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Future Office: A Comparative Study on the Acceptance and Utilization of Generative AI Technologies

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***Abstract*—As Generative AI technologies continue to evolve, understanding their impact and potential for integration across various sectors becomes increasingly important. This paper explores the acceptance and utilization of Generative AI in diverse industries through the 'Knowledge Behavior Gap Model'. Analyzing survey data from Germany via Structural Equation Modeling, it uncovers the significant impact of knowledge and acceptance on the behavioral adoption of these technologies. This research contributes to understanding how knowledge dissemination and acceptance are crucial for integrating innovative technologies like Generative AI in organizations. It fills a gap in existing literature and offers practical implications for organizations seeking to harness Generative AI for improved efficiency and innovation. This study stands out for its novel approach in linking knowledge, acceptance, and usage of Generative AI, highlighting its significance in the strategic technology adoption landscape.**

Keywords—Generative AI, Technology Adoption, Digital Transformation, Artificial Intelligence

I. Introduction

In terms of digital transformation, artificial intelligence (AI) and machine learning (ML) have been transformative, reshaping numerous sectors [1]. Generative AI can be seen as an extension of this transformation process and further accelerates it. Capable of engaging in human-like conversations and tackling complex challenges, ChatGPT raises the central question of whether *Generative AI* can revolutionize business operations, offering avenues for enhanced efficiency and innovation [2]. Recent research on *Generative AI* in business contexts explores mainly ChatGPT's impact on business competitiveness and specific improvements in communication while also providing an overview of its capabilities across industries.

Ausat et al. 2023 explore the role of ChatGPT in aiding companies to compete effectively in the digital age, focusing on its impact on business performance [3]. Dwivedi et al. 2023 use an interdisciplinary approach to explore opportunities and risks ChatGPT offers for different disciplines [4]. Additionally, some studies investigate how the implementation of ChatGPT can enhance communication efficiency, service quality, or online marketing in business settings [5]–[8]. Gozalo-Brizuela and Garrido-Merchán provide a comprehensive taxonomy of large generative models, such as ChatGPT, and assess their transformative impact on various industries [9].

The research landscape regarding the use, adoption, and acceptance of *Generative AI* in businesses is still relatively unexplored. While Agrawal (2023) provides a broad overview of the organizational and technological factors affecting *Generative AI* adoption, our research delves into the behavioral aspects, filling a gap in the existing literature [10]. We adapt the “Knowledge Behavior Gap Model” to scrutinize the adoption of *Generative AI* technologies, seeking to unearth the profound links between knowledge acquisition and the ensuing attitudes and behaviors towards *Generative AI* [11]. Summed up, we address three pivotal research questions regarding the acceptance, impact, and adoption of *Generative AI* technologies.

RQ1: To what extent do businesses accept and adopt *Generative AI* technologies?
RQ2: How can *Generative AI* enhance and transform various aspects of modern office environments, including communication, efficiency, and innovation?
RQ3: What are the key factors influencing the successful adoption of *Generative AI* technologies and how do businesses navigate these challenges?

By addressing these questions, our research provides a more comprehensive understanding of the role of *Generative AI* in the modern organizational landscape. We first examine the current state of digital transformation and *Generative AI*, focusing on their impact on companies and organizations. We then employ the Knowledge Behavior Gap Model to analyze survey data on the acceptance and utilization of *Generative AI* in Germany. We interpret our findings to discuss their industry-wide implications and challenges. Based on our findings, we provide suggestions to inform strategic

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decisions regarding integrating and promoting *Generative AI* technologies.

II. Generative AI in the Light of Digital Transformation

Digital transformation can be defined as the comprehensive integration of digital technologies into all facets of an organization, fundamentally altering its operations, processes, and how it delivers value to its customers and stakeholders [12]. It represents a holistic shift beyond mere digitization or the adoption of individual technologies; it encompasses a strategic reimagining of the entire business model [13]. At its core, digital transformation leverages cutting-edge technologies, such as AI, Internet of Things (IoT), cloud computing, and data analytics, to empower organizations to become more agile, data-driven, and customer-centric [14]. It enables them to use data and technology to drive innovation, optimize operations, and enhance the overall customer experience [15].

