

NAVIGATING PUBLIC SENTIMENT: ACCEPTANCE OF DISRUPTIVE INNOVATIONS CREATED BY TRANSFORMATIONAL CREATIVE GENERATIVE AI

Completed Research Paper

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Abstract

The advance of generative artificial intelligence (GenAI) is rapidly progressing and inundating markets with its outputs. Moreover, the creativity of these systems is increasing, potentially leading to the creation of disruptive innovations in the future. Previously, research has examined acceptance of Artificial Intelligence (AI) systems and disruptive innovations independently. We are combining two research areas to shift the focus from studying the acceptance of AI systems to examining the acceptance of GenAI generated disruptive innovations. Thus, we ask, what factors drive the acceptance of disruptive innovations created by GenAI? Therefore, we conducted 18 interviews with 19 AI experts and identified several factors that could enhance acceptance in this case. The perceived usefulness of disruptive innovations appears to be the key factor, which indicates internal validity with existing research. However, higher quality expectations and the desire for traceability and comparability of disruptive innovations suggest a distinction from human-created ones.

Keywords: Generative artificial intelligence, acceptance, disruptive innovation, creativity

1 Introduction

Disruptive innovations have the potential to significantly improve the well-being of populations and address, for example, sustainability and medical challenges globally (Kivimaa et al., 2021). These solutions could make breakthrough progress toward previously unsolved issues. According to Sternberg (2021), the imperative value of transformational creative individuals' work lies in its potential for meaningful and enduring effects on the world. However, transformational creativity is not inherent in every individual and its absence can pose a serious challenge. Thus, Sternberg (2021) notes the rarity of such innate creativity, indicating the crucial role of AI in bolstering transformational creativity where it is otherwise lacking. This presence of transformational creativity in GenAI is what we call "transformational creative GenAI".

Creative work areas have long been deemed challenging to automate, thus considered less susceptible to replacement by AI (Badet, 2021; Makridakis, 2017). However, the emergence of GenAI has brought forth a groundbreaking technology era that will test this presumption. In fact, some scholars have incorporated creativity in their definition of AI (Rai et al., 2019). This innovative technology enables the production of intricate and imaginative content. GenAI displays remarkable human-like competence, as demonstrated by ChatGPT's natural language generation. Its potential for integration within human-machine interaction offers unprecedented possibilities, especially in fields such as art, literature, and medicine, where innovation thrives on creativity.

A notable instance of GenAI fostering innovation is in the rapid development of messenger ribonucleic acid (mRNA) vaccines during the COVID-19 pandemic. As an example, where GenAI helped to foster innovation. This disruptive innovation (Giacomini and van der Graaf, 2022), was invented with the

assistance of AI, reducing vaccine development time significantly, as reported by the Council of Europe (2021). With the speedy progress of GenAI and the introduction of advanced forms of transformational creativity, it may be possible for GenAI to create disruptive innovations (e.g., novel vaccine types) with desired characteristics in the future (Bagabir et al., 2022; Schneider, 2019).

This progress raises a pertinent question: How will individuals react to accepting an mRNA vaccine developed by GenAI? The answer to this question is crucial, as highlighted by Stanton and Jensen (2021), because the endorsement of groundbreaking innovations by GenAI is essential for their effective implementation and societal benefit. Previous research indicates that factors like perceived usefulness, trust, and innovation diffusion theory are instrumental in the acceptance of revolutionary innovations. Yet, it remains unclear if there's a difference in the acceptance of disruptive innovations based on their origin – whether developed by GenAI or humans.

Over the years, AI has been discussed not only as an opportunity but also in a critical manner. Concerns over a potential loss of control over AI and the unclear and untraceable nature of some results produced by AI-based systems are among the fears expressed (Bjerring and Busch, 2021; Feldman et al., 2019). However, as AI has the potential to provide more benefits than risks, previous studies have aimed at establishing trust in AI (Glikson and Woolley, 2020; Kaplan et al., 2023; Rossi, 2018). Moreover, research in this field has resulted in multiple models that have significantly impacted the public's acceptance of AI (Hecker et al., 2017; Scheuer, 2020; Siau and Wang, 2018; Zhang et al., 2010). As the significance and innovative potential of AI continues to grow (Rust and Huang, 2021), papers have also explored the implementation of autonomous AI in innovation processes (HYVE, 2019) and AI creativity (Boden, 1998; Rust and Huang, 2021). Previous research has explored the factors that support the acceptance of GenAI & AI in the context of its direct interaction with humans. However, there has been limited discussion on the acceptance of (disruptive) innovations produced by transformational creative GenAI and their acceptance by humans (Amabile, 2019).

In summary, previous research has discussed the factors that promote trust and acceptance between humans and AI. Transformational creativity is still in development for AI, but it is expected to be achievable soon. Given the rapid pace of AI development and creativity, it may be crucial for society and businesses to understand the conditions that facilitate the acceptance of disruptive innovations created by GenAI with transformational creativity. The differentiation between transformational creativity and other forms of creativity, such as combinatory or exploratory creativity, is crucial to consider since these systems are necessary for creating groundbreaking innovations that have a significant positive impact on society. Therefore, our aim is to address the following research enquiry:

What factors drive the acceptance of disruptive innovations created by transformational creative GenAI?

An answer to this query would provide substantial economic and reputational benefits to firms, as they would have access to a cutting-edge GenAI that creates disruptive innovations. Individual's approval of such innovations could grant them unparalleled influence and leadership within their industry.

After defining key terms and summarizing previous research on human acceptance of AI and disruptive innovations, as well as the current state of AI creativity in generating such innovations, this study will conduct 18 semi-structured interviews with 19 experts in AI and innovation to gain insights from their perspectives. These insights will then be analyzed according to Strauss' (1989) coding strategy and compared to existing research in the subsequent stage. Finally, our results indicate internal validity with prior research by confirming factors like perceived usefulness while identifying acceptance factors for GenAI's disruptive innovations, including comparability and traceability, that extends previous research.

2 Theoretical Background

The theoretical basis of this paper is grounded in two research areas. Firstly, previous research has examined the factors that foster acceptance of the interaction between AI systems and humans. Secondly, research has explored acceptance of disruptive innovations. By combining these research areas, we aim to identify the factors that support acceptance of disruptive innovations created by

transformational creative GenAI to learn from both research areas and add further acceptance factors.

2.1 Acceptance of AI systems

“Artificial intelligence (AI) refers to systems that display intelligent behavior by analyzing their environment and taking actions – with some degree of autonomy – to achieve specific goals” (European Commission, 2018, p. 1). Scenarios in which AI systems would autonomously make decisions without human control have caused fear in the public, particularly as the decision-making processes of AI often appear opaque (Bjerring and Busch, 2021; Feldman et al., 2019). Consequently, prior research has examined factors that can increase trust in AI or in its sub-fields, such as robotics, leading to acceptance (Choung et al., 2023; Scheuer, 2020). The research uncovered that elderly individuals, who were role-playing as individuals receiving medication from a robot, had a more favorable experience with service robots that possessed greater anthropomorphic characteristics. In contrast to this and other studies that view anthropomorphic features of artificial intelligence and robotics as promoting acceptance (Rietz et al., 2019), the “Uncanny Valley” theory describes a phenomenon in which human acceptance suddenly drops significantly as anthropometry increases (Mori, 1970; Watson, 2014). Siau and Wang (2018) argue that to enhance humans' trust in AI, it must be transparent and reliable. Additionally, norms and standards play a vital role in AI's trust and application (Donner, 2021). Establishing these norms and standards can unify the aforementioned trust-building elements, ensuring their validity and consistency across large regions when using disruptive innovations, such as autonomous cars interregional.

