the estimated sampling distribution of sample means.

3.2. Computer Simulation Results

We conducted a computer simulation using the heights of a sample of students: 187.5, 187.5, 172, 184, 194, 180, 188, 173, 157, and 178 cm. The 95 % confidence interval produced by the bootstrapping method was [173.69875, 185.80125] cm.

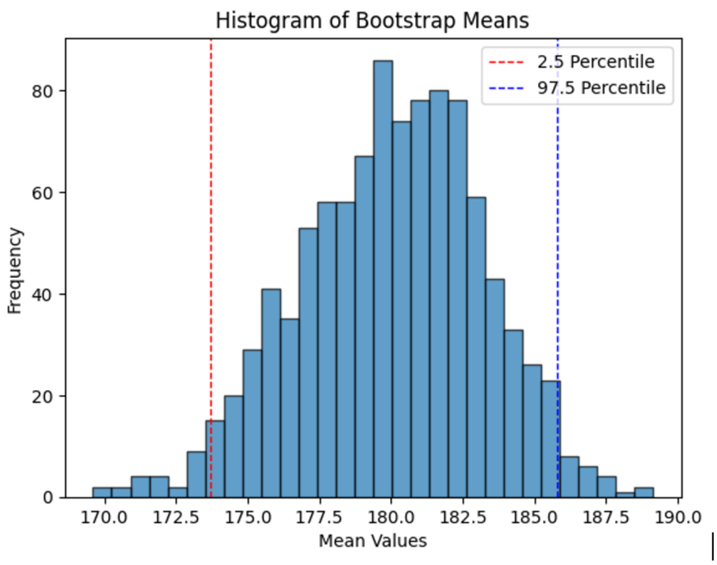

FIGURE 5. bootstrap distribution of sample means for student heights.

Using the traditional parametric method, the 95 % confidence interval was [172.43, 187.77] cm.

3.3. Quiz Results Report

When asked about the main advantage of the bootstrap method over traditional methods for constructing confidence intervals, 8 students responded that it does not require assumptions about the data distribution, while 1 student mentioned that it uses smaller samples, and another believed that calculation is quicker. Regarding the meaning of resampling with replacement in the bootstrap method, 7 students correctly answered that it involves taking samples and returning them before resampling. One student incorrectly thought it involved changing the data set values before sampling, and other two believed it meant taking samples without returning them to the data set. On the recommended number of bootstrap samples for constructing a reliable confidence interval, 6 students indicated 1000 samples, 1 chose 10000 samples, and 1 opted for 50 samples, and two students answered 10. For the question about the best description of a confidence interval, 7 students correctly identified it as the range of values likely to contain the population parameter. Two students thought it was a method to adjust the sample data to fit the population data, and 1 student answered a single point estimate of a population parameter. When interpreting a 95 % confidence interval for the sample mean [10, 20], 5 students stated that it means there is a 95 % probability that the sample mean is between 10 and 20, 3 students correctly thought there is a 95 % confidence that the true population mean lies between 10 and 20. Two students answered that true population mean is between 10 and 20. Concerning the percentiles used for constructing a 95 % bootstrap confidence interval, 7 students accurately answered 2.5 % and 97.5 %, while 3 students chose 5 % and 95 %. Finally, when asked why the bootstrap method can be applied to non-normally distributed data, 7 students correctly answered that it empirically estimates the sample distribution through resampling. Three students incorrectly believed it involves modifying data to fit a normal distribution.

3.4. Feedback Report

Students were asked to give their feedback regarding previously mentioned activities. When asked how engaging they found the card game activity for understanding the concept of bootstrapping, 5 students responded that it was "very engaging," and 5 students found it "somewhat engaging." Regarding how clearly the computer simulation activity helped them understand the concept of bootstrapping and confidence intervals, 5 students answered that it was "very clear," and 4 students found it "somewhat clear." One student was "neutral." Furthermore, when comparing the effectiveness of the bootstrapping approach to traditional methods in helping them understand confidence intervals, 4 students found it "much more effective," and 5 students found it "more effective." One student thought it was "about the same." Concerning their confidence in applying the bootstrapping method to construct confidence intervals in real-world data analysis, 3 students felt "very confident," 6 students were "somewhat confident," and 1 student was "neutral."

Overall, 7 students were "very satisfied" with the bootstrapping approach to learning about confidence intervals, and 2 students were "satisfied." One student was "neutral."

3.5. Discussion and Final Remarks

In the traditional approach to learning confidence intervals, students focus on the assumptions of the problem and choosing the correct formula based on those assumptions. This often involves using statistical tables to find quantiles, which can be confusing and difficult for students. In contrast, bootstrapping requires students to understand each step of the process without relying on specific data distribution assumptions, making the empirical process and variability more intuitive. Bootstrapping integrates well with programming, essential for modern statistical analysis. By coding bootstrap simulations, students automate the resampling process, visualize results, and deepen their understanding.

