

Research on the Integration and Application of Design Thinking and Large Language Models in the Innovation Design of Fintech Products

Wenjing WANG^{a,1} and Baixi XING^b

^aZhejiang University, Hangzhou, China

^bZhejiang University of Technology, Hangzhou, China

Abstract. This study explores the integration and application of Design Thinking and Large Language Models (LLMs) in fintech product innovation design from the perspective of requirements management. Design thinking is human-centered, focusing on discovering and solving problems, integrating innovative solutions, and enhancing product value. By understanding and generating natural language, LLMs provide "on-demand" intelligent services through information retrieval, content creation, and human-like dialogue, meeting individualized needs. Through literature review and analysis, this paper reveals that the combination of the two can promote the full intelligence and continuous improvement of the innovation design process, enhancing the R&D efficiency and user experience of fintech products. This research aims to provide innovation design methods for the fintech field and promote its continuous innovation and development.

Keywords. Design Thinking; Large Language Models; Fintech; Product Innovation Design; Requirements Management

1. Introduction

With the rapid development of Fintech, the innovation research and development of fintech products are increasingly valued by banks and other financial institutions. Major banks have successively established fintech innovation departments or innovation R&D laboratories. Different from the information technology departments of banks, software centers, and fintech companies, such non-profit R&D innovation institutions directly established by the headquarters focus more on the top-level design of product innovation and the prototype research and development of new products, and focus on product research and development and requirements management in software engineering. When promoting specific innovation projects in the form of flexible teams, R&D personnel come from different functional backgrounds such as finance, IT, or management, and sometimes invite experts or users from other industries to participate. However, they often lack specialized knowledge in design and innovation management, and co-innovation faces the challenges of communication and collaboration as well as

¹ Corresponding Author.

knowledge integration, which makes it necessary to introduce advanced innovation design methods and tools.

Design thinking is a human-centered, iterative, experimental problem-solving method and a systematic collaborative method for creatively solving complex problems, playing an important role in the designs of various products and services [1]. LLMs have demonstrated excellent natural language understanding, generation, and knowledge integration capabilities by learning massive text data. However, there is very little research on the integration and application of the two. In order to explore the integration and application of design thinking and LLMs in the innovation design of fintech products, this paper will investigate from the perspective of improving the requirements management process of new product design.

This study mainly focuses on researching and analyzing more than 80 pieces of literature on the intersection of Design Thinking, AI, LLMs, Fintech, and Requirements Management (Requirements Engineering). We use Python programs to extract text from PDF files and perform word frequency analysis on the literature, as well as generate word frequency heat maps and word clouds based on country regions. The analysis reveals that China, India, Brazil, and Europe appear more frequently in these documents, indicating that emerging economies are very active in research in related fields.

