buildings

MDPI

*Article*

# How Does the Alienation of Project Digital Responsibility Form? Perspectives from Fraud Risk Factor Theory and Information Asymmetry Theory

**Jianglin Gu and Feng Guo ***

School of Civil Engineering, Central South University, Changsha 410018, China; jianglingu@csu.edu.cn
* Correspondence: gf700137@csu.edu.cn

**Abstract:** During the digital transformation of construction projects, the significant volume of project data raise a multitude of data responsibility issues. Project stakeholders, often motivated by financial interests and other considerations, frequently engage in data fraud, namely the alienation of project digital responsibility (APDR), which ultimately hinders the benefits released by the digital transformation of projects. However, the causes of APDR are still unclear. This study aims to bridge this knowledge gap by empirically investigating the factors influencing APDR and delineating their pathways. A model outlining the mechanism of APDR formation, rooted in fraud risk factor theory (FRFT) and information asymmetry theory (IAT), is proposed. To collect data from 276 Chinese construction project practitioners, a questionnaire was meticulously designed. Confirmatory factor analysis (CFA) was subsequently applied to assess the validity of the proposed model. Finally, the proposed model consisting of six variables was examined using structural equation modeling (SEM). The results showed that opportunity (OPP), motivation (MOT), and information asymmetry (INF) had a positive effect on APDR, while exposure probability (EXP), penalty strength (PEN), and ethics (ETH) had a negative effect on APDR. Through revealing the formation mechanism of APDR, the findings are beneficial for understanding why stakeholders adopt APDR at the risk of being penalized. This study aims at deepening the systematic understanding of APDR and enriches the relevant theories on project digital responsibility (PDR). Such knowledge would also contribute to project managers proposing effective interventions to inhibit APDR and promote PDR.

**Keywords:** project digital responsibility; alienation; influencing variables; structural equation modeling; fraud risk factor theory; information asymmetry theory



**Citation:** Gu, J.; Guo, F. How Does the Alienation of Project Digital Responsibility Form? Perspectives from Fraud Risk Factor Theory and Information Asymmetry Theory. *Buildings* **2023**, *13*, 2690. https://doi.org/10.3390/buildings13112690

Academic Editors: Osama Abudayyeh and Irem Dikmen

Received: 22 September 2023
Revised: 22 October 2023
Accepted: 24 October 2023
Published: 25 October 2023



## 1. Introduction

The rapid digital transformation of the construction industry has brought about a substantial increase in the volume of data generated within the sector. It is noteworthy that the volume of data generated by the construction industry tripled between 2018 and 2021 [1]. To effectively address the challenges related to project digital responsibility (PDR) arising from this digital transformation, stakeholders involved in construction projects should proactively engage in PDR [2]. However, it is important to acknowledge that not all project stakeholders are equally proactive in PDR, some may even exhibit APDR. This can manifest as actions like data leakage, data tampering, data abuse, and data theft, all of which compromise project data interests and PDR. Furthermore, the temporary nature, complexity, uncertainty, and the level of information asymmetry inherent in construction projects [3] make stakeholders more susceptible to APDR, particularly when driven by financial gain and work pressure [4,5]. Surprisingly, there has been limited research conducted on APDR, and its formation mechanisms are still unclear, along with a lack of guidance on how to mitigate it. Consequently, there is an urgent need for research in the domain of APDR.

To date, most of the research on digital responsibility (DR) has focused on the necessity for DR [6], the implementation of DR [7], and the framework construction of DR [8].

Unfortunately, little attention has been paid to the alienation of DR (ADR). While Pearse [9] did explore the erosive effects of digital irresponsibility on digital trust in Big Tech and social media platforms, this did not delve into the formation of ADR. The factors influencing APDR remain unclear, and there are substantial gaps in the governance of APDR. This study aims to rectify this by elucidating the formation mechanisms of APDR with the ultimate goal of contributing to effective governance strategies.