Generative AI, underpinned by algorithms like transformers, has evolved as a pivotal research and development area with applications spanning various industries. *Generative AI* refers to algorithms and models that can create new content or data based on patterns learned from existing data [16]. Notable models like ChatGPT, introduced in 2022, exemplify the capabilities of Large Language Models (LLMs) in Natural Language Processing (NLP) [17]. Earlier generations of language models, such as Recurrent Neural Networks (RNNs) or Long Short-Term Memory Neural Networks (LSTMs), were already used for generative tasks [18], [19]. Although these models were powerful in their time, they were computationally limited, a constraint overcome by the Transformer architecture's parallel processing and attention mechanisms [18], [20], [21].

Building on this architecture, LLMs like GPT, LLaMa, BLOOM, PaLM, or FLAN-T5 have made enormous strides and can now perform complex tasks in natural language [22]–[27]. These models represent Pretrained Foundation Models (PFMs) that can be fine-tuned for domain-specific tasks, broadening their applicability [28]. Unlike traditional code-based approaches, LLMs are accessible to non-programmers, expanding the scope of AI applications [29]. Therefore, *Generative AI* has found numerous applications in the business world. Application areas such as customer service, marketing, content creation, and business automation are suitable for content generation [6]–[8], [30]. Furthermore, it found its application in various industries such as banking, hospitality, tourism, and information technology or improving business activities such as management and marketing [4], [31], [32].

III. Methodology

In the rapidly evolving sphere of technology, understanding and analyzing the acceptance and utilization of innovations, particularly in AI, is a vital endeavor. We adopt the Knowledge Behavior Gap Model devised by Stibe et al., 2022 as a guiding framework to explore the intricate dynamics between knowledge acquisition and the subsequent behavioral responses toward *Generative AI* technologies [11]. Through a meticulous adaptation of the model to the contemporary context, this research aims to shed light on the nuances of acceptance and utilization of *Generative AI*, thereby paving the way for more informed and strategic approaches in integrating and promoting these technologies.
To capture the main constructs of the model: knowledge, acceptance, intention, and use, the study by Stibe et al. 2023 refers to five behavioral and technology use theories, which are listed in the following and are relevant for the Knowledge Behavior Gap model.

Table I. Main relevant constructs from behavioral and technology use theories [11].

Theory	Knowledge	Acceptance	Intention	Behavior
TRA [33]		Attitude	Behavioral intention	Behavior
TPB [34]		Attitude towards the behavior	Intention	Behavior
TAM [35]		Attitude towards using	Behavioral intention to use	Usage behavior
IDT [36]	Know-ledge	Persuasion	Decision	Implementation
UTAUT [37]		Expectancy	Behavioral intention	Use behavior

Their study establishes a strong positive correlation between Knowledge and Behavior, following a sequential pathway: Knowledge acquisition leads to acceptance, which in turn drives Intention and, ultimately, Behavior. This model is adaptable for assessing the acceptance and use of digital innovations, including AI [11]. In our study, we contextualized the constructs of the Knowledge Behavior Gap Model to focus specifically on *Generative AI*. According to this adaptation, Knowledge is defined as the comprehension of *Generative AI*'s functionalities and characteristics. We also introduce the construct of 'attitude,' which encompasses the notion of acceptance towards generative AI. The construct of Intention is defined as an individual's propensity to engage with *Generative AI* technology. Lastly, Behavior captures the actual usage patterns of individuals towards *Generative AI*.

We anticipate that Generative AI will exhibit a behavior pattern similar to persuasive system studied in Stibe et al. [11]. This is supported by the fact that technology acceptance and usage often rely on common principles and factors, regardless of the specific technology [35], [37]. This construct is also in accordance with the framework and is quantified through a 5-item measure [11]. By adapting these constructs to the specific context of *Generative AI*, this study

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aims to provide a nuanced understanding of how individuals interact with this emerging technology. We adapt the research construct to our context of *Generative AI* and, as a result, we formulate the hypotheses accordingly.