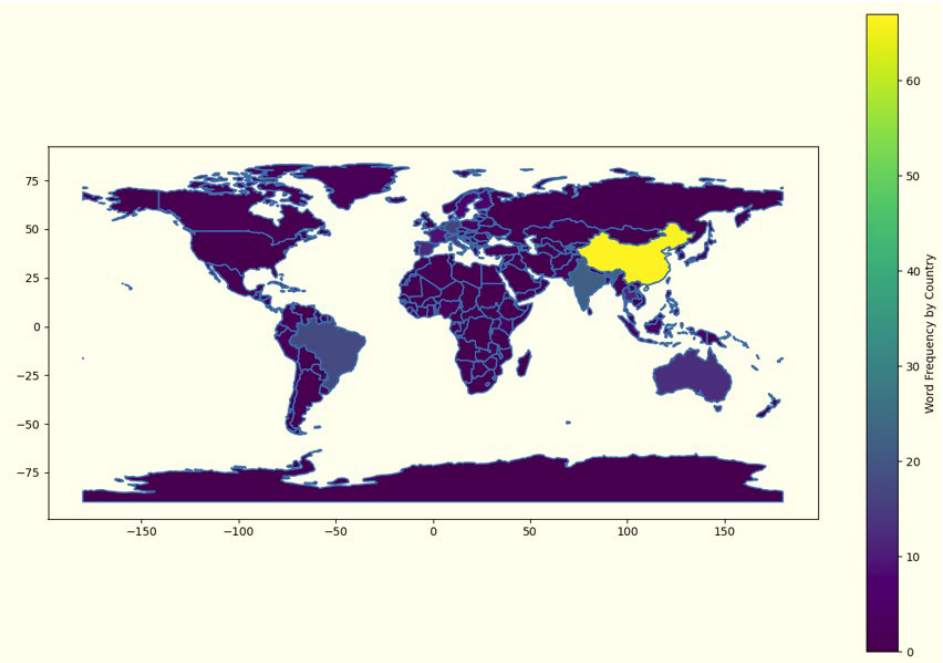


Figure 1. Word Frequency Heat Map by Country/Region

In this paper, we respectively describe the application of design thinking and LLMs in requirements management; and the positive impact of LLMs on fintech innovation; last but not least, we explore the possibility of integrating design thinking with LLMs and its potential value in fintech product innovation design.

quickly understand what works and what doesn't through rapid prototype creation and idea testing [7]. Using design thinking is beneficial for generating new ideas based on user and stakeholder needs and can support software developers during the requirements acquisition process [8]. In the context of innovation with uncertainty and complexity, where all requirements are not assumed to be known at the outset but are learned and experimented with throughout the project lifecycle, traditional requirements management methods are no longer effective. Design thinking can help teams adapt to a constantly changing environment and improve project outcomes [6].

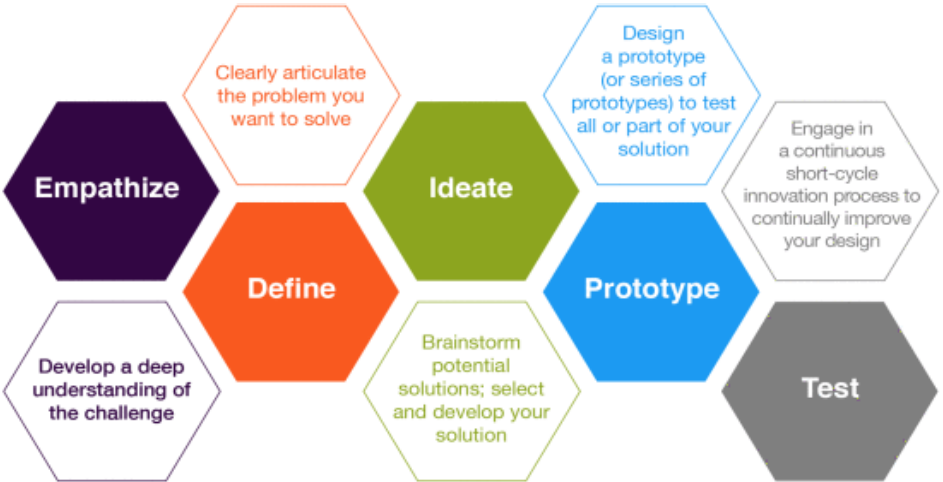


Figure 3. The five basic design thinking stages established by Stanford University's School of Design.
Source: Center for Innovation in Teaching & Learning, University of Illinois Urbana-Champaign
<https://citl.illinois.edu/paradigms/design-thinking>

Design thinking helps us to observe and establish an empathetic relationship with target users, ensuring that the needs of all stakeholders are considered. Help us to question: question problems, question assumptions, and question implications. Design thinking effectively addresses ill-defined or unknown problems [9] and ensures that the solutions obtained are feasible and sustainable. Therefore, introducing design thinking into fintech project requirements management will have a positive impact on the incubation of innovation projects and new product design. Applying design thinking to the financial sector will create more human-centric financial products and services, better meeting consumer needs.

3. Application of LLMs in Requirements Management

LLMs refer to natural language processing models trained based on deep learning technology. They can capture rich knowledge from pre-trained data and can be regarded as experts in specific domains. Recent research has explored the use of LLMs to solve domain-specific tasks and assess their adaptability. The following briefly describes three typical emergent capabilities of large models: 1) Context learning, where GPT-3 generates the expected output of a test instance by completing a sequence of words from the input text; 2) Instruction adherence, whereby fine-tuning a multi-tasking dataset formatted with instructions, LLMs can perform new tasks without the use of explicit