The card game helps students understand the bootstrap algorithm and the concept of resampling, showing that the mean of (re)samples is typically close to the population mean. Computer Simulation I reinforces this by allowing efficient repetition of the bootstrap process. Shading parts of the histogram helps students understand confidence interval construction, addressing Misconception 1, and realizing that (re)samples estimate where the population mean might be, correcting Misconception 2.

Computer Simulation II uses an interactive interface to show that sample size affects confidence interval width, addressing Misconception 3. Larger sample sizes result in narrower intervals. This simulation also clarifies that it's incorrect to say the probability of μ being in a specific 95 % confidence interval is 95 %. Instead, confidence intervals represent the proportion of intervals that would contain the population mean if the study were repeated, further addressing Misconception 2.

4. Conclusion

In conclusion, this study demonstrates the potential of the bootstrapping method as an effective alternative to traditional approaches for teaching confidence intervals. The preliminary findings suggest that bootstrapping enhances students' understanding and engagement by simplifying complex concepts and making statistical inference more intuitive. Future research involving a larger sample of students will also compare two groups—one taught using traditional methods and the other using bootstrapping—to more comprehensively evaluate the effectiveness of bootstrapping in statistical education.

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Challenges and Traps of Digitalization in Higher Education: Do We Need Dedigitalization or Rehumanisation?

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Abstract

The integration of digital technologies in higher education has dramatically changed the way students learn [1], however, it has also raised critical concerns about the personal and social aspects of digital learning. Digitalization in higher education has gained significant momentum in the wake of the Covid-19 pandemic, with institutions rapidly adopting new technologies to facilitate remote learning. The paper presents a case of digitalization in higher education at the Fundamentals of Management course at the School of Economics and Business University of Ljubljana, where a digital platform E-tutor Fundamentals of management (https://vodici.cek.ef.uni-lj.si/tm) [2] was developed in cooperation with the pedagogical team and team of experts by the Central Library of School of Economics and Business University of Ljubljana. The digital platform was designed to support remote learning at the Fundamentals of Management course during the Covid-19 pandemic by offering access to academic resources, including over 800,000 scientific articles. Our results contribute to the importance of digitalization in higher education by presenting the case of the digitalized learning platform.

Keywords: *Higher education, digitalization, digital learning, e-tutor digital platform.*

1. Introduction

Over the past two decades, digitization has exerted a profound influence on higher education, reshaping enrollment processes, teaching materials, and instructional practices, with significant portions of these elements transitioning to digital platforms [3]. Concurrently, higher education policies have frequently overlooked the emergent inequalities brought about by these changes or have dismissed them as temporary challenges that students and faculty can mitigate through individual efforts. The current paradigm shift, which views technology as a dynamic, interconnected environment fostering digital learning, is closely tied to institutions' integration of technological advancements [4]. In this context, digitization is increasingly recognized as essential for higher education institutions aiming to attract a more diverse and academically robust student body while simultaneously improving the quality of their curricula, instructional resources, and training programs.

2. Digitalization in Higher Education: The Case of Digital Platform E-tutor Fundamentals of Management

2.1. Digitalization in Higher Education

While digitalization in higher education is not a novel concept, its rapid acceleration during the pandemic has been unprecedented. Al-Fraihat et al. (2020) [5] argue that the transition to digital platforms has fundamentally transformed the delivery and consumption of knowledge. These platforms provide flexibility, accessibility, and access to an extensive resource repository that surpass traditional educational models' capabilities. Bates & Sangrà (2011) [6] emphasize that digitalization enables personalized learning experiences, accommodating diverse student needs and learning styles. The literature highlights the critical role of digital platforms in sustaining continuous learning, even amid disruptive circumstances. [7]

2.2. The Case in Digitalization in Higher Education: E-tutor Fundamentals of Management Digital Platform

The Covid-19 pandemic has served as a catalyst for the accelerated digital transformation of education systems globally [8]. As universities swiftly transitioned to online learning environments, the demand for digital resources to support remote education experienced a significant surge. In response to this demand, the Fundamentals of Management course pedagogical team at the School of Economics and Business University of Ljubljana developed the "E-Tutor Fundamentals of Management digital platform" (https://vodici.cek.ef.uni-lj.si/tm) [2]. The development of the E-Tutor digital platform was a collaborative endeavor, involving a partnership between experts from the Central Library at the School of Economics and Business University of Ljubljana and educators specializing in management studies. This initiative represents a pioneering advancement in digital learning within the field of management, providing students with unparalleled access to global academic resources (Figure 1). The E-Tutor for management topics platform represents an innovative digital resource explicitly designed for management students at the School of Economics and Business University of Ljubljana. Developed in response to the educational challenges precipitated by the Covid-19 pandemic. It functions as a comprehensive repository of academic materials, offering access to databases, articles, books, and video content. Through this digital platform, students can engage with top-ranked journals in management, leadership, and organizational studies, thereby enhancing their academic experience and supporting their educational objectives.