H1: More knowledge about Generative AI leads to higher acceptance of Generative AI.
H2: More knowledge about Generative AI leads to an intention to use Generative AI.
H3: More knowledge about Generative AI leads to an actual Generative AI use behavior.
H4: Higher Generative AI acceptance leads to higher intention to use Generative AI.
H5: Higher Generative AI acceptance leads to an actual Generative AI use behavior.
H6: Higher intention to use leads to an increased Generative AI use behavior.

The six hypotheses formulated serve as the empirical backbone of our research, guiding the subsequent data collection and analysis.

IV. ACCEPTANCE OF GENERATIVE AI IN BUSINESS PROCESSES

A. Data Collection

We conducted an online survey in Germany between 4th of September and 25th of September 2023. For the data collection, a structured questionnaire was developed to investigate the utilization, knowledge, acceptance, intention, and use behavior of *Generative AI* methods. The participant pool was not limited to a specific category, ensuring inclusivity and allowing for the exploration of potential differences in the utilization and acceptance of the technology between different company types. We recruited participants via LinkedIn postings and professional networks. The questionnaire consisted of two parts: Questions about the usage of *Generative AI* and about the Knowledge-Behavior Gap Model. The questions about the utilization included whether *Generative AI* is already being used, and if so, in which areas and for which purpose. Also, the respondents were inquired about potential challenges when using *Generative AI*. The following Table 2 provide a foundational understanding of the demographic characteristics of the participants in our survey, which serves as a basis for our research.

Table II. Descriptive Statistics (n=56)

Company size	
SMEs	69.64 %
Large Enterprises	30,36 %
Position	
Employees	70.18%
Management	24.56%
Executive	1.75%
Other	3.51%
Industries	
Services	35.09%
Healthcare/Education/Social	17.54%,
Manufacturing	15.79%
Retail	5.26%
Public Administration/Politics	5.26%
Crafts	1.75%"
Other	19.30%,

In our survey, we encountered various positions within the participating organizations. Small and medium-sized enterprises (SMEs) make up the majority, comprising 69.64% of the surveyed companies. In contrast, Large Enterprises account for 30.36% of the surveyed companies. The participant roles are predominantly employees, accounting for 70.18%, management roles comprise 24.56%, and executive roles are 1.75%. An additional 3.51% fall into the 'Other' category. We further include a broad array of industries, showcasing the diverse professional backgrounds of the respondents, in which we also aimed at assessing the level of knowledge in AI among participants. A small fraction of 3.57% considered their knowledge of AI to be at the lowest level. 14.29% slightly above that, and the majority, 35.71%, consider their understanding to be moderate. Additionally, 32.14% believe they have above-average expertise, and 14.29% rate their knowledge at the highest level.

B. Data Analysis

In our study, we investigate the interplay of knowledge about *Generative AI*, acceptance of *Generative AI*, intention to use *Generative AI*, and actual *Generative AI* use behavior. The objective is to validate our hypotheses that postulate how these variables are interrelated. To this end, we employ bootstrapping techniques to assess the significance of the path coefficients. This statistical resampling method allows us to estimate the sampling distribution of the estimator by generating numerous resampled datasets. In our study, bootstrapping is crucial due to our dataset's deviation from normal distribution and limited sample size, making traditional parametric tests unsuitable. The significance of the path coefficients is then determined based on t-values or confidence intervals, thereby providing robust statistical inferences [38]. The results are quantitatively summarized in Table 3, where the path coefficients, bootstrapped results and confidence intervals for HTMT, and corresponding reliability coefficients are reported.

Table III. Bootstrapped results and confidence intervals for HTMT and reliability indicators

Construct	Path	ß	T Statistics	5% CI	95% CI	Cronbach's alpha	Composite reliability	AVE	Reliability coefficient
Knowledge	Knowledge → Acceptance	0.421	2.382	0.118	0.658	0.951	0.962	0.835	0.993
	Knowledge → Intention	0.120	0.829	0.102	0.359				
	Knowledge → Behavior	0.291	1.565	0.066	0.548				
Acceptance	Acceptance → Intention	0.614	5.553	0.451	0.800	0.682	0.682	0.448	0.746
	Acceptance → Behavior	-0.137	-0.742	0.413	0.192				
Intention	Intention → Behavior	0.485	3.049	0.217	0.742	0.852	0.852	0.637	0.870
Behavior						0.867	0.905	0.657	0.885