samples, perform well on tiny tasks, and improve generalization capabilities; 3) Progressive reasoning, through the chain-of-thinking reasoning strategy, LLMs can solve such tasks to arrive at a final answer by utilizing a prompt mechanism involving intermediate reasoning steps [10]. Although LLMs have the potential to solve general tasks, these abilities may not be manifested explicitly when performing specific tasks. Therefore, designing suitable task instructions or context-specific strategies, such as thought-chaining prompts, as well as instruction tuning for LLMs, are effective ways to stimulate these abilities and improve generalization to unseen tasks [11]. In requirements management, LLMs can be used to automate the processing of large amounts of user feedback and requirements data, extract key information, predict trends in user requirements, and even generate requirements documents [12, 13]. The application of LLMs will greatly improve the efficiency and granularity of requirements management, and the initial practice of LLMs has proved to be very positive in supporting requirements management [10]. LLMs have been proven to support demand management in a very positive way [10]. The application of LLMs will greatly improve the efficiency and refinement of requirements management.

Thanks to LLMs, artificial intelligence has evolved from perceiving and understanding the world to generating and creating it. Significant progress has been made in the field of Generative AI (AIGC). In a broad sense, AIGC can be seen as AI technology with human-like generative capabilities. It can autonomously generate and create new content and data based on training data and generative algorithm models, including initiating new scientific discoveries, creating new value and meaning, etc. AIGC emphasizes human-centricity and human-intelligence interaction. It is a digital content generation method in which humans and machines participate collaboratively, breaking the boundaries between humans, machines, and information resources and reshaping the paradigms of information resource generation and use [14]. AIGC is increasingly involved in the creative generation of digital content, releasing value in a human-machine collaborative manner, and becoming the foundational infrastructure for future internet content production [15]. AI becomes the main body of design, capable of "independently" completing certain tasks and ultimately deeply interacting and collaborating with designers to complete the design work [16].

LLMs can serve as a knowledge base providing expert knowledge and can be used to analyze and extract requirements from large amounts of unstructured data, such as customer feedback, social media posts, and user comments. LLMs can also be used to generate personas and conduct user interviews, generating information that can be used to understand user needs and develop solutions that meet these needs. They can promote collaboration among stakeholders by sharing context, generating requirement summaries, providing requirement feedback, and helping resolve conflicts. They can be used to conceive solutions and assess the feasibility and sustainability of these solutions.



practices and research. With the emergence of LLMs, its large pre-trained corpus becomes a deeply promising source of knowledge capable of generating multiple ideas. The text generation mechanism of LLMs produces responses probabilistically and refines ideas or creativity through interaction with users, echoing early research on the integration of design and computational thinking.

Recently, LLMs have shown tremendous potential in simulating human behavior, opening up new possibilities for creating realistic, interactive artificial agents. The introduction of generative agents simulates coherent and realistic human behavior, offering new perspectives in areas like human-computer interaction and virtual worlds [27]. The key to generative agents lies in storing, integrating, and retrieving relevant memories to dynamically generate behaviors based on the environment and experience. This new type of interactive agent has broad application prospects but also brings ethical risks. Researchers have delved deeply into whether LLMs can understand language and the physical and social contexts it encodes in a human-like manner [28]. Some researchers have applied psychological tests to LLMs, finding that in some cases, LLMs exhibit human-like responses in the theory of mind tests [29, 30]. This suggests that LLMs have the potential to act as intelligent agents for specific tasks and be applied in daily work.

The Chain of Thought (CoT) offers LLMs a new way to demonstrate complex reasoning processes, significantly improving the model's performance in handling complex reasoning tasks. Scientists are exploring the workings behind CoT and how it unlocks the potential of LLMs [31]. The reasoning power of CoT reveals that models can not only imitate but also learn complex thinking patterns, paving the way for them to gain true design capabilities.

By using LLMs to simulate and study the process of design thinking, we can explore the accessibility and connectivity of ideas, providing quantitative analysis and guidance for design thinking. The integration of design thinking and LLMs has become a burgeoning interdisciplinary field full of endless possibilities, promising to deeply reveal the cognitive laws and process mechanisms of design creativity and inspire new design innovation ways.

Design thinking and LLMs each have their strengths, and their combined use in requirements management holds significant potential. Design thinking can guide LLMs to understand requirements from a human-centric perspective; LLMs can quickly process large-scale user data, supporting design thinking [16], and can also support the generation of requirement solutions [32]. The two complement each other, facilitating the comprehensive intelligent transformation of the requirements management process. Future research can continue to delve into the collaborative ways of design thinking and LLMs in requirements management, such as intelligent extraction, analysis, and re-expression of requirements information; intelligent generation of requirement solutions; rapid prototype creation, etc. The integration of methods is expected to further enhance the R&D efficiency and success rate of fintech products.