FRFT and IAT are highly compatible with the research on APDR governance. FRFT is one of the well-known theories for the study of fraudulent behavior [10]. Previous studies in different fields have shown the effectiveness of FRFT in revealing fraudulent behavior such as financial fraud [11] and violation [12]. Importantly, IAT not only fits the characteristics of construction projects [13], but is also widely used in construction management research [14]. Given the fraud nature of APDR and the double information asymmetry of construction projects and APDR, this paper proposes a model of factors influencing APDR based on FRFT-IAT. The FRFT-IAT model helps to investigate the key influencing variables on APDR and the formation mechanism of it.

This paper explores the following research questions around the formation mechanism of APDR. One is what are the factors that influence APDR? Another is what are the paths of the influencing factors on APDR and how do the factors correlate with each other? In order to address these two research questions, this study aims to validate the model of APDR formation mechanism through SEM. Firstly, we examine the influencing factors on APDR from the existing literature and relevant theories. Secondly, we propose corresponding hypotheses and form a research model to explore the relationship between the factors. Finally, the research model is validated by testing the measurement model and the structural model. In this manner, this study not only identifies the influencing factors of APDR, but also reveals the formation mechanism of APDR. The findings contribute to expanding the research related to PDR from an alienation perspective as well as providing ideas on how project managers can regulate the APDR behavior of stakeholders.

## 2. Theoretical Background and Hypotheses Development

A clear definition of APDR is indeed a fundamental prerequisite for the successful execution of this study. Meanwhile, FRFT and IAT are the two most core theories of this study, and it is necessary to elaborate on the adaptability of FRFT and IAT. Furthermore, the process of hypotheses development is intricately intertwined with our comprehensive review of existing APDR-related research. Therefore, this literature review section consists of three parts, namely the definition of APDR, FRFT, and IAT, and hypotheses development.

### *2.1. Definition of APDR*

The current body of the literature concerning the concept of APDR remains notably scarce, despite our diligent efforts to conduct a comprehensive review. This study adopts a conceptual approach in order to define APDR.

As a superordinate concept to APDR, the investigation of alienation in social responsibility has been around since the 1970s. Pioneering this field, Armstrong [15] was the first scholar to provide a formal definition of alienation in social responsibility, characterizing it as a decision-making behavior that prioritizes personal gains at the expense of communal well-being, ultimately leading to the generation of negative externalities.

Jones et al. [16], on the other hand, conceptualize the notion of the alienation of corporate social responsibility (ACSR) as a collection of corporate practices that exert detrimental influences on society, economy, and business. In a similar vein, Clark and Grantham [17] posit that ACSR and corporate social responsibility (CSR) represent two extremes on a continuum, with ACSR encompassing all unsustainable business practices undertaken by corporations, while the concept of unsustainability encompasses economic, social, and environmental dimensions.

Even fewer studies have been conducted on the alienation of responsibility at the project level. Xie et al. [18] contend that the alienation of project environmental respon-

sibility refers to the behavior of project stakeholders who act to the detriment of the environmental interests of the project or society for their own benefit.

Considering the pertinent concepts discussed above, we posit that APDR refers to the behaviors undertaken by project stakeholders across the project lifecycle that prove detrimental to the overall interests of the project or society in terms of the project data. These actions may be either deliberate or inadvertent. The overall interests are economic, social, environmental, and digital interests. APDR encompasses various behaviors such as data leakage, data tampering, data abuse, data theft, and opportunistic conduct.

APDR shares similarities with PDR opportunistic and PDR avoidance behaviors but retains fundamental distinctions. PDR opportunistic behaviors primarily pertain to actions intentionally carried out by stakeholders in pursuit of their personal interests, whereas PDR avoidance behaviors revolve around the inaction of stakeholders. In contrast, APDR encompasses both these categories of behaviors, while also extending to actions unintentionally instigated by stakeholders, which likewise result in the detriment to the interests of the project or society.

### *2.2. FRFT and IAT*

Fraud risk factor theory (FRFT) stands out as one of the most extensively developed theories concerning fraud risk factors to date [19]. FRFT categorizes these factors into two distinct dimensions. The environmental dimension pertains to external elements affecting fraud, including exposure probability, penalty strength, and opportunity. The subject dimension factors refer to ethics and motivation. FRFT has been used in various fields of fraud research. For example, Fan and Yu [20] employed FRFT to analyze instances of consumer fraud, while Al-Dhubaibi and Sharaf-Addin [21] utilized this theory to demonstrate the enhanced effectiveness of external auditors compared to their internal counterparts in detecting and assuring against fraud. APDR typically encompasses fraudulent behavior, making FRFT an appropriate choice for exploring this behavior.