In our study, knowledge shows exceptionally high internal consistency with a Cronbach's Alpha of 0.951, although this may indicate potential indicator redundancy. Intention and behavior also exhibit strong reliability and validity. However, the Cronbach's Alpha for acceptance is 0.682, which is marginally below the commonly accepted threshold of 0.7 for internal consistency. In the analysis of path coefficients, we observe that knowledge exerts a strong and highly significant positive influence on acceptance of *Generative AI*. The estimate for this path is 0.421, substantiated by a T-Statistics of 2.382. Thus, Hypothesis *H1* can be confirmed. Knowledge also exhibits a positive but statistically insignificant effect on both intention to use *Generative AI* and actual *Generative AI* use behavior. Therefore, Hypotheses *H2* and *H3* are not supported by the data. Furthermore, acceptance has a markedly strong and highly significant positive effect on intention to use *Generative AI*. As such, Hypothesis *H4* is confirmed. Conversely, acceptance exhibits a slight but statistically insignificant negative impact on actual *Generative AI* use behavior. Therefore, Hypothesis *H5* is not supported. Finally, intention demonstrates a strong and statistically significant positive influence on actual *Generative AI* use behavior. This supports Hypothesis *H6*. Overall, three out of the six paths are statistically significant, highlighting the complexity of the relationships between the variables analyzed. In addition to our primary findings, we also examined differences between SMEs and large corporations concerning *Generative AI* adoption. Intriguingly, no significant disparities were observed, implying that the size of an organization may not be a determining factor for *Generative AI* adoption.

V. Discussion

A. *Discussion of the results*

Our study employs the Knowledge Behavior Gap Model to unravel the causal relationships between knowledge about *Generative AI*, its acceptance, intention to use it, and actual use behavior. The model's quality was evaluated using indicator reliability, internal consistency, and composite reliability. Three out of six hypothesized paths were statistically significant. *H1* was confirmed, indicating that increasing knowledge about *Generative AI* positively impacts its acceptance. This is a critical finding as it emphasizes the role of educational and awareness programs in fostering a more accepting attitude toward *Generative AI*. Confirmation of *H4*, linking acceptance to intention, implies that enhancing acceptance could be a strategic lever to increase users' intent to employ *Generative AI*. *H6* was also confirmed, showing that intention strongly predicts behavior. This demonstrates the power of intent as a precursor to action, making it a critical variable to target for increasing Generative AI adoption.

However, *H2*, *H3*, and *H5* were not supported, which invites scrutiny. In particular, knowledge did not significantly impact intention or behavior, and acceptance did not substantially affect behavior. This implies that, contrary to the hypothesis, higher acceptance of *Generative AI* does not necessarily lead to a statistically significant increase in actual use behavior. Moreover, the relationship between knowledge, intention and behavior may be more complex for *Generative AI* than anticipated. These non-confirmations should not be dismissed but should rather inspire more focused research to explore underlying factors that might be influencing these relationships.

B. Implications Across Industry Domains and Working Environments

In addition to implementing the Knowledge Behavior Gap Model, we also incorporated auxiliary questions aimed at gaining insights into the perceptions and awareness of *Generative AI* applications. 89.47% of respondents affirmed their awareness of *Generative AI* applications, such as text generation, image synthesis, or music composition. A smaller proportion reported unfamiliarity with these applications. This data indicates that most participants possess knowledge of *Generative AI*, although a minority remains either unaware or uncertain about these advanced AI capabilities.

Generative AI models have shown their potential usefulness across a spectrum of fields. In the realm of *Art and Creativity*, 23.19% of respondents view *Generative AI* as a valuable tool. In the domain of *Medicine and Healthcare*, 17.87% of respondents see the promise of generative AI. In the *Video Game Development* sector, 16.43% of respondents believe that *Generative AI* models can play a significant role. In *Finance*, 11.59% of respondents recognize the value of *Generative AI*. Additionally, respondents mentioned various other areas where *Generative AI* can be beneficial, such as *Marketing*, *Agriculture*, *Literature*, *Education*, *Sales*, *Film* and *TV Production,* and *Content Generation*. One respondent highlighted that *"AI has the potential to be beneficial in all imaginable areas"*.

