UNIVERSIDAD COMPLUTENSE DE MADRID

FACULTAD DE CIENCIAS ECONÓMICAS Y EMPRESARIALES

TESIS DOCTORAL

Crowdfunding companies: rendimiento contable financiero en China

Crowdfunding companies: financial accounting performance in China

MEMORIA PARA OPTAR AL GRADO DE DOCTORA

PRESENTADA POR

Chang Jiang

DIRIGIDA POR

Raquel Pérez Estébanez

UNIVERSIDAD COMPLUTENSE DE MADRID

FACULTAD DE CIENCIAS ECONÓMICAS Y EMPRESARIALES

TESIS DOCTORAL

CROWDFUNDING COMPANIES RENDIMIENTO CONTABLE FINANCIERO EN CHINA. CROWDFUNDING COMPANIES FINANCIAL ACCOUNTING PERFORMANCE IN CHINA.

MEMORIA PARA OPTAR AL GRADO DE DOCTOR

PRESENTADA POR

Chang Jiang

DIRECTORES

Raquel Pérez Estébanez

Fecha: Octubre de 2024

Madrid

UNIVERSIDAD COMPLUTENSE DE MADRID

FACULTAD DE CIENCIAS ECONÓMICAS Y EMPRESARIALES

Doctorado en Administración y Dirección de Empresas

TESIS DOCTORAL

CROWDFUNDING COMPANIES RENDIMIENTO CONTABLE FINANCIERO EN CHINA.
CROWDFUNDING COMPANIES FINANCIAL ACCOUNTING PERFORMANCE IN CHINA.

MEMORIA PARA OPTAR AL GRADO DE DOCTOR

PRESENTADA POR

Chang Jiang

DIRECTORES

Raquel Pérez Estébanez

Fecha: Octubre de 2024

Madrid

Quotes

“It All Depends on Human Effort.”

Menglong Feng

ACKNOWLEDGEMENTS

With an excited heart, I write these words, for this has always been the most anticipated part of my doctoral journey. I am grateful for choosing this path, fraught with thorns and challenges, there are also many unforgettable sceneries along the way.

Firstly, I would like to express my heartfelt gratitude to my tutor Raquel Pérez Estébanez, who have accompanied me since my graduate studies. I would also like to thank Professor Elena Urquía Grande, who has also given me a lot of love. I am thankful for their care, which transcends mere academic guidance, encompassing their encouragement during moments of despondency. I deeply appreciate their support, without which I would not have reached this point today. In addition, I would like to thank Professor Cristina del Campo. Although she is not my tutor, she has given me a lot of help in my study and life, and I am very grateful. Also, thank you to the academic tribunal for their assistance and advice in the annual evaluation of my work.

I am grateful to my parents, who despite being miles apart, have offered me unwavering support. Thanks to my husband for accompanying me every step of the way. And gratitude to my cat for keeping me company through every working night.

Thanks to Professor Enrico Battisti for his guidance and help at the University of Turin.

Lastly, I want to express gratitude to myself, for I have accomplished it. I dedicate this research to all those who have supported and helped me along the way, and I will persevere, continuing to advance on the academic journey.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

The crowdfunding industry has experienced rapid growth in recent years, and existing research indicates that it can contribute significantly to various domains such as entrepreneurship, creative product development, and charitable donations. Crowdfunding companies refers to enterprises or organizations that raise funds through crowdfunding platforms, which primarily serve as facilitators of fundraising for actual projects rather than platforms. However, as an emerging sector, the crowdfunding industry continues to confront various uncertainties. Challenges such as information asymmetry and insufficient disclosure policies for crowdfunding projects remain prevalent. Therefore, examining the financial performance of crowdfunding projects not only enables us to uncover hidden information that may not be directly observable but also enhances project transparency effectively. Moreover, this analysis facilitates rational resource allocation planning within the industry and ultimately improves overall project quality, a crucial factor for fostering a healthy and sustainable development of the entire crowdfunding ecosystem.

This thesis aims to investigate the accounting and financial performance of crowdfunding projects through a bibliometric analysis and four empirical parts utilizing data from equity, reward-based, and donation-based crowdfunding platforms.

First, this thesis lays a theoretical foundation for the current research through a systematic literature review. It found that crowdfunding research in general can be divided into two main lines of research. The first line of research mainly includes the definition of crowdfunding, crowdfunding platform models and the motivations of crowdfunding

participants. These studies focus on understanding nature and development trends of crowdfunding. Another research direction is the study of performance and success factors of internal crowdfunding activities, which mainly includes research on project success factors and various crowdfunding information. These studies aim to understand the underlying mechanisms and influencing factors of crowdfunding. In addition, the application of artificial intelligence in crowdfunding research started late, but it has strong development potential.

The initial phase of the empirical study focuses on examining the factors that influence the success of equity crowdfunding projects. To assess its impact on actual project returns, a novel profitability indicator called "Return on Registered Capital (RCR)" was devised. RCR is calculated based on the registered capital and total dividends collected in this thesis. This analysis confirms that RCR significantly influences project returns and concurrently validates the effectiveness and advantages of utilizing a neural network model to analyze success factors in equity crowdfunding. Overall, this section emphasizes the importance of financial performance within the crowdfunding industry and contributes to its sustainable development.

The second part of the empirical study focuses on identifying the factors that influence the financing performance of reward-based crowdfunding projects. The funding-to-target ratio is employed as a measure of their funding performance. It is observed that project information variables, such as the number of project supporters, project progress, and project minimum investment, significantly impact project performance. Furthermore, this dissertation introduces an indicator of macroeconomic environment - PCDI (Per capita disposable income) - which also affects the financing performance of these projects.

The third part focuses on investigating the factors influencing the successful financing of donation-based crowdfunding in environmental and animal protection projects. It introduces innovative financial transparency scoring indicators, combines commonly used research indicators in crowdfunding studies, and identifies financial transparency as the most crucial positive factor impacting project success. Additionally, this analysis introduces a neural network model and demonstrates its ability to enhance discrimination accuracy compared to traditional binary logistic regression models.

The fourth empirical research section aims to gain a comprehensive understanding of individuals' internal decision-making processes regarding donations to animal and environmental protection (AEP) donation-based crowdfunding (DCF) projects. By investigating participants' intention to contribute towards such initiatives, this study examines the influence of four dimensions: self-perception emotion, altruism or sacrificialism, community belonging, and financial transparency on their propensity to donate to AEP-DCF projects. The findings reveal that community belonging and financial transparency significantly impact individual motivations for donating. This dissertation offers valuable insights into the underlying motivations driving AEP crowdfunding donation behavior while also providing practical references for related fields.

Overall, project financing performance is important in research in the field of crowdfunding. Moreover, it is also of practical significance to consider the impact of financial transparency on financing performance. With the continuous advancement of technology and the strengthening of supervision, the crowdfunding industry will become more transparent, which will help the sustainable development of the crowdfunding field.

Keywords: Crowdfunding, Equity Crowdfunding, Reward-based Crowdfunding, Donation Crowdfunding, Financial Performance, Financial Transparency, Environmental Protection, Animal Protection, Neural Networks, Donation intention, SEM analysis

RESUMEN

La industria del crowdfunding ha experimentado un rápido crecimiento en los últimos años y las investigaciones existentes muestran que puede contribuir significativamente a diversos campos como el emprendimiento, la creación artística y la donación. Las empresas de crowdfunding se refieren a entidades u organizaciones que recaudan fondos a través de plataformas de crowdfunding, las cuales actúan principalmente como facilitadoras de la recaudación de fondos para proyectos reales, más que como plataformas en sí mismas. Sin embargo, como un sector emergente, la industria del crowdfunding sigue enfrentándose a diversas incertidumbres. Desafíos como la asimetría de la información y las políticas de divulgación insuficientes para los proyectos de crowdfunding siguen siendo prevalentes. Por lo tanto, examinar el desempeño financiero de los proyectos de crowdfunding no solo nos permite descubrir información oculta que puede no ser directamente observable, sino que también mejora la transparencia del proyecto de manera efectiva. Además, este análisis facilita la planificación racional de la asignación de recursos dentro de la industria y, en última instancia, mejora la calidad general del proyecto, un factor crucial para fomentar un desarrollo saludable y sostenible de todo el ecosistema de crowdfunding.

Esta tesis tiene como objetivo investigar el desempeño contable y financiero de proyectos de crowdfunding a través de un análisis bibliométrico y varios análisis empíricos utilizando datos de plataformas de crowdfunding basadas en acciones, recompensas y donaciones.

Primero, esta tesis sienta una base teórica para la investigación actual a través de una revisión sistemática de la literatura. Se observó que la investigación sobre crowdfunding en general se puede dividir en dos líneas principales de investigación. La primera línea de investigación incluye principalmente la definición de crowdfunding, los modelos de plataformas de crowdfunding y las motivaciones de los participantes del crowdfunding. Estos estudios se centran en comprender la naturaleza y las tendencias de desarrollo del crowdfunding. Otra línea de investigación es el estudio de los factores de desempeño y éxito de las actividades internas de crowdfunding, que incluye principalmente la investigación sobre los factores de éxito del proyecto y diversa información sobre crowdfunding. Estos estudios tienen como objetivo comprender los mecanismos subyacentes y los factores que influyen en el crowdfunding. Además, la aplicación de la inteligencia artificial en la investigación del crowdfunding comenzó tarde, pero tiene un gran potencial de desarrollo.

La fase inicial del estudio empírico se centra en examinar los factores que influyen en el éxito de los proyectos de crowdfunding de capital. Para evaluar su impacto en los rendimientos reales de los proyectos, se diseñó un indicador novedoso de rentabilidad llamado 'Retorno sobre el Capital Registrado (RCR)'. El RCR se calcula en función del capital registrado y los dividendos totales obtenidos en esta tesis. Este análisis confirma que el RCR influye significativamente en los rendimientos de los proyectos y, al mismo tiempo, valida la eficacia y las ventajas de utilizar un modelo de red neuronal para analizar los factores de éxito en el crowdfunding de capital. En conjunto, esta sección destaca la importancia del rendimiento financiero dentro de la industria del crowdfunding y contribuye a su desarrollo sostenible.

La segunda parte del estudio empírico se centra en identificar los factores que influyen en el desempeño financiero de proyectos de crowdfunding basados en recompensas. La tasa a la que se superan los objetivos de financiación se utiliza para medir el desempeño financiero de un proyecto. Se observa que las variables de información del proyecto, como el número de partidarios del proyecto, el progreso del proyecto y la inversión mínima del proyecto, impactan significativamente en el desempeño del proyecto. Además, esta disertación introduce un indicador del entorno macroeconómico RDB (la Renta Disponible Bruta) que también afecta el desempeño financiero de estos proyectos.

La tercera parte se centra en investigar los factores que influyen en la financiación exitosa del crowdfunding basado en donaciones en proyectos medioambientales y de protección animal. Introduce indicadores innovadores de puntuación de transparencia financiera, combina indicadores de investigación comúnmente utilizados en estudios de financiación colectiva e identifica la transparencia financiera como el factor positivo más importante que influye en el éxito del proyecto. Además, este análisis introduce un modelo de red neuronal y demuestra su capacidad para mejorar la precisión de la discriminación en el crowdfunding de donaciones en comparación con los modelos tradicionales de regresión logística binaria.

La cuarta parte de investigación empírica tiene como objetivo obtener una comprensión integral de los procesos internos de toma de decisiones de los individuos con respecto a las donaciones a proyectos de financiación colectiva basada en donaciones (DCF) de protección animal y ambiental (AEP). Al investigar la voluntad de los participantes de contribuir a tales iniciativas, este estudio examina la influencia de cuatro dimensiones: autopercepción emocional, altruismo o sacrificialismo, pertenencia a la comunidad y

transparencia financiera en su propensión a donar a proyectos AEP-DCF. Los hallazgos revelan que la pertenencia a la comunidad y la transparencia financiera impactan significativamente las motivaciones individuales para donar. Esta disertación ofrece información valiosa sobre las motivaciones subyacentes que impulsan el comportamiento de donación de crowdfunding de la AEP y, al mismo tiempo, proporciona referencias prácticas para campos relacionados.

En general, el desempeño de la financiación de proyectos es importante en la investigación en el campo del crowdfunding. Además, también tiene importancia práctica considerar el impacto de la transparencia financiera en el desempeño financiero. Con el avance continuo de la tecnología y el fortalecimiento de la supervisión, la industria del crowdfunding se volverá más transparente, lo que ayudará al desarrollo sostenible del campo del crowdfunding.

Palabras clave: Crowdfunding, Crowdfunding de equidad, Crowdfunding basado en recompensas, Crowdfunding de donaciones, Desempeño financiero, Transparencia financiera, Protección ambiental, Protección animal, Redes neuronales, Intención de donación, Análisis SEM

1

INTRODUCTION

The Internet has revolutionized social communication and transformed people's lifestyles, exerting a profound influence on financial industry innovation. Particularly for entrepreneurs, especially those operating small and medium-sized enterprises (SMEs), securing business loans or investments during the early stages of their ventures can be challenging, often leading to project failures. However, with the continuous development of Internet finance, various new financing methods have emerged. Crowdfunding is one method that operates as a "pre-consumption" model by raising investments from ordinary backers to fund projects while also allowing them to earn future profits through these endeavors (Belleflamme et al., 2013; Jiang et al., 2021). The fundamental concept behind crowdfunding involves individuals in need of funds presenting their projects through online crowdfunding platforms and connecting with willing supporters. This process engages multiple actors including individuals, entrepreneurs, non-governmental organizations (NGOs), and project backers. One notable characteristic of crowdfunding is that it enables backers to support projects with minimal funding via the internet while simultaneously enabling projects in need of funding to raise target amounts through collective investment from numerous backers. In comparison to traditional financing methods, crowdfunding leverages the power of the internet which transcends geographical limitations and temporal constraints thereby facilitating its rapid growth.

Concurrently, in response to the emergence and development of Internet crowdfunding, traditional donation models are also adapting to the changing society. Increasingly, individuals are relying on online platforms as a means to contribute towards charitable causes. As a contemporary fundraising approach, it has witnessed exponential growth in recent years. With the continuous progression of the Internet and social media, crowdfunding has become more prevalent, convenient, and diverse. Simultaneously, it also offers enhanced support and opportunities for innovators and philanthropic endeavors (Li et al., 2020; Mazzocchini & Lucarelli, 2022; Rahmayanti et al., 2023; Thomas-Walters et al., 2020; Teunenbroek et al., 2023).

This rapidly expanding crowdfunding phenomenon has garnered significant attention and scholarly interest. Numerous academic studies have emerged, encompassing the categorization of crowdfunding platforms (e.g, Ahlers et al., 2015; Graziano et al., 2023; Mazzocchini & Lucarelli, 2022; Troise et al., 2023) , examination of investor motivation (Baah-Peprah et al., 2024; Belleflamme et al., 2014; Shneor et al., 2024), and analysis of project performance (Ma, 2023). Based on existing research, four distinct types of crowdfunding have been identified: equity crowdfunding, reward-based crowdfunding, lending crowdfunding, and donation-based crowdfunding (Jiang et al., 2022, 2023; Wang et al., 2024).

Equity crowdfunding (ECF) involves project backers acquiring shares or similar rights from the project sponsor by supporting crowdfunding projects. ECF has emerged as a rapidly growing sub-category within the field of crowdfunding. The future development of ECF will present significant challenges to traditional investment sectors such as venture capital and business angel financiers (Jiang et al., 2022; Mazzocchini & Lucarelli, 2022). Research on the theme of ECF has experienced rapid growth recently, encompassing various aspects such as its relationship with pervasive finance (Graziano et al., 2023; Troise et al., 2023), market size and geographical distribution (Ma, 2023), and imitation of product ideas (Cowden & Young, 2020). Additionally, researchers have focused on internal factors influencing ECF's performance and success, which has become a prominent area of study in recent years. Some research has examined project sponsors' social capital (Graziano et al., 2023; Vismara, 2018), static factors like campaign outcomes for innovative companies (Hornuf & Schwienbacher, 2018; Mazzocchini & Lucarelli, 2022), as well as return on investment considerations (Jiang et al., 2022; Troise et al., 2023) all contributing to understanding factors affecting project success.

Reward crowdfunding (RCF) refers to the practice where project backers receive non-monetary incentives for supporting a project, such as limited edition signed CDs or priority access to new products. Among various forms of crowdfunding, RCF exhibits the highest level of activity, the fastest growth rate, and holds significant importance among the four types (Huang et al., 2023; Jiang et al., 2021; Ryu, 2024). Belleflamme et al. (2015) proposed that RCF enables entrepreneurs to secure financing through platforms while offering backers benefits in the form of premium versions; however, these backers do not anticipate financial returns.

Lending crowdfunding refers that project sponsors obtaining a lower cost of capital, and lenders will also have high-return investment opportunities (Ahlers et al., 2015; Belleflamme et al., 2014). Since this thesis does not focus on this type, it will not be discussed in depth.

Donation-based crowdfunding (DCF) projects typically fall under the category of non-profit initiatives. What sets these types of crowdfunding projects apart is that unlike the other three types mentioned earlier, backers in DCF projects usually do not receive any form of return, whether monetary or non-monetary. Whether it involves protecting the ecological environment or rescuing homeless stray animals, providing medical assistance to those in need, or aiding disadvantaged individuals in society, DCF acts as an invisible hero that serves as a lifeline. The primary purpose of DCF is to raise funds for supporting specific charities, personal needs, or nonprofit organization projects without involving investors who expect financial returns or equity stakes. DCF places emphasis on goodwill and encourages voluntary support for social causes such as environmental conservation and personal endeavors (Corsini & Frey, 2024; Jiang et al., 2023; Teunenbroek et al., 2023). Although DCF has revolutionized traditional donation models, its ultimate goal remains unchanged: assisting those in need by facilitating access to necessary funds (Zhang et al., 2020). Several existing studies have analyzed factors influencing the success of DCF projects (Corsini & Frey, 2024; Gallo-Cajiao et al., 2018; Kubo et al., 2021).

Environmental and animal protection have received global attention in recent years. Most NGOs currently rely heavily on donations, which are also an important funding source for environmental and animal protection work. However, the shortage of funds remains a major challenge faced by these projects (Corsini & Frey, 2024; Veríssimo et al., 2018; Waldron et al., 2017). DCF can help alleviate the current massive funding gap. Currently, most research on environment and animal protection focuses on offline fundraising projects, and there is little research on online donation projects(Lundberg et al., 2019;

Veríssimo et al., 2018). The few existing studies focus on environmental protection crowdfunding projects and analyze the factors that influence project success (Gallo‐Cajiao et al., 2018; Kubo et al., 2021). Considering the homogeneity between the nature of DCF and traditional donation behavior, existing research on traditional animal protection and environmental protection donation projects and DCF can be referred to, which mainly focuses on exploring the motivations of donation behavior (Chapman et al., 2022; Y. Li et al., 2018; Moritz & Block, 2016; Neumayr & Handy, 2019; Van Teunenbroek & Hasanefendic, 2023).

At the same time, there is a growing global concern regarding environmental and animal protection issues. Increasing numbers of individuals are becoming aware of the gravity of challenges such as climate change and biodiversity loss. However, most non-governmental organizations (NGOs) and charities still rely on traditional donation models to sustain their operational and project funding needs (Thomas-Walters et al., 2020; Van Teunenbroek & Hasanefendic, 2023; Veríssimo et al., 2018). As environmental and ecological challenges continue to escalate, these projects face significant funding gaps (Chapman et al., 2022; Maxwell et al., 2020; Waldron et al., 2017). Against this backdrop, DCF has emerged as a potential solution to alleviate current financing difficulties. This approach offers more flexible and sustainable funding support for environmental projects while providing non-profit organizations with greater economic leeway to effectively address pressing environmental issues. It is anticipated that this novel financing model will foster innovative and sustainable advancements in environmental protection while offering stronger support in tackling the world's ecological challenges.

Furthermore, it is worth noting that artificial intelligence has emerged as a crucial tool across various industries, including finance, medicine, and manufacturing, owing to the rapid advancements in big data technology. Machine learning algorithms have already demonstrated their ability to rival human experts in multiple domains (LeCun et al., 2015). However, most of the existing research on crowdfunding still relies on traditional regression models for analysis, which may not adequately address the growing volume and complexity of data. Consequently, there is an inevitable trend towards adopting more advanced machine learning techniques. In social sciences too, an increasing number of studies are utilizing artificial intelligence tools to effectively analyze data (Mullainathan & Spiess, 2017). Neural network models have long been extensively employed as a representative component of artificial intelligence in numerous studies for enhanced processing of sample data and identification of latent relationships within the dataset.

1.1 JUSTIFICATION AND OBJECTIVES OF THE TOPIC

According to the "2024-2029 Crowdfunding Industry Status and Future Development Trend Analysis Report" (China Industry Research Network, 2024), the scale of China's crowdfunding market had reached 300 billion yuan by the end of 2023, representing a growth rate exceeding 25% compared to the previous year. This remarkable upward trend can be primarily attributed to the rapid advancement in Internet technology and sustained public interest in innovative projects. The diversification of crowdfunding models, including equity crowdfunding, reward-based crowdfunding, and donation-based crowdfunding, has significantly contributed to the expansion of this market.

By the end of 2023, the number of crowdfunding platforms in China has surpassed 400, encompassing diverse sectors such as equity crowdfunding, product crowdfunding, and charity crowdfunding. These platforms offer a multitude of financing channels for various projects and cater to the funding requirements of different ventures. In terms of platform categorization, equity crowdfunding platforms constitute the largest proportion at approximately 45% of the total; followed by product crowdfunding platforms accounting for around 20%. Although relatively fewer in number, charity crowdfunding platforms are experiencing steady growth momentum (China Industry Research Network, 2024).

China's donation-based crowdfunding has witnessed significant growth in recent years, showcasing the remarkable potential of digital charity to transcend traditional limitations of region, time, and space. According to the data presented in the “China Digital Charity Development Report 2023” (China Charity Alliance, 2023), online digital fundraising in China has surged from 436 million yuan (RMB) in 2014 to an impressive 10 billion yuan (RMB) more recently, accompanied by a substantial increase in participants from an initial count of 118 million to over 10 billion. In 2011, the total amount of social donations in China stood at 84.5 billion yuan (RMB), which soared to reach a staggering sum of 145 billion yuan (RMB) by 2022—an overall twofold increase.

Furthermore, the World Bank projects that the global crowdfunding market is expected to reach $300 billion by 2025, with developing countries accounting for a projected increase to $96 billion, of which China's market share is estimated at approximately $50 billion (Funk & Funk, 2019; World Bank, 2013). This prospect underscores the vast potential and scope for growth in China's crowdfunding industry, thereby rendering the utilization of Chinese crowdfunding data for this thesis purposes highly significant and practically relevant.

The main objective of this dissertation is to explore the financial performance of different crowdfunding types. It discusses the influencing factors of financial performance through empirical research on three crowdfunding methods: ECF, RCF and DCF.

Based on this main objective, in the theoretical research part, as the first sub-goal of this thesis, it aims to build the theoretical basis of this study through literature review.

As the second sub-goal of this thesis, this part of the empirical study explores the factors influencing the success of ECF.

As a new investment and financing mechanism, entrepreneurs who need funds can use ECF for rapid financing. The public can also use ECF to support projects that require funds and obtain high returns. However, it brings uncertainty. Therefore, the present research proposes a new idea to improve the performance research of ECF. Unlike most existing studies, it has not focused on ECF projects' performance in the raising or financing. This analysis in chapter concentrates on the subsequent implementation performance of projects that have completed financing, which is the project's actual return. It intends to use empirical research to explore the factors that can affect the returns on ECF projects' investment. The project’s financial return can better reflect the quality of the project. ECF backers are most concerned about the project’s return. Research on the influencing factors of project returns can contribute to the platform, backers, or fundraisers. This chapter aims to fill the gap in the current research on ECF's financial profitability. At the same time, this research uses traditional linear regression and DNN models to conduct exploration empirical analysis, focusing on the factors that affect the return on investment of ECF projects. Neural networks have shown clear advantages in some evaluation projects, demonstrating their potential in predicting crowdfunding project funding. Therefore, this study uses the Python deep learning framework as a tool to construct the success factors of the DNN-based ECF identification model.

According to the research purpose of this part, the corresponding research questions are defined as follows:

RQ1: What factors affect the return on investment of ECF projects in China?

The third sub-goal of this thesis focuses on the factors influencing the financing performance of RCF. RCF is the most popular of the four crowdfunding types, has the highest level of activity, and is also the fastest growing crowdfunding type. RCF's research mainly reflects the financing performance based on whether the crowdfunding project can achieve their goals. However, there are some specialized studies on the ratios of financing over goals of the projects (Liao et al., 2015). They use the ratios of financing over goals as a measure of the financing performance of crowdfunding projects. Compared with other studies on crowdfunding performance, this research branch is small and imperfect. For example, the choice of independent variables lacks theoretical basis, and the degree of explanation of the obtained regression results is not high. Therefore, in this section, the purpose of this chapter is to study the factors that influence the financing performance (the ratios of financing over goals) of RCF projects. The "ratios of financing over goals" refers to the ratio between the actual funds raised by a crowdfunding project and its pre-set fundraising goal. This ratio is used to measure the project's financing performance. First of all, this research considers expanding the sample size because previous studies usually have limitations on this issue. This chapter will use selected projects that have achieved the financing goals in the Chinese RCF platform as data to study the financing performance of the projects. This study will further explain which variables can affect the financing performance of RCF projects.

The research question of this study is defined as follows:

RQ2: Which factors determine the financing performance in RCF *projects in China?*

The fourth sub-goal of this research conducts an in-depth study of DCF, aiming to study the factors affecting the successful financing of animal and environmental protection DCF projects. A DCF project is considered successful when it achieves its desired funding goal. Existing research on DCF mainly focuses on donor motivation and project sponsors. Few studies have considered transparency in discussing projects from a financial perspective. The most crucial factor affecting general donation behavior is transparency, and online DCF has its particularity, making its projects more difficult to control. Some studies have begun to focus on this online-offline gap, such as (Salido-Andres et al., 2022). At the same time, this part of the research will establish a Backpropagation (BP) neural network model based on the traditional multiple linear regression model, study the influencing factors of the success of DCF projects for environmental and animal protection, and compare the ability of the two models to predict project success.