A preliminary envisioned integrated application model is where design thinking is responsible for defining the direction and principles of requirements management, ensuring a "human-centric" engineering ethic. Design thinking leads the insight and solution direction of requirements, LLMs quickly produce multiple requirement solutions for evaluation, design thinking is responsible for solution evaluation, providing qualitative input, and LLMs provide quantitative analysis. LLMs offer powerful language analysis and generation capabilities, achieving process automation. This

leverages human wisdom as well as computational intelligence and a powerful knowledge base.

6. Conclusion and Outlook

Artificial Intelligence is ushering in a new round of explosive development, and the application of LLMs technology, represented by GPT, will have great value and impact in all walks of life, and profoundly change the way of production and life and the way of thinking of human beings. We should actively embrace technological innovation and fully consider the utilization of advanced tools in scientific research and work, while also facing the problems and risks of arithmetic bottleneck, commercial landing, and engineering ethics.

Design Thinking and LLMs have their specialties and show great potential in the field of requirements management. They not only help teams deepen their understanding of user requirements and innovate solutions but also improve the efficiency and accuracy of requirements management and promote the intelligent transformation of requirements management. However, at present, there are few cases of the integration of design thinking and LLMs applied to innovation design, and there is a lack of systematic and practical research. In the innovation design of cross-cutting fields, a macro-understanding of the involved fields becomes necessary, which includes understanding the mechanisms and modes of action of the main problems and, based on this, encapsulating the complex technologies and constructing a complete cognitive system of technological problems to more accurately identify and define the design problems [16]. In the future, it is necessary to further study the synergistic mechanism and key technologies of the two in demand management, especially how to realize the comprehensive intelligence and rapid iterative optimization of the demand management process. More empirical studies will also help to verify the effectiveness of the integration application, improve the efficiency and success rate of the development of financial technology products, and provide theoretical and practical references for researchers and developers in this field.

In the future, in-depth research on the integration and application of design thinking and LLMs will open up new ways for innovation and development in the field of financial technology. This integration is expected to promote the intelligent transformation of requirements management, shorten product development cycles, improve user satisfaction, and promote the prosperity of innovation design of fintech products.

References

- [1] T. Brown, *Design Thinking*, 2008.
- [2] V.C., B.W., U.F., P.C., From Palaces to Yurts: Why Requirements Engineering Needs Design Thinking, *IEEE INTERNET COMPUTING* 20 (2013), 91–94.
- [3] H. Ferreira Martins, A. Carvalho De Oliveira Junior, E. Dias Canedo, R.A. Dias Kosloski, R. Ávila Paldês, E. Costa Oliveira, *Design Thinking: Challenges for Software Requirements Elicitation*, Series Design Thinking: Challenges for Software Requirements Elicitation 10, 2019.
- [4] E. Kahan, A. Oliveros, M. Genero, A systematic mapping study on the application of design thinking in requirement engineering, *Journal of Universal Computer Science* 2021.