The E-Tutor Fundamentals of Management digital platform is systematically designed to support students across all stages of their study program, from undergraduate studies to doctoral research and beyond. Its key features include (E-Tutor Fundamentals of Management, 2024) [2]: (1) Extensive database access: The platform grants access to over 800,000 scientific articles drawn from more than 60 top-tier academic journals, including the Harvard Business Review and the Journal of Management. This expansive repository ensures that students can readily access relevant, up-to-date materials essential for their studies. (2) Specialized econtent for management studies: The platform's content is meticulously curated to focus on management, leadership, and organizational studies. This targeted approach ensures that students have access to the most pertinent resources in their field od management and organization. (3) Integration of international resources: The E-Tutor Fundamentals of Management digital platform incorporates a diverse range of international resources, including video content, offering students a comprehensive global perspective on management topics. (4) User-friendly interface: Designed with ease of use in mind, the platform features a user-friendly interface that allows students to efficiently navigate the extensive database and access the materials they require. (5) Support for advanced academic work: Beyond serving as a resource for coursework, the platform is a valuable tool for the preparation of seminar papers, theses, and dissertations in the field of management.

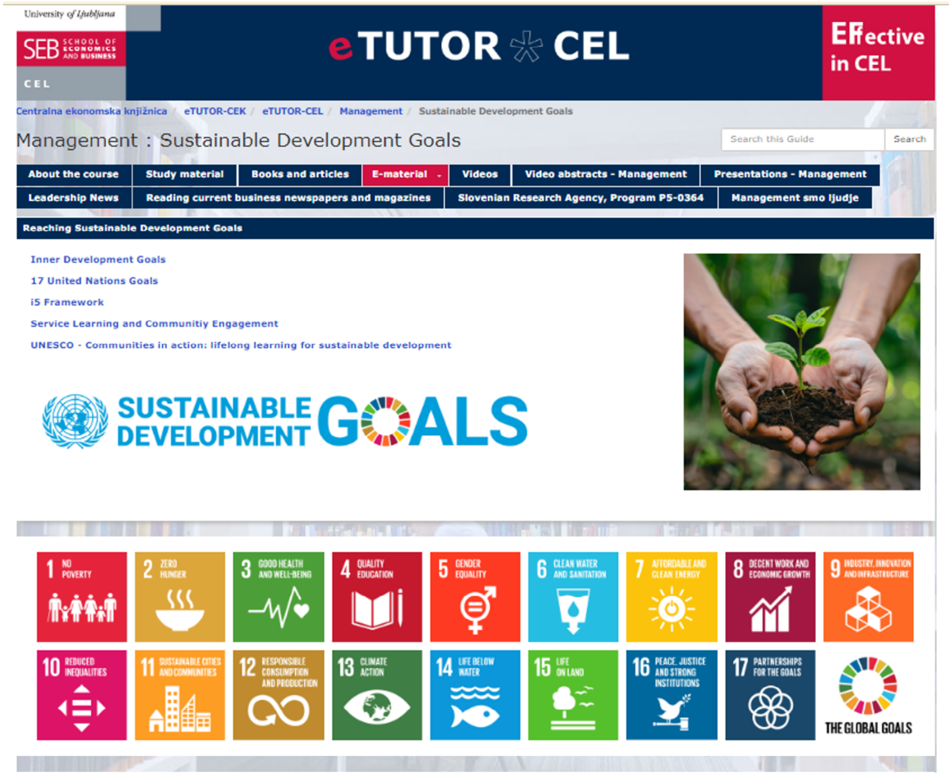

FIGURE 1. E-tutor Fundamentals of Management: Page on Sustainable Development Golas – https://vodici.cek.ef.uni-lj.si/c.php?g=685677&p=5218068

In the Foundations of Management course, beyond the materials provided through the E-Tutor digital platform, we have integrated contemporary economic and societal issues, particularly in relation to the implementation of the 17 Sustainable Development Goals (SDGs; https://vodici.cek.ef.uni-lj.si/c.php?g=685677&p=5218068, 2024) [9]. At our school, we prioritize SDGs that are especially relevant to management education, including decent work and economic growth (SDG 8), industry, innovation, and infrastructure (SDG 9), health and well-being (SDG 3), and responsible consumption and production (SDG 12). These SDGs are central to driving sustainable development within the European Union. In this course, sustainable development themes are woven into the curriculum through a project-based seminar assignment, where students reflect on how their analysis of managerial challenges can contribute to building and strengthening local communities. By leveraging the high-quality management literature curated for the E-Tutor digital platform, we aim to foster a collaborative learning environment where students not only develop essential research skills and a deep understanding of managerial functions but also actively engage in supporting the local community of managers.