Therefore, the corresponding research question is defined as follows:

RQ3: What factors affect the success of environment and animal protection DCF projects in China analyzed through BP neural network models?

The fifth sub-goal of this dissertation aims to use the SEM model to investigate the donation motivations of donors in animal and environmental protection crowdfunding projects through survey analysis. Currently, whether it is a traditional donation project or a DCF project, few studies consider whether project transparency affects donation motivation from a financial perspective. Therefore, in the field of crowdfunding, it has not yet been determined whether the project's information transparency will also affect donors' donation behavior (Hariwibowo et al., 2022; Salido-Andres et al., 2022). Therefore, this study uses a SEM model to investigate the donation motivations of donors in environmental protection and animal protection crowdfunding projects.

Therefore, the corresponding research question is defined as follows:

RQ4: Does self-perceived emotion have a positive impact on the intention to donate to AEP-DCF projects?

RQ5: Do altruism and sacrificialism have a positive impact on the intention to donate to AEP-DCF projects?

RQ6: Does a sense of community belonging have a positive impact on the intention to donate to AEP-DCF projects?

RQ7: Does financial transparency have a positive impact on the intention to donate to AEP-DCF projects?

The specific research sub-questions of this sub-goal will be introduced in detail in the Chapter 7.

The present thesis will make contributions in the following aspects:

First, this thesis combs the relevant theoretical research on this topic through a systematic literature review and contributes to the theoretical basis of the current research.

As the world's second largest economy, conducting research on this topic in China is conducive to discussing Chinese crowdfunding projects, deepening the understanding of the crowdfunding field, and making contributions to the field.

In the study of ECF, it focusses on factors affecting project returns can contribute to the platform, backers or fundraisers. At the same time, it provides support for future research on the financial profitability of ECF projects. In addition, it also combines neural networks with Internet finance, providing many practical implications for future research.

In the study of RCF, it will further explain which variables affect the financing performance of RCF projects. More broadly, it can provide evidence for research across the entire field of RCF financing performance. At the same time, it also considers that previous studies often have limitations in sample size. It therefore expands the sample size, contributing to the power of the results.

In the study of factors for successful financing of DCF projects, first of all, it focuses on animal and environmental protection projects, improving the problem of insufficient content of existing related research issues. Secondly, this part considers the impact of financial transparency on donation motivation in the model, providing new ideas for related research. Finally, it also established a BP neural network model and compared its predictive ability with the traditional linear regression model, contributing to the applicability of neural networks in DCF research.

Also, this thesis based on the exploratory construction of a SEM model of donation motivations for animal and environmental DCF projects in existing research, helps to reveal the various intrinsic motivations of donors, it used Lisrel 8 to check the fitting index of the model. While its results can provide an empirical reference for animal and environmental crowdfunding projects, aiming to help projects improve their fundraising capabilities and make contributions.

1.2 RESEARCH STRUCTURE

This thesis is structured as follows:

It divides this study into seven chapters: In the first chapter, the topic is introduced, and the study is justified, and the purpose of the study is presented.

Chapter 2 conducts a systematic review of existing relevant literature through a bibliometric analysis to construct a theoretical basic framework for this topic. First, it provides an in-depth understanding of the current status of existing research, sorts out and analyzes the key influencing factors of crowdfunding performance, aiming to reveal the development and trends of existing research. Secondly, in addition to the literature analysis on crowdfunding, it will also explore and discuss other research and theories related to crowdfunding to establish a more complete and profound theoretical foundation. At the same time, it discusses the artificial intelligence neural network theory and analyzes its discussion and expansion in crowdfunding.

In Chapter 3, it details the sources of the research data, the collection method, and the credibility and validity of the data, ensuring the reliability and scientific of the study.

Chapter 4 studies the factors that affect the financial performance of ECF projects. This chapter focuses on the actual returns after the completion of the ECF project. This chapter employs both traditional linear regression and neural network models to conduct exploratory empirical analysis, emphasizing the factors impacting the return on investment of ECF projects.

Chapter 5 studies the factors affecting RCF financing performance. This chapter considers expanding the sample size based on existing literature. It uses projects from China's RCF platform that have achieved financing goals as samples to study the financing performance of projects. This chapter aims to explore which variables can affect the financing performance of RCF projects.

Chapter 6 focuses on DCF and aims to explore the factors that affect the successful financing of DCF animal and environmental protection projects. This chapter pioneered the introduction of financial transparency indicators based on existing research, and it also uses projects from China's largest DCF platform as samples. At the same time, this chapter will establish a back propagation (BP) neural network model based on the traditional multivariate linear regression model and compare the two models' predictive ability for the success of DCF projects.

Chapter 7 studies DCF projects based on animal and environmental protection and examines the factors that influence supporters' willingness to donate. It uses the SEM model to investigate the donation motivations of donors in animal and environmental protection crowdfunding projects through survey analysis.

Lastly, in Chapter 8, the overall conclusions of this study are drawn, and limitations and further research opportunities are discussed.

2

LITERATURE REVIEW

First, this study will conduct a bibliometric analysis to gain an in-depth understanding of current research, sort out and analyze the key influencing factors of crowdfunding performance, and aim to reveal the development and trends of existing research. Secondly, in addition to the literature analysis on crowdfunding, it will also conduct in-depth exploration and discussion of other existing research and theories related to crowdfunding to establish a more complete and profound theoretical foundation. At the same time, this dissertation will also study artificial intelligence neural network theory and analyze its discussion and expansion in crowdfunding. It will provide a deeper perspective for understanding crowdfunding performance and provide more powerful support and guidance for the empirical exploration of this research.

2.1 CROWDFUNDING

The financial sector is essentially a service industry with its primary objective being to serve the real economy. Its main function involves facilitating the transfer of funds from investors to fundraisers through financing activities. Information technologies, such as the Internet, have significantly impacted traditional financial models. In addition to conventional commercial banks and capital markets, there exists an alternative financing model known as Internet finance. This model has been steadily growing in the modern economy, with crowdfunding serving as one of its prominent manifestations.

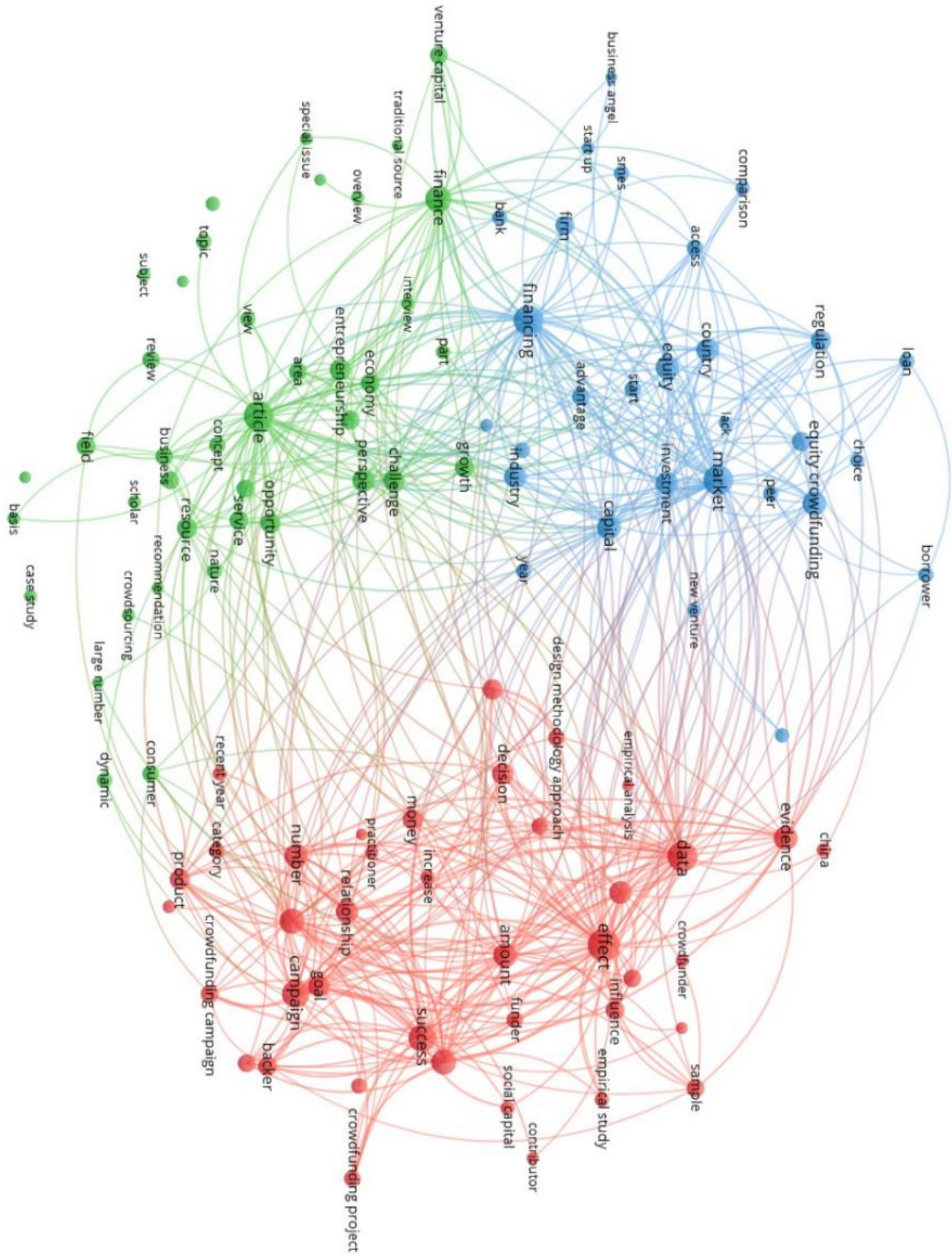

Figure 2.1. Map of keywords

This thesis focuses on the classification of Internet finances in the context of crowdfunding. A literature search was conducted using 'crowdfunding' as a keyword in the 'Web of Science', resulting in 835 articles. After selecting relevant fields such as accounting, finance, economics, and administration, a total of 385 articles were identified. To analyze and visualize the bibliometric maps within this literature, the present thesis utilized “VOSviewer”, a software tool capable of constructing co-occurrence map based on citation, bibliographic coupling, co-citation, or co-authorship relations (see Figure 2.1). This map can help identify high-frequency keywords appearing in these documents. This map serves as valuable tools for efficiently and accurately identifying relevant research lines in the field of crowdfunding, thereby providing a solid theoretical foundation for this thesis, and significantly reducing the time required for literature collection and organization.

The right area depicted in Figure 2.1 reveals prominent high-frequency keywords such as "CF project," "data," "impact," "success," and "empirical analysis." These keywords suggest a prevalent utilization of empirical analysis within this domain, focusing on the collection of CF data and examination of CF project success. Conversely, the left side encompasses keywords like "finance," "entrepreneurship," and "market."

By integrating the findings and drawing upon the specific content of existing literature, this study identifies two primary research directions in the field of crowdfunding. On the one hand, some papers are mainly related to research of crowdfunding development, such as the definition of crowdfunding, the discussion of the crowdfunding model, and the relationship between crowdfunding and innovative companies and investment (Mollick 2014; Kuppuswamy & Bayus 2017). On the other hand, researchers have studied crowdfunding activities' performance and success factors (Kuppuswamy & Bayus 2018; Clauss et al. 2018).

2.1.1 Crowdfunding development and motivations

Some early studies discussed crowdfunding's definition regarding the first primary research line on crowdfunding development. Belleflamme et al. (2013) considered that crowdfunding could be an activity that rewards the backers with experience, services, or products in exchange for financial resources. Based on the previous research, Mollick (2014) defined crowdfunding more strictly as a business model where each backer provides a small amount of money and obtains physical goods, services or equity.

For this main research line, some studies have also focused on the crowdfunding model. They believed that crowdfunding could be divided into four categories: donation-based, reward-based, equity, and lending. Donation-based crowdfunding means backers don’t get paid for their support for donations. Incentive crowdfunding means that project backers can receive non-monetary rewards for supporting the project. Equity crowdfunding refers to project backers obtaining shares or similar rights of project sponsors by supporting crowdfunding projects. Lending crowdfunding means that project sponsors obtain lower capital costs, and lenders will also have high-return investment opportunities (Ahlers et al., 2015; Graziano et al., 2023; Mazzocchini & Lucarelli, 2022; Troise et al., 2023). This classification is also the mainstream view recognized by current crowdfunding research.

Some research has focused on the motivations of crowdfunding participants, including backers and project sponsors. "Backers" are individuals or organizations that provide financial support for crowdfunding projects. Usually, they support the realization of the project through donations, investments, or other forms of funding. "Project Sponsors" refers to the individuals or organizations responsible for initiating and managing the project. They are the primary drivers of the project, responsible for its planning, execution, and oversight. Some studies have focused on backer motivation. Belleflamme et al. (2014) found that 78% of the backers researched wanted to obtain various returns, such as capital, cash, pre-order products or services through investments. Kuppuswamy & Bayus (2017) considered that when backers demonstrated that their investment would make sense for realizing crowdfunding projects, especially when they are close to their deadline. However, investment motivation will be reduced when the project reaches its stated goal. Backers often feel a positive sense of belonging from building relationships with creators and other backers, which can make them feel more valued (Shneor et al., 2024). (Baah-Peprah et al., 2024) believed that crowdfunding platforms have some characteristics of online communities, such as the existence of common values, which is an important motivation for backers. Daskalakis & Yue (2017) proposed that young men with higher education are more inclined to invest in crowdfunding projects. Some research has also paid attention to the impact of gender on crowdfunding investment, found that female backers are more likely to unite and support same-sex entrepreneurs than male backers (Groza et al., 2020; Suseno & Abbott, 2021).

Some studies have focused on the motivations of project sponsors. Belleflamme et al. (2014) discovered that the three main reasons project sponsors choose crowdfunding: are financing, exposure, and testing products before entering the market. Some authors also discussed the motivations of project sponsors other than obtaining funding. Bretschneider & Leimeister (2017) believed that the motivation of project sponsors is to attract more followers. Ryu (2024) proposed that the motivation of project sponsors is to experience more value together with backers. Cowden & Young (2020) found that the project sponsor's motivation was not strictly as positive as it was shown. Some speculators copied and imitated others' projects and gave higher returns to absorb investment. The financing motive for these projects is only fraud.

2.1.2 Performance and success factors of crowdfunding internal activities

The second primary research line mainly covers crowdfunding's internal activities' performance and success factors. Compared with the primary research line, this research line contains more empirical research. Nevertheless, the views of scholars have not yet been unified and even have some contradictory conclusions. It makes it necessary to organize and improve relevant research. Pioneers who started this line, such as Ahlers et al. (2015) believed that the geographical distance between backers and project sponsors influences backers' investment decisions, especially in the initial stage of the project financing. Some research also believed that backers are sensitive to geographic factors, the crowdfunding platform has eliminated or reduced some of the economic frictions caused by geographical factors through the Internet (e.g. Carbonara, 2021; Ma, 2023).

Another pioneering study with significant influence comes from Mollick (2014). The author found that crowdfunding projects' success was the project's quality, updates, misspellings, and the size of the owner's network. Some research found that disclosing information about professional backers can increase the attractiveness of subsequent investments (e.g. Vismara, 2018; Wang et al., 2024; Wang et al., 2024). Bretschneider & Leimeister (2017) pointed out that investment preparation and presentation positively impact the project's success. Financing goals, the running time of the event, and the expected delivery of rewards negatively impact the project's success. Kuppuswamy & Bayus (2018) proposed that the lower the frequency of project updates and the higher financing goals, the more difficult it will be to achieve project financing goals. Mahmood et al. (2019) found that the more complex the Logo, the more unique it will be and positively impact backers. Calic & Shevchenko (2020) believed that project information does not only have a positive or negative monotonous effect on financing performance. Signals of autonomy, innovativeness, competitive aggressiveness and risk-taking have an inverted-U-shaped relationship with crowdfunding performance.

Also, some other studies have focused on the social capital ownership of crowdfunding. Bretschneider & Leimeister (2017) found that social relations and interaction with crowds will positively impact the project's success. Clauss et al. (2018) considered that increasing social activities during the project's financing could increase the success rate. Kuppuswamy & Bayus (2018) believed that family roles and social influences would positively impact its success. Some research proposed that crowdfunding projects related to social movements have a higher success rate than general projects (e.g. Hsieh et al., 2019; Troise & Yablonsky, 2023). Simon et al. (2019) found that social closeness and contact frequency did not increase the contribution, while the feelings of obligation and the fear of loss would increase the investment.

2.1.3 Donation and DCF

Traditional donations and DCF share a great degree of similarity. Given the narrow focus of existing research on DCF, this study will briefly review the existing literature on DCF and traditional donations. In addition to some studies focusing on the environment and animal protection(e.g. Corsini & Frey, 2024; Gallo-Cajiao et al., 2018; Kubo et al., 2021), have focused on environmental and animal protection, this chapter finds that most of the existing research on DCF is usually divided into two aspects: the research on the donor and the project sponsor. For donors, it typically orbits around donation motivation, as shown in Table 2.1.

ID	The main point of view	Authors
1	Emotion-based	Isa et al. (2015); Body & Breeze (2016); Moritz & Block (2016)
2	Altruism or sacrificialism	Gleasure & Feller (2016); Liu & Hao (2017); Majumdar & Bose (2017); Y.-Z. Li et al. (2018)
3	A sense of belonging	Smith et al. (2015); Cockrell et al. (2016); Lacan & Desmet (2017); Neumayr & Handy (2019);
4	Other	Verhaert & Van den Poel (2011); Althoff & Leskovec (2015)

Table 2.1. Research on donation motivation

Some studies have proposed emotion-based donation motives, such as Isa et al. (2015) took into account that a person's self-perception can influence donation behavior. Body & Breeze (2016) believed that one of the essential donation motivations is emotion, which can increase the intention of donors by describing the cause or increasing the donation amount. Moritz & Block (2016) also have similar views. They believed donors' giving behaviors are realized through the intrinsic motivation of personal interests, beliefs, empathy, social influence and trust, and the extrinsic motivation to improve social problems and knowledge.

Some studies suggested that this is a form of altruism or sacrificialism. Gleasure & Feller (2016) found that donors of DCF projects are motivated by pure altruism. Liu & Hao (2017) thought of donations as an act of sacrifice, and interestingly, donors often look forward to possible future returns that are generally not financially derived. Similarly, Majumdar & Bose (2017) argued that donors in DCF help people in need based on emotional rather than financial rewards. On this basis, some studies have also found that performance expectancy and effort expectancy are essential factors in determining donation behavior. These backers know they won't get a monetary return and are willing to back projects they love, a motivation different from those of other types of crowdfunding (Li et al., 2018).

The reason for motivation may also stem from a sense of belonging. Lacan & Desmet (2017) found that the cause of individual donors is a sense of belonging to the community. Because of prosocial emotional and empathic concerns, individual donors' emotional skills and abilities also motivate them to donate (Neumayr & Handy, 2019). Differently, age may also be an essential factor in donation motivation. Cockrell et al. (2016) believed that DCF donors are affected by age, with younger donors more inclined to donate to DCF projects. Interestingly, Smith et al. (2015) considered the "peer effects" of the donor to be significant in the donation process. By studying donor responses to "peers" who donated simultaneously, they found that donor behavior was influenced by early donation information so past donations can also affect future donation motivations.

In addition, some studies have focused on other motivations for donation. Althoff & Leskovec (2015) studied that a proportion of donors continued to donate after the success of their first donation project, the authors also proposed that past projects’ success can influence donor motivations.

Some existing literature also studied DCF sponsors, as shown in Table 2.2. For example, some studies focused on the relationship and interaction between donation sponsors and donors, and their impact on the fundraising capacity of donation projects. Mano (2014) believed that using social media promotes donations for DCF projects. The increase in the online donation rate does not affect the situation of offline donations because social media use affects donors' awareness of social issues, which increases their voluntary participation and contributions to DCF projects. Althoff & Leskovec (2015) explored how the DCF platform influenced donors' giving behavior. Timely and positive interaction and recognition of their donation behavior can improve donor retention rates and prevent donors from losing on the platform. Choy & Schlagwein (2016) found that whether project sponsors use crowdfunding platforms for fundraising or not will not affect the final fundraising results.

ID	The main point of view	Authors
1	The relationship and interaction	Mano (2014); Althoff & Leskovec (2015); Choy & Schlagwein (2016)
2	The fundraising system	Buccoliero et al. (2015); Solomon et al. (2015); Beltran et al. (2015)
3	The distribution of donations	Ndeffo Mbah & Gilligan (2011); Dragojlovic & Lynd (2014); Lee et al. (2016); Tan et al. (2021)

Table 2.2. Research on the project sponsor

In online fundraising, the fundraising system will also impact the fundraising results. Buccoliero et al. (2015) studied the impact of mobile communication technology on donations, and they found that donation projects through mobile Internet can get more support. Solomon et al. (2015) focused on the impact of DCF project deadlines on donor motivation, and they found that project sponsors can promote project progress if they can attract donations in the early stage. Beltran et al. (2015) studied the impact of conditional donations on DCF projects. By introducing a crowdfunding system CODO (Conditional Donations) and designing the DCF interface, donations will only be made when the project meets certain donation criteria. They found that more donors chose conditional donations than general programs.

Other scholars have paid attention to the distribution of donations, such as the optimal distribution of donations received, which can be confirmed by an agent-based simulation model (Ndeffo Mbah & Gilligan, 2011). Dragojlovic & Lynd (2014) proposed that in some particular fields, such as medical oncology and rare disease drug development, researchers can obtain some initial funding through DCF. It is an essential driver for DCF project sponsors, although it is not a substitute for government funding. Similarly, Lee et al. (2016) also adopted an agent-based simulation model to distribute donations between projects efficiently. It can also be consistent with the donor's preferred project, thereby increasing the success rate of the DCF project. Tan et al. (2021) proposed that, unlike traditional donation methods, through DCF, donors can decide the distribution of donations and choose their preferred projects and beneficiaries. This change will also increase the donation number of donors.

2.2 PERFORMANCE

2.2.1 Performance theory

The term "performance" came from management. McDonnell & King, (2013) believed that it is a combination of achievement and effectiveness, which refers to the outcome of work, behavior or methods over a certain period and its impact on the objective world. There are many stakeholders in crowdfunding projects, and the most direct ones are the sponsors and backers of the project. For project sponsors, improving financing performance can help them raise funds more or faster. For backers, they are more concerned about the progress of the project in the implementation process, that is, the project's performance. Therefore, in the operation of crowdfunding projects, two aspects of performance are involved: financing performance and implementation performance.

The main body of financing performance in the traditional sense is the economics and efficiency of the financing activities adopted by enterprises or groups, that is, the comparison of financing costs and financing effects of enterprises or groups in the process of financing. Wang et al. (2017) believed that in the field of crowdfunding, financing performance refers to the overall results of crowdfunding projects from the beginning to the end of financing. Mainly manifested in the financing amount, whether the financing target is achieved, and the degree of completion of the financing target. Liang et al. (2019) considered that implementation performance refers to the execution status of a task or work and is often used to measure the implementing performance of process matters. Most scholars choose the overall satisfaction degree of backers as an indicator to measure the implementation performance of the project. Since this chapter will focus on the financing performance of crowdfunding projects, the theoretical basis of crowdfunding projects' implementation performance will not be discussed in depth.

2.2.2 Financing performance of a crowdfunding project

As an emerging field, crowdfunding has grown exponentially in recent years, many scholars have begun to pay attention to this field. There is more and more research on the financing performance of crowdfunding. Through reviewing the literature, this chapter finds that the financing performance of crowdfunding projects can be roughly divided into three research lines.

The first line of research explored the influence of geographic location and network relationships on the financing performance of crowdfunding projects. Some studies have focused on the influence of geographic location on project financing performance.

Carbonara (2021) considered that geographic location affects backers' decision-making. Backers are more inclined to invest in project sponsors with similar cultural backgrounds and closer geographic locations. The geographic distance between the backers and the project sponsors affects the backer's choice of project. Some research held the same opinion on this view, believed that the geographic distance between backers and project sponsors influences backers' investment decisions, which affects the project's financing performance (e.g. Ma, 2023). Similarly, Guenther et al. (2018) believed that backers' sensitivity to geographic factors would affect the project's financing performance. They proposed that the crowdfunding platforms have eliminated or reduced some of the economic frictions caused by geographic factors. However, due to the limited development of network technology, the crowdfunding phenomenon has not alleviated the distance's sensitivity. Therefore, geographic distance negatively correlates with the investment probability of domestic backers, but the degree of influence by distance factors on overseas backers is not obvious.

There are also some studies that have focused on the influence of network relationships on project financing performance. Brown et al. (2008) believed that the main factor to ensure the stable development of online communities is the relationship between community members. Younkin & Kashkooli (2016) also agreed with this view and pointed out that crowdfunding can develop rapidly because of the communication characteristics between the network and the community's user nodes. Based on this view, researchers tend to start research from the perspective of social networks. For example, Mollick (2014) conducted an empirical analysis by collecting data of product-type project on Kickstarter (the largest reward-based crowdfunding platform) and concluded that an essential factor in determining the project is the personal network relationship of the project sponsor. Inbar & Barzilay (2014) considered the degree of communication between project sponsors and backers to influence project financing performance. Similarly, Jung et al. (2015) found in empirical research t that the key to the project's financing performance is the relationship among backers, the project sponsors and the platform. Lin & Viswanathan (2016) found in the recent project research on peer-to-peer (P2P) that community members' online relationship was positively correlated with the successful financing rate of the project, and negatively correlated with the loan interest and repayment delay rate.