However, trust is not the sole determinant of acceptance. Hecker et al. (2017) identified further supporting factors for the relationship between AI and humans. They argue that an AI should possess empathy (Pelau et al., 2021) and functionality, as people are more likely to accept AI when it offers specific, beneficial functions for a given use case. (Wittpahl, 2019) emphasizes that suggestions provided by an AI should be explainable and comprehensible to promote acceptance by humans. Additionally, Scheuer (2020) developed a comprehensive model for illustrating the acceptance of AI that consists of three main parts. One of these parts is the Technology Acceptance Model (TAM) by Davis (1989), which highlights the perceived usefulness factor that is frequently employed for assessing user acceptance of AI systems (Ismatullaev and Kim, 2024; Kelly et al., 2022; Sohn and Kwon, 2020). Furthermore, performance and effort expectancy were also identified to positively influence the willingness and use of AI systems by humans.

GenAI is a sub-group of artificial intelligence that denotes systems capable of creating varied forms of creative output, such as text, images, code, and art, which revolutionizes the ability of machines to be creative (Benbya et al., 2024; Davenport and Mittal, 2022). This ability to create individualized, new outputs on its own, makes it possible to automate creative tasks (Benbya et al., 2024). In comparison to other forms of AI, the rise of GenAI has facilitated the democratization of AI among the public through tools like ChatGPT (Kanbach et al., 2023). The rapid acceptance of these recent GenAI advancements has spurred further research into the acceptance of AI systems. ChatGPT, for example, achieved the fastest-growing user base in the history of digital technologies before the launch of the social media platform Threads by Meta in July 2023 (Rao et al., 2023). Prior to that, no other platform had achieved one million active users within five days and over 100 million active users after two months of launch (Edwards, 2023). TikTok, well known for its rapid acceptance and spread in society, took nine months to reach 100 million active users (Edwards, 2023). To investigate the acceptance theory of this phenomenon, researchers have analyzed the traits and perspectives of users that lead to their acceptance of systems such as ChatGPT (de Winter et al., 2023; Strzelecki, 2023; Tiwari et al., 2023).

The supporting factors for acceptance as mentioned earlier are all discussed in the collaboration between human and AI systems. Currently, research focuses on determining the conditions under which users accept these AI systems (Shen et al., 2023). In acceptance theories of AI systems, like TAM or UTAUT, as well as current literature reviews, perceived usefulness or performance expectancy seem to be the key factors to drive acceptance (Davis, 1989; Ismatullaev and Kim, 2024; Venkatesh et al., 2003). In the case of ChatGPT or Midjourney, this approach is reasonable since the system and the creative output it generates are both experienced by the user, thereby influencing the acceptance of the creative outcome.

However, if a company has a GenAI that produces creative output without direct interaction with the end-user, we must take into account the acceptance of that creative output by humans.

2.2 Creativity as a parameter for the level of innovation created by GenAI

“Creativity (...) generates novel and useful (...) elements (...) and (...) solves a problem [better] (...) [or] produces a (...) product not clearly present before” (Pesut, 1985, p. 5). Earlier, scholars believed that professions that require high levels of creativity were less susceptible to being replaced by technology (Badet, 2021; Makridakis, 2017). Currently, research indicates that AI systems such as ChatGPT are just as imaginative as, if not more imaginative than, humans (Guzik et al., 2023; Koivisto and Grassini, 2023). Utilizing substantial data and sophisticated insights, AI systems can devise more user-centered innovations than humans (Verganti et al., 2020). The creative ability of GenAI systems enable them to create individual solutions to changing contexts and requirements. Colton and Wiggins describe the creation of ideas by computational systems with the computational creativity theory (2012).

Boden (1998) categorizes AI creativity into three key types. The first, combinational creativity, creates new concepts through merging existing ones. This method is currently present in AI (Boden, 2005). The second type is exploratory creativity, where new concepts form within a structured environment, such as a set of rules. This form is also present in AI (Boden, 2005). The third form of creativity is termed as transformational creativity. It engenders novel ideas in a completely fresh arrangement, by autonomously adapting the existing set of rules (Ławrynowicz, 2020) to create something entirely unusual, like a vaccine against cancer. This type of creativity is still in its development (Boden, 1998; Kantosalo and Toivonen, 2016; Lee, 2022) and will be the primary focus of this research as it is necessary for AI to achieve breakthroughs (Lee, 2022), which are characterized as disruptive innovations (Christensen et al., 2015). In addition to the uncharted territory of transformational creativity, there is evidence that AI systems are already contributing to (transformational) creative processes, indicating that the development of transformational creative AI is already underway (de Cremer et al., 2023; Townsend and Hunt, 2019).

2.3 Acceptance of disruptive innovations

According to Afuah, “innovation is the use of new knowledge to offer a new product or service that customers want” (2020, p. 13). Innovation acceptance research mainly builds on the perceived value, trust and innovation diffusion theory (Carter and Bélanger, 2005; Pérez Pérez et al., 2004; Yuen et al., 2020), which describe the importance of perceived value, trust, relative advantage, compatibility, complexity, trialability and observability as acceptance enhancing for innovations. As an example, Yuen et al. studied autonomous vehicles as an innovation and confirmed the relevance of perceived value, trust and innovation diffusion theory as acceptance fostering (2020). Hussein Saleh Zolait et al. (2009) found that increased knowledge, awareness, and experience in internet banking enhances the acceptance of innovations in this field. In addition, Moradi Abadi et al. (2017) concluded that innovation acceptance is promoted by information transparency.

Disruptive innovations are innovations that pose significant uncertainty regarding the targeted market since they create a previously non-existent market (Christensen et al., 2015). As market acceptance is vital for the success of an innovation (Dunphy and Herbig, 1995), prior research has examined human traits, such as personal innovativeness, that contribute to the acceptance of disruptive innovations (Cui et al., 2021; Garrelfs et al., 2023; Reinhardt and Gurtner, 2015).

Sandberg (2002) examined market proactiveness during the launch phase of a disruptive innovation to ascertain the circumstances under which the disruptive innovation would be welcomed by the market. Her findings propose that innovative companies can best prepare the market for their disruptive innovation by creating awareness and educating potential customers in advance.

Recent studies have focused on the disruptive innovation itself, highlighting factors such as perceived usefulness and ease of use (Cardone and Zavjalova, 2023). These factors are also known from Davis’ Technology Acceptance Model (1989). Existing research has mainly focused on the acceptance

conditions of disruptive innovations created by humans. Our goal is to investigate the differences when placing GenAI in the position of the inventor of disruptive innovations to ensure profiting from them.