2.3 Theoretical Implications of Digitalization and Artificial Intelligence in Higher Education

While the E-Tutor Fundamentals of Management digital platform has achieved significant success, its development and implementation were accompanied by notable challenges. A primary concern was ensuring the platform remained current with the latest academic publications, given the rapid advancement of research in the field of management and organization. Additionally, the team encountered technical difficulties related to the integration of multiple databases and the need to ensure seamless access for students. The E-Tutor platform provides a resource students can utilize throughout their academic and professional careers. Its extensive database and regularly updated content position it as a valuable tool for ongoing professional development in management. Digitalization has transformed higher education by enabling new knowledge delivery and engagement forms. According to Javed (2024) [10] transformative learning theory is widely used in higher education because it provides advice on how people might discover meaning in their lives. Looking forward, the development team is committed to enhancing the digital platform by incorporating new features and expanding its resource offerings. Future plans also include exploring the integration of artificial intelligence to personalize the learning experience, offering students tailored recommendations based on their individual interests and academic needs.

The integration of artificial intelligence in education introduces new theoretical dimensions, particularly in the realm of personalized learning [11]. Rapid advances in artificial intelligence have opened up new possibilities in various fields, and education is no exception. It can potentially transform the traditional pedagogical approach to education by providing personalized learning experiences tailored to individual student needs. This personalized approach aligns with the theory of multiple intelligences proposed by Gardner (1983) [12], which suggests that students have different types of intelligence and learning preferences. AI-powered educational tools can cater to these diverse learning styles by adapting content delivery to suit individual preferences, thereby enhancing learning outcomes. The E-Tutor platform could, in the future, incorporate artificial intelligence to personalize the learning experience further, making it more effective and engaging for students.

2.4. Practical Implications of Personalized Digital Education in Higher Education

Artificial intelligence (AI) and learning analytics advancements have created new opportunities for personalized education within higher education institutions [13]. By utilizing AI algorithms and data analytics, institutions can offer tailored feedback to students, addressing their unique strengths and areas needing improvement. The practical implications of digitalization and AI for enhancing educational quality and outcomes are profound. These technologies enable educational institutions to deliver more engaging and interactive learning experiences, transcending the limitations of traditional lectures and textbooks. AI-powered tools can provide real-time feedback, enabling students to identify areas for improvement and guiding them toward mastery of the subject matter. In Figure 2, personalized education corner is presented; this AI-driven approach to management education can potentially improve learning outcomes by enabling more targeted interventions and support for struggling students.

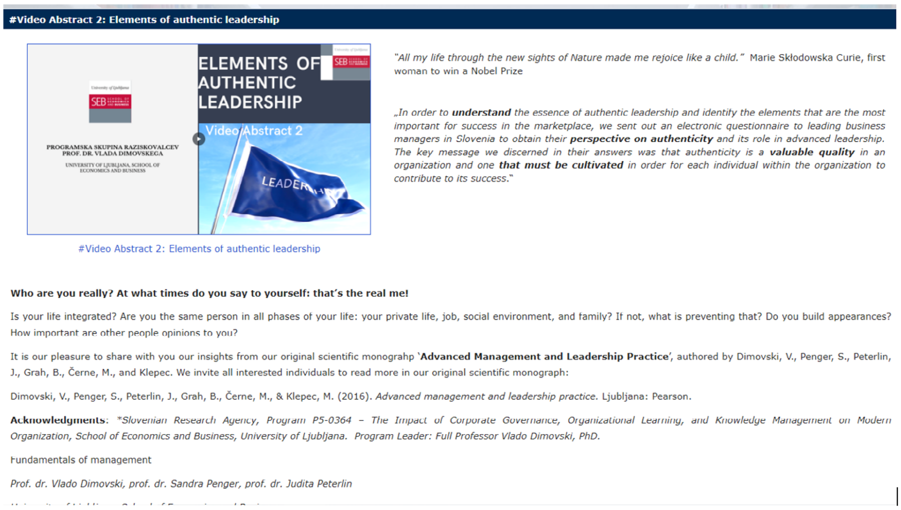

FIGURE 2. E-tutor Fundamentals of Management: Video corner with personalized education on management topics – https://vodici.cek.ef.uni-lj.si/tm/videi-tm [14]

Challenges will occur in areas related to the volume of data, in the understanding of digital education or in solving problems with the proper use of teaching methods. In addition, a further challenge for the higher education system will be the unification or introduction of education standards for humanities and social sciences, as the effectiveness and ability to influence the student will be important with the use of AI in education. More importantly, it will contribute to its mobility and openness to change [15].