The second research line is the influence of project information on project financing performance. Many scholars have found that project information is an important indicator that affects network users and indirectly affects the financing performance of crowdfunding projects. Allison et al. (2015) found that the investment speed of P2P-type crowdfunding project is affected by project information. Demonstrating care and responsibility in the project description can enable the project to reach the financing goal faster. However, overemphasizing achievement and diversification will slow down the financing speed and even fail to achieve the goal. Furthermore, the authors also proposed that projects that appear to be investment opportunities are not as easy to achieve financing goals as projects that seem to help others. Backers prefer projects that seem to help others. This phenomenon also confirms that project information indirectly affects the financing performance of crowdfunding projects. Similarly, Belleflamme et al. (2014) also believed that non-profitability projects are easier to attract backers than profitable projects and could achieve financing goals faster. Moss et al. (2015) proposed that crowdfunding projects' description has a specific impact on backers' decision-making through empirical research. Mazzocchini & Lucarelli (2022) studied the differences in success or failure of crowdfunding projects. The authors proposed that project forecast information can affect the financing performance of crowdfunding project, and positive forecast information can improve project financing performance. Some research proposed that the language style of crowdfunding projects can promote social activities, it has effect on the financing performance of crowdfunding projects and commercial activities (e.g. Wang et al., 2024; Wang et al., 2024). Kunz et al. (2017) studied the influence of reward-based crowdfunding project financing performance. The authors found that the preparation and presentation of the investment, communication and mutual assistance with the group, and the rewards provided significantly impact the success of the crowdfunding project. Similarly, Bretschneider & Leimeister (2017) also studied the factors that affect project financing performance. The authors found that investment preparation and project presentation positively impact the financing performance of the project. Financing goal, the running time of the event and the expected delivery of rewards all negatively impact on the project's financing performance. Kuppuswamy & Bayus (2018) proposed that the higher project update frequency and lower project financing goals can improve project financing performance. An excessively high financing goal will cause backers to retain investment and reduce the likelihood of successful project financing. Block et al. (2018) found that there is a significant positive correlation between the frequency of project updates and the number of investments. The updated content and the relaxed language style of the project can improve the financing performance of the project; the length of the update and the content of business development or cooperation projects will not have much impact. Mahmood et al. (2019) studied the impact of inefficient visual cues on project financing performance. The author found inefficient visual cues such as Logos, and the complexity of Logos. The proponents of the project believe that the complexity of the Logo is a signal of risk innovation. The more complex the Logo, the more unique it will be, and it will also have a positive impact on backers.

The third research line focuses on the influence of project social capital and value on project financing performance. Some research has concerned the influence of project social capital on project financing performance. Koning & Model (2013) believed that capital ownership would affect crowdfunding projects' financing performance. The authors proposed that capital ownership generally refers to human capital, social capital, and intellectual capital. The social capital of the project sponsors is not only capital possession in real life, but also on social platforms such as Facebook, which affects the financing performance of crowdfunding projects. The author considered that especially the social capital of social platforms has a significant impact on financing performance. Beier & Wagner (2014) researched tourism-based projects on the crowdfunding platform and found that an important factor affecting project financing performance is the project sponsor team's human capital. Ahlers et al. (2015) believed that the project sponsors' intellectual capital will also affect financing performance of crowdfunding projects, but the impact is not significant. Also, they found that the ratio of these two indicators, per capita investment is also an important indicator that most scholars study and is often used to measure crowdfunding projects' financing performance. Vismara (2016) focused on the influence of information about project backers on project financing performance. The author collected a total of 212 project samples through three platforms in the UK, and found that the public information of professional backers can improve the financing performance of the project, and all projects supported by professional backers have reached the financing goals. Bretschneider & Leimeister (2017) found that social relations and interaction with crowds will positively impact the project's financing performance.

Clauss et al. (2018) believed that increasing social activities in the process of project financing can improve the project's financing performance, which indicates that the success of the project is related to the number of backers and the perception and common attributes of backers. Borst et al. (2018) proposed that social networks can improve the project's financing performance, and new types of social media can provide more social capital. Gafni et al. (2019) believed that the project sponsor's performance on social media affects its financing performance. The more frequently the project sponsors mention their names to potential backers, the higher the success rate.

Wash & Solomon (2014) believed that project value mainly includes economic value, service value and donation value. The cost is generally considered to be the monetary cost of the backer when investing. Through research on donation-based crowdfunding projects, Meer (2014) discovered that the donation's cost directly affects the backer's motivation to contribute, and it also affects the financing performance of the project. Pitschner & Pitschner-Finn (2014) compared profitable and non-profit projects. The authors found that non-profit projects are more likely to achieve financing goals and receive higher personal investment than profitable projects. Cholakova (2015) proposed that by comparing the project's economic and non-economic factors, economic factors significantly impact the project's financing performance. However, non-economic factors did not have much impact. Profatilov et al. (2015) believed that project value affects financing performance because backers' primary motivation is the return. The higher the project value, the easier it is to get a better return. Gorczyca & Hartman (2017) considered that charitable crowdfunding projects are more likely to attract backers' attention and have a higher investment rate, which also confirms the view that project value impacts financing performance. Carè et al. (2018) found that urban development's social value can affect projects' financing performance, such as smart cities in Italy. These projects are generally donation-based or reward-based, and most of the time without high return. However, these social values have improved the project’s financing performance. Hsieh et al. (2019) studied some crowdfunding projects in Asia. The authors proposed that the success rate of crowdfunding projects related to social movements is higher than that of general projects, especially those projects with public orientation. This view also confirms the influence of project value on project financing performance. Besides, some scholars have put forward different perspectives, such as Cowden & Young (2020) found that some project sponsors obtained higher financing performance by copying or imitating other projects regardless of the loss of their project value.

2.3 INTEGRATIVE THEORIES IN CROWDFUNDING: AI, NEURAL NETWORKS, AND PERFORMANCE EVALUATION

2.3.1 Basic theory of the neural networks

Artificial neural networks mimic the neural way the human brain processes information. It can be trained using sample information to have brain-like memory and recognition capabilities (Thakial & Arora, 2019). The neural networks signal processing needs to satisfy formula (1):

$$\varphi = y(\sum_{j=1}^{i} N_j \mathcal{F}_j - \beta \quad (1)$$

Input i signals in the neuron, through the activation function $y(i)$ of the neuron, and the threshold β of signal processing, the final output signal φ, N_j represents the weight of the input point.

A complete neural network is formed by combining several different neurons at a scientific level and sequence (Lee et al. 2018). The neural network generally consists of three parts: input layer, hidden layer, and output layer.

The neural network is a typical topological structure. The research field divides the neural network topology into feedforward neural networks and feedback neural networks. The feedforward neural network adopts a unidirectional multi-layer structure. Each neuron is only connected to the neurons in the previous layer, and there is no feedback between layers. In the feedback neural network, neurons not only need to receive signals from other neurons but also need to receive their own feedback signals (Lee et al. 2018). Supposing that there are two neurons in the output layer, three neurons in the input layer and the hidden layer, x is the sample size, which is expressed as:

$$\mathrm{Train} = \{(\mathrm{K}_1, \mathrm{M}_1), (\mathrm{K}_2, \mathrm{M}_2), \ldots, (\mathrm{K}_\mathrm{x}, \mathrm{M}_\mathrm{x})\} \ (2)$$

In the case where each side in the neural network has a weight, supposing the weight matrix between the hidden layer and the input layer is:

$$Q^{[1]} = \begin{bmatrix} a11 & a21 & a31 \\ a12 & a22 & a32 \\ a13 & a23 & a33 \end{bmatrix} \ (3)$$

The number of rows in the matrix is equal to the number of neurons in the hidden layer, and the number of columns in the matrix is equal to the number of neurons in the input layer.

$$Q^{[2]} = \begin{bmatrix} a11a21 & a31 & a41 \\ a12a22 & a32 & a42 \end{bmatrix} \ (4)$$

In the above matrix, the number of rows of the matrix is equal to the number of neurons in the output layer, and the number of columns of the matrix is equal to the number of neurons in the hidden layer. The biases of the hidden layer and the output layer are respectively recorded as:

$$p^{[1]} = [p1^{[1]}, p2^{[1]}, p3^{[1]}, p4^{[1]}]x^{i} \ (5)$$

$$p^{[2]} = [p1^{[2]}, p2^{[2]}, p3^{[2]}, p4^{[2]}]x^{i} (6)$$

2.3.2 AI and crowdfunding

Artificial neural networks are an effective prediction technique. Many existing studies have proved that using neural networks can improve the prediction accuracy of traditional models (Thakial & Arora 2019). Using neural network models to study the influencing factors of the financial performance of ECF is the focus of current research. Existing studies such as Thakial & Arora (2019) briefly review the development of artificial neural networks at the current stage. Techniques and applications such as multilayer perceptron, T-S fuzzy neural network, support vector machine, radial basis function network, Levenberg-Marquardt algorithm, and backpropagation are also proposed. They also proposed a neural network-based candidate prediction model for predicting projects for various candidates based on certain parameter ratings.

Existing research provides evidence that deep learning can help predict the outcome of crowdfunding projects in advance. Whether project sponsors, project backers, or crowdfunding platforms can benefit from predicting the outcome. Several studies have focused on using artificial intelligence models to predict the success of crowdfunding projects. Lee et al. (2018) built a DNN model with textual data from item descriptions as samples. The results show that their neural network model can predict the success of crowdfunding projects well. Cheng et al. (2019) have studied how to predict the success of crowdfunding projects based on neural networks, and they believe that image features in project descriptions are the key. Duan et al. (2020) investigated whether an entrepreneur's facial trustworthiness affects the success of a crowdfunding project by using machine learning-based face detection technology. They found that the facial trustworthiness of entrepreneurs positively affected the success of crowdfunding projects, and it was particularly significant in female entrepreneurs.

More recently, Wang et al. (2020) introduced a deep learning algorithm (Multilayer Perceptron) and used it to predict crowdfunding performance. They compare deep learning to other commonly used machine learning algorithms. The experimental results show that the prediction accuracy of the deep learning model for crowdfunding fundraising results is 92.3%, giving the best prediction results. Shi et al. (2021) used machine learning to study the impact of multimedia information in crowdfunding projects. They demonstrated that artificial intelligence could be used to predict the success of crowdfunding projects by training a machine learning model based on audio analytics. Korzynski et al. (2021) focused on artificial intelligence in technology-related videos to predict the success of crowdfunding projects. They found that self-presentation and exemplification techniques positively impacted project success, while intimidation was the opposite.

Some studies also focus on AI's impact on crowdfunding performance. Yuan et al. (2016) developed a text analysis-based neural network model, Domain-Constrained Latent Dirichlet Allocation (DC-LDA) topic model, to study the topic features of texts in project descriptions, thereby helping entrepreneurs to screen the most crucial text information in the project description and improve the financing performance of the project. Shafqat & Byun (2019) focused on fraudulent activities in crowdfunding projects and used a neural network architecture based on language modeling to classify the content of comments in crowdfunding projects, thereby helping backers find safer and more suitable projects. Raab et al. (2020) studied the impact of facial expressions on investment motivation using machine learning based on emotion contagion theory. They found that happy and sad facial expressions were positively correlated with investment motivation, but high-intensity facial expressions were negatively correlated with investment motivation expressions. Peng et al. (2021) have studied the application of ensemble-based machine learning algorithms in medical crowdfunding, and they believe that the fundraising amount of medical crowdfunding projects can be predicted by machine learning.

2.3.3 Nural networks and crowdfunding successful prediction

In recent years, artificial intelligence and machine learning have been constantly mentioned by scholars. Machine learning has also become an efficient tool for researchers in data analysis and has been applied to various research fields (Ghahramani, 2015). As one of the essential fields of artificial intelligence, artificial neural network (ANN) has also developed rapidly. Many existing studies have proved the advantages of the ANN model in data regression prediction analysis, and the ANN model has a good performance in optimizing the prediction ability of traditional models (Thakial & Arora, 2019).

Many scholars have confirmed that ANN models can optimize crowdfunding project success predictions, which can help all participants in crowdfunding. Earlier studies, such as Greenberg et al. (2013), pioneered testing a variety of machine learning classifiers, and their model was able to predict crowdfunding project success with 68% accuracy. Mitra & Gilbert (2014) studied a large amount of phrase data from crowdfunding platforms and social media based on neural network models, they found that the data can be surprisingly predictive of the success of crowdfunding projects. Li et al. (2016) defined the success of crowdfunding projects as a matter of survival. They also developed a neural network algorithmic model to predict the success of crowdfunding projects based on big data from Twitter. Similarly, Lee et al. (2018) established an ANN prediction model and proved through empirical research that the ANN model can accurately predict the success of crowdfunding projects.

In DCF's research, there is enormous variability between projects and much uncertainty about donors so that machine learning can capture the nuances correctly. Cheng et al. (2019) developed a multimodal crowdfunding neural network prediction model, which can recognize information such as images, text, phrases, etc., and improve the prediction ability of the machine learning model. Wang et al. (2020) compared standard machine learning algorithm models, including decision tree, random forest, logistic regression, support vector machine, and K-nearest neighbors. After adjustment, their neural network algorithm model can predict crowdfunding results with 92.3% accuracy. Shi et al. (2021) focused on the impact of audio information on crowdfunding project success. They trained an audio perception model through machine learning techniques and used it to predict the success of crowdfunding projects. In addition to audio information, there is also video information. Korzynski et al. (2021) established a machine-learning model based on video information released by crowdfunding projects to predict the success of crowdfunding projects.

In addition to neural networks, some authors, such as Duan et al. (2020), have also focused on the application of machine learning in predicting the success of crowdfunding projects. Based on facial recognition technology, they found that the facial credibility of project sponsors can affect the success of crowdfunding projects. Similarly, Yeh & Chen (2020) built a successful prediction model for crowdfunding projects based on big data from social media, and their research developed a machine learning modeling method to extract relevant features of crowdfunding projects. Peng et al. (2021) developed an integrated machine-learning algorithm model to predict the financing performance of crowdfunding projects. Jiang et al., (2022) used neural networks in the equity crowdfunding success factor analysis model, and their model predicted project success with a 97% accuracy rate.

3

THE DATABASES

As a populous country with immense market potential, China has experienced rapid development despite its delayed entry into the crowdfunding industry. As of May 2020, China's crowdfunding projects have surpassed those of any other nation in terms of total value, reaching $7.049 billion and continuing to grow at an annual rate of 13.1%. It is projected that by 2023, the total transaction volume will reach $10.2083 billion (STATISTA, 2020). This thesis posits that China's crowdfunding industry data serves as a more representative example for many emerging economies.

This thesis comprises four empirical studies that examine the financing performance of three types of crowdfunding, namely ECF, RCF, and DCF. Additionally, it investigates the motivations behind donations from DCF supporters. In this chapter, a detailed analysis of each empirical study's database will be conducted.

3.1 EQUITY CROWDFUNDING FINANCING PERFORMANCE RESEARCH SAMPLE

3.1.1 Sample

In the first empirical investigation, this study uses the project on China's first and the largest ECF platform, "Renrentou"[1] as a sample. Renrentou is one of China's leading private crowdfunding platforms and an online investment and financing platform focusing on ECF. Renrentou has been at the forefront of promoting the growth of private crowdfunding in China, aiming to provide funding channels for startups and small enterprises while enabling ordinary investors to participate in their development. The operational mechanism of Renrentou involves startups or small businesses showcasing their projects on the platform to attract investments from a diverse range of investors. This platform operates with utmost transparency and standardization, mandating comprehensive project information such as business plans and financial data to ensure that investors have a thorough understanding of project circumstances and associated risks. Furthermore, regular monitoring and tracking mechanisms are implemented by the platform to safeguard investor interests. Investors can peruse various projects through the platform based on their interests and investment strategies.

In "Renrentou", all projects must have physical store chains with more than two stores, and the minimum investment of the project part is 10% of its equity. The platform backers are mainly based on ordinary people. Moreover, as one of China's largest civil crowdfunding platforms, it is the only platform that allows us to obtain data on the

---

[1] http://www.renrentou.com.

projects' dividends. Therefore, this study collected data on 600 projects that have been funded on this platform (“N" represents the number of samples). Since these data are independent and decentralized, various information needs to be searched separately and cannot be obtained with tools, so they need to be collected manually.

This thesis collected and used quarterly reports instead of annual reports of the projects published on the platform "Renrentou". Then, there are two companies in the sample have gone bankrupt when collecting sample data. However, their performance has been announced and does not affect this research.

3.1.2 Variable

Regarding the selection of variables, this chapter divides them into three types of influencing factors based on the data collected: the project sponsor company information, the company representative information, and the project-self information, as shown in Table 3.1.

VARIABLE		DESCRIPTION	SOURCE
The project sponsor company's information	D	"D" represents the number of years since the establishment of the company that initiated the project. The year in which the company that started the project was founded is "D", based on 2018, it calculates the time started up to the present.	Platform “Renrentou"
	E	“E” is the number of existing employees of the company that started the project. As the company usually publish their number of employees is a range of numbers , and as a result, the number of employees is floating. Therefore, this article uses the average of the numerical range.	Platform “Renrentou"
	NT	"NT" indicates the number of stores opened by the company that started the project. This article only considers the number of its direct stores. Since the assets of the chain stores are not part of the company that started the project, this article does not consider them.	Platform “Renrentou"

The company representative's information	ES	“ES” refers to the educational background of the person in charge of the company that initiated the project. This paper considers that a university degree or higher is higher education.	Platform “Renrento u"
	SP	"SP" indicates the gender of the person responsible for the company that initiated the project.	Platform “Renrento u"
The project-self information	OC	“OC” is the goal of crowdfunding. Similarly, the original data is RMB, and the calculation method is the same as “CR”.	Platform “Renrento u"
	CII	“CII” is the initial investment amount, which is the minimum amount of each investment, and the calculation method is settled in Euro.	Platform “Renrento u"
	TRE	“TRE” is the expected rate of return for the company that launched the crowdfunding project. The expected rate of return for most projects is not fixed, so this article uses the average.	Platform “Renrento u"
Calculated	TRR	“TRR” (ROE) is the actual rate of return for project investors. Delete the percent sign and use the decimal form to make it easier to calculate.	Calculated in this chapter
	RCR	(RCR) is calculated based on the currently collected projects' registered capital and total dividends.	Calculated in this chapter

Table 3.1. Variable definitions

The project sponsor company's information includes the company's operating time, number of employees and the number of branches already opened (Kuppuswamy & Bayus, 2018; Mahmood et al., 2019; Mazzocchini & Lucarelli, 2022; Mollick, 2014). The company's operating time (D) refers to the years from establishing the project sponsor company to the project's collection deadline (2020). Employees (E) refer to the number of existing employees of the project sponsor company. Since the number of employees in a company is continuously changing, the company usually announces its number as an interval value. Therefore, this chapter uses the average numbers. The number of stores (NT) refers to the number of branches opened by the project sponsor company. The present chapter only takes the number of its direct stores. Chain stores do not consider it because their assets do not belong to the project sponsor company. These variables are common financial indicators that can reflect the strength of the project sponsor company.

The company representative's information refers to its knowledge level (ES) and gender (SP) collected in this chapter. The company representative is the core of the company team. For startups, it often plays a decisive role (Daskalakis & Yue, 2017; Groza et al., 2020; Suseno & Abbott, 2021).

For the project-self information, since this study is aimed at ECF projects, the benefits will be more concerned. Therefore, this chapter uses the expected rate of return (TRE) announced by the project as a variable, reflecting the project sponsor company's prediction of the project quality. It also focuses on the initial investment amount (CII) and financing goal (OC). The initial investment amount refers to the minimum investment amount of the project. The financing goal refers to the expected value of the project sponsor company to raise funds. These two indicators also reflect the quality of the project.

In addition, based on the projects' collected financial data, this chapter calculates the actual rate of return, which is the indicator's ROE, which refers to the actual rate of return for project backers. Simultaneously, return on registered capital (RCR) is calculated based on the currently collected projects' registered capital and total dividends. It uses ROE and RCR as profitability indicators because they reflect the true quality of the project. Considering the general situation of the project, their industries have not been distinguished. The ROE calculation method this chapter used was the method commonly used in accounting calculated as the net income of a company divided by the total equity of the company. In the data published in these projects, the present chapter collected their net income and total investment through their quarterly reports to calculate the ROE. However, as these reports often lack many items, it is difficult to calculate other indicators.

3.2 REWARD CROWDFUNDING PERFORMANCE RESEARCH SAMPLE

3.2.1 Sample

In the second empirical study, this thesis will use data on RCF from China to study the financing performance of projects, that is, the ratios of financing over goals, and will use empirical analysis to explore which factors will affect the financing performance of these projects.

This research will use selected projects on China's reward-based crowdfunding platform JingDong[2] as data for empirical research.

As an innovative financing platform of JD Group, JD Crowdfunding aims to provide financial support for start-ups and innovative projects and attract a large number of consumers to participate. As one of China's leading e-commerce platforms, JD.com has leveraged its huge brand influence and user base to build a safe, transparent and efficient crowdfunding platform.

JingDong launched a crowdfunding business in 2014. Its extensive customer base and brand advantages have developed rapidly in the field of crowdfunding. According to the (China) January 2020 Crowdfunding Industry Monthly Report in January 2020, the number of projects on the JingDong platform that reached the financing goal was 241, an increase of 67.36% from the previous month, and it is also the platform with the most

[2] https://www.jd.com/

backers of successful financing projects, with about 177,600 users, an increase of 195.66% from December 2019.

The operating mechanism of JD crowdfunding is as follows: Entrepreneurs or project parties can publish their innovative projects on the platform and raise funds from users. These projects span multiple fields, including technological innovation, smart hardware, life aesthetics, etc. JD Crowdfunding provides a stage for start-ups to showcase their products and ideas, and also provides them with a financing channel to help them achieve rapid development of their projects.

Therefore, as a representative of China's reward-based crowdfunding platform, this research will use projects that have been successful on this platform to study the factors that affect financing performance.

First, this chapter uses web crawler software to collect 1,600 completed financing projects on JingDong from June 28, 2018, to April 13, 2019, all of which have completed at least 100% of the financing goal. This study also collects the dates from these projects, including project name, financing deadline, financing goals, actual financing amount, the number of project backers, the number of project followers, “Likes”, project progress and the minimum investment amount.

3.2.2 Variables

According to the research question raised in this thesis, the dependent variable is the ratio of financing over goals. It is an indicator to measure the performance of project financing, which is used to evaluate the over-fulfillment of the actual financing amount relative to the preset target amount. Specifically, this ratio is used to reflect the extent to which the funds obtained by the project during the financing process exceed the initially set target amount. This indicator is used to measure the financing performance of the project. The projects collected in this chapter are allowed to obtain financing beyond the financing goal within the financing period. The size of this indicator can be used to judge whether a project is popular with backers. As a result, it has more practical significance than general indicators for measuring financing performance, such as "success or no" or "whether the financing target is reached".

ID	VARIABLE	CATEGORY	DESCRIPTION	REFERENCES
1	Project followers	Social capital	The number of people interested in this project.	Bretschneider & Leimeister (2017); Clauss et al. (2018); Borst, et al. (2018)
2	Likes	Social capital	The number of people who like this project.	Gafni et al. (2019)
3	Project backers	Project information	The number of investors who have already invested in this project.	Kunz et al. (2017); Bretschneider & Leimeister (2017); Kuppuswamy & Bayus (2018)
4	Project progress	Project information	The project sponsor announces the progress of the project, also can continue the events there.	Block, et al. (2018)
5	Minimum investment amount	Project information	The minimum investment amount for project backers to participate in project financing.	Mahmood et al. (2019)
6	PCDI	Macroeconomic environment	The sum of final consumption expenditure and savings that residents can use.	Gallo et al. (2016)

Table 3.2. Independent variables

Regarding the choice of independent variables, this chapter is divided into three categories based on the collected data: social capital, project information, and the macroeconomic environment, as shown in Table 3.2.

This chapter selected the number of project followers and “likes” as the independent variables of social capital. Number of project followers is the number of people interested in this project. “Likes” is the number of people who like this project. Users who are interested in the project or support it can learn about the project through social media, follow or “like” it, so that the project can get more attention. The attention of the project measures the feedback mechanism of the crowdfunding platform and users on the crowdfunding project. This feedback mechanism not only reflects the encouragement and affirmation of potential backers to the project sponsor, but also explains the amount of social capital owned by the project to a certain extent (Dellarocas, 2003). When backers are faced with a large number of crowdfunding projects, only when the project successfully attracts potential backers can it be possible to convert social capital ownership into final investment. For example, Mollick (2014) pointed out that the degree of attention a project receives can mostly represent its final financing level.

The independent variables of the project information category include the number of project backers, project progress, and the minimum investment amount. The number of project backers is the number of investors who have invested in this project. Project progress refers the project sponsor announces the progress of the project, also can continue the events there. The minimum investment amount is the minimum investment amount for project backer to participate in project financing. Many researchers explored the impact of project information on financing performance from backer behavior and project value. They believed that project information such as project backers, project progress, and the minimum investment amount, are important aspects of measuring its value. It is of great significance to backers' decision-making and can affect backers' investment intention and investment quota. Therefore, researchers believed that project information affects financing performance (Mollick, 2014).

At present, many scholars such as Gallo et al. (2016) have paid attention to the relationship between the macroeconomic level and the microeconomic level. Also, considering that the macroeconomic environment may affect this chapter's results, a new variable has been added to the model: Per Capita Disposable Income Nationwide in China (PCDI). According to the definition of the (*Website "NATIONAL BUREAU OF STATISTICS OF CHINA,"* n.d.) (NBS). Disposable Income Nationwide refers to the sum of final consumption expenditure and savings that residents can use that contains income at the disposal of all residents, including cash and physical. Corresponding to the existing data, this chapter collects the PCDI of the NBS for each quarter from 2018 to 2019. Since the original data is the quarterly cumulative amount, this chapter regards it as the actual amount per quarter. Besides, as we know, financing is a continuous process rather than a time point. According to JingDong's data, the period is generally 60 days. this chapter needs to find the PCDI corresponding to the project financing period. The data collected includes project deadlines. Subtract them from the 30-day average financing period to obtain the corresponding PCDI. Therefore, to explore the relationship of PCDI on the ratios of financing over goals, this chapter speculates that PCDI will affect the ratios of financing over goals. In other words, the more deposits available to people, the more willing to participate in crowdfunding investments. Then, the original data is classified according to the quarter corresponding to the adjusted date. Because the quarter sample is unordered multi-classification data, it converts it into a dummy variable for regression analysis.

3.3 DONATION CROWDFUNDING PERFORMANCE RESEARCH SAMPLE

3.3.1 Sample

In the third empirical study, this research uses the projects on China’s largest DCF platform “Tencent Public Welfare”[3] as a sample. Tencent Charity is a social welfare platform launched by Tencent Group, which aims to promote the development and popularization of social welfare undertakings through technology and the Internet. As one of China's leading Internet companies, Tencent makes full use of its huge user base and technological advantages to build an open, transparent and efficient public welfare ecosystem, providing convenient channels and platforms for more people to participate in public welfare undertakings.