3 Method

With this paper, we redirect acceptance research from the relationship between AI systems and humans to the relationship between AI-created disruptive innovations and humans. Therefore, in contrast to previous research, our study focuses on disruptive innovations created by GenAI rather than those created by humans. This topic remains largely unexplored; hence we intend to employ explorative qualitative research methods to delve into it. As part of our empirical methodology, data will be collected through expert interviews to identify specific patterns and analyze their correlation (Bergin, 2018).

3.1 Data collection and sample selection

We gathered the paper’s primary data through semi-structured interviews. This research design was chosen as it permits the acquisition of opinions on a specific topic (Hammarberg et al., 2016) and enables a more adaptable interview situation, where questions can be modified based on the conversation with the interviewee (Adams, 2015). Additionally, the interviews as a qualitative method fit well to the explorative approach that we take in this paper since they deliver a high quality of different ideas (Fern, 1982). Our aim of the interviews was to investigate the circumstances in which transformational creative GenAI-created disruptive innovations could be embraced. The suggested enhancements in this paper can serve as a foundation for future investigations.

For the sample collection, we followed Glaser & Strauss’ (1967) theoretical sampling concept, where initial interviewees are selected purposely. Upon analyzing the data, subsequent interviewees are then chosen based on the focus required for the next round of interviews. In this study, we selected the first four interviewees due to their extensive experience in AI. The second set of interviews (I5-I9) consisted of specialists with expertise in contemporary AI techniques, including deep learning. The final round of interviews (I10-I19) aimed to acquire interdisciplinary knowledge in AI-related fields such as AI Ethics, AI Creativity and AI in the field of medicine. The detailed overview of the interviewees can be found in Table 1. Our interview series yielded insights, covering a wide range of sectors including plant engineering, traffic infrastructure, IT consulting, and the medical industry. These diverse perspectives are poised to contribute to applicable findings across various industries in the future. In total, we conducted eighteen interviews with nineteen different participants via phone or Zoom/ Microsoft Teams, each with an average duration of forty minutes. After 18 interviews (out of which one was an interview with two experts), we concluded the research process due to a significant decline in the discovery of new findings. The final interviews served to confirm earlier ones, indicating theoretical saturation (Glaser and Strauss, 1967).

Interviewee	Professional title	Related industry	Years of experience in the field of AI	Duration (min.)
Interview round 1 – Focus on experts with extensive experience in AI				
I1	Innovation and IP Manager	Machinery and plant engineering	30	34
I2	Professor of Information Systems	Research, IT-Consulting	35	30
I3	Head of AI & Innovation	IT-Consulting	30	36
I4	Director of AI Consultancy	Research, AI-Consulting	40	32
Interview round 2 – Focus on experts knowledgeable in contemporary AI techniques				
I5	Professor of renewable systems and simulation	Research, AI-Consulting	10	27
I6	Software Consultant	IT(AI)-Consulting	6	34
I7	Head of Infrastructure Data Management	Plant engineering	7	22
I8	Principal Researcher	Research in AI	20	39

I9	Managing Director and Associated Researcher	Research in autonomous AI, Consulting	4	45
Interview round 3 – Focus on interdisciplinarity at the interface of AI				
I10	Professor of Computer-Assisted Drug Design	Research and AI-Consulting in Medicine	35	48
I11	Professor of Computation, Information and Technology	Research in NLP	28	60
I12	Research associate in AI and Art, AI Ethics	Research in AI Ethics, Consulting	3	36
I13	Research associate in AI and Creativity	Research in AI Creativity	1	45
I14	Professor of Innovation and Transformation Management	Research in Transformation Management	10	54
I15	Managing Partner and Consultant	Software Development, Consulting	11	49
I16	Director AI & Data	Software Development, Consulting	10	50
I17	Principal Digital Engineering Center	Data analysis & AI consulting	10	45
I18	I18: CEO, Head of Strategy & Engineering	Data science & AI consulting	10	40
I19	I19: Practice Lead Data & AI		15	
Average duration				40

Table 1. Overview of the interviewed experts.

Prior to the interviews, we crafted an open-question guide to steer the discourse efficiently whilst refraining from influencing the interviewee. The guide evolved iteratively during the course of the interview cycles, with fresh question ideas contingent on prior responses. We commenced the interview session with a briefing on the contextual background of the research subject. Following this, the interview delved into the fundamental definition of AI, the various categories of creativity, and the current standing of research pertaining to this field. As AI and creativity possess variable interpretations, this interview structure guarantees the participants' comprehension of the given framework, promoting fair and effective comparison of their individual responses.

The interview questions were categorized into three segments to establish a preliminary structure for the interview (Mayring, 1997), which we defined prior to the first interview. The questions of the first category focused on the characteristics of the disruptive innovation itself created by GenAI. This category aims to highlight the disruptive innovations created by GenAI itself, rather than the acceptance of AI systems or disruptive innovations created by humans, as was the case in previous studies. These questions were not based on theory, as the acceptance of GenAI's disruptive innovation is uncharted territory. Initially, we posed the interviewee an open question to elicit an unbiased response. Specifically, we asked the interviewee to identify the key features a disruptive innovation generated by a transformational creative GenAI should manifest to facilitate its acceptance. Following their response, the interviewee was subsequently asked a series of targeted questions, for example whether the differences between physical and software-based products influenced such acceptance.

The second category inquiries about the activities of a company, that employs GenAI technology to create disruptive innovations, that would increase the acceptance of individuals, such as transparent reporting on technological advancements or a trustworthy country of origin. The interviewees mentioned these examples, rather than us suggesting them during the interviews, to avoid bias. By creating this category, our aim is to provide companies with actionable steps to responsibly promote the acceptance of their disruptive innovations, thereby successfully delivering valuable impact on society. Additionally, the third category sought acceptance-enabling environmental factors, such as testing or adhering to norms and standards. This category collects additional factors that may not belong to the first two categories but further describe the acceptance of disruptive innovations created by transformational GenAI.

3.2 Data analysis strategy

In our research, we employed MaxQDA software for data analysis, adhering to Strauss' (1989) coding methodology. This approach starts with open coding of the interviews to identify key concepts, followed by obtaining additional samples based on these initial findings to refine objectives for subsequent interviews. Prior to each new interview phase, we engaged in axial coding to establish connections between codes, a process that allowed for crucial flexibility and early analytical insights, as noted by Eisenhardt (1989). This iterative procedure of open and axial coding continued throughout the data collection, ceasing only when we had thoroughly explored the data. Our ultimate aim was to define essential categories through selective coding, which involved crafting a coherent narrative and theoretical framework from our findings, a technique underscored by Wolfswinkel et al. (2013). This structured yet flexible approach ensured a comprehensive understanding of the data, aligning with our research objectives.