3. Conclusion

The E-Tutor Fundamentals of Management digital platform marks a significant advancement in the digitalization of higher education. The proposed framework of digital platform also provides researchers and educators with valuable insights on the use of digital technologies in higher education to support digital learning and highlights the importance of digitalization in higher education. By offering students extensive access to academic resources and enabling flexible, digital, and remote learning, the platform has established a new benchmark for digital education in the management field. As higher education continues to adapt in the post-pandemic era, platforms like E-Tutor Fundamentals of Management will play a pivotal role in facilitating student learning and academic success. The digitalization of higher education, as exemplified by platforms such as E-Tutor Fundamentals of Management, represents a profound shift in the educational landscape. The theoretical implications of this shift underscore the transformative potential of digital and artificial intelligence-driven learning environments, which resonate with contemporary pedagogical theories emphasizing personalized, networked, and student-centered learning.

From a practical perspective, the ongoing integration of digitalization and artificial intelligence in higher education promises to enhance accessibility, flexibility, and the overall quality of education. However, this progression also demands careful consideration of equity and ethical issues to ensure that the advantages of these technologies are available to all students. As institutions continue to evolve in response to these technological advancements, it is imperative that they embrace these changes while remaining cognizant of their broader societal implications.The main limitation of this study is to be found in its qualitative nature – it does not allow generalization to the population. As a possible avenue for further research, a longitudinal, quantitative study should be performed.

4. Acknowledgements

This paper is part of research program group Program P5-0441 – Regeneration of economy and business and part of research program group Program P5-0364 – The Impact of Corporate Governance, Organizational Learning, and Knowledge Management on Organizations in Ageing Societies, which is supported by the Javna agencija za znanstveno-raziskovalno in inovacijsko dejavnost Republike Slovenije (angl. Slovenian Research and Innovation Agency; ARIS) (14. Člen Splošnega akta o stabilnem financiranju znanstvenoraziskovalne dejavnosti (Uradni list RS, št. 87/22 in 103/22 – popr.). The authors would also like to thank experts in the Central Economics Library (http://www.ef.uni-lj.si/cel) for their participation and cooperation in the project of E-tutor Fundamentals of management.

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Capturing Complex Patterns: Classroom Examples of Traditional Statistics vs Gradient Boosting for Regression and Classification Tasks

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Abstract

This paper compares traditional statistical methods with gradient boosting techniques for regression and classification tasks, utilizing classroom-applicable examples. Traditional methods often underperform with nonlinear relationships in large datasets, whereas ensemble methods like gradient boosting enhance predictive accuracy and robustness, represented by XGBoost, LightGBM, and CatBoost. We illustrate these comparisons through three scenarios: a basic regression problem demonstrating sinusoidal relationships, a modified classroom card game as a classification task, and a real-world medical dataset analyzing heart therapy outcomes. The results indicate that gradient boosting models, particularly XGBoost and LightGBM, significantly outperform traditional methods, affirming their utility in educational settings and complex data analysis. This paper contributes to the understanding and application of machine learning techniques over standard statistical approaches, providing valuable insights for educators and practitioners in data-driven disciplines.

Keywords: *traditional statistical methods, gradient boosting, regression, classification tasks.*

1. Introduction

Discovering and understanding complex patterns in data is crucial for accurate analytics and predictions. Traditional statistical methods, such as linear regression, often fall short when dealing with nonlinear relationships present in big datasets. Ensemble methods, particularly gradient boosting algorithms, have emerged as powerful tools in applications such as credit scoring, bioactive molecule prediction, energy prediction, and most importantly, medical data analysis. These methods combine the strengths of multiple models to enhance predictive performance and robustness [1]-[3]. XGBoost, developed by Chen and Guestrin (2016) [1], has gained prominence for its scalability and efficiency, making it a frequent top contender in machine learning competitions. LightGBM, designed by Ke et al. (2017) [2] with the intent on fast training performance by employing techniques like selective sampling of high gradient instances. CatBoost (Cat is short for Categorical), introduced by Prokhorenkova et al. (2018) [3], addresses the issue of prediction shift to enhance model accuracy.