- [5] R.G. Cooper, S.J. Edgett, E.J. Kleinschmidt, Benchmarking Best NPD Practices—II, *RESEARCH-TECHNOLOGY MANAGEMENT* 47 (2004), 50-59.
- [6] S.B. Mahmoud-Jouini, C. Midler, P. Silberzahn, Contributions of Design Thinking to Project Management in an Innovation Context, *Project Management Journal* 47 (2016), 144-156.
- [7] E. Gonen, Tim Brown, Change by Design: How Design Thinking Transforms Organizations and Inspires Innovation (2009), Markets, globalization & development review 10 (2019).
- [8] E.D. Canedo, A.T.S. Calazans, G.R.S. Silva, P.H.T. Costa, R.P. De Mesquita, E.T.S. Masson, Creativity and Design Thinking as Facilitators in Requirements Elicitation, *INTERNATIONAL JOURNAL OF SOFTWARE ENGINEERING AND KNOWLEDGE ENGINEERING* 32 (2022), 1527-1558.
- [9] I.D. Foundation, R.F. Dam, T.Y. Siang, What is design thinking and why is it so popular?, Interaction Design Foundation, 2021.
- [10] J. Wei, X. Wang, D. Schuurmans, M. Bosma, B. Ichter, F. Xia, E. Chi, Q. Le, D. Zhou, Chain-of-Thought Prompting Elicits Reasoning in Large Language Models, 2023.
- [11] W.X. Zhao, K. Zhou, J. Li, T. Tang, X. Wang, Y. Hou, Y. Min, B. Zhang, J. Zhang, Z. Dong, Y. Du, C. Yang, Y. Chen, Z. Chen, J. Jiang, R. Ren, Y. Li, X. Tang, Z. Liu, P. Liu, J. Nie, J. Wen, A Survey of Large Language Models, 2023.
- [12] J. Devlin, M. Chang, K. Lee, K. Toutanova, Bert: Pre-training of deep bidirectional transformers for language understanding, *arXiv preprint arXiv:1810.04805*, 2018.
- [13] A. Radford, J. Wu, R. Child, D. Luan, D. Amodei, I. Sutskever, Language models are unsupervised multitask learners, *OpenAI blog* 4 (2019).
- [14] Li Baiyang, Bai Yun, Zhan Xini, Li Gang, Technical Characteristics and Evolutionary Trends of Artificial Intelligence Generated Content (AIGC), *Library and Information Knowledge* 23 (2023), 1-9.
- [15] Tencent Research Institute, AIGC Development Trend Report 2023, 2023.
- [16] Wu Qiong, Innovative Design Thinking in the Era of Artificial Intelligence, *Decoration* 19 (2019), 18-21.
- [17] J.L. Bower, C.M. Christensen, Disruptive technologies: catching the wave, 1995.
- [18] Li Jianping, Wu Dengsheng, Hao Jun, Research on Management Science and Engineering Driven by Technology, *Chinese Management Science* 22 (2022), 9-14.
- [19] T. Eloundou, S. Manning, P. Mishkin, D. Rock, GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models, 2023.
- [20] Y. Shen, K. Song, X. Tan, D. Li, W. Lu, Y. Zhuang, HuggingGPT: Solving AI Tasks with ChatGPT and its Friends in HuggingFace, 2023.
- [21] H.M. Elsaid, A review of literature directions regarding the impact of fintech firms on the banking industry, *Qualitative Research in financial Markets* 13 (2021).
- [22] S. Wu, O. Irsoy, S. Lu, V. Dabrovolski, M. Dredze, S. Gehrmann, P. Kambadur, D. Rosenberg, G. Mann, BloombergGPT: A Large Language Model for Finance, 2023.
- [23] H. Yang, X. Liu, C.D. Wang, FinGPT: Open-Source Financial Large Language Models, 2023.
- [24] M. Dowling, B. Lucey, ChatGPT for (Finance) research: The Bananarama Conjecture, *Finance Research Letters* 23 (2023), 103662.
- [25] L. Bard, G. AI, Exploring the role of artificial intelligence in enhancing academic performance: A case study of chatgpt, *Artificial Intelligence in Education* 23 (2023), 1-15.
- [26] R. Sosa, J.S. Gero, The creative value of bad ideas: A computational model of creative ideologies, 2013.
- [27] J.S. Park, J.C. O'Brien, C.J. Cai, M.R. Morris, P. Liang, M.S. Bernstein, Generative Agents: Interactive Simulacra of Human Behavior, 2023.
- [28] M. Mitchell, D.C. Krakauer, The debate over understanding in AI's large language models, *Proceedings of the National Academy of Sciences* 23 (2023).
- [29] B.A.U.E. Y Arcas, Do large language models understand us? *DAEDALUS* 22 (2022), 183-197.
- [30] S. Trott, C. Jones, T. Chang, J. Michaelov, B. Bergen, Do Large Language Models know what humans know? 2023.
- [31] G. Feng, B. Zhang, Y. Gu, H. Ye, Di He, L. Wang, Towards Revealing the Mystery behind Chain of Thought: A Theoretical Perspective, 2023.
- [32] S.G. Bouschery, V. Blazevic, F.T. Piller, Augmenting human innovation teams with artificial intelligence: Exploring transformer-based language models, *JOURNAL OF PRODUCT INNOVATION MANAGEMENT* 23 (2023), 139-153.