The initial round of interviews comprised of four discussions, generating 65 coded text segments. Following this, we conducted the second round, encompassing five conversations, which produced 148 coded text segments. The third and final round involved nine interviews, resulting in 260 coded text segments. When analyzing the coded text segments per interview in each round, the first round produced 16.25 codes per interview, while the second and third rounds generated 29.6 and 28.8 codes per interview, respectively. When analyzing the number of codes per interview in rounds one and two, we observe an increase, suggesting that more knowledge was obtained from interviews over time. However, in comparing rounds two and three, there is a slight decrease in the number of codes per interview, indicating theoretical saturation as the number of codes decreased with further interviewing of experts. Although differences in codes per interview could also arise from varying sample sizes per round, the differences in code output per round decreased visibly, indicating saturation. Consequently, we conclude that this is a justifiable point at which to cease the qualitative method.

Overall, from 18 interviews totaling 726 minutes, we analyzed 473 text segments through open coding. These utterances were consequently classified into 66 minor subcategories, including factors like traceability and comparability for the subcategory "within the subjective limits of expectations". Then, we further classified these minor subcategories into the sixteen subcategories of Table 2 and further summarized them into the three main categories mentioned above.

4 Results

Table 2 presents all categories obtained from the interviews, including main categories, related subcategories, the number of mentions, and the interviewees who mentioned each factor. The number of mentions indicates the significance of each factor, with a higher count signifying greater relevance for promoting acceptance (Swan and Worrall, 1974). It is possible for a single factor to be mentioned multiple times in one interview, indicating its importance to the interviewee. To determine the significance of factors across all interviews, the number of mentions is introduced as a metric. Factors with a high number of mentions indicate greater overall importance. While the number of mentions is a useful metric, the number of interviewees who mention a factor is a more reliable indicator of expert consensus, as it avoids artificially inflating a factor's importance through repetition. The two measurements are highly compatible as they effectively cancel out each other's weaknesses. The following sections will explain the factors that determine the circumstances under which individuals are likely to accept disruptive innovations created by transformational creative GenAI.

Main category	Subcategory	Number of mentions	Mentioning Interviewee
Category 1: Characteristics of the by GenAI created	Perceived usefulness (relative to effort)	55	I1-I19
	Within the subjective limits of expectations (new, not too complex, comparable, traceable)	29	I10-I15, I17-I19
	Fulfilment of high-quality expectations/ higher than by human	16	I1, I4-I14, I16

disruptive innovation	created		
	Transparency (data used, liability, functions, inventor)	12	I4, I9, I12, I14-I18
	Physical disruptive innovations rather than software-based ones	9	I4-I6, I8, I13, I19
	The more scientific the area, the less disruptive should the innovation be	7	I10, I13, I14, I16, I19
Category 2: Environmental factors	More education about GenAI	18	I5, I8-I10, I12, I14-I17, I19
	Trustworthy country of origin of company	15	I1- I9, I12, I14-I17, I19
	Legal framework for AI/ data security	12	I7-I9, I12, I14-I16
	Times of crisis as acceptance supporter if associated with disruptive innovation	10	I1-I3, I7-I9, I16, I19
	Human responsibility	7	I5, I7-I10, I12, I16
	Open culture towards technology of market	7	I10, I12, I13, I16, I18
Category 3: Activities of a company that has a transformational creative GenAI	Testing the created disruptive innovation	35	I1, I2, I4-I10, I12, I14-I17, I19
	Adhering norms and standards for disruptive innovation	9	I7-I9, I12, I14, I16
	Building trust	5	I3, I8, I9, I16
	Showing transparency regarding their technological progress/ open-source community	4	I9, I16, I17

Table 2. Conditions for the acceptance of GenAI created disruptive innovations.

4.1 Characteristics of the GenAI created disruptive innovation

The initial category outlined the features of the disruptive innovation created by GenAI. This analysis provides insight into the attributes required for an individual to accept a GenAI-created disruptive innovation. The main category encompasses six subcategories. The interviewees consistently emphasized **perceived usefulness** as a factor that enhances the acceptance of the disruptive innovation. “The key consideration for [individuals] is that it provides significant advantages and offers greater convenience, lighter weight, improved comfort, lower cost” (I1). If one of these characteristics is met, I14 states that individuals are not considered to think: “Oh, that’s from an AI, I do not use that, it’s just a question of does it help or does it not help” (I14).

In addition to usefulness, it is essential that any disruptive innovation created by GenAI lays **within the subjective limits of expectations**. This involves producing a creative outcome that is both new and impactful, whilst avoiding excessive complexity that might render it inscrutable, as one participant noted: “if it’s sufficiently complex, I cannot distinguish it from magic” (I11). This quote, originating from Arthur Clarke, was originally attributed to advanced technologies, but remains applicable to the outcomes of advanced technologies, such as the case being presented. Comparability to previous outcomes and traceability are crucial factors for successful disruptive innovation. To meet the approval of medical scientists, a cancer vaccine must bear resemblances to existing medication, such as an mRNA-based cancer vaccine akin to the Covid vaccine and be traceable in its functionality. The variability in expectations stems from people’s varying levels of familiarity with AI systems, which lead to differing conceptions of the potential creative outcomes (I13). Traceability and comparability are vital factors in GenAI-created disruptive innovation since there is no human inventor to provide a subjective evaluation or frame the innovation in relation to existing concepts.

Another AI-specific acceptance enhancing factor of disruptive innovations is the **fulfillment of high-quality expectations** that exceed those of innovations created by humans. This may be derived from the perception of AI as an infallible system. Therefore, any failure of a disruptive innovation created by GenAI is likely to be less forgiven than if it were created by a human, as “AI is subject to an unattainable standard of perfection” (I6). Furthermore, I16 states that “I don’t have to settle for the second-best search engine. I have the option to switch, which sets high expectations for the quality of my search results.” Through the widespread availability of various GenAIs, the expectations for their output

largely raised.

Transparency of the created disruptive innovation is crucial for its acceptance. As per interviewee I12, it ought to be transparent which data was used to create the disruptive innovation since *“it is also a straightforward way of ensuring people feel included in some way”* (I12). Additionally, they propose revealing whether the disruptive innovation's inventor was a human or a GenAI to prevent individuals from feeling deceived if they discover it independently. Moreover, transparency regarding the functions of the innovation and clarification of liability are crucial for acceptance. For instance, if a GenAI develops a new algorithm for autonomous driving, it is essential for individuals to comprehend the system's task and who holds responsibility for driving the vehicle.

The next aspect considered was whether there would be any difference in acceptance between a purely physical disruptive innovation created by GenAI and a software-based one. It appears that **physical disruptive innovations are more likely to be accepted** than software-based ones. Several reasons support this observation. *“If one possesses a physical object [as a disruptive innovation], it inherently carries a higher level of acceptance than any black box algorithm. This is because the mechanisms behind the algorithm are not comprehensible”* (I19). Additionally, physical products are generally easier to comprehend, for example through reverse engineering, and seem more transparent due to their physicality. Even software developers may encounter difficulties in comprehending unfamiliar codes that a service relies on - like the Google search algorithm, for instance. Interviewee I13 also posits that physical objects are imbued with a *“a certain inertia. So, physical things somehow have been developed, but they are static for the time being, other digital things are ever evolving”*. Thus, comprehending these objects is also a never-ending process.