The operating mechanism of Tencent's public welfare is to push information on public welfare projects, fundraising activities, etc. through Tencent's multiple platforms (such as WeChat, QQ, etc.) to attract users to participate. These public welfare projects involve education, environmental protection, poverty alleviation, medical care and other fields, aiming to solve various problems and difficulties in society. Users can make donations, volunteer services and other forms of support through Tencent's public welfare platform to participate in and contribute to public welfare undertakings.

[3] https://gongyi.qq.com/

Because it has the most environmental and animal protection projects. This research selects all environmental and animal protection projects that have completed donations on the platform as samples. After excluding items with incomplete data, 700 items were finally obtained. Considering the particularity of these projects, they are independent, decentralized, and cannot be collected by existing technologies, so this research collected them manually.

3.3.2 Variables selection

Regarding the selection of variables, this chapter selects variables commonly used in existing DCF research. The definitions and sources of the variables are shown in Table 3.3.

ABBREVIATION	VARIABLE	DEFINITION EXPLANATION	SOURCE
R	Result	The dependent variable as the "success R" of the project, which is a binary variable. When the actual fundraising amount reaches the target amount, R is "1", indicating that the project is successful. Otherwise, R is "0", indicating that the project fails.	Calculated in this chapter
ND	The number of donors	The number of donors is often used in DCF research and is the most intuitive measure of a project's popularity (Belleflamme et al., 2014).	Platform “Tencent Public Welfare”
T	Project sponsor	Usually an individual or NPO, which is a binary variable, which may influence the motivation to donate.	Platform “Tencent Public Welfare”
NW	The number of words	The content of the project presentation may also affect the final donation amount (Solomon et al., 2015; Gallo-Cajiao et al., 2018).	Platform “Tencent Public Welfare”
NP	The number of pictures	The content of the project presentation may also affect the final donation amount (Solomon et al., 2015; Gallo-Cajiao et al., 2018).	Platform “Tencent Public Welfare”
TS	Transparency score	Developed based on four indicators that measure transparency. Each indicator corresponds to one point. Four points are awarded if four indicators are met. The higher the score, the more complete the materials, the clear and transparent the use of raised funds, and the more transparent the information disclosure of project sponsors.	Calculated in this chapter

Table 3.3. Variable definitions

Table 3.3 shows the definitions, interpretations, and sources of all variables in this chapter, depending on the goals, it hopes to examine what factors influence the success of environmental and animal protection projects in DCF. Then this chapter defines the dependent variable as the result "R" of the project. The target completion rate is not considered in this chapter because the target fundraising amount of the project is different, and the difficulty of achieving the same degree of completion is also different. Hence, it is not meaningful in the present chapter.

In addition, it considers project financial transparency as a variable (Hariwibowo et al., 2022; Král & Cuskelly, 2018; Ortega-Rodríguez et al., 2020; Zainon et al., 2014). In measuring transparency, this chapter collects four variables, shown in Table 3.4.

ID	Variable	Source
a	Whether there is an invoice	Platform "Tencent Public Welfare"
b	Whether the invoice is complete	
c	Whether there are financial statements (Balance Sheet, Income Statement, Cash-Flow Statement, Statement of Changes in Equity, Notes)	
d	Whether the invoice is consistent with the accounts	

Table 3.4. The financial transparency definition

The four variables shown in Table 3.4, are meaningful in projects completed by DCF. Although it does not directly affect the donation amount, it can reflect the public attitude toward the project sponsor. First, check whether there are invoices to ensure that the organization's financial activities are formally recorded (Hariwibowo et al., 2022; Ortega-Rodríguez et al., 2020). Invoices serve as a documentary record of transactions and help verify whether the organization is conducting formal financial operations. After the project is completed, the specific content of the use of funds will be published on the website, and invoices are the most common content. Secondly, a complete invoice should contain all necessary details, such as invoice number, invoice date, amount, service or product description, supplier information, etc (Ortega-Rodríguez et al., 2020; Rahmayanti et al., 2023). This information ensures the legitimacy and validity of the invoice. In addition to invoices, some projects also provide relevant financial statements for the use of funds, including information such as assets, liabilities, income, expenses and cash flow (Rahmayanti et al., 2023). Finally, verifying the consistency of invoices with accounts is a key step to ensure the accuracy of financial records (Hariwibowo et al., 2022; Zainon et al., 2014). This process involves comparing the invoice information with the ledger records to identify any discrepancies or omissions, this process is manually conducted by the author. In this chapter, a Transparency Score (TS) was developed based on these four indicators. Each indicator corresponds to one point, the higher the score, the more complete the materials, the clear and transparent the use of raised funds, and the more transparent the information disclosure of project sponsors.

3.4 DONATION CROWDFUNDING MOTIVATION RESEARCH SAMPLE

In the fourth empirical study, this research will discuss donor motivations for donating to AEP crowdfunding projects through the "Wen Juan Xing"[4] online survey. "Wen Juan Xing" is a Chinese online questionnaire platform that provides users with tools and services to create, share and analyze questionnaires. It is designed to provide users with convenient and flexible survey design, data collection and analysis solutions. As a professional provider of survey tools, Wen Juan Xing is committed to helping users design and manage various types of questionnaires and provides rich data analysis

[4] https://www.wjx.cn/

functions to meet users' needs in market research, academic research, social surveys and other fields. It provides almost the same functionality as "Google Workspace" and is widely used in China.

The operating mechanism of Wen Juan Xing is that users can register an account on the platform for free and design their own questionnaire using a simple interface and diverse templates. The platform provides a variety of question types and survey design tools that users can customize according to their needs. After the design is completed, users can publish the questionnaire online through the generated questionnaire link or embed code and invite respondents to participate in the survey.

To ensure the accuracy and credibility of the collected data, this research opts for the paid data collection service provided by the platform. Wen Juan Xing boasts over 2.6 million registered members, enabling the platform to effectively target and distribute the survey to the intended demographic. To enhance the accuracy of the survey distribution, this research plans to send out 2,000 questionnaires to users on the platform, aiming to achieve at least 1,000 valid responses. By utilizing the paid service, the platform can precisely match respondents according to the study's requirements, ensuring that the questionnaire reaches the appropriate audience efficiently.

During the data collection process, special attention was given to obtaining feedback from respondents with relevant knowledge about AEP projects. To ensure that the responses were representative and meaningful, the collected questionnaires were initially screened to exclude those from individuals with limited or no understanding of AEP projects. This screening process involved evaluating the respondents' familiarity with AEP projects to ensure that the final sample was both relevant and valid. After excluding invalid or incomplete responses, this research ultimately gathered 710 valid responses.

Following the completion of data collection, Wen Juan Xing's comprehensive data analysis tools were utilized. These tools include data aggregation, statistical analysis, and visualization features. Through these analytical capabilities, this research was able to perform an in-depth analysis of donor motivations and investigate the factors influencing donation intentions. The insights gained from this analysis provide valuable information for understanding donor behavior in relation to AEP crowdfunding projects and offer data-driven support for further research and practical applications.

4

IS EQUITY CROWDFUNDING THE LEAPFROG TO COMPANIES’ SUCCESS? FINANCIAL PERFORMANCE IN CHINA[5]

[5] This chapter has been Published in August 2022:

Jiang, C., Pérez-Estébanez, R., & Urquía-Grande, E. (2022). Is Equity Crowdfunding the Leapfrog to Companies’ Success? Financial Performance in China. *Computational Intelligence and Neuroscience*, 2022(C), 7814550. https://doi.org/10.1155/2022/7814550

Equity crowdfunding (ECF) has had a substantial impact on the traditional investment field. As a new investment and financing mechanism, entrepreneurs in need of funds can use ECF for quick financing. Therefore, this chapter proposes new ideas for improving ECF performance research. It focuses on the subsequent execution performance of projects that have completed financing, that is, the actual return of the project. It is planned to explore the factors affecting the investment return of ECF projects through empirical research. Research into factors that influence project returns can contribute to platforms, backers or fundraisers.

This chapter uses traditional linear regression and DNN models to conduct exploratory empirical analysis, focusing on the factors that affect the investment return of ECF projects. Neural networks have shown clear advantages in several evaluation projects, demonstrating their potential in predicting funding for crowdfunding projects. This chapter combines neural networks and Internet finance to provide many practical implications for future research. Henceforth, this chapter will address the following research questions:

RQ1: What factors affect the return on investment of equity crowdfunding projects in China?

4.1 METHODOLOGY

4.1.1 Traditional regression model

This chapter studies what factors can affect the return of investment on ECF projects in China. Therefore, it will use the project's profitability indicators, TRE, and RCR as independent variables. The project announces TRE, reflecting the project sponsor company's expectations of its returns. This chapter calculates RCR. It is the total dividend divided by the registered capital to calculate RCR. It is not the same as the ROA used in traditional accounting, as registered capital reflects potential rather than current actual capital, providing insights into profitability expectations. The present research focuses on the expected rate of return announced during financing and analyzes only projects that have completed their financing process. Since the financial statements required for traditional accounting methods are unavailable, alternative indicators are used. Moreover, using the actual rate of return (TRR), that is, ROE as the dependent variable. As the most direct measurement indicator, it can reflect the real return on investment of the enterprise.

In this chapter, the multiple linear regression model is used for testing after using the Poisson model to eliminate the autocorrelation factors between independent variables. It can reflect whether the two profitability indicators of TRE and RCR can affect the true rate of return, as shown in formula (4-1).

$$TRR = \beta_0 + \beta_1 TRE + \beta_2 RCR + \varepsilon \quad (4\text{-}1)$$

This chapter’s pre-testing revealed that even after applying logarithmic transformations to both the independent and dependent variables in the OLS regression model, heteroscedasticity persisted. Therefore, this chapter adopts the Binary Logistic Regression model to mitigate the influence of heteroscedasticity on the results, thereby providing a better explanation for *RQ1* of this thesis. Therefore, it defines a new independent variable R. The independent variable R represents the result. When the value of TRR is greater than or equal to TRE's value, R is "1", which means the project is a "success". When the value of TRR is less than TRE’s, R is "0", indicating that the project failed. Therefore, the research model currently is:

$$R = \beta_0 + \beta_1 D + \beta_2 E + \beta_3 RCR + \beta_4 NT + \beta_5 ES\_yes + \beta_6 \mathrm{SP\_woman} + \beta_7 \mathrm{OC} + \beta_8 \mathrm{CII} + \beta_9 \mathrm{TRE} + \varepsilon \quad (4\text{-}2)$$

Where:

D is “the company's operating time”; E is “number of employees”; NT is “the number of branches already opened”; ES is “the knowledge level of company representative, that is, whether the company representative has received higher education”, as a dummy variable, it is divided into "ES_yes" and " ES_no"; SP is “gender of company representative”, as a dummy variable, it is divided into "SP_woman" and "SP_man".; OC is “financing goal”; TRE “expected rate of return”; CII is “the initial investment amount”.

In this chapter, the sample data were preprocessed, and the natural logarithm of all numerical variables was taken to eliminate the effect of scale between variables.

4.1.2 Applicability of the DNN model

The DNN model is relatively cumbersome and complex, involving a large number of training parameters. How to choose the training method and to obtain the required learning parameters is a key link worthy of in-depth thinking. In the era of artificial neural networks, the depth of the model is at most three layers, and the learning parameters involved are relatively small. It can obtain a completer and more reasonable model through a simple BP algorithm. With this advantage, the BP algorithm is favored and respected by people in the industry, and it has been vigorously promoted and actively applied in many fields. However, BP neural network is not perfect. It also has its limitations. In practical analysis, due to the use of a large number of parameters, the search space of the algorithm is huge, resulting in more complex error surfaces, and it is easy to obtain poor local optimal solutions. And the experimental sample data is directly related to the final performance of the algorithm. If the sample is poorly representative or contradictory, it is difficult for the model to achieve the expected performance. In the process of training through the BP algorithm, the gradient dispersion phenomenon tends to be further aggravated, affecting the performance of the model. Moreover, compared with other neural networks, the operation speed of BP neural network is slower.

For the above problems and deficiencies, pre-training methods can be used to avoid them. Exploiting unlabeled data in an unsupervised form provides objective and accurate initial parameters for subsequent training. Satisfactory results can be obtained even with very little labeled data. Given the problems of the recurrent neural network, the farther the node is from the current node, the effect of the current node processing gets smaller and smaller. However, this chapter considers that the data parameter dimension in this research is not constrained in terms of efficiency. Therefore, the DNN model established in this chapter corresponds to Formula (4-2), and the output layer is the binary logic result, that is, the "success" or "failure" of the crowdfunding project.

4.2 RESULTS

4.2.1 Traditional linear regression analysis

To address RQ1, which investigates the factors influencing the return on investment of ECF projects in China, this chapter conducts two empirical analyses. The first analysis examines the effect of two selected profitability indicators on the expected profitability of the projects. The regression analysis is performed using model (4-1), and the corresponding results are presented in Table 4.1.

Model (4-1)	Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	R Square	Adjusted R Square	Durbin-Watson
(Constant)	-2.316	0.176		-13.148	0			
LINT(LnRCR)	0.207	0.033	0.409	6.271	0	0.18	0.171	1.772
LINT(LnTRE)	-0.231	0.092	-0.164	-2.517	0.013			

Table 4.1. Regression Results for Model (4-1)

First, the R-square value is 0.180, and the Adjusted R-square value is 0.171. Since the equation in this research belongs to the explanatory regression equation in social sciences, 17.1% descriptive degree has specific statistical significance (Similarly, such as Mollick, 2014 proposed the optimal R-square among the six models in his research is 0.18). Durbin-Watson’s value is 1.772, which indicates that the variables in this chapter have no serial correlation, and the equation is not pseudo-regression. Since the Sig. values of LnRCR and LnTRE are 0.000 and 0.013, both are less than 0.05. Reject the null hypothesis within the confidence interval of P=0.05. That is, both independent variables can significantly affect the dependent variable TRR.

The B value of LnRCR is 0.207, which is significantly positively on TRR. This shows that the higher the RCR of the project sponsor company, the higher the actual rate of return. This is consistent with the speculation in this chapter when selecting variables. The higher the expected value of the project's profitability, the more actual returns. The B value of LnTRE is -0.231, which has a negative impact on the dependent variable TRR. This means that the higher the expected rate of return of the project sponsor company, the lower the project’s actual return. This result also reflects that project sponsors may overestimate their projects' quality and set excessive project return expectations to attract backers. Moreover, this negative effect shows that this phenomenon is not an exception in this chapter's samples.

The second test tests the effect of all independent variables on return on investment. In this part, it uses the binary logistic regression model that is the model (4-2) for analysis.

Observed		Predicted		
	Result	Failure	Success	Percentage Correct
Step 1	Failure	495	15	97
	Success	45	45	50
	Overall Percentage			90

a. The cut value is .500

Table 4.2. Classification table

According to the definition of this research, the R-value is 1 equal to the project "success", the R-value is 0 means the project "failure". As shown in Table 4.2, "success" occurred

90 times, and "failure" appeared 510 times. The research model of this chapter simulates the overall prediction accuracy of 90.0%.

Table 4.3 reflects the impact of the nine independent variables on the dependent variable. The value of the R-squared of Cox and Snell is 0.260, indicating that the degree of interpretation of the independent variable by the dependent variable is 26.0%. Nagelkerke's R-square value is 0.455, which shows that the model in this chapter is meaningful.

Model (4-2)	B	S.E.	Wald	df	Sig.
LnD	1,384	,549	6,354	1	,012
LnE	-,492	,297	2,743	1	,098
LnNT	-,011	,163	,004	1	,947
ES_YES	-,940	,533	3,106	1	,078
SP_WOMAN	-,693	,798	,754	1	,385
LnOC	-,172	,329	,274	1	,601
LnCII	,260	,498	,273	1	,601
LnTRE	-1,526	,285	28,571	1	,000
LnRCR	,190	,108	3.088	1	,079
Constant	-2,651	4,315	,377	1	,539
-2 Log likelihood	108.763a				
Cox & Snell R Square	0.26				
Nagelkerke R Square	0.455				

Table 4.3. Regression Results for Model (4-2)

The results in Table 4.3 show that the project sponsor company's operating time has a statistically significant positive effect on the investment return within the confidence interval of p-value of 0.05. This implies that the longer the project sponsor’s company has been operating, the more likely the actual rate of return of the project will reach the expected rate of return. This result confirms the variable selection in this chapter that a powerful company can only operate for a long time. In contrast, a company lacking strength cannot operate sustainably. Companies that have been operating for a longer time tend to have accumulated deep experience, which enables them to better respond to various market changes and challenges.

Surprisingly, the results found that the number of employees of the project sponsor company and the return on investment was statistically negatively correlated within a confidence interval of a p-value of 0.05-0.10. The number of employees of the project sponsor company has a statistically negative effect on the investment return within the confidence interval of p-value of 0.05-0.10. This means that the greater the number of employees in the project sponsor company, the more difficult it is for the actual rate of return of the project to reach the expected rate of return. This result is contrary to the speculation of variable selection in this chapter. Although not a statistically significant negative correlation, this result is also noteworthy. This chapter speculates on the reason for this result, which may be due to a large number of employees, making the company’s management more difficult. However, this chapter cannot determine the specific cause of this phenomenon.

The knowledge level of the company representative has a statistically negative effect on the investment return within the confidence interval of p-value of 0.05-0.10. This implies that if the company representative of the project sponsor company has received higher education, their project’s actual rate of return is more challenging to achieve the expected rate of return. This result is inconsistent with common sense. this chapter speculates that this phenomenon may be because the highly educated company representative overestimated the project's rate of return.

The expected rate of return of the project has a statistically significant negative effect on the investment return within the confidence interval of a p-value of 0.05. That shows that the higher the expected rate of return of the project, the more difficult it is to achieve the actual rate of return of the project. This result also reflects that the project sponsor may overestimate the quality of its project, making it difficult for the actual rate of return to reach the expected rate of return they have announced. The research of Cowden & Young (2020) also had similar results. They found that some speculators' projects only care about the amount of financing, not the project's quality. These projects give backers false and generous return signals, but these projects did not perform well after being financed. If a project sets an expected rate of return that is too high, it may give the impression that the project is mainly intended to attract investors rather than focusing on achieving the actual goals of the project or providing assistance to the beneficiaries. This mismatch may cause the project to fail to achieve the expected rate of return.

The registered capital return and investment return are positively correlated within the confidence interval with a p-value of 0.05-0.10.

The registered capital return has a statistically positive effect on investment return within the confidence interval of p-value of 0.05-0.10. When the project's registered return on capital is higher, the project's expected rate of return is more likely to be reached. This result also confirms the speculation in the selection of variables in this chapter. This profitability indicator reflects the real quality of the project. A company with higher profitability is more likely to succeed in the project.

4.2.2 Deep neural network analysis

The establishment of the DNN model structure in the research is built using the Keras framework. Keras is a deep learning API written in Python, it can speed up the training of the model (*Keras*, 2022). In this model, the selected neuron activation function is the ReLU function. The ReLU function is the most used activation function in deep learning model training, it is relatively simple to calculate, and it is easier to optimize when the operation of the neural network model is linear or close to linear. The loss function in this study is cross-entropy, Adam is chosen by the iterative optimizer, and the connection weights and biases of each layer are initially randomly generated. For the training of the model, after synthesizing the literature and the actual situation, this chapter decides that the number of times each training is 50, with a total of 10 iterations, and the model is evaluated after the training. The present chapter considers the model by outputting the loss function value of the DNN model and the accuracy of the test set.

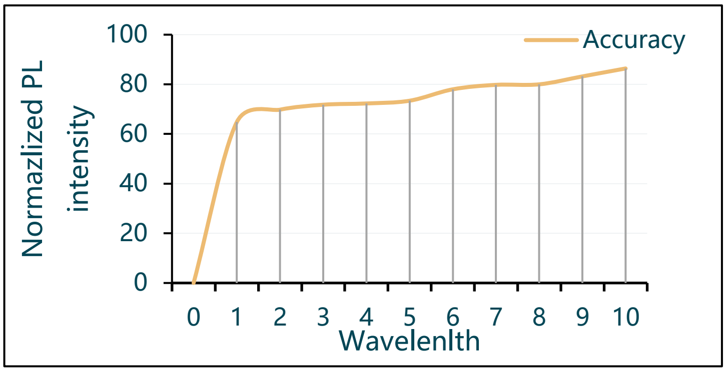

Figure 4.1. Prediction results of DNN after 10 times of training

As shown in Figure 4.1, the experimental results of the DNN model shown in the above figure show that after only 10 times of training, the accuracy rate on the test set has reached 86.4%. This good prediction effect preliminarily proves that the DNN model can be applied in the research field of success factors of Internet ECF projects. Therefore, in the following work of this chapter, the number of trainings will be increased to observe the prediction accuracy after training.

This research uses the Python deep learning framework as a tool to build DNN-based success factors for the ECF identification model. In this chapter, the data is made according to the ratio of the training set and the test set to 2:1. After the production, there are 400 training sets and 200 test sets. To maintain consistency with the regression experiments in 4.1 of this chapter, it defined two types of ECF projects: “failures” or “success”. So, the class of the output layer is 2, and a SoftMax classifier is used to calculate the output probability for each category. The schematic diagram of the ReLU activation function expression used is shown in Figure 4.2, and the expression is as follows:

$$y(u) = \frac{1}{1+c^{u}} \quad (4\text{-}3)$$

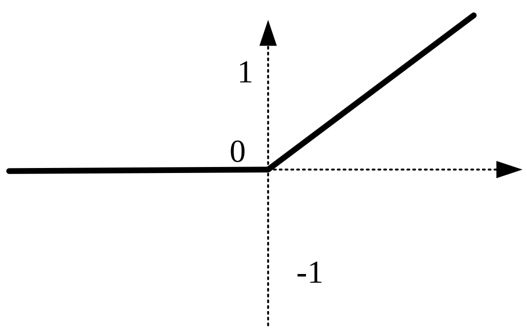

Figure 4.2. ReLU function diagram

Then set the hyperparameters, the learning rate set to 0.001, the number of iterations is set to 40, the number of batches for each processing is 10, and the loss function selects the cross-entropy loss function, and the training method is retraining. During the training process, we always need to pay attention to the changes in the two parameters of loss and accuracy. The loss curve and accuracy curve of the built DNN model is shown in Figure 4.3:

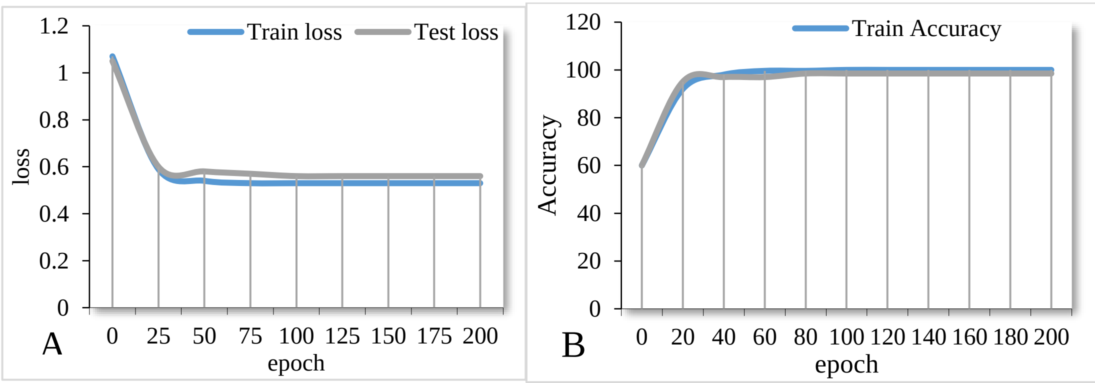

Figure 4.3. The loss curve and accuracy curve of the neural network model

As seen from the loss graph shown in Figure 4.3-A, there are two curves in the figure, and the change trends of the two curves are basically the same. It starts to drop rapidly from the loss value of about 1, and after 25 iterations, the curve declines slowly. Then the curve gradually becomes stable after 100 times. It shows that the network begins to converge, the training is completed after 200 rounds, and the loss value drops below 0.6.

From the accuracy curve shown in Figure 4.3-B, the training accuracy curve of the DNN network increases significantly with the increase of the number of iterations. It starts to slow down around 15 rounds, and as the level increases, it converges at around 80 rounds, and the accuracy rate reaches 100%, and it remains stable until the end of the training. The changing trend of the test accuracy rate is slightly different. The accuracy rate starts to rebound sharply at 60% in the 5th round and is roughly the same as the changing trend of the training accuracy rate, reaching 95% in the 14th round. After the hierarchical increase, it converged in about 60 rounds, and the accuracy rate went to 98.5%, and it remained stable until the end of the training. It can be seen from the loss curve and accuracy curve that the DNN network converges stably. As can be seen from the accuracy and loss values, the generated model performs better.

Observed		Predicted		
	forecast result	0 (Failures)	1 (success)	Percentage
The actual situation	0 (Failures)	167	3	98.2
	1 (success)	3	27	90
	Overall Percentage			97

Table 4.4. Neural network model confusion matrix

After it is concluded that the generated model is convergent and has good performance, the verification analysis of the developed classification model is carried out, and some common indicators test the model performance. The first is the confusion matrix analysis. From the production of the data set, there are 200 data in the test set. The classification results of the data are shown in Table 4.4.

After the model operation, the prediction results can be seen in Table 4.4. Through this table, we can clearly and intuitively understand that the total error of DNN classification is about 3%, which clearly shows that DNN has a decisive advantage in predicting ECF projects. Compared with the 90% accuracy of the prediction results of the logistic regression model in this chapter (shown in Table 4.2), the DNN model predicts 97% better performance.

ROC (Receiver Operating Characteristic Curve) curve is a comprehensive index reflecting continuous variables of sensitivity and specificity, and each point on it reflects the sensitivity to the same signal stimulus. In this study, the ROC curve can reflect the binary classification prediction results of the neural network model. Generally, the image plane area between the ROC curve and the coordinate axis is usually used as an important indicator to evaluate the prediction accuracy of the model, the higher the value, the better the prediction accuracy.