From a practical perspective, we mention the research by Nori et al. (2019) [4] that investigates the effectiveness of machine learning in predicting dementia using electronic health records, or Torres-Barrán et al. (2017) [5], which applied these techniques to solar and wind energy prediction. In the financial sector, Xia et al. (2017) [6] considered the application of ensemble methods in credit scoring, showcasing their ability to handle imbalanced datasets and improve prediction accuracy. Fernández-Delgado et al. (2014) [7] and Caruana and Niculescu-Mizil (2006) [8] compare several ensemble methods, including random forests and gradient boosting. Recent advancements necessitate further analyses, particularly focusing on hyper-parameter tuning, computational efficiency, and efficient implementations [9, 10].

This study builds on previous research to provide a comparison of XGBoost, LightGBM, and traditional statistical methods, focusing on examples of varying complexity that highlight the complementary strengths of machine learning approaches over standard statistics. We use three distinct examples intended to be demonstrated in the classroom, compatible with the knowledge of non-informatics or computer science programs in the context of extracurricular content with the prerequisite of college level mathematics and statistics courses: a basic regression problem, a classroom-implementable card game as a classification problem, and a real-world healthcare dataset examining heart therapy outcomes. This study aims to advance the understanding of gradient boosting algorithms while offering practical guidance for educators and practitioners in selecting and optimizing these powerful tools to meet their specific needs.

2. Materials and Methods

Gradient boosting is an ensemble technique that constructs a model from an ensemble of weak learners. The core idea is to build the model in a stage-wise manner, where each new model corrects the errors made by the previous models. The process can be summarized as follows:

1. Initialization: Start with an initial model, usually a constant prediction.

2. Additive Modeling: Sequentially add new models to the ensemble. Each new model is trained to minimize the error of the current ensemble.

3. Update Rule: The updated prediction is given by:

$$\widehat{y_m}(x) = \widehat{y_{m-1}}(x) + \eta h_m(x),$$

where is the learning rate controlling the contribution of each new model.

2.1. Objective Function and Gradient Descent

The objective in gradient boosting is to minimize a loss function over the dataset. For regression tasks, common loss functions include the mean squared error (MSE). Usually, the optimization is performed using (some variant of) gradient descent, where the gradient of the loss function with respect to the predictions is computed and used to update the model:

$$g_i = \frac{\partial L(y_i,\widehat{y_i})}{\partial \widehat{y_i}}.$$

Each new model is trained to predict the negative gradient (pseudo-residuals) of the loss function:

$$h_m(x) = -g_i.$$

2.2. Functional Gradient Descent

The gradient boosting algorithm can be interpreted as an optimization in function space, rather than parameter space. In functional gradient descent, we iteratively add functions to our model that point in the direction of the negative gradient of the loss function.

The algorithm can be outlined as follows:

1. Initialization: Set the initial model to a constant function:

$$\widehat{y_0}(x) = \arg\min_\gamma \sum_{i=1}^{n} L(y_i, \gamma).$$

2. Iterative Refinement: For :

2.1 Compute the pseudo-residuals:

$$r_i^{(m)} = -\left[\frac{\partial L\left(y_i, \widehat{y^{(m-1)}}(x_i)\right)}{\partial \widehat{y^{(m-1)}}(x_i)}\right].$$

2.2 Fit a base learner (e.g., a decision tree) to the pseudo-residuals:

$$h_m(x) = \arg\min_h \sum_{i=1}^{n} \left(r_i^{(m)} - h(x_i)\right)^2.$$

2.3 Update the model:

$$\widehat{y^{(m)}}(x) = \widehat{y^{(m-1)}}(x) + \eta h_m(x),$$

where, is the learning rate as before.

2.3. Regularization Techniques

To prevent overfitting, gradient boosting incorporates regularization techniques such as:

- Shrinkage: Scaling the contribution of each base learner by a factor.
- Subsampling: Using a random subset of the data to fit each base learner.
- Tree Constraints: Limiting the depth or the number of leaves of the individual decision trees.

2.4. XGBoost and LightGBM Enhancements

Both XGBoost and LightGBM introduce enhancements to the basic gradient boosting framework. Namely, XGBoost implements regularization techniques to prevent overfitting, supports parallel processing, and includes advanced tree learning algorithms such as exact and approximate greedy algorithms. LightGBM is designed to ensure efficiency and scalability, employing techniques like Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB) to handle large datasets and high-dimensional feature spaces.

2.5. Overfitting issues

To reduce the risk of overfitting, which occurs when a model performs extremely well on the training data but fails to capture the underlying pattern and generalize properly to unseen data, several regularization techniques were applied. In gradient boosting, overfitting can be controlled by adjusting the learning rate, using shrinkage, or subsampling the dataset. Shrinkage reduces the contribution of each tree by a factor, preventing the model from over-adjusting to the training data. Subsampling involves training each tree on a random subset of the data, enhancing the model's generalization ability. Additionally, constraints were applied to tree depth, limiting the model's complexity and further reducing the chances of overfitting. XGBoost and LightGBM both incorporate these strategies to ensure that the models generalize well while maintaining high predictive performance.