Another aspect was raised by Interviewee I10 and concurred by the following interviewees (I11-I15). He mentioned that *“scientific work does not take big steps but is incremental”* and thus for his experience the rule holds true that **the more scientific the area** is in which the GenAI generates creative output, **the less disruptive** should **the created innovation** be to get accepted. This relates to the second factor in this category, whereby disruptive innovations created by GenAI should be subjectively constrained to expectations and comparable to previous developments.

In summary, the most frequently cited acceptance driving factors included perceived usefulness of the disruptive innovation, aligning it with subjective expectations and meeting high-quality expectations.

4.2 Environmental factors

The second main category comprises six environmental factors and demonstrates the circumstances under which individuals accept the disruptive innovations created by GenAI. **Educating individuals more about GenAI** appears to be the most crucial aspect, based on the number of mentions, as *“increased acceptance of AI systems in industry can be achieved by ensuring users possess comprehensive understanding of the systems they are handling. This includes understanding the type of systems they are dealing with”* (I10). According to I5, many misconceptions must be dispelled, and individuals need to understand *“we want to solve this with an AI. Why do we want to solve this with an AI, why don't we do it with humans? [...] What are the consequences for the social fabric? I'm talking about these soft factors that the whole thing affects. I think you must communicate and present them very early on. Then you can achieve acceptance”*. This factor is connected to placing disruptive innovation within subjective expectations. Further education can expand the subjective range of expectations, leading to greater acceptance of disruptive innovation due to enhanced understanding of GenAI outputs by individuals.

The next factor that was identified as acceptance enhancing is a **trustworthy country of origin of the company** that owns such a transformational creative GenAI generating disruptive innovations. This seems to be very important since as a customer *“it may not always be feasible to [...] [fully] reconstruct the objectives that have been employed [...] [and] what was thought in the development process [of the disruptive innovation]”* (I6). I15 states that *“it has a big influence on my personal acceptance, and this is not determined by nationality, but rather the governing system in place. I posit that an autocratic system would have vastly different implications than one governed by a liberal democracy. This factor*

would be decisive for me since the potential for abuse within such a system is unfathomable, and the amount of power it holds is astonishing”.

The subsequent factor that results in a higher level of acceptance towards disruptive innovations created by GenAI is the establishment of a **legal framework for the creation of GenAI**, “that also considers data privacy topics” (I9). It is imperative to have clear definitions of the scope of possibilities for transformational creative GenAI, as well as the data on which it relies and the legal ownership of such disruptive innovation. Greater transparency and comprehensibility will undoubtedly bolster acceptance of transformational creative GenAI's disruptive innovations.

Times of crisis are known as innovation enhancer (Skulmowski and Rey, 2020) and also seem to be an acceptance supporter. The current Covid-19 pandemic also exemplifies the previously observed phenomenon of increased acceptance of specific innovations during crises. The novel mRNA vaccine, a disruptive innovation that was partially developed with the aid of artificial intelligence, was widely embraced due to its perceived efficacy in resolving the ongoing pandemic. The severity of this crisis expedited acceptance procedures at all societal levels, ranging from governmental processes to the acceptance of society as a whole. This highlights its impact on the acceptance process. I19 further argues that “if there is a need [because of a crisis] and the [disruptive innovation] is there, then the benefit is even more present and even more direct” (I19).

The next acceptance-fostering aspect is **human responsibility**. One justification was that there “should be in any case a human instance in between” (I10) that still has the responsibility and control over such a transformational, creative GenAI, which coincides with the concept of human-in-the-loop (Zanzotto, 2019). Even if the system could generate novel content, it remains essential that a human is accountable for the results and oversees them. A further point in support of this factor was made in Interview I5. The argument emphasizes that disruptive innovation should be based on human responsibility rather than solely on the creative abilities of GenAI. The reason being that “there is something missing. There needs to be a human in place, to whom I can say, if necessary, it's your fault” (I5).

The final factor of this main category is an **open culture towards technology** of the market. As Interviewee I14 mentioned there must be a “generation change. [...] I do this for 30 years and there has only been an acceptance of this for the last five years across the board and also among managers in the industry. There is simply a new generation.” Furthermore, I14 thinks “that we [as a society] are longing more and more for such disruptive changes, significant changes”. This element also accompanies the necessity of instructing individuals on current technological advancements. This cultivates receptive individuals, willing to accept disruptive consequences arising from transformational creative GenAI.

In summary, especially more education for individuals about GenAI, a trustworthy country of origin of the owning company of such an innovative GenAI, and a legal framework for the generating creative AI serve as acceptance supporting environmental conditions for GenAI created disruptive innovations.

4.3 Acceptance fostering activities of a company that has a transformational creative GenAI

The final category identified through induction is concerned with the actions that companies can take with their transformational creative GenAI systems to promote acceptance among individuals. This category encompasses four subcategories detailing approaches that can foster acceptance of the disruptive innovations brought about by GenAI. **Testing the developed disruptive innovation** appeared to be the primary concern among the interviewees. By doing this, the company can validate the value of it and show if it is better or not than human created things. “I probably, I must think about what are the test criteria, test and acceptance criteria that I need in order to be able to bring a [disruptive innovation] that was no longer developed by humans but by an AI to the market in the same way. [...] And I believe this also applies to customer acceptance, these [disruptive innovations] will be accepted by the customers” (I1). The test ought to be standardized and constructed by human beings. “The question would then be who sets these guidelines, [...] who says this data is good as it is, or this behaviour is good as it is. The keyword is interdisciplinary. Yes, suddenly [...] the population and

politicians, engineers, AI people, data people suddenly a lot of people must work together and come up with something like that” (I8). Particularly renowned independent bodies guarantee public acceptance in this respect. These commission could also place a quality label on disruptive innovations created by GenAI as “this plays a major role for the acceptance. We also see this with organic labels, with food” (I12). I17 further mentions that quality labels could be acceptance enhancing if they address AI ethics or responsibility so that companies “can [for example] say we are now EU AI Act compliant” (I17).

Standardization in testing and **adherence to norms and standards** are essential for gaining acceptance of disruptive innovation. “This is similar to genetic engineering that we clearly clarify the use cases. [...] This is an essential factor, otherwise the acceptance is gone” (I7). The interviewees suggest that standardisation of interfaces for disruptive innovations, such as Car2X communication, and data security is essential. Without this, it is difficult to observe a scaling effect if disruptive innovations or services are incompatible with each other. Additionally, a code of training excellence could be valuable in evaluating whether data sets are biased.

Another factor is that a company should **build trust** “at least somehow by giving people access to the algorithm so that they can try it out in some way or experience something. I think that would probably be very helpful for many people” (I8). If the disruptive innovation then works, is useful and trusted, it will lead to acceptance. The final aspect in this category is for a company to **be transparent about their development of disruptive innovations**, utilising a transformational creative GenAI system, and to not conceal this from the public to prevent any potential distrust. Additionally, being a member of an open-source community could potentially boost approval ratings for the company by sharing new developments with other individuals and organizations, increasing opportunities for mutual learning instead of keeping these accomplishments private.