AUC (Area Under Curve) is defined as the size of the area enclosed by the coordinate axis under the ROC curve, and the value ranges from 0.5 to 1. The closer the value of AUC is to 1, the higher the real degree of its use method, and when the AUC is equal to 0.5, it means that it has no practical value. In the Figure 4.4, the AUC values of category 0 and category 1, are 0.995 and 0.992, respectively, and close to 1. For an ideal classification model under study, if and only if the AUC value is 1. It can be seen that the performance of the DNN model proposed in this chapter is relatively good.

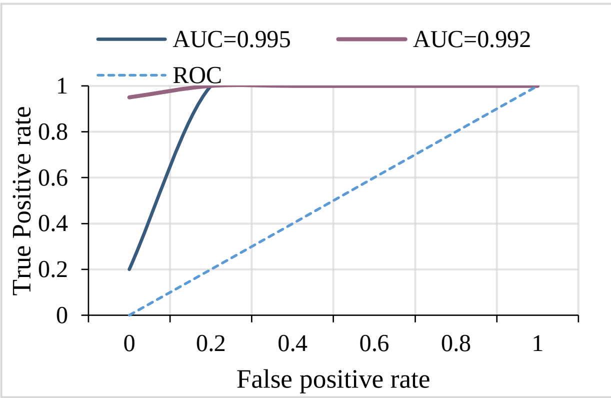

Figure 4.4. ROC curve and AUC value

This research uses the ROC package in the R language to draw random forests, decision trees, and support vector machine ROC curves, as shown in Figure 4.5.

As shown in A, B, and C in Figure 4.5, after calculation, the predicted AUC values of random forest three classifications are 0.99 and 0.97. The three-category prediction AUC values of the decision tree were 0.98 and 0.89. The support vector machine’s three-category prediction AUC values were 0.996 and 0.98. Compared with the above results, the three-category prediction AUC value of the DNN algorithm has the best effect and the highest accuracy. In particular, category 1 is significantly higher than other algorithms. It shows that the DNN model has exceptionally high sensitivity and accuracy in identifying ECF project success.

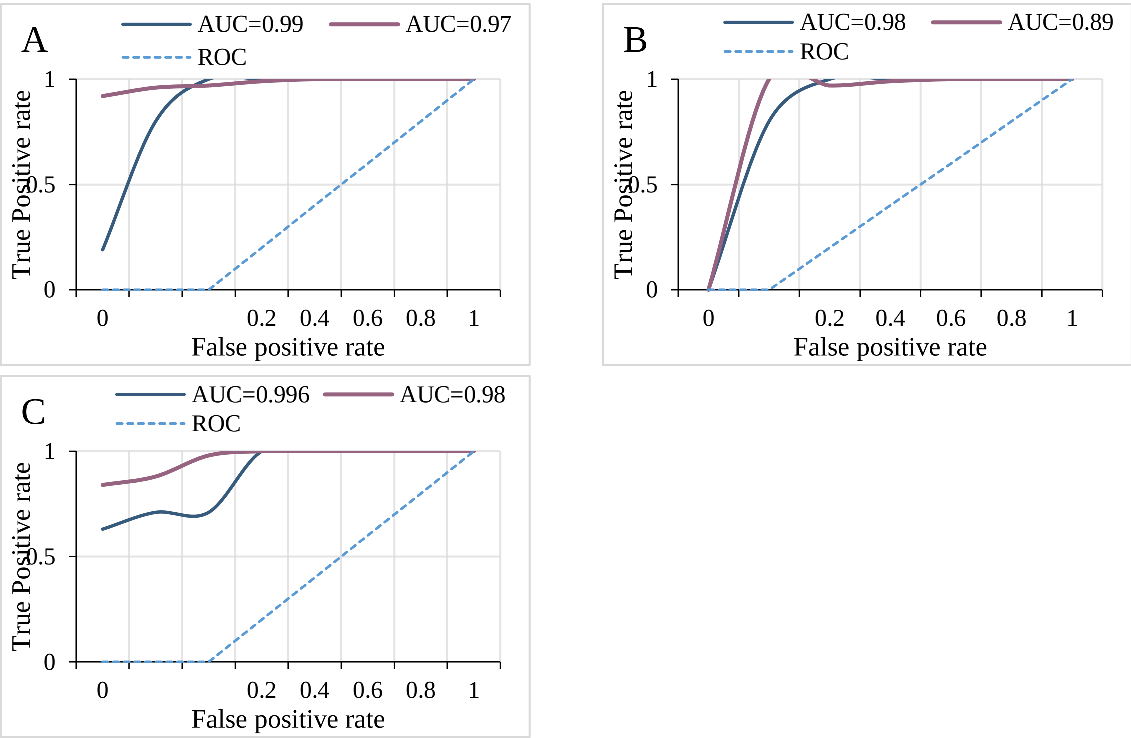

Figure 4.5. ROC curve and AUC value

At the same time, to minimize the impact of the different distribution of training samples on the accuracy of model analysis, this research uses the ten-fold cross-check method to test the model’s fur. First, we divided the research index data into ten parts on average, then defined nine index data as datasets according to a particular order. The selected data were used for testing, and ten repeated results were obtained. The average misjudgment rate was used to measure the pros and cons of the DNN for ECF projects.

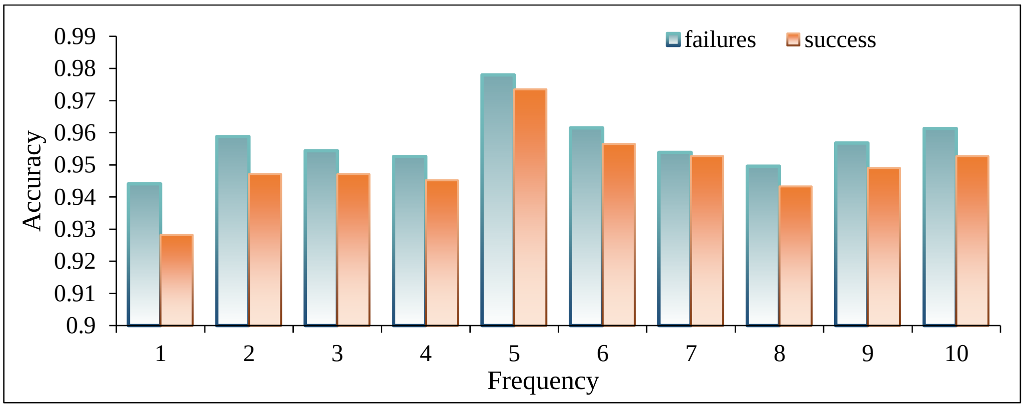

Figure 4.6. Ten-fold cross-check results

It can be seen from Figure 4.6, the average model prediction accuracy of category 0 and category 1 are all-around 95%. It can be seen that the prediction accuracy of the model is high, which shows the validity and objectivity of the sample classification.

feature	Importance
D	13
E	-5.8
RCR	3
NT	-1.6
ES	-6
SP	-0.6
OC	-0.1
CII	0.1
TRE	-14

Table 4.5. Importance of features

According to Table 4.5, factors such as the company's operating time, number of employees, expected rate of return, and the actual rate of return that can be borne have an important impact on the success of the ECF project. Among them, the company's operating time and the expected rate of return have the most significant effect on ECF projects. The results are similar to our results in the linear model (4-2).

4.3 RESULTS DISCUSSION AND CONCLUSIONS

This chapter uses traditional linear regression and DNN models to conduct exploratory empirical analysis, focusing on the factors that affect the investment return of ECF projects, aiming to answer *RQ2* proposed in this thesis, which factors determine the financing performance in RCF projects in China.

This chapter finds that the expected rate of return and registered capital rate of return indicators defined in this study can significantly affect the actual rate of return. Facts have proven that profitability indicators calculated using financial data can truly reflect the quality of the project (Graziano et al., 2023; Mazzocchini & Lucarelli, 2022). However, regarding the negative impact of expected return, this chapter believes that project sponsors may overestimate project quality and set higher project return expectations to attract investors.

For the logistic regression model, the results show that companies that can operate in the long term are stronger, and companies with certain strength are better able to formulate reasonable and achievable expected returns and are more likely to succeed. Additionally, it was found that having too many employees makes it more difficult to manage a company. This will affect the healthy operations of the company and lead to poor financial conditions and difficulty in achieving success. Additionally, this chapter finds that highly educated company representatives are likely to overestimate project returns. Furthermore, this chapter speculates that company representatives without higher education are more willing to show funders the reality of their projects and that their entrepreneurial goals appear more authentic.

Besides, this chapter proposes to use a DNN model to gradually identify and predict the influencing factors that affect the success of the financing. It also trains and indicates the model to obtain better training prediction results. It proves that the prediction performance of the DNN model on the ECF factor of success is relatively good. After the verification and analysis of the classification evaluation index of the DNN model, it shows the scientific, objectivity, and rigor of the empirical evidence, using cross-validation with other classification models. It shows that compared with the traditional regression model, random forest, support vector machine, and decision tree, the comprehensive effect of the DNN model is the best, and the accuracy is the highest.

This chapter does not discuss why the success rate is so low. However, Cowden & Young (2020) pointed out one of the alarming reasons in their study: some entrepreneurs steal other people's ideas to attract investment and use ECF to deceive backers. For ECF, although there is currently no way to eliminate these "junk" projects, the transparency of the project will increase as the industry develops and matures. As industry supervision improves, project quality will also improve.

However, this chapter cannot trace and characterize the specific influencing factors of all results. This is also one of the research limitations of this chapter. Another limitation is that the ECF project has been unable to obtain complete financial statements for the project. This article is based on some original financial variables. Research on the financial transparency of ECF projects will become one of the new goals of future ECF research. More transparent financial statements can encourage supporters to invest, and from a macro perspective, can also contribute to the sustainable development of the crowdfunding industry.

5

RESEARCH ON THE PERFORMANCE FACTORS OF REWARD-BASED CROWDFUNDING: EVIDENCE FROM CHINA[6]

[6] This chapter has been Published in October 2021:

Jiang, C., Urquía-Grande, E., & Estébanez, R. P. (2021). Research on the performance factors of reward-based crowdfunding: evidence from China. *Revista Raites*, 7(15).

Compared with traditional financing methods, crowdfunding is based on the Internet and breaks through the limitations of geographical, time and other factors, thus enabling the rapid development of crowdfunding. Reward-based crowdfunding (RCF) is one of the most popular types of crowdfunding supporters. In this chapter, this analysis uses the ratios of financing over goals to measure the funding performance of crowdfunding projects. Therefore, in order to contribute to this research direction, the purpose of this chapter is to study the factors that influence the financing performance (the ratios of financing over goals) of RCF projects.

This chapter considers expanding the sample size because previous studies often have limitations on this issue. It will select projects that have achieved financing goals on China's RCF platforms as data to study the financing performance of the projects. The current chapter will further explain which variables influence the financing performance of RCF projects. More broadly, it could provide evidence for research in the entire field of RCF performance. Henceforth, this chapter will address the following research questions:

RQ2: Which factors determine the financing performance in RCF *projects in China?*

5.1 METHODOLOGY

For the value of "y" (the ratios of financing over goals), this chapter found in the exploratory test that at least 6 decimal places must be retained to avoid interference with the regression results due to small differences, for example, if only 2 decimal places were kept as usual, this will cause the "y" value of most projects to be the same value, so this chapter keeps 8 decimal places.

Next, to reduce the influence of outliers on the results, this chapter has eliminated 1% of the extreme value data, which is the first 0.5% and the last 0.5% of the maximum value of "y".

In addition, this chapter no longer classifies all projects, because in the process of collecting data, whether it is Kickstarter or JingDong, the classification of the projects is very uncertain. Taking JingDong as an example, JingDong classifies all the projects into 8 categories: science and technology, food, home appliances, design, entertainment, culture, public welfare and others. However, the inclusion of multiple classifications in many projects hinders their clear categorization. Consequently, this chapter argues against classifying crowdfunding projects based on their ideas as it is deemed unreasonable and not recommended.

Anyway, first, this chapter constructs the following OLS model based on original data:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \gamma_1 + \gamma_3 + \gamma_4 + \varepsilon \quad (5\text{-}1)$$

Where:

y is the ratio of “financing goal” divided by “actual financing amount” of each project; X_1 is “project backers”; X_2 is “project followers”; X_3 is “likes”; X_4 is “project progress”; X_5 is “minimum investment amount”;X_6 is “PCDI”; γ_1 is “corresponding to 2019 first quarter”; γ_2 is “corresponding to 2018 second quarter”; γ_3 is “corresponding to 2018 third quarter”; γ_4 is “corresponding to 2018 fourth quarter”. In particular, γ_1-γ_4 are not arranged in chronological order.

Before regression analysis, in order to exclude the influence of multicollinearity between independent variables, this chapter uses the Poisson model to import all independent variables into the model. The results show that there is no multicollinearity among all the independent variables.

To obtain more accurate results, it is necessary to eliminate the influence of variable scale on the results and avoid heteroscedasticity in regression process. This chapter takes a natural logarithm for all variables when using SPSS.

5.2 RESULTS

After importing the sorted data into SPSS, Table 5.1 obtained the following results. Since the equation used in this chapter belongs to the explanatory regression equation in the social sciences, when R-square's value is greater than 0.2, it indicates that this equation can explain the data well. According to Table 5.1, the R-square value is 0.557, and the adjusted R-square value is 0.311, which shows that this regression equation can explain the data very well. The DW value is 2.033, indicating that there is no sequence correlation between the data, and the equation is not a pseudo-regression.

	Standardized Coefficients			Collinearity Statistics	
	Beta	t	Sig.	Tolerance	VIF
(Constant)		-15.029	<0.001		
LnX1	0.523	18.408	<0.001	0.548	1.823
LnX2	0.109	2.396	0.017	0.213	4.689
LnX4	0.057	2.351	0.019	0.741	1.35
LnX3	-0.092	-2.288	0.022	0.275	3.631
LnX5	0.115	5.118	<0.001	0.879	1.137
γ1	0.071	2.018	0.044	0.356	2.806
γ3	0.114	2.825	0.005	0.271	3.694
γ4	0.084	2.088	0.037	0.271	3.687
R-square = 0.311					
Durbin-Watson=2.033					

Table 5.1. Results

According to Table 5.1, the sig. values of X_1 (project backers), X_2 (project followers), X_3 ("likes"), X_4 (project progress), and X_5 (minimum investment amount) are all less than 0.05, and these independent variables will affect the dependent variable y (the ratios of financing over goals). In addition, the VIF values of all independent variables are less than 10, which means that there is no multicollinearity between independent variables. Then through their specific coefficients, it can be concluded that X_1 (project backers), X_2 (project followers), X_4 (project progress) and X_5 (minimum investment amount), all these dependent variables have a positive correlation effect on the independent variable y (the ratios of financing over goals); X_3 ("likes") has a negative correlation effect on y (the ratios of financing over goals); for other independent variables, this chapter did not find statistical significance and correlation with the dependent variable.

Then, this chapter continues to explore the impact of PCDI on the ratios of financing over goals. According to Table 5.1, γ_1(2019 first quarter), γ_3(2018 third quarter) and γ_4(2018 fourth quarter) are converted into dummy variables, and the reference variable is γ_2(2018 second quarter). Since the sig values of dummy variables are all less than 0.05, it means that they all have significance. Next, the B values of γ_1, γ_3, and γ_4 are 0.161, 0.207, and 0.154, respectively, which indicates that the impact of the first quarter of 2019, the third quarter of 2018, and the fourth quarter of 2018 on the ratios of financing over goals is higher than the second quarter of 2018. Comparing the PCDI collected in the original data, the first quarter of 2019 was 8493 yuan, the second quarter of 2018 was 6248 yuan, the third quarter of 2018 was 6972 yuan, and the fourth quarter of 2018 was 7193 yuan. PCDI was the lowest in the second quarter of 2018, so the null hypothesis was established, and there was a positive correlation between PCDI and the ratios of financing over goals.

5.3 RESULTS DISCUSSION AND CONCLUSIONS

As a financing tool that has now been widely used, crowdfunding is well known. More and more small and micro entrepreneurs are also using it to raise funds. Entrepreneurs initiate projects, and backers invest and support projects, so projects' financing performance becomes critical. this chapter takes the projects of the Chinese RCF platform as a sample, measures the financing performance by studying the ratios of financing over goals of the project, and discusses the factors that affect the financing performance.

The empirical part addresses RQ2 proposed in this thesis and aims to analyze the factors affecting the financing performance of crowdfunding projects. First, this chapter uses a multiple linear regression model for regression analysis, which involves six dependent variables: “project backers”, “project followers”, “likes”, “project progress”, “minimum investment amount” and “PCDI”. It also includes four quarterly dummy variables: “2018 second quarter”, “2018 third quarter”, “2018 fourth quarter” and “2019 first quarter”.

Through empirical analysis, it is concluded that the “project backers”, “project followers”, “project progress”, and “minimum investment amount” are all positively related to the financing performance of the project. Unexpectedly, the “likes” is negative correlation with the financing performance of the project. First, the more backers in a project, the higher the project's financing performance. This conclusion is logical. The number of project followers positively correlates with the project's financing performance. The social capital of the project sponsor can affect the financing performance of the project. This result is consistent with the previous views (Ramli et al., 2022). The more complete the project process, the higher the project's financing performance. It shows that the update speed and information quality of the project can improve the project's financing performance. This conclusion also confirms the views of researchers such as (Mazzocchini & Lucarelli, 2022; Moss et al., 2015). The higher the minimum investment amount, the higher the project's financing performance. One of the reasons is that the higher the minimum investment amount, the higher the value of the project. This chapter also speculates that the cost of the project product itself is high or that the project sponsor has confidence in its product and hopes to control the number of backers and screen out better backers. Therefore, the minimum investment amount is also positively related to the financing performance of the project. Previous views and some researchers are also consistent with the results of this research (e.g. Profatilov et al., 2015; Ramli et al., 2022). The number of “likes” is negatively correlated with project financing performance, which is different from general common-sense logic. This chapter speculates that this phenomenon is because the number of “likes” can only indicate the popularity of the project, and the people who like it may not necessarily invest in the project. The phenomenon can be linked to the research of social media “likes” behavior. This chapter do not provide in-depth confirmation of this problem. But it will be an interesting topic for future research.

To discover more interesting factors, this chapter also attempts to study the macro factors and introduces the macroeconomic indicator of “PCDI”. For the four quarterly dummy variables in “PCDI”, it finds that the values in the third quarter of 2018, the fourth quarter of 2018, and the first quarter of 2019 are greater than the values in the second quarter of 2018. The value of the second quarter of 2018 is not added in the model. Nevertheless, the other three quarterly dummy variables have a significantly positive correlation with it. In other words, in this test, the level of “PCDI” will have an impact on “the ratios of financing over goals”. The impact of the other three quarters is more significant than the second quarter of 2018 because when this chapter compares their values, it is found that the value in the second quarter of 2018 is the smallest. The conclusion of this chapter is that the greater the “PCDI”, the greater the impact on “the ratios of financing over goals”, that is, the greater the impact on the project's financing performance. However, it cannot continue to quantify the magnitude of this positive correlation. This result will open up new research ideas for this topic. In the future, researchers interested in this field can further explore the macroeconomic environment's impact on crowdfunding performance. Of course, this kind of performance not only refers to the project financing performance that is concerned in this chapter, but also the implementation performance of the project.

When collecting data in this chapter, there is very little reference information about the platform projects, which makes it limited to the selection of variables. Some interesting variables, such as project financial information and project sponsor company information, were not published. Therefore, in future research, the information transparency of RCF platforms can be studied.

Since most of the variables selected in this chapter are based on social capital, there is a common limitation in related research on social capital. That is, there are many uncertainties in social capital. Scholars have been discussing the quantification of social capital and its theoretical basis. To this day, it is still a problem. In future research, capture and determine the real value of social capital and its application in crowdfunding will also become a meaningful research direction.

Also, for the crowdfunding industry, this chapter believes that it will usher in a reshuffle of the industry, plus the impact of the COVID-19 on the global economy in 2020, which will accelerate the crowdfunding industry's reform. It does not know what the crowdfunding industry will become in the future, but the crowdfunding industry will not disappear. For crowdfunding research, researchers need to pay more attention to its updates and discuss the science related to crowdfunding.

6

WHICH FACTORS CAN CONTRIBUTE TO THE SUCCESS OF ENVIRONMENTAL AND ANIMAL PROTECTION PROJECTS IN DONATION-BASED CROWDFUNDING? A NEURAL NETWORK MODEL[7]

[7] This chapter has been published in November 2023:

Jiang, C., Urquía-Grande, E., & Pérez-Estébanez, R. (2023). Which Factors Can Contribute to the Success of Environmental and Animal Protection Projects in Donation-based Crowdfunding? A Neural Network Model. *International Journal on Recent and Innovation Trends in Computing and Communication*, 11(9), 1414–1425 https://doi.org/10.17762/ijritcc.v11i9.9120.

This chapter explores the influencing factors of donation-based crowdfunding (DCF) financing performance through empirical research. DCF is a crowdfunding model that raises funds from the public through a crowdfunding platform to help people in need. It is a typical non-profit project. Existing DCF research mainly focuses on donation motivations and project sponsors. Few studies discuss project transparency from a financial perspective. In addition, in recent years, the environment and animal protection have received global attention. Most NGOs currently rely heavily on donations. The main problem facing such projects is a lack of funding, and DCF can help alleviate the current huge funding gap. The practical significance of this study lies in how to help environmental protection and animal protection practitioners gain more support.

In addition, it must be mentioned that in recent years, with the rapid development of big data, artificial intelligence has been applied to various industries. However, most current crowdfunding research still explores traditional regression models. As the most representative part of artificial intelligence, many studies have long used neural network models to better process sample data. Therefore, this chapter will build a backpropagation (BP) neural network model based on the traditional multiple linear regression model to study the influencing factors of environmental and animal protection DCF project success, and compare the ability of the two models to predict project success. Henceforth, this chapter will address the following research questions:

RQ3: What factors affect the success of environment and animal protection DCF projects in China analyzed through BP neural network models?

6.1 METHODOLOGY

6.1.1 Linear regression

From the variables defined in this research, R (Result) represents the final result of the project. ND (The number of donors) is an important indicator of the attractiveness and popularity of the project. T (Project sponsor) represents the project sponsor, that is, the organization or individual of the project. NW (The number of words) and NP (The number of pictures) can affect the attractiveness of the project and the interest of investors. TS (Transparency score) is a transparency score that measures the transparency of the project in terms of financial and operational information disclosure. The following multiple linear regression equation can be defined:

$$R = \beta_0 + \beta_1 ND_1 + \beta_2 T_2 + \beta_3 NW_3 + \beta_4 NP_4 + \beta_5 TS_5 + \varepsilon \quad (6\text{-}1)$$

Where:

R is a binary categorical variable, with “1” for “success” and “0” for “failure”. For the variables ND, NW, NP and TS, which are positive numerical variables, to eliminate the influence of scale on the results, this chapter performed natural logarithmic processing on them to eliminate the effect of scale on the regression results. As for the categorical variable T has only two categories: “1” is initiated by an institution or organization, and “0” means an individual. Equation (6-1) uses a binary logistic regression model to explore the effect of the independent variables defined in this chapter on project success. At the same time, it will also analyze the model's ability to predict project success in logistic regression.

6.1.2 Artificial neural network model

This chapter will also consider the performance of models. Artificial neural network (ANN) model mimics the way the human brain processes information. A trained ANN model can have memory and knowledge-processing capabilities (Thakial & Arora, 2019). This study uses the BP (Back Propagation) neural network model. BP neural network is a multi-layer feed-forward neural network, mainly using the error backpropagation algorithm and the gradient descent method to obtain the minimum approximation value. It is generally divided into three layers: input, hidden, and output. The basic algorithm is as follows:

$$y_i = 1/[1 + \exp\left(-\sum_{i=1}^{n} w_{ij} x_i\right)] \text{ (6-2)}$$

$$w_{ij}(k+1) = w_{ij}(k) + \eta \sigma_j x_i + \alpha[w_{ij}(k) - w_{ij}(k-1) \text{ (6-3)}$$

Where:

x_i is the sample data input in the j nodes of the $(k-1)$ layer. η represents the learning coefficient of the model and α is the impact coefficient. Then the output equation is equation (6-4), y_j and d_j are expressed as the actual output value and expected output value of the j node.

$$\sigma_j = y_j(1 - y_j)(d_j - y_j) \text{ (6-4)}$$

The hidden layer node is reversely calculated as shown in formula (6-5), where x_j is the actual output value of the j node.

$$\sigma_j = x_j(1 - x_j)\sum_{i=0}^{m}\sigma_j w_{ij} \quad (6\text{-}5)$$

BP neural network is currently the most widely used neural network model, and it does not necessarily need to rely on a large amount of data for training. Therefore, it is often used in research such as predictive classification (W. Wang et al., 2020). The general neural network model requires a large number of training parameter settings, and the simple algorithm of the BP neural network model can avoid this step and simplify the operation process. But it also has relative limitations, such as the BP algorithm will bring gradient dispersion phenomenon, and for fewer sample data, this problem is alleviated. Therefore, this research will establish a three-layer BP neural network model. To facilitate comparison, according to formula (6-1), the input layer of the BP neural network model has five neurons corresponding to five independent variables, the hidden layer is one layer, and the output layer is a binary neuron dependent variable.

At the same time, this study will use the pre-training method to analyze the relevant parameters of the neural network. After the pre-training of the sample, the optimal local parameters of the sample can be obtained, avoiding the gradient dispersion phenomenon caused by excessive iteration. At the same time, the parameter setting is more objective, and the confidence is higher. This study uses Python to train neural networks. The training set is 60% of the total sample, or 420 items, and the test set is 40% or 280 items.

6.2 RESULTS

6.2.1 Binary logistic regression

First, this study will use the binary logistic regression model shown in formula (6-1) to test to validate the *RQ3*. The variables' descriptive analysis and the results of the Hosmer and Lemeshow test are shown in Table 6.1.