The metrics we measured, such as Mean Squared Error (MSE), R-squared (R^2), and Mean Absolute Error (MAE), provide insight into possible overfitting. A model that overfits would exhibit very low MSE and high R^2 on the training data but perform poorly on the test data, with increased MSE and reduced R^2. Similarly, a significant gap between the training and test set performance in terms of MAE would indicate that the model is overfitting, capturing noise rather than the true underlying patterns in the data. These metrics help assess whether the model is generalizing well or overfitting to the training set.

2.6. Examples of Nonlinear Relationships

To illustrate the ability of GBTs to capture nonlinear relationships, we present three examples:

Example 1: Basic Nonlinear Relationship.

To simulate the sinusoidal relationship, we generated a dataset consisting of 1000 data points. The input variable was uniformly spaced between 0 and. The corresponding output was calculated using the equation, where represents random noise. We considered two levels of noise (0, 0.1) and (0, 0.2).

For both noise levels, the data was split into training and test sets with an 80-20 ratio with the use of default hyper-parameters. The models were trained on the training set and evaluated on the test set by calculating Mean Squared Error (MSE) and R-squared (R^2).

Example 2: Card Game Prediction: Blackjack Lite.

We introduce a version of Blackjack, called "Blackjack Lite," where the goal is to predict whether the total value of a player's hand is within a winning range, but with additional (nonlinear) rules. Each card has a value between 1 and 10, and the game uses a standard deck.

Rules:

Each player draws two cards initially. The player can draw, in total, up to three cards.

The player draws a third card if the sum of the first two cards is less than 12.

Special Rule: If the sum of the card values is exactly 13, the player wins automatically.

Special Rule: If the player draws a third card and the sum of all three cards is between 15 and 21, the player wins.

The player loses if the sum exceeds 21 or does not meet any winning condition.

Outcome Classification:

Win: If the sum meets any of the winning conditions.

Lose: Otherwise.

The simulations and experiments were conducted as follows. We simulated 1000 rounds of the "Blackjack Lite" game. For each round, two cards were drawn randomly from the deck. If the sum of the two cards was less than 12, a third card was drawn. The sum of the card values and the outcome (win/lose) were recorded based on the above rules. The data was structured into a DataFrame with columns for each card value, the sum of the card values, and the outcome. The features (card values) and the target variable (outcome) were defined for model training and evaluation. The dataset was split into training (80%) and test (20%) sets. Three models were trained on the training set: logistic regression, LightGBM, and XGBoost. The models were evaluated on the test set using several performance metrics, including accuracy, precision, recall, F1 score, ROC-AUC. Accuracy measured the proportion of correctly classified instances among all instances. Precision measured the proportion of true positive predictions among all positive predictions. Recall (sensitivity) measured the proportion of true positive predictions among all actual positives. The F1 score, the harmonic mean of precision and recall, was also calculated. ROC-AUC measured the area under the receiver operating characteristic curve, giving insight into model's ability to distinguish between classes. All simulations were conducted in Python using the 'numpy', 'pandas', 'scikit-learn', 'lightgbm', and 'xgboost' libraries. The nonlinear combinations of the card values, along with special rules, make this an interesting classification problem.

Example 3: Healthcare Data, Example from Literature.

This example is based on the article [1] which provides a detailed comparison between traditional statistical methods and modern machine learning techniques in analyzing cardiovascular pharmacotherapy data. The study involved 386 heart failure patients with reduced ejection fraction (HFrEF) who were initiated on sodium-glucose co-transporter-2 (SGLT2) inhibitor treatment. The goal was to identify predictors of improved outcomes.

3. Results and Discussion

Example 1: Sinusoidal Relationship.

The performance of the linear regression, LightGBM, and XGBoost models was evaluated on a sinusoidal dataset with two levels of noise: 0.1 and 0.2. The noise was mathematically formulated as follows: for each data point in the dataset, the corresponding value was generated as, where is random noise (0, 0.1) or (0, 0.2).

For the dataset with noise level 0.1, linear regression achieved a Mean Squared Error (MSE) of 0.00996, and an R-squared (R^2) of 0.694. In contrast, LightGBM demonstrated better with an MSE of 0.00264, and an R^2 of 0.938. XGBoost performed similarly, achieving an MSE of 0.00227, and an R^2 of 0.946.