Overall, the need for human testing of the disruptive innovation is a valuable activity of a company that can enhance the acceptance of individuals for disruptive innovations created by GenAI.

5 Discussion

The research on acceptance driving factors of AI systems has been extensively explored. However, current literature mostly focuses on the examination of the systems themselves, rather than their outcomes. With the rapid advancement of GenAI, AI-generated outcomes are becoming prevalent in all industries. Thus, it is pertinent to investigate the acceptance of AI-created output and identify the driving factors behind it. Similar research regarding the acceptance of disruptive innovations requires exploration as well. Prior studies have examined the acceptance of innovations, but without distinguishing whether AI or humans created the innovation and its effect on individuals’ acceptance.

In this paper, we combined these two research areas to determine the circumstances under which generative AI-created disruptive innovations would be accepted. We will subsequently analyze the results to identify those that are specifically relevant to this topic and expand upon existing literature.

5.1 Theoretical and managerial implications

Some of the identified factors, such as perceived usefulness, share similarities with existing acceptance research on AI systems and disruptive innovations (Davis, 1989; Ismatullaev and Kim, 2024; Kelly et al., 2022; Siau and Wang, 2018; Sohn and Kwon, 2020). Environmental factors like “more education about AI” and “open culture towards technology of market” emphasize the importance of informing individuals about the disruptive innovation and its creator. Also Moradi Abadi et al. (2017) contend that information transparency positively affects innovation acceptance and Sandberg (2002) mentions the importance of educating the market before approaching it to achieve acceptance. Additionally, Donner (2021) mentions norms and standards as acceptance enhancing for AI systems. These factors were confirmed within the context of this study. Other factors, such as the legal framework for AI and the need for data security and privacy, human responsibility, performing tests, and a trustworthy country of origin of a company demonstrate the pursuit of trust in AI-generated outcomes among individuals, just like previous studies showed for the acceptance of AI systems (Glikson and Woolley, 2020; Kaplan et

al., 2023). These similarities between this paper's findings and previous research suggest the generalizability of these findings and indicate internal validity at the intersection of acceptance research on AI systems and disruptive innovations (Eisenhardt, 1989).

Other factors, such as meeting quality standards that surpass those typically expected of disruptive innovations created by humans, expands prior studies on the acceptance of disruptive innovations. The heightened quality standards underscore the distinctive features between disruptive innovations created by humans and GenAI-created ones. As previously mentioned, high expectations surrounding AI may be due to the perception of infallibility and the replaceability of AI-generated outcomes. This trend is already apparent in existing systems such as ChatGPT or Midjourney, which flood markets with their fast and convenient output. Therefore, researchers that previously identified perceived value as an acceptance enhancing factor for innovations (Carter and Bélanger, 2005; Pérez Pérez et al., 2004; Yuen et al., 2020) should reassess whether the higher quality expectations of GenAI created disruptive innovations also lead to higher requirements of perceived value.

The view that disruptive innovation falls within "subjective expectations" may also apply to innovations created by humans. However, the subfactors of comparability and traceability suggest that the innovation should be more comprehensible and relatable to existing things since AI system decisions are frequently opaque. This process of comparability and traceability may be simpler for humans when they explain their own thought process about its development as opposed to when it is done by a system, highlighting the AI-specific nature of this discovery. Humans might feel more capable of assessing human behavior than a system's behavior. The factor determining whether a physical disruptive innovation is more acceptable than a software-based one may also follow the same logic. The interviewees who advocated for physicality as a means of enhancing acceptance justified their stance by citing the benefits of improved traceability through reengineering and a static, non-dynamically changing outcome. Additionally, it seems that generating disruptive innovation in highly scientific fields should result in less disruptive outcomes, which is a reasonable assertion within the scientific context. However, this may also imply the need for referencing previous outcomes for traceability. The factors of comparability and traceability have not been mentioned in innovation acceptance literature (Cardone and Zavjalova, 2023; Pérez Pérez et al., 2004; Yuen et al., 2020), but interestingly traceability has in the research area of acceptance of AI systems (Wittpahl, 2019). This indicates that GenAI as an inventor leads to the addition of the factor of traceability in innovation acceptance research.

What can be managerially inferred from these theoretical implications is that companies possessing a transformational creative GenAI capable of creating disruptive innovations should strive for high usefulness and quality of outcomes to achieve acceptance. The quality must be verified by tests. Additionally, credible institutions could aid in educating individuals about ongoing technological advancements and the means of creating such disruptive innovations. In addition, independent organizations could issue quality labels for AI outcomes conforming to the EU AI Act. This would allow them to utilize the existing legal framework for AI.

5.2 Limitations and suggestions for future research

Before concluding, this paper will be critically assessed to outline its limitations and suggest directions for future research. In this study, the primary data solely consists of qualitative research methods, specifically interviews. To enhance the reliability of this paper's findings, it is crucial that the results are quantitatively tested in the future. Another key feature of a sound methodology is its validity, which requires that it is free from bias. We made efforts to ensure the interview guides were objective, although on occasion, questions were posed by referencing the statements of others and inquiring about their level of agreement. This type of questioning may introduce bias into the method, and thus further quantitative analysis could be useful to verify the results. In addition, validating these findings with non-experts can enhance their significance, as AI experts may often display support for AI technologies, making it easier to gain acceptance among them. Additionally, to fully assess the acceptance of the ordinary public ranging from experts to non-experts, further research should especially evaluate the results with the non-expert public to add to the findings of this paper.

6 Conclusion

In summary, this study contributes to the existing literature by examining the conditions that enhance acceptance of disruptive innovations created by GenAI among individuals. The identified factors describe acceptance-enhancing characteristics of the innovation itself, the activities of the company that owns GenAI, and environmental aspects. Based on the number of mentions, perceived usefulness emerges as the most critical factor for individual acceptance. Most individuals appear to prioritize the usefulness of disruptive innovation rather than whether it was created by humans or a GenAI. Objective evaluation of the origin of such innovations therefore seems not to be a significant factor for most people. However, other frequently cited factors, such as the attainment of higher standards than those achieved by human-created disruptive innovations, and the significance of traceability and comparability, signal a slight disparity in expectations between GenAI-created and human-created disruptive innovations. Hence, companies should contemplate these facets in addition to usefulness to achieve acceptance.