	N	Minimum	Maximum	Average	Standard Deviation
R（Result）	700	0	1	0.19	0.392
T（Project sponsor）	700	0	1	0.68	0.466
ND（The number of donors）	700	3	103429	2683.954	7846.4942
NW（The number of words）	700	915	4278	1735.044	364.2264
NP（The number of pictures）	700	2	18	7.839	2.1856
TS（Transparency score）	700	0	4	2.148	1.3447
Hosmer and Lemeshow Test	Chi-square	5.998			
	Sig.	0.647			

Table 6.1. Descriptive Statistical Analysis and Hosmer and Lemeshow Test

As can be seen from the original data in table 6.1, R and T are binary variables, and the mean of R is 0.19, proving that most sample items are unsuccessful. The mean of T is greater than 0.5, which proves that most projects have NPO support. Whereas ND, NW, and NP have very different value spans in projects. The mean of the TS variable of 2.148 proves that most projects provide at least two pieces of financial transparency information. The Hosmer and Lemeshow test null hypothesis is that the model fits the results better. In this study, significance is 0.647 to accept the null hypothesis, which proves that the model of this study has a good fit.

	Observed	Predicted		
	Result	failure	success	Percentage Correct
Step 1	failure	530	38	93.31
	Success	42	90	68.18
	Overall Percentage			88.57

Table 6.2. Classification Table

Table 6.2 shows this study's binary logistic regression model prediction results. As defined in the methodology of this study, an outcome "R" with a value of 1 is "success" and 0 is "failure". The prediction results in this research model have an accuracy of 93.31% for failure and 68.18% for success, and comprehensive prediction accuracy of 88.57%.

Variable	B	S.E.	Wald	df	Sig.	Exp(B)
lnND	0.460	0.127	13.082	1	0.000	1.584
lnNW	-1.721	1.011	2.897	1	0.089	0.179
lnNP	-0.231	0.715	0.104	1	0.747	0.794
lnTS	8.573	1.259	46.329	1	0.000	5284.373
T(1)	0.973	0.410	5.624	1	0.018	2.645
Constant	-3.570	7.297	0.239	1	0.625	0.028
-2 Log likelihood	166.323					
Cox & Snell R Square	0.402					
Nagelkerke R Square	0.648					

Table 6.3. Variables in the Equation

Table 6.3 reflects the degree of influence of independent variables on the results of binary logic. Among them, ND, TS and T reject the null hypothesis within the 0-0.05 confidence interval, the coefficients are all positive, and all have significant statistical significance. ND had a positive correlation with results, suggesting that the number of donors can positively influence the success of the DCF project. Of course, this conclusion confirms the existing crowdfunding research on the positive relationship between the number of backers and crowdfunding financing performance (Belleflamme et al., 2014). Researchers generally use “herd behavior” as the theoretical basis for explaining this result. Second, the positive effect of TS on the results confirms the hypothesis of this study that greater financial transparency is more likely to attract donations. In a study on NPO financial transparency, organizations with greater transparency were more likely to attract donations (Ortega-Rodríguez et al., 2020). The coefficient of T is positive, indicating that if the project sponsor is an NPO, it can positively impact the project's success. Projects initiated by NPOs can increase the project's credibility and influence supporters' motivation.

In addition, within the 0.05-0.1 confidence interval, lnNW had a negative impact on the results. It is contrasted with existing research on the performance of other types of CF financing (Xu et al., 2014). This study found that a higher number of words in the description adversely affected the results. The reason is that this study speculates that the crowdfunding type is donation-based, and too much descriptive text will reduce the intention of supporters to donate. The value of Cox & Snell R Square is 0.402, which means that the independent variable in this research model explains 40.2% of the dependent variable. The Nagelkerke R Square value was 0.648, reflecting the high statistical significance of the model in this study.

6.2.3 BP neural network analysis

This research adopts the Keras neural network framework to build a BP neural network model. Keras is an application programming interface (API) for deep learning based on Python. Its primary function is to optimize the model structure and significantly improve the training speed of neural network models (Keras, 2022). In pre-training, this study selects the Rectified Linear Unit (ReLU) function as the activation function of the model neurons in this study. The ReLU function is one of the most commonly used functions in neural network model training. Its most significant advantage is that it is simple to calculate and performs better when the model sample data is linear or close to linear. The ReLU function has high computational efficiency. Compared with other activation functions (such as Sigmoid and Tanh), ReLU is computationally simpler and can accelerate convergence. The nonlinear characteristics of the ReLU function can effectively alleviate the gradient vanishing problem, thus facilitating the training of deep neural networks.

Meanwhile, this study adopts cross-entropy as the model’s loss function, and uses adaptive moment estimation (Adam) as the optimization algorithm of the model. The Adam algorithm can dynamically adjust the learning rate for each parameter according to the first-order moment estimation and the second-order moment estimation of the gradient of each parameter by the loss function, so it is convenient to set the corresponding parameters better. In this study's pre-training of the BP neural network model, each layer's connection weights and biases are initially randomly generated, the epoch is set to 10, and the model is evaluated after training. This study evaluates the model’s performance by outputting the accuracy of the loss function of the DNN model. The results of the model are shown in Figure 6.1.

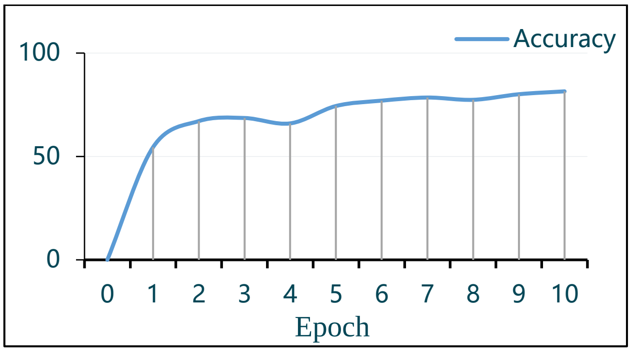

Figure 6.1. Training accuracy results

Figure 6.1 shows the pre-training fitting results of the BP neural network model constructed in this research. After the epoch is 2, the fitting degree of the model has nearly reached 67.1% and tends to be stable in the subsequent epochs. Finally, when the epoch is 10, the accuracy of the BP neural network model reaches 81.5%, indicating that the BP neural network model has a good degree of adaptation to the samples in this study.

According to the pre-training results, this study sets the learning rate to 0.001 in the complete training, the number of iterations to 42, the number of batches per processing to 10, and the loss function to be cross-entropy. Figure 6.2 shows the loss curve and accuracy of the BP neural network model.

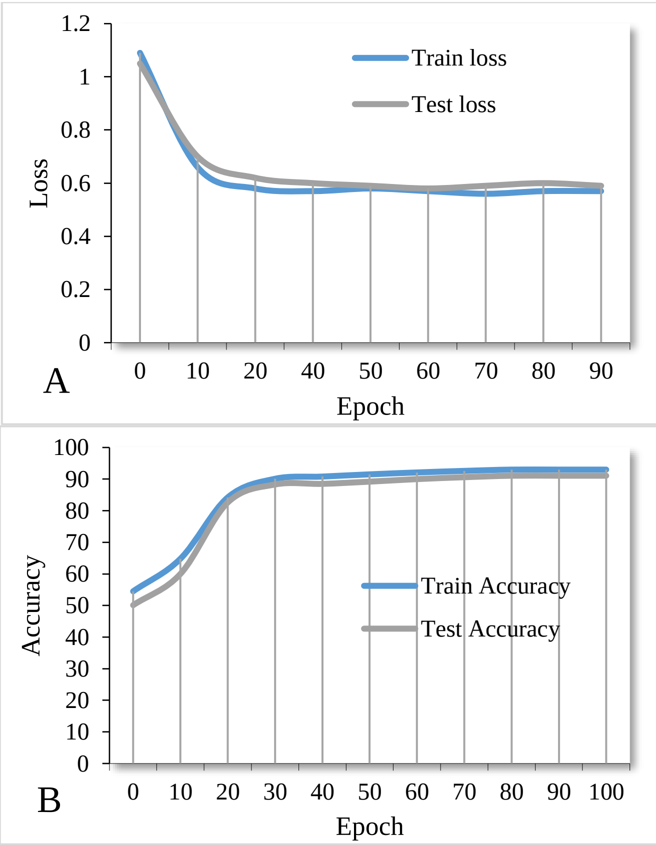

Figure 6.2. Loss and accuracy curve of the BP neural network model

According to the results shown in Figure 6.2-A, the change trends of the loss curves of the training set and test set of the BP neural network model are basically the same. The loss value for the test set is 0.7 at epoch 10, which remains stable thereafter, and the loss value for the test set at epoch 100 is 0.59. And Figure 6.2-B shows the accuracy curves of model training and testing. According to the results in the figure, when the Epoch is

30, the accuracy of the training set reaches 90.1 and begins to converge, while the accuracy of the test set is 88.3% and begins to converge. After 70 rounds of convergence, when the epoch is 100, the accuracy of the training set reaches 93%, and the accuracy of the test set reaches 91.07%. The results in Figure 6.2 show that the performance of the BP neural model is excellent. At the same time, this study analyzes the model's discriminant accuracy, and the confusion matrix analysis results are shown in Table 6.4.

Observed	Predicted			
	R	failure	success	Percentage Correct
The actual situation	failure	212	15	93.39
	Success	10	43	81.13
	Overall Percentage			91.07

Table 6.4. BP neural network model confusion matrix

The results of the confusion matrix analysis are shown in Table 6.4, with a total of 280 items in the test set. The overall prediction accuracy is 91.07%, which is better than the 88.57% accuracy of binary logistic regression in Table 6.4. Comparing the two models, the prediction accuracy of project failure is about 93%, but the prediction accuracy of project success is very different. The accuracy rate of the BP neural network in successful projects is 81.13%, which is much higher than 68.18% of binary logistic regression, indicating that the BP neural network model has better performance in predicting project success in this study sample.

At the same time, to minimize the impact of different distributions of training samples on the accuracy of model analysis, after comprehensive consideration, this study decided to use a ten-fold cross-check method to test the validity of the model further. In this research, the sample test set was equally divided into ten parts, and each part was tested separately.

The prediction accuracy is used to measure the discriminative performance of the BP neural network model on the project results, which are shown in Figure 6.3.

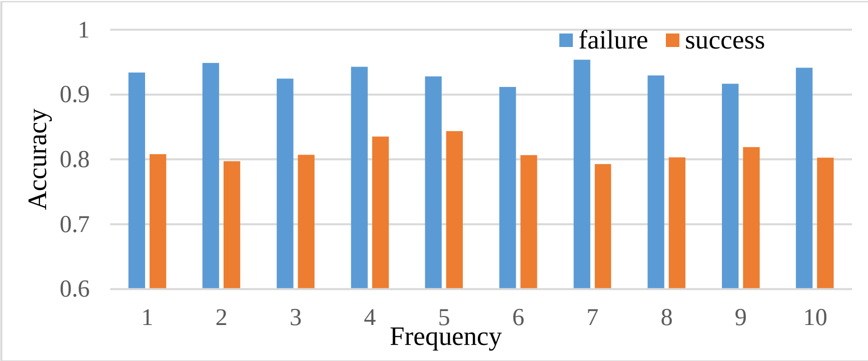

Figure 6.3. Ten-fold cross-check results

According to Figure 6.3, there is little difference in the model's predictive ability in each part. In the test of some samples, the accuracy of the model's prediction of project failure is still higher than that of project success. Therefore, this study's prediction performance of the BP neural network model is effective and objective.

Variable	Importance
lnND	0.53
lnNW	-2.71
lnNP	-0.03
lnTS	12.17
T(1)	1.17

Table 6.5. Importance of independent variables

Table 6.5 shows the importance of each independent variable of the BP neural network model. The results show significance similar to those of binary logistic regression in Table 6.3. The number of donors (ND), the Transparency Score (TS) and the type of project sponsor (T) can all positively affect the success of DCF projects, while the number of words (NW) and the number of pictures (NP) DCF project success has a negative impact. And the importance of TS is much greater than other independent variables, which verifies the main conclusion in this research, that is, higher financial transparency can attract donations.

6.3 FINDINGS DISCUSSION AND CONCLUSIONS

As an emerging online donation method, DCF has recently received much attention. DCF projects are typically not-for-profit projects, so backers usually don't receive any material return. It has changed the traditional donation model and made it easier to participate in charitable causes.

Therefore, this chapter pioneered DCF projects related to environmental and animal protection, combined with financial transparency of the project, to study the success factors of the project. This chapter addresses *RQ3* proposed in this thesis through empirical analysis. The results of this chapter confirm that financial transparency is the most critical factor influencing the success of environmental and animal protection DCF projects. The more financial transparency a project is, the easier it is for the project to be successful. At the same time, this study also confirms that if the project sponsor is an NPO, it increases the project's credibility and positively impacts its success. Second, the number of donors can also be beneficial to project success. In addition, this study found that excessive descriptions of the projects were detrimental to the project’s success.

In addition, this study also uses the BP neural network model and the traditional binary logistic regression model for comparative analysis. The results of this study confirm that the BP neural network model can optimize the traditional binary logistic regression model in the successful prediction of DCF and improve the prediction accuracy to 91.07%. And the prediction accuracy of the project “success” of the binary logistic regression model is largely optimized. At the same time, this study also conducted a ten-fold cross-check on the BP neural network model, and the results show that the model has good accuracy.

The overall success rate of DCF projects related to environmental and animal protection is not high. In addition to the negative factors identified in this study, such as the item's description word count, there must be other, more critical reasons. The inability to investigate further here is one of the limitations of this study. It is of great practical interest to discuss those potential factors in future research to aid the project's environmental and animal protection causes. At the same time, in terms of the financial transparency of DCF projects, the inability to obtain more relevant indicators is also one of the limitations of this study. As the financial transparency of non-profit organizations improves, this study anticipates that the finances of DCF projects will also become more transparent in the future. This enhanced transparency is expected to not only elevate the overall quality of the industry but also bolster donor trust. Moreover, by advancing transparency, it can contribute to the sustainable development of various public welfare initiatives.

7

EMPOWER CHANGE: CROWDFUNDING FOR ANIMAL AND ENVIRONMENTAL PROTECTION[8]

[8] This chapter has been sent to a high impact journal for publication.

In recent years, the world has paid increasing attention to animal and environmental protection (AEP) issues. More and more people are becoming aware of the seriousness of issues such as climate change and biodiversity loss. However, currently most non-governmental organizations (NGOs) and charities still rely on traditional donation models to sustain the funding needs of their operations and projects. In this context, DCF becomes a potential solution to alleviate current financing difficulties. This new financing model is expected to promote the development of environmental protection in a more innovative and sustainable direction and provide stronger support for solving the ecological challenges facing the world.

In addition, whether it is a traditional donation project or a DCF project, few studies have considered whether project transparency affects donation motivation from a financial perspective. In the field of crowdfunding, it has not yet been determined whether a project's information transparency also affects donors' donation behavior. Therefore, this chapter adopts the SEM model to investigate the donation motivations of donors in AEP crowdfunding projects. This chapter is based on the exploratory construction of existing research on the SEM model of donation motivations for AEP-DCF projects and contributes to revealing the various intrinsic motivations of donors. It also considers the impact of financial transparency on donation motivation in the model, providing new ideas for related research. This chapter is intended to help projects improve their fundraising capabilities and contribute to project success.

7.1 BACKGROUND AND RESEARCH QUESTIONS

7.1.1 Self-perception emotion

A large body of existing research provides evidence to support that general donation motivations arise from self-perception emotion (Isa et al., 2015; Zhang et al., 2020). Common manifestations of self- awareness of emotions are: "emotional motivation" may choose to donate out of sympathy, joy, anger, guilt, or other emotions (Body & Breeze, 2016; Chapman et al., 2022). Andreoni (1990) proposed the warm glow of giving. He believed that people would get their own happiness when doing good things. And he believed that donation is an impure altruistic behavior. The motivation for donation comes from the hope of realizing one's social expectations and psychological satisfaction through donation. In particular, small donors tend to donate based on personal aspirations and satisfaction (Chapman et al., 2022; Karlan & Wood, 2017).

Griskevicius et al. (2010) believed that emotions can affect decision-making motivation, and that positive emotions have the function of promoting supporters' donation intentions. Research on positive emotions, such as Paramita et al. (2020) studied the differences between positive emotions and they believed that emotions based on pride have a positive impact on donation. In addition, some studies have found that when a donor perceives himself as a generous person, this positive emotion also increases giving. But not all positive emotions can increase donations. For example, gratitude has no impact on donations, while happiness actually reduces donations (J. Liang et al., 2016).

Self-perception emotions allows them to more clearly recognize the impact these emotions have on their decision-making; "Self-satisfaction" By helping others, individuals may feel happy and satisfied, and this feeling can inspire more charitable behaviors; “Emotional decision-making” makes it possible for donors to choose to support a charity or project that is relevant to their emotional experience. Similarly, some studies believe that the intrinsic motivation for donation mainly comes from self-perception emotion of emotions, including personal interests, beliefs, etc (Alessandrini, 2007; Reinstein, 2011; Skarmeas & Shabbir, 2011). Therefore, this study proposes the following research questions in this dimension:

RQ4: Does self-perceived emotion have a positive impact on the intention to donate to AEP-DCF projects?

RQ4a: Does emotional motivation have a positive impact on the intention to donate to AEP-DCF projects?

RQ4b: Does self-satisfaction have a positive impact on the intention to donate to AEP-DCF projects?

RQ4c: Does emotional decision-making have a positive impact on the intention to donate to AEP-DCF projects?

7.1.2 Altruism or Sacrificialism

Existing research has confirmed that general donation behavior may also be motivated by altruism or sacrificialism. Nagel (2016) defined altruism as the intention to do something for others without focusing on oneself. Research has found that donors may donate purely out of selfless altruistic motives. At this time, donation behavior is not affected by personal interests, rewards or other motives, but is entirely based on concerns and wishes for others. Such as volunteering and blood donation are based on altruism (Alessandrini, 2007). Van Vugt et al. (2007) found that status motivation is also a kind of competitive altruism, paying more attention to others rather than one's own prosocial behavior, and proactively donating in order to compete for each other's social reputation and status. Karlan & Wood (2017) pointed out that large donors are generally based on altruism and regard donation as a substitute, hoping to add more social welfare, and they focus on effectiveness. Egoism is also considered a kind of impure altruism, which can be explained by the warm light giving theory mentioned above, because supporters know that helping others can bring satisfaction and pleasure to themselves, there is no denying that it has a great motivating effect on donation decisions (Habib et al., 2023).

Slightly different from the focus of altruism, sacrificial donors do not expect financial rewards; they emphasize sacrifices for the greater benefit of society in the future(Liu & Hao, 2017; Majumdar & Bose, 2017). Griskevicius & Kenrick (2013) proposed that the kin care system will inspire sacrificialism, which prompts people to pay attention to vulnerable groups, give them the support and help they need, and include donations. Donors who are altruistic or sacrificial can be willing to provide support to the project without caring about any current rewards (Y. Li et al., 2018). Therefore, this study proposes the following research questions:

RQ5: Do altruism and sacrificialism have a positive impact on the intention to donate to AEP-DCF projects?

RQ5a: Does altruism have a positive impact on the intention to donate to AEP-DCF projects?

RQ5b: Does sacrificialism have a positive impact on the intention to donate to AEP-DCF projects?

7.1.3 Community belonging

Some studies have found that community belonging is one of the main drivers of intention to donate (Lacan & Desmet, 2017). Prosocial emotions, that is, community belonging will significantly enhance the intention to donate. When individuals have strong prosocial emotions and empathy, they are more likely to understand the needs and suffering of others and are, therefore, more willing to provide help and support (Neumayr & Handy, 2019). According to statistics, Alessandrini (2007) found that more than one-third of blood donors in Australia have a strong sense of belonging to their community, believe they have obligations, and hope to give back to the community, thus choosing to donate blood. Affiliation motivation can also inspire donation behavior rather than personal enjoyment, and it can also drive people around you who have a sense of belonging to donate (Griskevicius & Kenrick, 2013; Mead et al., 2011).

This study believes that "community belonging" should include the following content: "Community needs recognition" makes it easier for individuals to identify and understand the needs and problems of the community to which they belong. “Community emotional connections” can inspire care and concern for the community and may create peer effects. And "community participation" is the actual embodiment of community belonging. Some studies believe that age’s “sense of belonging” also affects donor intention. Young people are more likely to donate to DCF projects because their community belonging comes from online communities (Cockrell et al., 2016). Some studies have also found that community belonging can produce a peer effect, and the donation behavior of peers can positively affect future donation intentions (Smith et al., 2015; Van Teunenbroek & Hasanefendic, 2023). Based on this, this study proposes the following research questions:

RQ6: Does a sense of community belonging have a positive impact on the intention to donate to AEP-DCF projects?

RQ6a: Does recognizing community needs have a positive impact on the intention to donate to AEP-DCF projects?

RQ6b: Do emotional connections within the community have a positive impact on the intention to donate to AEP-DCF projects?

RQ6c: Does community participation have a positive impact on the intention to donate to AEP-DCF projects?

7.1.4 Financial transparency

Unlike existing research, this study considers the impact of financial transparency on donation intention. Financial transparency is a key factor in giving, ensuring that donors have a clear understanding of how their donations are being used and where project funds are going. Buell et al. (2017) emphasized that transparency during project operations is positively correlated with financing performance. Balsam & Harris (2018) believed that timely updating of project information can improve the financing performance of the non-profit sector. (Mejia et al., 2019) proposed that during the project process, project updates and certification of financing projects can improve the project's financing performance.

Online DCF has its own particularities and faces some unique challenges in terms of transparency, making the supervision and control of the project more complex. These challenges may include tracking funding flows, reporting on project progress, and platform oversight of projects (Hariwibowo et al., 2022; Salido-Andres et al., 2022).

Donors are likely to have their donation decisions affected by project breaches of trust. However, in the field of crowdfunding, it has not yet been determined whether the project's information transparency will also affect donors' donation behavior. Therefore, this study proposes the following research questions:

RQ7: Does financial transparency have a positive impact on the intention to donate to AEP-DCF projects?

RQ7a: Does the transparency of fund flow have a positive impact on the intention to donate to AEP-DCF projects?

RQ7b: Do timely reports on project progress have a positive impact on the intention to donate to AEP-DCF projects?

RQ7c: Does the improvement of platform supervision have a positive impact on the intention to donate to AEP-DCF projects?

7.2 INSTRUMENTS AND METHODOLOGY

Based on the research questions in the second part, this study aims to investigate the validity of its proposed research questions. The questionnaire consisted of two parts: respondent demographics and a scale containing four independent variable dimensions. The independent variable dimensions include self-perception and emotion, altruism or sacrificialism, community belonging and financial transparency, while the dependent variable is the intention to donate to DCF projects for AEP. This study first conducted a pretest to ensure the quality of the questionnaire. By analyzing and evaluating the pre-test results, the questionnaire was optimized and questions irrelevant to the study were eliminated. Finally, the adjusted questionnaire scale is as follows (see Table 7.1):

DIMENSION	VARIABLES	QUESTIONS	REFERENCE
Self-perception emotion	Emotional Motivation	EM1. You think you're often more emotionally driven than rationally driven when it comes to donating. EM2. Do you think emotional factors such as sympathy, joy, anger, guilt, etc., largely influence your decision to donate?	(Body & Breeze, 2016; Isa et al., 2015; Karlan & Wood, 2017)
	Self-satisfaction	SS1. Will you feel satisfied and happy after you donate? SS2. Get more self-satisfaction when you donate larger amounts?	(Isa et al., 2015; J. Liang et al., 2016; Paramita et al., 2020)
	Emotional decision-making	ED1. When you make a donation decision, do you typically consider its impact on your emotional state? ED2. You have chosen to support a donation project because of an emotion such as personal interest or belief.	(Griskevicius et al., 2010; Paramita et al., 2020)
Altruism or sacrificialism	Altruism	AL1. When you consider making a donation, are you motivated solely by concern for the project and wanting to help? AL2. When you consider making a donation, you do not consider your own benefits in return at all.	(Habib et al., 2023; Karlan & Wood, 2017; Van Vugt et al., 2007)
	sacrificialism	AR1. When you consider making a charitable donation, you are willing to make some personal sacrifices to support a charitable cause. AR2.When you consider making a donation, you do not consider your own interests at all and expect to bring greater returns to the public welfare in the future.	(Y. Li et al., 2018; Liu & Hao, 2017; Majumdar & Bose, 2017)
Community belonging	Community needs recognition	CN1. When you consider donating, do you consider the needs of the community? CN2. Would you rather donate when your community faces an urgent need or issue?	(Griskevicius & Kenrick, 2013; Lacan & Desmet, 2017)
	Community Emotional Connection	CE1. Would you rather donate to the community where you live or work, including online communities, than elsewhere? CE2. When you know that your friends in the community, including online communities, have donated, you want to do the same.	(Cockrell et al., 2016; Lacan & Desmet, 2017; Mead et al., 2011; Van Teunenbroek & Hasanefendic, 2023)
	Community participation	CP1. You like to participate in activities or projects organized by your community, including online communities. CP2. Your participation in giving activities in the community will give you a greater sense of belonging than participating elsewhere.	(Alessandrini, 2007; Griskevicius & Kenrick, 2013; Smith et al., 2015)
Financial transparency	Transparent fund flow	TF1. When considering making a donation, would you prefer projects that disclose in greater detail where the funds are going? TF2. Have you ever decided not to donate because of the transparency of the funds disclosed by the project?	(Grimmelikhuijsen et al., 2013; Hariwibowo et al., 2022; Salido-Andres et al., 2022)
	Transparent project progress report	TP1. When considering making a donation, would you prefer projects that disclose more detailed progress reports? TP2. Have you ever decided not to donate because of issues with project disclosure progress reporting?	(Buell et al., 2017; Mejia et al., 2019)
	Platform supervision	PS1. When considering making a donation, would you prefer projects on crowdfunding platforms with complete supervision? PS2.Have you ever decided to give up donating because the crowdfunding platform lacks relevant supervision?	(Grimmelikhuijsen et al., 2013; Hariwibowo et al., 2022; Salido-Andres et al., 2022)
Donation intention		DI1. You have the intention to donate to environmental or animal protection projects or have already made donations before.	

	DI2. There's a good chance you'll make a donation to an environmental or animal conservation project.	(Habib et al., 2023; Karlan & Wood, 2017; Paramita et al., 2020)

Table 7.1. Questionnaire Design

This study measured all variables using a five-point Likert scale ranging from "1 = Strongly Disagree" to "5 = Strongly Agree". At the same time, in order to conduct structural equation modeling (SEM) analysis of the data, we chose to use SPSS 22 software on the Microsoft Win10 system for data processing and analysis.