As the noise level increased to 0.2, the performance of all models declined. Linear regression recorded an MSE of 0.036, and an R^2 of 0.462. LightGBM maintained superior performance with an MSE of 0.020, and an R^2 of 0.738. XGBoost also showed robustness against the increased noise, achieving an MSE of 0.018, and an R^2 of 0.741. Despite the deteriorating performance with higher noise levels, LightGBM and XGBoost continued to outperform linear regression.

Example 2: Card Game Prediction.

The performance of the logistic regression, LightGBM, and XGBoost models was evaluated. The logistic regression model achieved an accuracy of 0.745, with a precision of 0.618, recall of 0.531, and an F1 score of 0.571. The ROC-AUC for logistic regression was 0.743, with a log loss of 0.546. In comparison, the LightGBM model showed significantly better performance, with an accuracy of 0.93. The model's precision was 0.879, recall was 0.906, and F1 score was 0.892. The ROC-AUC was 0.981, with a log loss of 0.165. The XGBoost model demonstrated the highest performance among the three, with an accuracy of 0.945. Precision was 0.896, recall was 0.938, and the F1 score was 0.916. The ROC-AUC was 0.984, with a log loss of 0.138.

TABLE 1. The performance of the logistic regression, LightGBM, and XGBoost models.

Metric	Logistic Regression	LightGBM	XGBoost
Accuracy	0.745	0.930	0.945
Precision	0.618	0.879	0.896
Recall	0.531	0.906	0.938
F1 Score	0.571	0.892	0.916
ROC-AUC	0.743	0.981	0.984

The results show that LightGBM and XGBoost outperform logistic regression across all metrics.

Example 3: Healthcare Data, Example from the Literature.

Data Description: The study [11] involved 386 heart failure patients with reduced ejection fraction (HFrEF) who were initiated on sodium-glucose co-transporter-2 (SGLT2) inhibitor treatment. The patients receiving the maximum doses of beta-blockers (chi-square test, p-value = 0.036) and those newly initiated on sacubitril- valsartan (chi-square test, P = .023) demonstrated better outcomes. The goal was to identify predictors of improved outcomes. Frequentist statistical analyses, such as chi-square tests and Cox proportional hazards models, were employed to investigate the impact of pharmacological treatments. None of the pharmacological features emerged as independent predictors of improved outcomes in the Cox proportional hazards model. However, in the case of variables with non-linear relationships, additional interpretative techniques may be required. This is particularly evident for body mass index (BMI), a variable known for its U-shaped relationship with the outcomes of numerous cardiovascular entities. Both high and low BMI values are linked with worse outcomes. Dependence plots may prove superior to comprehend the nature of correlations (Figure 5 in [11]). The strikingly blank part of Figure 5B for positive SHAP values (i.e., association with the worse outcome), between BMI values of 27.5 and 32.5 kg/m2 is obvious.

While these methods showed that patients receiving the highest doses of beta-blockers and those newly initiated on sacubitril-valsartan had better outcomes, these features did not emerge as independent predictors in the Cox model. In contrast, the application of XGBoost and Shapley additive explanations (SHAP) revealed several strong predictors. The XGBoost algorithm inherently accommodates nonlinear distribution, multicollinearity, and confounding.

The success of GBTs in the presented examples highlights their practical utility for various tasks, from educational toy-examples to scientific research and healthcare. Additionally, such ML methods can be employed in the mathematical modeling of complex systems to estimate parameters for Partial Differential Equations (PDE) models [12,13]. These models enable us to uncover hidden patterns and make guidelines for informed decisions based on the data, balancing decisions beyond hunches.

In the experiments, both LightGBM and XGBoost demonstrated strong performance in capturing the underlying patterns of the data, even with added noise. The metrics we computed provided insight into how well the models were able to approximate the known underlying function. Since this was a regression task with a known underlying model, we did not rely on a separate test set but instead evaluated the models' ability to approximate the true function directly. Overfitting was a potential concern, especially at higher noise levels. However, the computed MSE and R-squared (R^2) values remained consistent across different noise levels, indicating that the models were not significantly overfitting. If overfitting had occurred, we would have observed much lower MSE and higher R^2 on noisy data points, while failing to approximate the smooth sinusoidal pattern in areas with less noise.

4. Conclusion

Gradient boosting trees, exemplified by XGBoost and LightGBM, are powerful tools for modeling and understanding nonlinear relationships in data. Their ability to capture complex interactions and dependencies often surpasses traditional statistical methods, making them indispensable in modern data analysis. The toy examples provided in this article illustrate the educational applications and advantages of GBTs, emphasizing their role in advancing our understanding of intricate data patterns.

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ISSN 2991-9371

ISSN 2991-9371