References

- Adams, W. C. (2015). "Conducting semi-structured interviews". In K. E. Newcomer, H. P. Hatry and J. S. Wholey (eds.) *Handbook of Practical Program Evaluation, 4th Edition*, pp. 492–505. San Francisco, Calif.: John Wiley & Sons.
- Afuah, A. (2020). "Innovation management-strategies, implementation, and profits".
- Amabile, T. (2019). "GUIDEPOST: Creativity, Artificial Intelligence, and a World of Surprises Guidepost Letter for Academy of Management Discoveries" *Academy of Management Discoveries*.
- Badet, J. (2021). "AI, Automation and New Jobs" *Open Journal of Business and Management* 09 (05), 2452–2463.
- Bagabir, S. A., N. K. Ibrahim, H. A. Bagabir and R. H. Ateeq (2022). "Covid-19 and Artificial Intelligence: Genome sequencing, drug development and vaccine discovery" *Journal of Infection and Public Health* 15 (2), 289–296.
- Benbya, H., F. Strich and T. Tamm (2024). "Navigating Generative Artificial Intelligence Promises and Perils for Knowledge and Creative Work" *Journal of the Association for Information Systems* 25 (1), 23–36.
- Bergin, T. (2018). *An introduction to data analysis: Quantitative, qualitative and mixed methods*.
- Bjerring, J. C. and J. Busch (2021). "Artificial Intelligence and Patient-Centered Decision-Making" *Philosophy & Technology* 34 (2), 349–371.
- Boden, M. A. (1998). "Creativity and artificial intelligence" *Artificial Intelligence* 103 (1-2), 347–356.
- Boden, M. A. (2005). "The creative mind. Myths and mechanisms" *Psychology Press*.
- Cardone, C. and A. Zavjalova (2023). "Examining the adoption of blockchain technology in the diamond industry : Benefits and challenges of embracing disruptive innovation in conservative sectors".
- Carter, L. and F. Bélanger (2005). "The utilization of e-government services: citizen trust, innovation and acceptance factors*" *Information Systems Journal* 15 (1), 5–25.
- Choung, H., P. David and A. Ross (2023). "Trust in AI and Its Role in the Acceptance of AI Technologies" *International Journal of Human-Computer Interaction* 39 (9), 1727–1739.
- Christensen, C., M. E. Raynor and R. McDonald (2015). "What Is Disruptive innovation?" *Harvard Business Review*.
- Colton, S. and G. A. Wiggins (2012). *Computational Creativity: The Final Frontier?* Fairfax: IOS Press, Incorporated.
- Council of Europe (2021). *AI und Kontrolle des Covid-19-Coronavirus*. URL: <https://www.coe.int/en/web/artificial-intelligence/ai-und-kontrolle-des-covid-19-coronavirus>.
- Cui, Y., T. Zhang, S. Kim and S. Feng (2021). "Antecedents of Accepting Disruptive Innovation: The Perspective of Value Congruence" *The Journal of Asian Finance, Economics and Business* 8 (2), 353–364.
- Davenport, T. H. and D. D. D'Augelli (2022). "How generative AI is changing creative work" *Harvard Business Review*.

- Davis, F. D. (1989). "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology" *MIS Quarterly* 13 (3), 319–340.
- de Cremer, D., N. M. Bianzino and B. Falk (2023). "How generative AI could disrupt creative work" *Harvard Business Review*.
- de Winter, J., D. Dodou and Y. B. Eisma (2023). "Personality and Acceptance as Predictors of ChatGPT use".
- Donner, S. (2021). "Standards für KI gesucht" *VDI Nachrichten* (12).
- Dunphy, S. and P. A. Herbig (1995). "Acceptance of innovations: The customer is the key!" *The Journal of High Technology Management Research* 6 (2), 193–209.
- Edwards, B. (2023). *ChatGPT sets record for fastest-growing user base in history, report says*. URL: <https://arstechnica.com/information-technology/2023/02/chatgpt-sets-record-for-fastest-growing-user-base-in-history-report-says/#:~:text=On%20Wednesday%2C%20Reuters%20reported%20that%20AI%20bot%20ChatGP%20T,according%20to%20a%20UBS%20investment%20bank%20research%20note>.
- Eisenhardt, K. M. (1989). "Building Theories from Case Study Research" *Academy of Management Review* 14 (4), 532–550.
- European Commission (2018). *Artificial Intelligence for Europe*. URL: <https://digital-strategy.ec.europa.eu/en/policies/european-approach-artificial-intelligence>.
- Feldman, R. C., E. Aldana and K. Stein (2019). "Artificial intelligence in the health care space: how we can trust what we cannot know" *Stan. L. & Pol'y Rev.* 30, 399–419.
- Fern, E. F. (1982). "The use of Focus Groups for Idea Generation: The Effects of Group Size, Acquaintanceship, and Moderator on Response Quantity and Quality" *Journal of Marketing Research* 19 (1), 1–13.
- Garrelfs, C., C. Schultz and M. Luengen (2023). "Employee acceptance of disruptive service innovations at the frontline: The role of collective sensemaking processes" *Creativity and Innovation Management* 32 (3), 388–406.
- Giacomini, K. M. and P. H. van der Graaf (2022). "The Pandemic as a Catalyst for Disruptive Innovation in Clinical Pharmacology" *Clinical pharmacology and therapeutics* 111 (3), 529–532.
- Glaser, B. G. and A. L. Strauss (1967). "The discovery of grounded theory. Strategies for qualitative research" *Sociology Press*.
- Glikson, E. and A. W. Woolley (2020). "Human Trust in Artificial Intelligence: Review of Empirical Research" *Academy of Management Annals* 14 (2), 627–660.
- Guzik, E. E., C. Byrge and C. Gilde (2023). "The originality of machines: AI takes the Torrance Test" *Journal of Creativity* 33 (3).
- Hammarberg, K., M. Kirkman and S. de Lacey (2016). "Qualitative research methods: when to use them and how to judge them" *Human Reproduction* 31 (3), 498–501.
- Hecker, D., I. Döbel and U. Petersen (2017). *Zukunftsmarkt Künstliche Intelligenz. Potenziale und Anwendungen*.
- Hussein Saleh Zolait, A., M. Mattila and A. Sulaiman (2009). "The effect of User's Informational-Based Readiness on innovation acceptance" *International Journal of Bank Marketing* 27 (01), 76–100.
- HYVE (2019). *How AI and Algorithms revolutionize Innovation Management*. URL: https://www.hyve.net/en/blog/how-ai-and-algorithms-revolutionize-innovation-management/?pi_content=404d908651eec5934aa8ad3ad542856b1d4d6d1355f80be45f7436c2398f8be2b (visited on 11/16/2023).
- Ismatullaev, U. V. U. and S.-H. Kim (2024). "Review of the Factors Affecting Acceptance of AI-Infused Systems" *Human Factors* 66 (1), 126–144.
- Kanbach, D. K., L. Heiduk, G. Blueher, M. Schreiter and A. Lahmann (2023). "The GenAI is out of the bottle: generative artificial intelligence from a business model innovation perspective" *Review of Managerial Science*, 1–32.
- Kantosalo, A. and H. Toivonen (2016). "Modes for creative human-computer collaboration: Alternating and task-divided co-creativity" *Proceedings of the seventh international conference on computational creativity*, 77–84.