7.3 FINDINGS, RESULTS AND DISCUSSION

7.3.1 Respondent analysis

Table 7.2 shows the basic profile of the respondents in this article.

Gender	Average age (years)		Higher education	Income (USD/annual)	
Male	Under 18	41 (5.8%)	Yes	Below 5,000	173(24.4%)
317 (44.6%)	18-30	183 (25.8%)	474 (66.8%)	5,001-10,000	300(42.3%)
Female	31-40	260 (36.6%)	No	10,001-30,000	152(21.4%)
393 (55.4%)	Over 40	226 (31.8%)	236 (33.2%)	30,000 and above	85(12%)

Table 7.2. Summary of Demographic Dimensions Respondent Characteristics

According to the results in Table 7.2, after screening responses from respondents who had some knowledge of AEP-DCF projects, this study finally collected 710 valid responses (the specific processing information has been detailed in 3.4), including 317 males and 393 females, with slightly more females than males. Considering that men are the majority in China as a whole, the study has reason to believe that women are more likely to pay attention to AEP-DCF projects. Overall, the respondents in this study were mainly in the 31-40 age group. The proportion of respondents under 40 years old reached 68.2%, and the average age is relatively young. This may be because the use of DCF involves smart devices such as computers and mobile phones, so DCF users are generally young. It is worth noting that 66.8% of the respondents have received higher education, which proves that people with higher education levels are more likely to understand AEP-DCF projects. This also shows that higher education plays an active role in raising public awareness of AEP. Among the respondents' income, middle-income people (5,000-10,000 USD) accounted for 63.7%.

7.3.2 Effect analysis

This study conducted a Cronbach's Alpha test for each item in the model to assess its internal consistency and validity. Typically, Alpha values range from 0 to 1, with larger values being more beneficial. For exploratory research, it is generally recommended that Alpha values in the range greater than 0.6 are acceptable, while values greater than 0.7 are considered very good (Straub, 1989). Table 7.3 presents the descriptive analysis and Cronbach's Alpha test results of all items and dimensions in detail.

Construct		Mean	Std. Deviation	Factor Loading	N	Cronbach's Alpha
Self-perception emotion						
Emotional Motivation (EM)	EM1	3.5900	1.0990	0.724	710	0.631
	EM2	3.3000	1.0120	0.69	710	
Self-satisfaction (SS)	SS1	3.4900	1.0270	0.721	710	0.681
	SS2	3.4700	1.1450	0.752	710	
Emotional decision-making (ED)	ED1	3.5100	1.0820	0.749	710	0.664
	ED2	3.2400	0.9890	0.69	710	
Altruism or sacrificialism						
Altruism (AL)	AL1	3.2300	0.9800	0.659	710	0.621
	AL2	3.5000	1.1490	0.758	710	

Sacrificialism (AR)	AR1	3.4700	1.0990	0.681	710	0.632
	AR2	3.3600	1.0930	0.727	710	
Community belonging						
Community needs recognition (CN)	CN1	3.7200	1.1600	0.819	710	0.756
	CN2	3.6200	1.1120	0.752	710	
Community Emotional Connection (CE)	CE1	3.6300	1.1070	0.752	710	0.723
	CE2	3.7700	1.1650	0.766	710	
Community participation (CP)	CP1	3.7800	1.1790	0.773	710	0.729
	CP2	3.6800	1.1720	0.767	710	
Financial transparency						
Transparent fund flow (TF)	TF1	3.4500	1.2250	0.7620	710	0.664
	TF2	3.3500	1.0980	0.6710	710	
Transparent project progress report (TP)	TP1	3.7200	1.1940	0.8010	710	0.760
	TP2	3.3400	1.2550	0.7760	710	
Platform supervision (PS)	PS1	3.4000	1.1190	0.7280	710	0.703
	PS2	3.4100	1.1290	0.7330	710	
Donation intention						
Donation intention (DI)	DI1	3.5600	1.0920	0.7600	710	0.652
	DI2	3.3000	1.0010	0.6760	710	

Table 7.3. Reliability Analysis Results

According to the data in Table 7.3, Cronbach's Alpha values for all projects in this study were higher than 0.6. Especially in the Community Belonging dimension and Financial Transparency dimension, the Alpha value of most items even exceeds 0.7. This indicates that the scale model adopted in this study performs well in terms of reliability. Meanwhile, the convergence test results of the scale are provided in Table 7.3. In order to evaluate the convergence of the scaling model, Kaiser's normalized rotating Varimax principal component factor analysis was used. In general, when the engineering structure load is greater than 0.6, it is considered acceptable. It is gratifying that all items in this study have factor loads of over 0.6, which further confirms that the scaling model adopted in this study is satisfactory in terms of convergence effect (Fornell & Larcker, 1981).

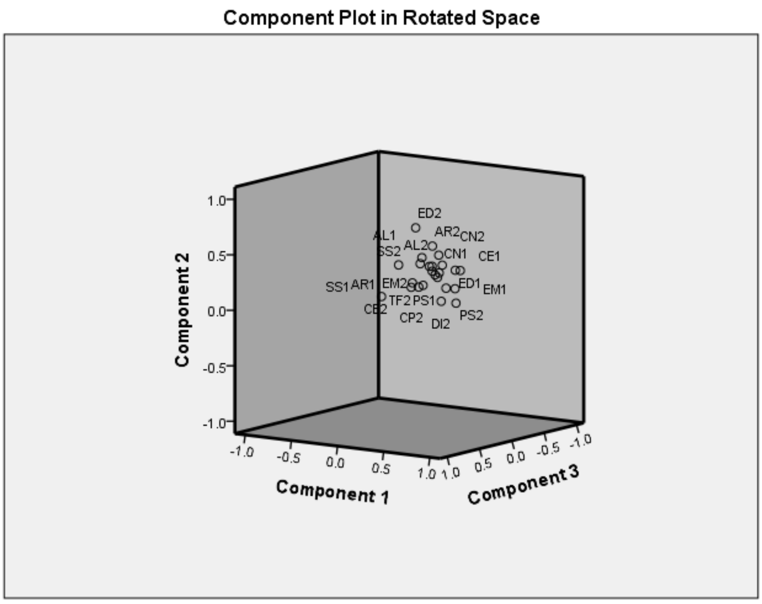

Figure 7.1. Component Plot Space graph

In the current study, in order to better observe the convergence of variable dimensions, it made a three-dimensional principal component diagram after rotation, and the results of the three-dimensional principal component diagram showed the close correlation and mutual relationship among various scale terms, which was specifically presented in Figure 7.1. As shown in Figure 7.1, it can be clearly seen that all scale terms are concentrated in the center of the space, reflecting a high degree of consistency among the measured variables, which clearly shows that the model constructed in this study performs satisfactorily in terms of convergence, enhancing the credibility of the research conclusions.

7.3.3 Variable dimension correlation matrix analysis

To exclude the effects of multicollinearity, Table 7.4 shows the correlation coefficient analysis for all items as a whole. As can be seen from the results of Table 7.4, the correlation coefficients of all dimensions in this study are less than 0.9, which can exclude the influence of multicollinearity, and all dimensions can achieve statistical significance within a confidence interval of 0.01.

	EM	SS	ED	AL	AR	CN	CE	CP	TF	TP	PS	DI
EM	1											
SS	.663**	1										
ED	.661**	.676**	1									
AL	.662**	.683**	.682**	1								
AR	.656**	.685**	.662**	.670**	1							
CN	.696**	.715**	.717**	.695**	.695**	1						
CE	.673**	.700**	.689**	.686**	.659**	.729**	1					
CP	.701**	.712**	.691**	.702**	.691**	.734**	.709**	1				
TF	.643**	.687**	.661**	.654**	.657**	.719**	.687**	.707**	1			
TP	.701**	.709**	.699**	.708**	.698**	.756**	.737**	.745**	.701**	1		
PS	.671**	.669**	.656**	.655**	.651**	.715**	.699**	.701**	.639**	.711**	1	
DI	.679**	.680**	.658**	.682**	.649**	.693**	.710**	.694**	.668**	.702**	.665**	1

** Correlation is significant at the 0.01 level (2-tailed).

Table 7.4. Item Correlation Coefficient Test Results

7.3.4 Structural model analysis

In this study, we used Lisrel 8 to check the fitting index of the model, and the model visualization is shown in Figure 7.2.

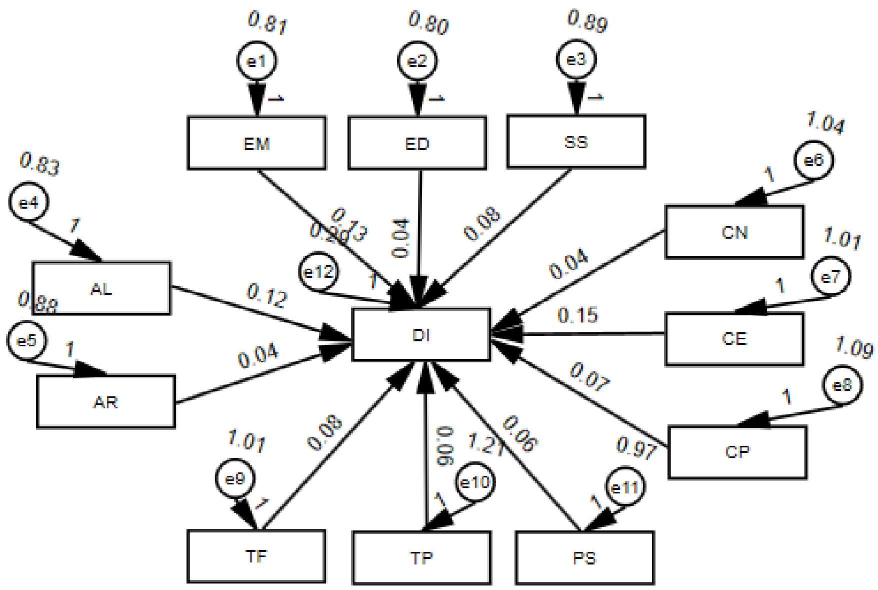

Figure 7.2. Research model path diagram

A number of standard indicators were used for comprehensive evaluation, including Chi-square to freedom ratio (CMIN/DF), residual root mean square (RMR), goodness of fit index (GFI), standard fit index (NFI), adjusted goodness of Fit index (AGFI), Comparative fit index (CFI), and approximate root mean square error (RMSEA).

Fit index	Recommended level	Default model	Structural model
CMIN/DF	<3.0	2.570	0.000
RMR	<0.08	0.059	0.000
GFI	>0.9	0.919	1.000
NFI	>0.9	0.970	1.000
AGFI	>0.9	0.915	0.999
CFI	>0.9	0.960	1.000
RMSEA	<0.08	0.042	0.040

Table 7.5. The Goodness of Fit Indices Results

Observing the data in Table 7.5, the CMIN/DF value is 2.57, which is within the acceptable range. Generally, when the significance is greater than 2 and less than 3, it indicates that the consistency of the model is high (Kline, 2023). The values of RMR, GFI, NFI, AGFI, and CFI all exceed the generally recommended level of 0.9, indicating that the model in this study is well adapted to the data (Shevlin & Miles, 1998). For the value of RMSEA, the generally set threshold is 0.08, and the value of the structural model in this study is 0.068, which is also within the acceptable range (McDonald & Ho, 2002).

RQ	Path	Estimate	S.E.	P-Value	Decision
RQ1a	EM➔DI	0.814	0.043	0.000	Supported
RQ1b	SS➔DI	0.803	0.043	0.000	Supported
RQ1c	ED➔DI	0.895	0.048	0.000	Supported
RQ2a	AL➔DI	0.826	0.044	0.000	Supported
RQ2b	AR➔DI	0.877	0.047	0.000	Supported
RQ3a	CN➔DI	1.037	0.055	0.000	Supported
RQ3b	CE➔DI	1.009	0.054	0.000	Supported
RQ3c	CP➔DI	1.085	0.058	0.000	Supported
RQ4a	TF➔DI	1.011	0.054	0.000	Supported
RQ4b	TP➔DI	1.208	0.064	0.000	Supported
RQ4c	PS➔DI	0.973	0.052	0.000	Supported

Table 7.6. Research Questions Results

This study further tests the proposed research questions through causal paths, using normalized path coefficients with values ranging from -1 to 1. According to the results in Table 7.6, all research questions are supported, therefore, the research path in Figure 7.2 of this study has been confirmed. TP (transparent project progress report) has a path coefficient of 1.208, showing the strongest positive effect, while EM (emotional motivation) has a path coefficient of 0.814, which has the smallest effect in the model. From the perspective of dimensions, the two dimensions of Community Belonging and Financial Transparency have the most significant positive impact on AEP-DCF projects, followed by Altruism or Sacrificialism. The Self-perception Emotion dimension has the most limited effect.

7.4 CONCLUSIONS

The chapter delves into the will behind crowdfunded donations in the AEP sectors. It designed four dimensions of Self-perception emotion, Altruism or sacrificialism, Community belonging and financial transparency through empirical investigation. The model presented in this chapter demonstrates a strong alignment with the data and exhibits a high level of reliability. Furthermore, its structural model showcases exceptional validity performance.

In the field of donation motivation analysis, causal path analysis shows that transparent project progress reports (TP) have the strongest positive impact on AEP-DCF project donations, while emotional motivation (EM) has a relatively small positive impact. These findings provide empirical support for improving transparency and communication strategies for crowdfunding projects.

In terms of dimensions, the Community belonging and the Financial transparency become the most important factors affecting the motivation of AEP crowdfunding donation, followed by altruism or sacrificialism. In contrast, the self-perceived emotion dimension has a relatively weak influence.

In essence, the study provides insights into the motivations for crowdfunding donations for AEP. These findings not only contribute to the academic understanding of the topic, but also provide a practical reference for the design and promotion of crowdfunding programs in the field of environmental protection.

Undoubtedly, there are certain limitations to the study. Firstly, the sample selection primarily relies on online surveys, potentially introducing self-selection bias and limiting the generalizability of research findings. Secondly, although model fit index testing using LISREL 8 is employed, the complexity of the model may not comprehensively encompass all potential influencing factors. Additionally, the variables and dimensions utilized in this chapter may not exhaustively explore all aspects of donation behavior; thus, future research should expand upon specific factors for further investigation.

8

GENERAL CONCLUSIONS

Crowdfunding is now widely acknowledged as a prevalent financing tool, with an increasing number of individuals seeking funds through crowdfunding platforms. Consequently, the financial performance of projects assumes paramount importance. On these platforms, project creators must present their projects in an enticing manner to attract sufficient backers. They should ensure that the project description is both lucid and captivating, effectively conveying its value and potential to prospective supporters. Simultaneously, project sponsors must demonstrate their credibility and capabilities to instill trust among backers. Backers themselves need to assess the worth and prospects of a project before deciding whether or not to support it; they typically scrutinize the project description along with relevant information about the sponsor meticulously. Prior to backing a project, they need to make sure they know it well enough to make an informed decision.

The financing performance of a project holds paramount importance for project sponsors and supporters. Project initiators must ensure timely and adequate support for their projects to achieve their funding objectives, while backers need to ascertain the return on their investment, whether it be financial or ethical. And their investment contributes to the success of the project.

Through the review of existing research, this thesis finds that crowdfunding research can be divided into two main research lines in general. The first research line is related to the development of crowdfunding, mainly including the definition of crowdfunding, the classification of crowdfunding platform models, and the motivation of crowdfunding participants. These studies focus on understanding the nature and development trends of crowdfunding in order to better understand the future trends and challenges of the crowdfunding industry. Another research line is the research on the performance and success factors of crowdfunding internal activities, mainly including the research on project success factors and various crowdfunding information. These studies aim to know the internal mechanism and influencing factors of crowdfunding to better improve the financing performance and success rate of projects.

In addition, the application of artificial intelligence in the research of crowdfunding started relatively late, but it has strong development potential. As an emerging technology, it has strong application potential and development prospects, especially in data analysis, risk assessment and portfolio optimization of crowdfunding platforms, user behavior analysis, and project success prediction. With the continuous development and application of artificial intelligence technology in the future, its role in crowdfunding research will become more and more important.

This thesis also reviews the relevant literature on the three types of crowdfunding: ECF, RCF, and DCF. It found that in the field of ECF, existing research mainly focuses on three aspects: investor behavior, success factors of crowdfunding projects, and the impact of crowdfunding platform operations on project success. In the field of RCF, research on the financing performance of crowdfunding projects is divided into three lines: the influence of geographical location and network relations, the influence of project information, and the influence of social capital and value. As an emerging online donation method, DCF has attracted much attention. It's usually a non-profit project, and backers usually don't receive anything material in return. This model makes it easier to get involved in philanthropy than the traditional model of charitable giving. However, the existing research on DCF mostly focuses on the motivation of donations and project sponsors, without considering the financial transparency of projects. In addition, research on the environment and animal protection tends to focus on traditional offline donation-raising projects, while research on online donation-based crowdfunding is relatively scarce.

This thesis explores the financial performance and success factors across different types of crowdfunding, integrating theoretical insights from existing research and empirical findings.

Chapter 4 examines the factors affecting the financial performance of equity crowdfunding projects. The results show that the expected return and the return on registered capital significantly impact on actual returns, with profitability indicators effectively reflecting project quality. However, inflated return expectations can harm performance by undermining investor trust. The logistic regression reveals that strong operational capabilities enhance financing success, while overstaffing and overly optimistic projections from highly educated representatives can hinder project outcomes. Transparency and realistic expectations are essential for building investor confidence. Additionally, the application of a Deep Neural Network (DNN) model proves more effective than traditional regression in predicting crowdfunding success, offering superior accuracy and insight.

Chapter 5 explores the factors influencing the financial performance of reward-based crowdfunding projects. The analysis reveals that the number of supporters, followers, and the sponsor's social capital are key drivers of success, as they enhance project visibility and investor trust. Well-structured project progress also boosts financing performance by demonstrating strong execution capabilities. A higher minimum investment threshold attracts experienced investors with greater financial resources, contributing to better project outcomes. Conversely, the number of "likes" shows a negative correlation with financing performance, likely due to its superficial nature, as investors focus more on tangible progress and project quality. Additionally, the introduction of the macroeconomic indicator "PCDI" highlights that economic conditions significantly influence crowdfunding success, with a healthier economy boosting investor confidence and participation.

Chapter 6 examines the factors that influence the success of donation-based crowdfunding projects in environmental and animal protection. Financial transparency is identified as the most critical factor, as it fosters donor trust and increases project success rates. The credibility of the project sponsor, particularly if it is a non-profit organization, also enhances success by boosting donor confidence. The number of donors positively impacts project outcomes, while over-describing projects can lead to unrealistic expectations, diminishing donor support. To improve predictions of success, this chapter employs a BP neural network model, which outperforms traditional logistic regression by better handling nonlinearities and offering stronger generalization across data sets. The results suggest that utilizing the BP neural network model in practice can help decision-makers more accurately forecast project success.

Chapter 7 explores the motivations behind donations in AEP crowdfunding, focusing on four dimensions: self-perception emotion, altruism, community belonging, and financial transparency. The results show that transparent project progress reports have the strongest positive impact on donations, while emotional motivation has a smaller influence. Community belonging and financial transparency are the most significant factors driving donation behavior, with altruism also playing a role, while self-perception emotion has the least impact. These findings offer valuable insights for improving the design and promotion of AEP crowdfunding projects by emphasizing transparency and fostering a sense of community.

However, this thesis also encountered some limitations.

The research on equity crowdfunding highlights the presence of "junk" projects, which contribute to the low success rate of projects. Although eradicating these projects entirely is currently unfeasible, the situation may improve with the industry's maturation and increased transparency. The study faced challenges due to data limitations, such as the inability to trace and characterize the specific reasons for all results and the incomplete financial statements of some equity crowdfunding projects. These limitations restricted the depth and breadth of the study. Additionally, the lack of comprehensive financial statements from equity crowdfunding projects further constrained the analysis. Future research should focus on financial transparency and information disclosure in equity crowdfunding to enhance understanding of industry development and trends.

The impact of macroeconomic indicators on reward-based crowdfunding was identified as a significant finding. However, there is a need for further research to explore and quantify how macroeconomic indicators affect crowdfunding performance to gain a better understanding of the industry's operating mechanisms and trends. The study also encountered a lack of reference materials for platform projects, limiting variable selection. Notably, some variables, such as project financial information and sponsor company information, were not available. Future research could address these gaps by examining information transparency in reward-based crowdfunding platforms to improve research credibility and accuracy. Additionally, research on social capital, which was a key aspect of this study, faces limitations due to uncertainties and ongoing debates about its quantification and theoretical foundations. Future work should aim to capture and determine the true value of social capital and its role in crowdfunding.

For donation-based crowdfunding, the overall success rate of projects related to environmental and animal protection was relatively low. This study identified negative factors but acknowledged that other critical reasons might also be influencing these outcomes. Future research should investigate additional key causes to help enhance the effectiveness of environmental and animal protection initiatives. Furthermore, limitations were noted in the financial transparency of donation-based crowdfunding projects. Improving financial transparency within this sector could enhance industry quality, bolster donor trust, and support sustainable development. Future research should explore strategies to increase financial transparency and promote a culture of transparency within the industry. The study's reliance on online surveys introduced potential self-selection bias, which may limit the generalizability of the results. Also, it may indicate that there are other factors or variables that have not been considered (such as socioeconomic factors, individual psychological factors, etc.) Moreover, while LISREL 8 was used for model fit index testing, the complexity of the model might not fully encompass all potential influencing factors. The variables and dimensions used may not cover every aspect of donation behavior, indicating a need for further exploration of specific factors.

Here are the proposed directions for future research.

The crowdfunding industry is continuously evolving, with a growing and diversifying market encompassing individual and corporate financing, as well as social welfare and innovation crowdfunding. As technology advances and regulatory oversight strengthens, the transparency and sustainability of the crowdfunding industry are expected to improve, leading to the emergence of new crowdfunding models and platforms.

Future research in the crowdfunding field should focus on several key areas: (a) Project Financial Transparency: Investigate how financial transparency impacts crowdfunding performance and donor trust and develop strategies to enhance transparency across various crowdfunding models; (b) Quantification of Social Capital: Further explore the quantification of social capital and its theoretical underpinnings. Research should aim to capture the true value of social capital and its application in crowdfunding contexts; (c) Development of Crowdfunding Models: Study the evolution of crowdfunding models and platforms, considering the influence and role of crowdfunding in the financial sector. This includes examining how new models can address existing limitations and contribute to the industry's growth.

Future development of AI technology Research in the field of crowdfunding can focus on the following key areas: Future research can explore how to use artificial intelligence (AI) to improve financial transparency, automate financial reporting, and enable real-time data monitoring to enhance transparency. Further explore the quantification of social capital and its theoretical basis. Research should aim to capture the true value of social capital and its application in crowdfunding.

In addition, this thesis defines “success” in a narrow sense as a project meeting crowdfunding expectation. In addition to pure crowdfunding achievements, future research should also consider incorporating other dimensions of success, including the social impact, economic benefits, and long-term sustainability of the project.

Overall, future research should aim to address these areas to improve understanding and practices within the crowdfunding industry, ultimately supporting its sustainable development and enhancing its effectiveness across various domains.

REFERENCES

Ahlers, G. K. , Cumming, D. , Günther, C. , & Schweizer, D. (2015). Signaling in Equity Crowdfunding. *Entrepreneurship Theory and Practice*, *39*(4), 955–980.

Alessandrini, M. (2007). Community volunteerism and blood donation: altruism as a lifestyle choice. *Transfusion Medicine Reviews*, *21*(4), 307–316.

Allison, T. H., Davis, B. C., Short, J. C., & Webb, J. W. (2015). Crowdfunding in a prosocial microlending environment: Examining the role of intrinsic versus extrinsic cues. *Entrepreneurship Theory and Practice*, *39*(1), 53–73.

Althoff, T., & Leskovec, J. (2015). Donor retention in online crowdfunding communities: A case study of donorschoose. org. *Proceedings of the 24th International Conference on World Wide Web*, 34–44.

Andreoni, J. (1990). Impure altruism and donations to public goods: A theory of warm-glow giving. *The Economic Journal*, *100*(401), 464–477.

Baah-Peprah, P., Shneor, R., & Munim, Z. H. (2024). “In this together”: on the antecedents and implications of crowdfunding community identification and trust. *Venture Capital*, 1–31.

Balsam, S., & Harris, E. E. (2018). Nonprofit executive incentive pay. *Review of Accounting Studies*, *23*(4), 1665–1714.

Beier, M., & Wagner, K. (2014). Crowdfunding Success of Tourism Projects-Evidence from Switzerland. *Available at SSRN 2520925*.

Belleflamme, P., Lambert, T., & Schwienbacher, A. (2013). Individual crowdfunding practices. *Venture Capital*, *15*(4), 313–333.

Belleflamme, P., Lambert, T., & Schwienbacher, A. (2014). Crowdfunding: Tapping the right crowd. *Journal of Business Venturing*, *29*(5), 585–609.

Belleflamme, P., Omrani, N., & Peitz, M. (2015). The economics of crowdfunding platforms. *Information Economics and Policy*, *33*, 11–28. https://doi.org/10.1016/j.infoecopol.2015.08.003

Beltran, J. F., Siddique, A., Abouzied, A., & Chen, J. (2015). Codo: Fundraising with conditional donations. *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology*, 213–222.

Block, J., Hornuf, L., & Moritz, A. (2018). Which updates during an equity crowdfunding campaign increase crowd participation ? *Small Business Economics*, *50*(1), 3–27.

Body, A., & Breeze, B. (2016). What are 'unpopular causes' and how can they achieve fundraising success? *International Journal of Nonprofit and Voluntary Sector Marketing*, *21*(1), 57–70.

Borst, I., Moser, C., & Ferguson, J. (2018). From friendfunding to crowdfunding : Relevance of relationships , social media , and platform activities to crowdfunding performance. *New Media & Society*, *20*(4), 1396–1414.

Bretschneider, U., & Leimeister, J. M. (2017). Not just an ego-trip: Exploring backers' motivation for funding in incentive-based crowdfunding. *The Journal of Strategic Information Systems*, *26*(4), 246–260.