Generative AI models have garnered significant interest in the workplace, with respondents identifying various tasks where these models could prove valuable: A substantial portion (24%) of respondents expressed a desire to leverage *Generative AI* for creating *social media content* and *email communications*. *Language translation* emerges as a prominent use case, with a significant 27.39% of respondents recognizing the potential of *Generative AI* in this domain. *Creativity* finds a companion in *Generative AI*, as nearly one-third of respondents indicated a willingness to employ these models in their creative endeavors. *Customer service and support* stand to benefit, with 14% of respondents considering *Generative AI* for addressing customer inquiries. 'Other' areas where *Generative AI* might prove beneficial span various tasks, including generating *technical term explanations*, *rapid text generation*, refining language formulations, *idea development*, *programming assistance*, *brainstorming support,* and *simplifying* complex *search engine queries*.

Conversely, implementing *Generative AI* in organizations brings forth a complex array of challenges substantiated by our study. A significant proportion of respondents highlighted difficulties in *assessing the quality of generated content* (30%), followed by concerns about *lack of transparency and explainability* (26%). These issues coalesce with previously mentioned challenges, such as *privacy* and *security concerns* (25.33%). Additionally, our study highlighted the noteworthy concern of *limited applicability in real-world scenarios* (14.67%), underscoring the need for targeted skill development to address the distinct challenges posed by Generative AI. These competencies encompass *linguistic proficiency*, *verification expertise*, and the *ability to design prompts* effectively. The deployment of *Generative AI* technologies brings to the fore several multifaceted security and ethical challenges. These include *data privacy*, *security*, and the potential for disseminating 'Fake News,' as confirmed by our study.

VI. Conclusion

In the future, the integration of AI technologies, especially *Generative AI*, promises to significantly alter workplace dynamics, positioning AI as a new kind of team member. Our research substantially contributes to understanding the dynamics of *Generative AI* adoption in business settings.

Investigating the adoption of *Generative AI* in business environments, our study reveals significant findings. Under RQ1, we discovered that while knowledge positively impacts acceptance of Generative AI, it does not significantly influence intention or behavior, highlighting a gap that needs further exploration. This finding is instrumental for organizations, emphasizing the necessity of educational initiatives to foster more acceptance towards *Generative AI*. RQ2's findings indicate that while there is high intention and confidence in *Generative AI*, its application in creative tasks faces significant challenges like assessing the quality of generated content. In addressing RQ3, our SEM analysis shows that acceptance predicts intention but not behavior, pointing to operational challenges in organizations, likely due to unsuitable adoption environments or organizational requirements. The study found no variation in AI adoption rates between SMEs and large companies, suggesting that barriers are more related to occupational specifics and organizational culture than to enterprise size. The importance of nurturing human skills like critical thinking and emotional intelligence in the AI-augmented workforce is also underscored. Establishing ethical guidelines for AI is essential for aligning with organizational values. Although our findings offer strategic insights for academia and industry, particularly in enhancing the acceptance and use of *Generative AI*, their generalizability is limited due to the geographical focus on Germany, indicating a need for future research in diverse regions for broader applicability.

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REFERENCES

[1] D. Leipziger, V. Dodev, D Leipziger, and V Dodev, "Disruptive Technologies and their Implications for Economic Policy: Some Preliminary Observations," 2016, doi: 10.13140/RG.2.2.21002.52167.

[2] Md. M. Rahman and Y. Watanobe, "ChatGPT for Education and Research: Opportunities, Threats, and Strategies," *Applied Sciences*, vol. 13, no. 9, p. 5783, May 2023, doi: 10.3390/app13095783.

[3] A. M. A. Ausat, H. K. Azzaakiyyah, M. Permana, and Y. Riady, "The Role of ChatGPT in Enabling MSMEs to Compete in the Digital Age," 2023.

[4] Y. K. Dwivedi *et al.*, "Opinion Paper: 'So what if ChatGPT wrote it?' Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy," *International Journal of Information Management*, vol. 71, p. 102642, Aug. 2023, doi: 10.1016/j.ijinfomgt.2023.102642.

[5] L. Cui, "Exploring Growth Strategies of European Small and Medium-sized Enterprises in the Service Sector using ChatGPT," *EIS*, vol. 1, no. 17, pp. 175–198, Sep. 2023, doi: 10.5755/j01.eis.1.17.33726.