- Kaplan, A. D., T. T. Kessler, J. C. Brill and P. A. Hancock (2023). "Trust in Artificial Intelligence: Meta-Analytic Findings" *Human Factors* 65 (2), 337–359.
- Kelly, S., S.-A. Kaye and O. Oviedo-Trespalacios (2022). "What factors contribute to the acceptance of artificial intelligence? A systematic review" *Telematics and Informatics* 77.
- Kivimaa, P., S. Laakso, A. Lonkila and M. Kaljonen (2021). "Moving beyond disruptive innovation: A review of disruption in sustainability transitions" *2210-4224* 38, 110–126.
- Koivisto, M. and S. Grassini (2023). "Best humans still outperform artificial intelligence in a creative divergent thinking task" *Scientific Reports* 13 (1), 13601.
- Ławrynowicz, A. (2020). "Creative AI: A new avenue for the Semantic Web?" *Semantic Web* 11 (1), 69–78.
- Lee, H.-K. (2022). "Rethinking creativity: creative industries, AI and everyday creativity" *Media, Culture & Society* 44 (3), 601–612.
- Makridakis, S. (2017). "The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms" *Futures* 90, 46–60.
- Mayring, P. (1997). *Qualitative inhaltsanalyse: Grundlagen und techniken*: Beltz Verlag.
- Moradi Abadi, A., A. Moradi Abadi and A. Jafari (2017). "Innovation acceptance and customer satisfaction. A survey on tax information systems" *AD-minister*, 149–171.
- Mori, M. (1970). "The uncanny valley: the original essay by Masahiro Mori" *IEEE Spectrum* 6.
- Pelau, C., D.-C. Dabija and I. Ene (2021). "What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry" *Computers in Human Behavior* 122 (2), 106855.
- Pérez Pérez, M., A. Martínez Sánchez, P. de Luis Carnicer and M. José Vela Jiménez (2004). "A technology acceptance model of innovation adoption: the case of teleworking" *European Journal of Innovation Management* 7 (4), 280–291.
- Pesut, D. J. (1985). "TOWARD A NEW DEFINITION OF CREATIVITY" *Nurse Educator* 10 (1), 5.
- Rai, A., P. Constantinides and S. Sarker (2019). "Next generation digital platforms : toward human-AI hybrids" *MIS Quarterly* 43 (1).
- Rao, P., N. Conte and S. Parker (2023). *How Long it Took for Popular Apps to Reach 100 Million Users*. URL: <https://www.visualcapitalist.com/threads-100-million-users/#:~:text=According%20to%20Meta%20founder%20Mark,required%E2%80%9494smashing%20all%20previous%20records> (visited on 11/16/2023).
- Reinhardt, R. and S. Gurtner (2015). "Differences between early adopters of disruptive and sustaining innovations" *Journal of Business Research* 68 (1), 137–145.
- Rietz, T., I. Benke and A. Maedche (2019). "The impact of anthropomorphic and functional chatbot design features in enterprise collaboration systems on user acceptance" *Proceedings of the 14th International Conference on Wirtschaftsinformatik*, 24–27.
- Rossi, F. (2018). "Building trust in artificial intelligence" *Journal of international affairs* 72 (1), 127–134.
- Rust, R. T. and M.-H. Huang (2021). *The feeling economy. How artificial intelligence is creating the era of empathy*. Basingstoke: Palgrave Macmillan.
- Sandberg, B. (2002). "Creating the market for disruptive innovation: Market proactiveness at the launch stage" *Journal of Targeting, Measurement and Analysis for Marketing* 11 (2), 184–196.
- Scheuer, D. (2020). *Akzeptanz von Künstlicher Intelligenz. Grundlagen intelligenter KI-Assistenten und deren vertrauensvolle Nutzung*. Wiesbaden: Springer Vieweg, Springer Fachmedien Wiesbaden.
- Schneider, G. (2019). *Wie KI bei der Medikamentenentwicklung hilft*. ETH Zürich. URL: <https://ethz.ch/de/news-und-veranstaltungen/eth-news/news/2019/03/blog-schneider-ai-medikamentenentwicklung.html> (visited on 11/16/2023).
- Shen, S., Y. Chen, M. Hua and M. Ye (2023). "Measuring designers 'use of Midjourney on the Technology Acceptance Model" *International Association of Societies of Design Research Congress*.
- Siau, K. and W. Wang (2018). "Building trust in artificial intelligence, machine learning, and robotics" *Cutter Business Technology Journal* 31 (2).

- Skulmowski, A. and G. D. Rey (2020). "COVID-19 as an accelerator for digitalization at a German university: Establishing hybrid campuses in times of crisis" *Human Behavior and Emerging Technologies* 2 (3), 212–216.
- Sohn, K. and O. Kwon (2020). "Technology acceptance theories and factors influencing artificial Intelligence-based intelligent products" *Telematics and Informatics* 47.
- Stanton, B. and T. Jensen (2021). *Trust and Artificial Intelligence*: National Institute of Standards and Technology (NIST).
- Sternberg, R. J. (2021). "Transformational Creativity: The Link between Creativity, Wisdom, and the Solution of Global Problems" *Philosophies* 6 (3), 75.
- Strauss, A. L. (1989). *Qualitative analysis for social scientists. (Repr.)*. Cambridge - New York etc: Cambridge Univ P XV.
- Strzelecki, A. (2023). "To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology" *Interactive Learning Environments*, 1–14.
- Swan, A. W. and B. M. Worrall (1974). "A new quantitative technique for identification of industrial and organizational problems" *International Journal of Production Research* 12 (2), 313–330.
- Tiwari, C. K., M. A. Bhat, S. T. Khan, R. Subramaniam and M. A. I. Khan (2023). "What drives students toward ChatGPT? An investigation of the factors influencing adoption and usage of ChatGPT" *Interactive Technology and Smart Education* ahead-of-print (ahead-of-print).
- Townsend, D. M. and R. A. Hunt (2019). "Entrepreneurial action, creativity, & judgment in the age of artificial intelligence" *Journal of Business Venturing Insights* 11.
- Venkatesh, Morris and Davis (2003). "User Acceptance of Information Technology: Toward a Unified View" *MIS Quarterly* 27 (3), 425.
- Verganti, R., L. Vendraminelli and M. Iansiti (2020). "Innovation and Design in the Age of Artificial Intelligence" *Journal of Product Innovation Management* 37 (3), 212–227.
- Watson, R. (2014). *50 Schlüsselideen der Zukunft*. Berlin, Heidelberg: Springer Berlin Heidelberg; Imprint: Springer Spektrum.
- Wittpahl, V. (2019). *Künstliche Intelligenz*. Berlin, Heidelberg: Springer Berlin Heidelberg.
- Wolfswinkel, J. F., E. Furtmueller and C. P. M. Wilderom (2013). "Using grounded theory as a method for rigorously reviewing literature" *European Journal of Information Systems* 22 (1), 45–55.
- Yuen, K. F., Y. D. Wong, F. Ma and X. Wang (2020). "The determinants of public acceptance of autonomous vehicles: An innovation diffusion perspective" *Journal of Cleaner Production* 270.
- Zanzotto, F. M. (2019). "Viewpoint: Human-in-the-loop Artificial Intelligence" *Journal of Artificial Intelligence Research* 64, 243–252.
- Zhang, T., D. B. Kaber, B. Zhu, M. Swangnetr, P. Mosaly and L. Hodge (2010). "Service robot feature design effects on user perceptions and emotional responses" *Intelligent Service Robotics* 3 (2), 73–88.

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