Brown, J., Broderick, A. J., & Lee, N. (2008). Interactions in Virtual Customer Environments. *Journal of Interactive Marketing*, *22*(4), 1–12.

Buccoliero, L., Bellio, E., Mazzola, M., & Solinas, E. (2015). A marketing perspective to "delight" the "patient 2.0": new and challenging expectations for the healthcare provider. *BMC Health Services Research*, *16*(1), 1–12.

Buell, R. W., Kim, T., & Tsay, C.-J. (2017). Creating reciprocal value through operational transparency. *Management Science*, *63*(6), 1673–1695.

Calic, G., & Shevchenko, A. (2020). How signal intensity of behavioral orientations affects crowdfunding performance: The role of entrepreneurial orientation in crowdfunding business ventures. *Journal of Business Research*, *115*(C), 204–220.

Carbonara, N. (2021). The role of geographical clusters in the success of reward-based crowdfunding campaigns. *The International Journal of Entrepreneurship and Innovation*, *22*(1), 18–32.

Carè, S., Trotta, A., Carè, R., & Rizzello, A. (2018). Crowdfunding for the development of smart cities. *Business Horizons*, *61*(4), 501–509.

Chapman, C. M., Louis, W. R., Masser, B. M., & Thomas, E. F. (2022). Charitable Triad Theory: How donors, beneficiaries, and fundraisers influence charitable giving. *Psychology & Marketing*, *39*(9), 1826–1848.

Cheng, C., Tan, F., Hou, X., & Wei, Z. (2019). Success Prediction on Crowdfunding with Multimodal Deep Learning. *IJCAI*, 2158–2164.

China Charity Alliance. (2023, September 22). *China Digital Charity Development Report 2023*. http://www.charityalliance.org.cn/news/14949.jhtml

China Industry Research Network. (2024, May 17). *2024-2029 Crowdfunding Industry Status and Future Development Trend Analysis Report*. https://www.chinairn.com/hyzx/20240517/140420682.shtml

(China) January 2020 crowdfunding Industry Monthly Report. (2020).

Cholakova, M. (2015). *E T & P Does the Possibility Investments ?* 145–172.

Choy, K., & Schlagwein, D. (2016). Crowdsourcing for a better world. *Information Technology & People*, *29*(1), 221–247.

Clauss, T., Breitenecker, R. J., Kraus, S., Brem, A., Clauss, T., Breitenecker, R. J., Kraus, S., & Brem, A. (2018). Directing the wisdom of the crowd : the importance of social interaction among founders and the crowd during crowdfunding campaigns. *Economics of Innovation and New Technology*, *27*(8), 709–729.

Cockrell, S. R., Meyer, D. W., & Smith, A. D. (2016). Electronic intervention and platforms and their impacts on crowdfunding behaviour. *International Journal of Business Information Systems*, *23*(3), 263–286.

Corsini, F., & Frey, M. (2024). Funding the Future of the Planet Through Crowdfunding. In *Crowdfunding for Environmental Sustainability and the Circular Economy: Empowered Strategies for Sustainable Growth* (pp. 37–59). Springer.

Cowden, B. J., & Young, S. L. (2020). The copycat conundrum: The double-edged sword of crowdfunding. *Business Horizons*, *63*(4), 541–551.

Daskalakis, N., & Yue, W. (2017). User's perceptions of motivations and risks in crowdfunding with financial returns. *Available at SSRN 2968912*.

Dellarocas, C. (2003). The digitization of word of mouth: Promise and challenges of online feedback mechanisms. *Management Science*, *49*(10), 1407–1424.

Dragojlovic, N., & Lynd, L. D. (2014). Crowdfunding drug development: the state of play in oncology and rare diseases. *Drug Discovery Today*, *19*(11), 1775–1780.

Duan, Y., Hsieh, T.-S., Wang, R. R., & Wang, Z. (2020). Entrepreneurs' facial trustworthiness, gender, and crowdfunding success. *Journal of Corporate Finance*, *64*(C), 101693.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

Funk, A. S., & Funk, A. S. (2019). *Crowdfunding in China*. Springer.

Gafni, H., Marom, D., & Sade, O. (2019). Are the life and death of an early-stage venture indeed in the power of the tongue ? Lessons from online crowdfunding pitches. *Strategic Entrepreneurship Journal*, *13*(1), 3–23.

Gallo, L. A., Hann, R. N., & Li, C. (2016). Aggregate earnings surprises, monetary policy, and stock returns. *Journal of Accounting and Economics*, *62*(1), 103–120.

Gallo-Cajiao, E., Archibald, C., Friedman, R., Steven, R., Fuller, R. A., Game, E. T., Morrison, T. H., & Ritchie, E. G. (2018). Crowdfunding biodiversity conservation. *Conservation Biology*, *32*(6), 1426–1435.

Ghahramani, Z. (2015). Probabilistic machine learning and artificial intelligence. *Nature*, *521*(7553), 452–459.

Gleasure, R., & Feller, J. (2016). Emerging technologies and the democratisation of financial services: A metatriangulation of crowdfunding research. *Information and Organization*, *26*(4), 101–115.

Gorczyca, M., & Hartman, R. L. (2017). The new face of philanthropy: The role of intrinsic motivation in millennials' attitudes and intent to donate to charitable organizations. *Journal of Nonprofit & Public Sector Marketing*, *29*(4), 415–433.

Graziano, E. A., Fattobene, L., Giovando, G., & Pellicelli, A. (2023). Contacts on LinkedIn: equity crowdfunding platforms' networks and creators' innovation performance. *European Journal of Innovation Management*.

Greenberg, M. D., Pardo, B., Hariharan, K., & Gerber, E. (2013). Crowdfunding support tools: predicting success & failure. In *CHI'13 extended abstracts on human factors in computing systems* (pp. 1815–1820).

Grimmelikhuijsen, S., Porumbescu, G., Hong, B., & Im, T. (2013). The effect of transparency on trust in government: A cross-national comparative experiment. *Public Administration Review*, *73*(4), 575–586.

Griskevicius, V., & Kenrick, D. T. (2013). Fundamental motives: How evolutionary needs influence consumer behavior. *Journal of Consumer Psychology*, *23*(3), 372–386.

Griskevicius, V., Shiota, M. N., & Nowlis, S. M. (2010). The many shades of rose-colored glasses: An evolutionary approach to the influence of different positive emotions. *Journal of Consumer Research*, *37*(2), 238–250.

Groza, M. P., Groza, M. D., & Barral, L. M. (2020). Women backing women: The role of crowdfunding in empowering female consumer-investors and entrepreneurs. *Journal of Business Research*, *117*(C), 432–442.

Guenther, C., Johan, S., & Schweizer, D. (2018). Is the crowd sensitive to distance?—How investment decisions differ by investor type. *Small Business Economics*, *50*(2), 289–305.

Habib, M. D., Filimonau, V., Coşkun, A., Wang, L., & Ermolaev, V. A. (2023). Altruistic and collectivistic values as the antecedents of surplus food donation intention. *Socio-Economic Planning Sciences*, *90*, 101729.

Hariwibowo, I. N., Wulandari, C. E., & Setyohadi, D. B. (2022). Agency Relation in Online Charity Crowdfunding: The Role of Transparency to Attract Donation. *IBIMA Business Review*, *18*.

Hornuf, L., & Schwienbacher, A. (2018). Market mechanisms and funding dynamics in equity crowdfunding. *Journal of Corporate Finance*, *50*(C), 556–574.

Hsieh, H., Hsieh, Y., Huyen, T., & Vu, C. (2019). How social movements influence crowdfunding success. *Pacific-Basin Finance Journal*, *53*(C), 308–320.

Huang, Y., Uy, M. A., Liu, C., Foo, M.-D., & Li, Z. A. (2023). Visual totality of rewards-based crowdfunding pitch videos: Disentangling the impact of peak negative affective visual expression on funding outcomes. *Journal of Business Venturing*, *38*(5), 106318.

Inbar, Y., & Barzilay, O. (2014). Community impact on crowdfunding performance. *Available at SSRN 2524910*.

Isa, N. A. M., Irpan, H. M., Bahrom, H. Bin, Salleh, A. B. M., & Ridzuan, A. R. Bin. (2015). Characteristic affecting charitable donations behavior: Empirical evidence from Malaysia. *Procedia Economics and Finance*, *100*(31), 563–572.

Jiang, C., Pérez-Estébanez, R., & Urquía-Grande, E. (2022). Is Equity Crowdfunding the Leapfrog to Companies' Success? Financial Performance in China. *Computational Intelligence and Neuroscience*, *2022*(C), 7814550.

Jiang, C., Urquía-Grande, E., & Estébanez, R. P. (2021). Research on the performance factors of reward-based crowdfunding: evidence from China. *RAITES*, *7*(15), 10–35.

Jiang, C., Urquía-Grande, E., & Pérez-Estébanez, R. (2023). Which Factors Can Contribute to the Success of Environmental and Animal Protection Projects in Donation-based Crowdfunding? A Neural Network Model. *International Journal on Recent and Innovation Trends in Computing and Communication*, *11*(9), 1414–1425.

Jung, E., Susarla, A., & Sambamurthy, V. (2015). Community Engagement and Collective Evaluation in Crowdfunding. *Available at SSRN 2606449*.

Karlan, D., & Wood, D. H. (2017). The effect of effectiveness: Donor response to aid effectiveness in a direct mail fundraising experiment. *Journal of Behavioral and Experimental Economics*, *66*, 1–8.

Keras. (2022). https://keras.io/guides/

Kline, R. B. (2023). *Principles and practice of structural equation modeling*. Guilford publications.

Koning, R., & Model, J. (2013). Experimental study of crowdfunding cascades: When nothing is better than something. *Available at SSRN 2308161*.

Korzynski, P., Haenlein, M., & Rautiainen, M. (2021). Impression management techniques in crowdfunding: An analysis of Kickstarter videos using artificial intelligence. *European Management Journal*, *39*(5), 675–684.

Král, P., & Cuskelly, G. (2018). A model of transparency: determinants and implications of transparency for national sport organizations. *European Sport Management Quarterly*, *18*(2), 237–262.

Kubo, T., Veríssimo, D., Uryu, S., Mieno, T., & MacMillan, D. (2021). What determines the success and failure of environmental crowdfunding? *Ambio*, *50*(9), 1659–1659.

Kunz, M. M., Bretschneider, U., Erler, M., & Leimeister, J. M. (2017). An empirical investigation of signaling in reward-based crowdfunding. *Electronic Commerce Research*, *17*(3), 425–461.

Kuppuswamy, V., & Bayus, B. L. (2017). Journal of Business Venturing Does my contribution to your crowdfunding project matter ? *Journal of Business Venturing*, *32*(1), 72–89.

Kuppuswamy, V., & Bayus, B. L. (2018). Crowdfunding creative ideas: The dynamics of project backers. In *The economics of crowdfunding* (pp. 151–182). Springer.

Lacan, C., & Desmet, P. (2017). Motivations for participation and e-WOM among supporters of crowdfunding campaigns. In *Strategic innovative marketing* (pp. 315–321). Springer.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444.

Lee, S., Lee, K., & Kim, H. (2018). Content-based success prediction of crowdfunding campaigns: A deep learning approach. *Companion of the 2018 ACM Conference on Computer Supported Cooperative Work and Social Computing*, 193–196.

Lee, Y.-C., Yen, C.-H., & Fu, W.-T. (2016). Improving donation distribution for crowdfunding: An agent-based model. *International Conference on Social Computing, Behavioral-Cultural Modeling and Prediction and Behavior Representation in Modeling and Simulation*, 3–12.

Li, Y., He, T., Song, Y., Yang, Z., & Zhou, R. (2018). Factors impacting donors' intention to donate to charitable crowd-funding projects in China: a UTAUT-based model. *Information, Communication & Society*, *21*(3), 404–415.

Li, Y., Rakesh, V., & Reddy, C. K. (2016). Project success prediction in crowdfunding environments. *Proceedings of the Ninth ACM International Conference on Web Search and Data Mining*, 247–256.

Li, Y.-M., Wu, J.-D., Hsieh, C.-Y., & Liou, J.-H. (2020). A social fundraising mechanism for charity crowdfunding. *Decision Support Systems*, *129*(C), 113170.

Liang, J., Chen, Z., & Lei, J. (2016). Inspire me to donate: The use of strength emotion in donation appeals. *Journal of Consumer Psychology*, *26*(2), 283–288.

Liang, T. P., Wu, S. P. J., & Huang, C. (2019). Why funders invest in crowdfunding projects: Role of trust from the dual-process perspective. *Information and Management*, *56*(1), 70–84. https://doi.org/10.1016/j.im.2018.07.002

Liao, C., Zhu, Y., & Liao, X. (2015). The role of internal and external social capital in crowdfunding: Evidence from China. *Revista de Cercetare Si Interventie Socialâ*, *49*, 187–204.

Lin, M., & Viswanathan, S. (2016). Home bias in online investments: An empirical study of an online crowdfunding market. *Management Science*, *62*(5), 1393–1414.

Liu, C.-J., & Hao, F. (2017). Reciprocity belief and gratitude as moderators of the association between social status and charitable giving. *Personality and Individual Differences*, *100*(111), 46–50.

Lundberg, P., Vainio, A., MacMillan, D. C., Smith, R. J., Verissimo, D., & Arponen, A. (2019). The effect of knowledge, species aesthetic appeal, familiarity and conservation need on willingness to donate. *Animal Conservation*, *22*(5), 432–443.

Ma, Z. (2023). Early backers' social and geographic influences on the success of crowdfunding. *Journal of Research in Interactive Marketing*, *17*(4), 510–526.

Mahmood, A., Luffarelli, J., & Mukesh, M. (2019). What's in a logo? The impact of complex visual cues in equity crowdfunding. *Journal of Business Venturing*, *34*(1), 41–62.

Majumdar, A., & Bose, I. (2017). *Demystifying the factors that impact the success of charitable crowdfunding postings*.

Mano, R. S. (2014). Social media, social causes, giving behavior and money contributions. *Computers in Human Behavior*, *31*(C), 287–293.

Maxwell, S. L., Cazalis, V., Dudley, N., Hoffmann, M., Rodrigues, A. S. L., Stolton, S., Visconti, P., Woodley, S., Kingston, N., & Lewis, E. (2020). Area-based conservation in the twenty-first century. *Nature*, *586*(7828), 217–227.

Mazzocchini, F. J., & Lucarelli, C. (2022). Success or failure in equity crowdfunding? A systematic literature review and research perspectives. *Management Research Review*, *46*(6), 790–831.

McDonald, R. P., & Ho, M.-H. R. (2002). Principles and practice in reporting structural equation analyses. *Psychological Methods*, *7*(1), 64.

McDonnell, M.-H., & King, B. (2013). Keeping up appearances: Reputational threat and impression management after social movement boycotts. *Administrative Science Quarterly*, *58*(3), 387–419.

Mead, N. L., Baumeister, R. F., Stillman, T. F., Rawn, C. D., & Vohs, K. D. (2011). Social exclusion causes people to spend and consume strategically in the service of affiliation. *Journal of Consumer Research*, *37*(5), 902–919.

Meer, J. (2014). Effects of the price of charitable giving: Evidence from an online crowdfunding platform. *Journal of Economic Behavior & Organization*, *103*, 113–124.

Mejia, J., Urrea, G., & Pedraza-Martinez, A. J. (2019). Operational transparency on crowdfunding platforms: Effect on donations for emergency response. *Production and Operations Management*, *28*(7), 1773–1791.

Mitra, T., & Gilbert, E. (2014). The language that gets people to give: Phrases that predict success on kickstarter. *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing*, 49–61.

Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of Business Venturing*, *29*(1), 1–16.

Moritz, A., & Block, J. H. (2016). Crowdfunding: A literature review and research directions. *Crowdfunding in Europe*, 25–53.

Moss, T. W., Neubaum, D. O., & Meyskens, M. (2015). The effect of virtuous and entrepreneurial orientations on microfinance lending and repayment: A signaling theory perspective. *Entrepreneurship Theory and Practice*, *39*(1), 27–52.

Mullainathan, S., & Spiess, J. (2017). Machine learning: an applied econometric approach. *Journal of Economic Perspectives*, *31*(2), 87–106.

Nagel, T. (2016). *The possibility of altruism*.

Ndeffo Mbah, M. L., & Gilligan, C. A. (2011). Resource allocation for epidemic control in metapopulations. *PLoS One*, *6*(9), e24577.

Neumayr, M., & Handy, F. (2019). Charitable giving: What influences donors' choice among different causes? *Voluntas: International Journal of Voluntary and Nonprofit Organizations*, *30*(4), 783–799.

Ortega-Rodríguez, C., Licerán-Gutiérrez, A., & Moreno-Albarracín, A. L. (2020). Transparency as a key element in accountability in non-profit organizations: A systematic literature review. *Sustainability*, *12*(14), 5834.

Paramita, W., Septianto, F., & Tjiptono, F. (2020). The distinct effects of gratitude and pride on donation choice and amount. *Journal of Retailing and Consumer Services*, *53*, 101972.

Peng, N., Zhou, X., Niu, B., & Feng, Y. (2021). Predicting Fundraising Performance in Medical Crowdfunding Campaigns Using Machine Learning. *Electronics*, *10*(2), 143.

Pitschner, S., & Pitschner-Finn, S. (2014). Non-profit differentials in crowd-based financing: Evidence from 50,000 campaigns. *Economics Letters*, *123*(3), 391–394.

Profatilov, D. A., Bykova, O. N., & Olkhovskaya, M. O. (2015). Crowdfunding: Online charity or a modern tool for innovative projects implementation? *Asian Social Science*, *11*(3), 146.

Raab, M., Schlauderer, S., Overhage, S., & Friedrich, T. (2020). More than a feeling: Investigating the contagious effect of facial emotional expressions on investment decisions in reward-based crowdfunding. *Decision Support Systems*, *135*, 113326.

Rahmayanti, P. L. D., Rahyuda, I. K., Ekawati, N. W., & Setiawan, P. Y. (2023). Intention to Donate on Online Charitable Crowdfunding: Systematic Literature Review and Future Research Agenda. *Journal of Economics, Business, and Accountancy Ventura*, *26*(3), 401–427.

Ramli, H. S., Abdullah, M. F., & Alam, M. K. (2022). Islamic crowdfunding practices in Malaysia: a case study on Nusa Kapital. *Asian Journal of Accounting Research*, *8*(2), 145–156.

Reinstein, D. A. (2011). Does one charitable contribution come at the expense of another? *The BE Journal of Economic Analysis & Policy*, *11*(1).

Ryu, S. (2024). Antecedents and Consequences of Relationship Motivation in Reward-Based Crowdfunding. *Journal of Alternative Finance*, 27533743241259492.

Salido-Andres, N., Rey-Garcia, M., Alvarez-Gonzalez, L. I., & Vazquez-Casielles, R. (2022). When the winner takes it all: online campaign factors influencing the success of donation-based crowdfunding for charitable causes. *International Review on Public and Nonprofit Marketing*, *19*(4), 763–780.

Shafqat, W., & Byun, Y.-C. (2019). Topic predictions and optimized recommendation mechanism based on integrated topic modeling and deep neural networks in crowdfunding platforms. *Applied Sciences*, *9*(24), 5496.

Shevlin, M., & Miles, J. N. V. (1998). Effects of sample size, model specification and factor loadings on the GFI in confirmatory factor analysis. *Personality and Individual Differences*, *25*(1), 85–90.

Shi, J., Yang, K., Xu, W., & Wang, M. (2021). Leveraging deep learning with audio analytics to predict the success of crowdfunding projects. *The Journal of Supercomputing*, *77*(7), 7833–7853.

Shneor, R., Maehle, N., Munim, Z. H., & Rykkja, A. (2024). What drives crowdfunding intentions of artist-entrepreneurs?–Evidence from Norway. *The International Journal of Entrepreneurship and Innovation*, 14657503241282940.

Simon, M., Stanton, S. J., Townsend, J. D., & Kim, J. (2019). A multi-method study of social ties and crowdfunding success: Opening the black box to get the cash inside. *Journal of Business Research*, *104*(C), 206–214.

Skarmeas, D., & Shabbir, H. A. (2011). Relationship quality and giving behaviour in the UK fundraising sector: Exploring the antecedent roles of religiosity and self-construal. *European Journal of Marketing*, *45*(5), 720–738.

Smith, S., Windmeijer, F., & Wright, E. (2015). Peer effects in charitable giving: Evidence from the (running) field. *The Economic Journal*, *125*(585), 1053–1071.

Solomon, J., Ma, W., & Wash, R. (2015). Don't wait! How timing affects coordination of crowdfunding donations. *Proceedings of the 18th Acm Conference on Computer Supported Cooperative Work & Social Computing*, 547–556.

STATISTA. (2020). https://www.statista.com/outlook/335/117/crowdfunding/china

Straub, D. W. (1989). Validating instruments in MIS research. *MIS Quarterly*, 147–169.

Suseno, Y., & Abbott, L. (2021). Women entrepreneurs' digital social innovation: Linking gender, entrepreneurship, social innovation and information systems. *Information Systems Journal*, *31*(5), 717–744.

Tan, J., Lu, Y., & Tan, Y. (2021). The Impact of Subscription Reciprocity on Charitable Content Creation and Sharing: Evidence from Twitter on Giving Tuesday. *Management Information Systems Quarterly*, *45*(2), 535–562.

Thakial, S., & Arora, B. (2019). Neural Network Based Prediction Model for Job Applicants. *Journal of Computational and Theoretical Nanoscience*, *16*(9), 3867–3873.

Thomas-Walters, L., McNulty, C., & Veríssimo, D. (2020). A scoping review into the impact of animal imagery on pro-environmental outcomes. *Ambio*, *49*(6), 1135–1145.

Troise, C., Battisti, E., Christofi, M., van Vulpen, N. J., & Tarba, S. (2023). How can SMEs use crowdfunding platforms to internationalize? The role of equity and reward crowdfunding. *Management International Review*, *63*(1), 117–159.

Troise, C., & Yablonsky, S. (2023). Reward crowdfunding and the success of campaigns: exploring the role of social capital of entrepreneurs and investors. *International Journal of Entrepreneurship and Small Business*, *50*(2), 133–150.

van Teunenbroek, C., Dalla Chiesa, C., & Hesse, L. (2023). The contribution of crowdfunding for philanthropy: A systematic review and framework of donation and reward crowdfunding. *Journal of Philanthropy and Marketing*, *28*(3), e1791.

Van Teunenbroek, C., & Hasanefendic, S. (2023). Researching the crowd: Implications on philanthropic crowdfunding and donor characteristics during a pandemic. *Journal of Philanthropy and Marketing*, *28*(1), e1773.

Van Vugt, M., Roberts, G., & Hardy, C. (2007). *Competitive altruism: A theory of reputation-based cooperation in groups*.

Veríssimo, D., Campbell, H. A., Tollington, S., MacMillan, D. C., & Smith, R. J. (2018). Why do people donate to conservation? Insights from a ‘real world’campaign. *PloS One*, *13*(1), e0191888.

Vismara, S. (2016). Equity retention and social network theory in equity crowdfunding. *Small Business Economics*, *46*(4), 579–590.

Vismara, S. (2018). Information cascades among investors in equity crowdfunding. *Entrepreneurship Theory and Practice*, *42*(3), 467–497.

Waldron, A., Miller, D. C., Redding, D., Mooers, A., Kuhn, T. S., Nibbelink, N., Roberts, J. T., Tobias, J. A., & Gittleman, J. L. (2017). Reductions in global biodiversity loss predicted from conservation spending. *Nature*, *551*(7680), 364–367.

Wang, M. , Zhang, J. Y. , Wang, F. H. , Peng, C. , & Yi, T. Y. ,. (2024). Success or failure of online crowdfunding: exploring the impact of project characteristics and market competition. *Electronic Commerce Research*, 1–20.

Wang, M., Zhang, J., Wang, F., Peng, C., & Yi, T. (2024). Success or failure of online crowdfunding: exploring the impact of project characteristics and market competition. *Electronic Commerce Research*, 1–20.

Wang, N. , Feng, S. , Yang, Y. X. , & Xue, Y. J. ,. (2024). Love at First Sight: A Text Analytical Study of Campaign Title Impact on Crowdfunding Success. *Information & Management*, 104048.

Wang, N., Feng, S., Yang, Y., & Xue, Y. (2024). Love at First Sight: A Text Analytical Study of Campaign Title Impact on Crowdfunding Success. *Information & Management*, 104048.

Wang, W., Zheng, H., & Wu, Y. J. (2020). Prediction of fundraising outcomes for crowdfunding projects based on deep learning: a multimodel comparative study. *Soft Computing*, *24*(11), 8323–8341.

Wang, Z., Li, H., & Law, R. (2017). Determinants of tourism crowdfunding performance: an empirical study. *Tourism Analysis*, *22*(3), 323–336.

Wash, R., & Solomon, J. (2014). Coordinating donors on crowdfunding websites. *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing*, 38–48.

Website "NATIONAL BUREAU OF STATISTICS OF CHINA." (n.d.). http://www.stats.gov.cn/

World Bank. (2013). *Crowdfunding's Potential for the Developing World*. http://hdl.handle.net/10986/17626

Xu, A., Yang, X., Rao, H., Fu, W.-T., Huang, S.-W., & Bailey, B. P. (2014). Show me the money! An analysis of project updates during crowdfunding campaigns. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 591–600.

Yeh, J.-Y., & Chen, C.-H. (2020). A machine learning approach to predict the success of crowdfunding fintech project. *Journal of Enterprise Information Management*. https://doi.org/https://doi.org/10.1108/JEIM-01-2019-0017

Younkin, P., & Kashkooli, K. (2016). What problems does crowdfunding solve? *California Management Review, 58*(2), 20–43.

Yuan, H., Lau, R. Y. K., & Xu, W. (2016). The determinants of crowdfunding success: A semantic text analytics approach. *Decision Support Systems*, *100*(91), 67–76.

Zainon, S., Atan, R., & Wah, Y. B. (2014). An empirical study on the determinants of information disclosure of Malaysian non-profit organizations. *Asian Review of Accounting*, *22*(1), 35–55.

Zhang, Y., Tan, C. D., Sun, J., & Yang, Z. (2020). Why do people patronize donation-based crowdfunding platforms? An activity perspective of critical success factors. *Computers in Human Behavior*, *112*, 106470.