[6] M. M. Mutoffar, S. Kuswayati, F. T. Anggraeny, and T. Sumarni, "Exploring the Potential of ChatGPT in Improving Online Marketing and Promotion of MSMEs," vol. 12, 2023.

[7] A. D. Subagja, A. M. A. Ausat, A. R. Sari, and M. I. Wanof, "Improving Customer Service Quality in MSMEs through the Use of ChatGPT," vol. 12, 2023.

[8] F. Sudirjo, A. M. A. Ausat, S. Rijal, and Y. Riady, "ChatGPT: Improving Communication Efficiency and Business Management of MSMEs in the Digital Age," 2023.

[9] R. Gozalo-Brizuela and E. C. Garrido-Merchan, "ChatGPT is not all you need. A State of the Art Review of large Generative AI models." arXiv, Jan. 11, 2023. Accessed: Oct. 13, 2023. [Online]. Available: http://arxiv.org/abs/2301.04655

[10] K. Prasad Agrawal, "Towards Adoption of Generative AI in Organizational Settings," *Journal of Computer Information Systems*, pp. 1–16, Jul. 2023, doi: 10.1080/08874417.2023.2240744.

[11] A. Stibe, N. Krüger, and A. Behne, "Knowledge Behavior Gap Model: An Application for Technology Acceptance," in *Mobile Web and Intelligent Information Systems*, vol. 13475, I. Awan, M. Younas, and A. Poniszewska-Marańda, Eds., in Lecture Notes in Computer Science, vol. 13475. , Cham: Springer International Publishing, 2022, pp. 3–17. doi: 10.1007/978-3-031-14391-5_1.

[12] S. Ziyadin, S. Suieubayeva, and A. Utegenova, "Digital Transformation in Business," in *Digital Age: Chances, Challenges and Future*, vol. 84, S. I. Ashmarina, M. Vochozka, and V. V. Mantulenko, Eds., in Lecture Notes in Networks and Systems, vol. 84. , Cham: Springer International Publishing, 2020, pp. 408–415. doi: 10.1007/978-3-030-27015-5_49.

[13] S. Gupta, *Driving digital strategy: a guide to reimagining your business*. Boston, Massachusetts: Harvard Business Review Press, 2018.

[14] S. Akter, K. Michael, M. R. Uddin, G. McCarthy, and M. Rahman, "Transforming business using digital innovations: the application of AI, blockchain, cloud and data analytics," *Ann Oper Res*, vol. 308, no. 1–2, pp. 7–39, Jan. 2022, doi: 10.1007/s10479-020-03620-w.

[15] M. Zaki, "Digital transformation: harnessing digital technologies for the next generation of services," *JSM*, vol. 33, no. 4, pp. 429–435, Sep. 2019, doi: 10.1108/JSM-01-2019-0034.

[16] A. Kusiak, "Convolutional and generative adversarial neural networks in manufacturing," *International Journal of Production Research*, vol. 58, no. 5, pp. 1594–1604, Mar. 2020, doi: 10.1080/00207543.2019.1662133.

[17] W. Hariri, "Unlocking the Potential of ChatGPT: A Comprehensive Exploration of its Applications, Advantages, Limitations, and Future Directions in Natural Language Processing." arXiv, Apr. 12, 2023. Accessed: Jul. 18, 2023. http://arxiv.org/abs/2304.02017

[18] I. Dhall, S. Vashisth, and S. Saraswat, "Text Generation Using Long Short-Term Memory Networks," in *Micro-Electronics and Telecommunication Engineering*, vol. 106, D. K. Sharma, V. E. Balas, L. H. Son, R. Sharma, and K. Cengiz, Eds., in Lecture Notes in Networks and Systems, vol. 106. , Singapore: Springer Singapore, 2020, pp. 649–657. doi: 10.1007/978-981-15-2329-8_66.

[19] S. Lu, Y. Zhu, W. Zhang, J. Wang, and Y. Yu, "Neural Text Generation: Past, Present and Beyond," 2018, doi: 10.48550/ARXIV.1803.07133.

[20] A. Vaswani *et al.*, "Attention Is All You Need," 2017, doi: 10.48550/ARXIV.1706.03762.

[21] C. Anil *et al.*, "Exploring Length Generalization in Large Language Models," 2022, doi: 10.48550/ARXIV.2207.04901.

[22] T. B. Brown *et al.*, "Language Models are Few-Shot Learners," 2020, doi: 10.48550/ARXIV.2005.14165.

[23] A. Chowdhery *et al.*, "PaLM: Scaling Language Modeling with Pathways," 2022, doi: 10.48550/ARXIV.2204.02311.

[24] H. W. Chung *et al.*, "Scaling Instruction-Finetuned Language Models," 2022, doi: 10.48550/ARXIV.2210.11416.

[25] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," 2018, doi: 10.48550/ARXIV.1810.04805.

[26] T. L. Scao *et al.*, "What Language Model to Train if You Have One Million GPU Hours?," 2022, doi: 10.48550/ARXIV.2210.15424.

[27] H. Touvron *et al.*, "LLaMA: Open and Efficient Foundation Language Models," 2023, doi: 10.48550/ARXIV.2302.13971.

[28] C. Zhou *et al.*, "A Comprehensive Survey on Pretrained Foundation Models: A History from BERT to ChatGPT," 2023, doi: 10.48550/ARXIV.2302.09419.

[29] J. D. Zamfirescu-Pereira, R. Y. Wong, B. Hartmann, and Q. Yang, "Why Johnny Can't Prompt: How Non-AI Experts Try (and Fail) to Design LLM Prompts," in *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, Hamburg Germany: ACM, Apr. 2023, pp. 1–21. doi: 10.1145/3544548.3581388.

[30] E. Brynjolfsson, D. Li, and L. Raymond, "Generative AI at Work," National Bureau of Economic Research, Cambridge, MA, w31161, Apr. 2023. doi: 10.3386/w31161.

[31] I. Carvalho and S. Ivanov, "ChatGPT for tourism: applications, benefits and risks," *TR*, Apr. 2023, doi: 10.1108/TR-02-2023-0088.

[32] Y. K. Dwivedi, N. Pandey, W. Currie, and A. Micu, "Leveraging ChatGPT and other generative artificial intelligence (AI)-based applications in the hospitality and tourism industry: practices, challenges and research agenda," *IJCHM*, Jun. 2023, doi: 10.1108/IJCHM-05-2023-0686.

[33] I. Ajzen and M. Fishbein, *Understanding attitudes and predicting social behavior*, Pbk. ed. Englewood Cliffs, N.J.: Prentice-Hall, 1980.

[34] I. Ajzen, "From Intentions to Actions: A Theory of Planned Behavior," in *Action Control: From Cognition to Behavior*, J. Kuhl and J. Beckmann, Eds., in SSSP Springer Series in Social Psychology. , Berlin, Heidelberg: Springer, 1985, pp. 11–39. doi: 10.1007/978-3-642-69746-3_2.

[35] F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, "User Acceptance of Computer Technology: A Comparison of Two Theoretical Models," *Management Science*, vol. 35, no. 8, pp. 982–1003, Aug. 1989, doi: 10.1287/mnsc.35.8.982.

[36] E. M. Rogers, "Diffusion of Innovations: Modifications of a Model for Telecommunications," in *Die Diffusion von Innovationen in der Telekommunikation*, M.-W. Stoetzer and A. Mahler, Eds., in Schriftenreihe des Wissenschaftlichen Instituts für Kommunikationsdienste. , Berlin, Heidelberg: Springer, 1995, pp. 25–38. doi: 10.1007/978-3-642-79868-9_2.

[37] V. Venkatesh, J. Thong, and X. Xu, "Unified Theory of Acceptance and Use of Technology: A Synthesis and the Road Ahead," *Journal of the Association for Information Systems*, vol. 17, no. 5, May 2016, doi: 10.17705/1jais.00428.

[38] J. F. Hair, T. M. Hult, C. M. Ringle, M. Sarstedt, N. P. Danks, and S. Ray, *Partial least squares structural equation modeling (PLS-SEM) using R: a workbook*. in Classroom Companion: Business. Cham: Springer, 2021.