IAT reflects situations where one party in a relationship possesses more adequate or timely information than the other parties. It has been extensively applied throughout management studies and in the realm of fraud research. Notably, Owusu-Manu et al. [22] addressed the challenge of moral hazard and adverse selection by presenting eight key factors to counter information asymmetry and insufficiency in public private partnership (PPP) projects. Given that information asymmetry is a prominent driver of APDR, IAT is highly relevant to the study of APDR.

Considering that APDR is a result of both instrumental and affective influences, the mainstream behavioral theories (e.g., the Theory of Planned Behavior) have neglected the explanation of affective influences to a certain extent [23]. At the same time, the combination of FRFT and IAT is comprehensive for both instrumental and affective influences. Additionally, FRFT and IAT have been successfully applied in the field of alienation and have achieved good results [18,24,25]. For these reasons, this study chose to use FRFT and IAT together to study the drivers of APDR.

### *2.3. Hypotheses Development*

#### 2.3.1. Exposure Probability

The lack of a proper internal audit system for construction projects makes it difficult to detect corruption and is a cause that promotes the growth of corruption [26]. Owusu et al. [27] directly point out that when there are loopholes in the regulatory system for construction projects, all the participants in the project are prone to corruption. These problems are also present in the environmental protection aspect of the project, where environmental fraud occurs due to a lack of regulation [26]. The fraud risk in the construction industry is inversely proportional to the frequency of regulation. The less regulation there is, the greater the fraud risk, especially the lack of regulation of fraud among senior personnel [28]. Therefore, the following hypothesis was proposed:

**H1.** *Exposure probability (EXP) has a negative impact on APDR.*

#### 2.3.2. Penalty Strength

The penalty strength has a significant impact on project fraud. The lenient penalties for project corruption lead to whistleblowers believing that there is little meaning in reporting, contributing to project corruption [26]. The Global Infrastructure Anti-Corruption Centre (GIACC) also noted the same conclusion that the lack of basis for the penalty strength has led to many lenient penalties for project fraud and does not provide an adequate deterrent [28]. Therefore, the following hypothesis was proposed:

**H2.** *Penalty strength (PEN) has a negative impact on APDR.*

#### 2.3.3. Opportunity

Opportunity refers to the convenience of project stakeholders to implement APDR. Project stakeholders often seek corruption for self-interest by finding and exploiting flaws and loopholes in the bidding process [26]. An inadequate political environment and political loopholes are equally prone to inducing unethical behavior among contractors [29]. Owusu et al. [27] also state that inadequate systems provide opportunities for corruption among stakeholders in construction projects. Therefore, the following hypothesis was proposed:

**H3.** *Opportunity (OPP) has a positive impact on APDR.*

#### 2.3.4. Ethics

Ethics refers to the perceptions and attitudes of project stakeholders toward APDR, and also to the overall atmosphere of the project or company toward the alienation of digital responsibility. Van Fossen [30] suggests that the team atmosphere contributes to financial fraud to a certain extent. A good team atmosphere and ethical education can reduce scientific fraud [31]. Focusing on the construction industry, a poor cultural atmosphere is an important driver of contractor violations [32]. Therefore, the following hypothesis was proposed:

**H4.** *Ethics (ETH) has a negative impact on APDR.*

#### 2.3.5. Motivation

Motivation refers to the motivation of project stakeholders to commit APDR. Deng et al. [33] found in a study investigating fraud in public construction projects that financial benefits were an important motivation for fraud. And in another survey of fraud in the Dutch construction industry, it was also found that many people attributed involvement with fraud to the alleviation of financial pressure [34]. The study by Welsh and Ordonez [35] states that fraud at work is influenced by high performance goals. The same conclusion appears in Mitchell et al.'s [36] study that employees are prone to fraud in order to meet a high organizational performance out of a need for self-protection. Some studies are more explicit in stating that fraud and job stress are proportional in procurement operations [37]. Therefore, the following hypothesis was proposed:

**H5.** *Motivation (MOT) has a positive impact on APDR.*

#### 2.3.6. Information Asymmetry

Information asymmetry in construction projects is prevalent. The opaqueness of the bidding process has led to collusion and manipulation in the bidding process, breeding corruption in the construction project [26]. During the construction phase, there is little need for project stakeholders to reveal details about the project, while commercial confidentiality has historically taken precedence over the public interest, leading to undetected project

fraud [28]. The opacity of project operations and data use leads to frequent environmental fraud [38]. Therefore, the following hypothesis was proposed:

**H6.** *Information asymmetry (INF) has a positive impact on APDR.*

Based on the above hypotheses, this study proposes a research framework as shown in Figure 1.

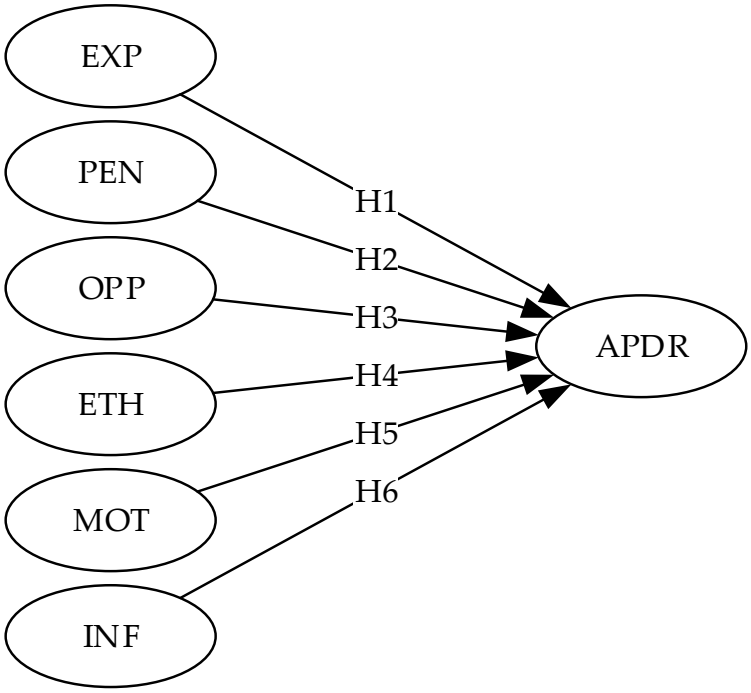


**Figure 1.** Research framework.

## 3. Research Methodology

This study consists of four major steps; in addition to the hypotheses development and research modeling (STEP 1) already completed in Section 2, it also includes data collection and basic analysis (STEP 2), measurement model analysis (STEP 3), and structure model analysis and hypotheses testing (STEP 4), which are detailed in Figure 2.

### *3.1. Questionnaire Design and Distribution*

Questionnaires were distributed to collect sample data for further research. A 7-point Likert scale was used for respondents to make quantitative choices, ranging from strongly disagree to strongly agree.

The questionnaire was developed in two steps. The first step was to determine the measurement items by referring to relevant studies. Secondly, referring to Yildirim [39], this study tested the internal validity of the items through small sample (sample size is 48) testing. This study took the top 27% and bottom 27% according to the total score from the highest to lowest for independent samples *t*-test, which found that all the items were significant at the 0.05 level of significance. It indicates that all the items have good internal validity and are ready for mass distribution. The final questionnaire is detailed in Table 1.

Considering that there are not many construction projects implementing PDR in China, the characteristics of the respondents (experienced in projects implementing PDR) were not obvious enough for questionnaire distributors. Therefore, a snowball method was used to distribute the questionnaire. Engineers who had experienced or were involved in projects implementing PDR were initially surveyed, and then relied on to provide eligible respondents (who had experienced or were experiencing projects implementing PDR), and so on to eventually collect a large enough sample size [40]. A total of 325 question-

naires were collected from January to May 2023. Excluding 49 invalid questionnaires that had not experienced projects implementing PDR, incomplete questionnaire completion, and more than one-third of consecutive questions selecting the same option, 276 valid questionnaires remained.

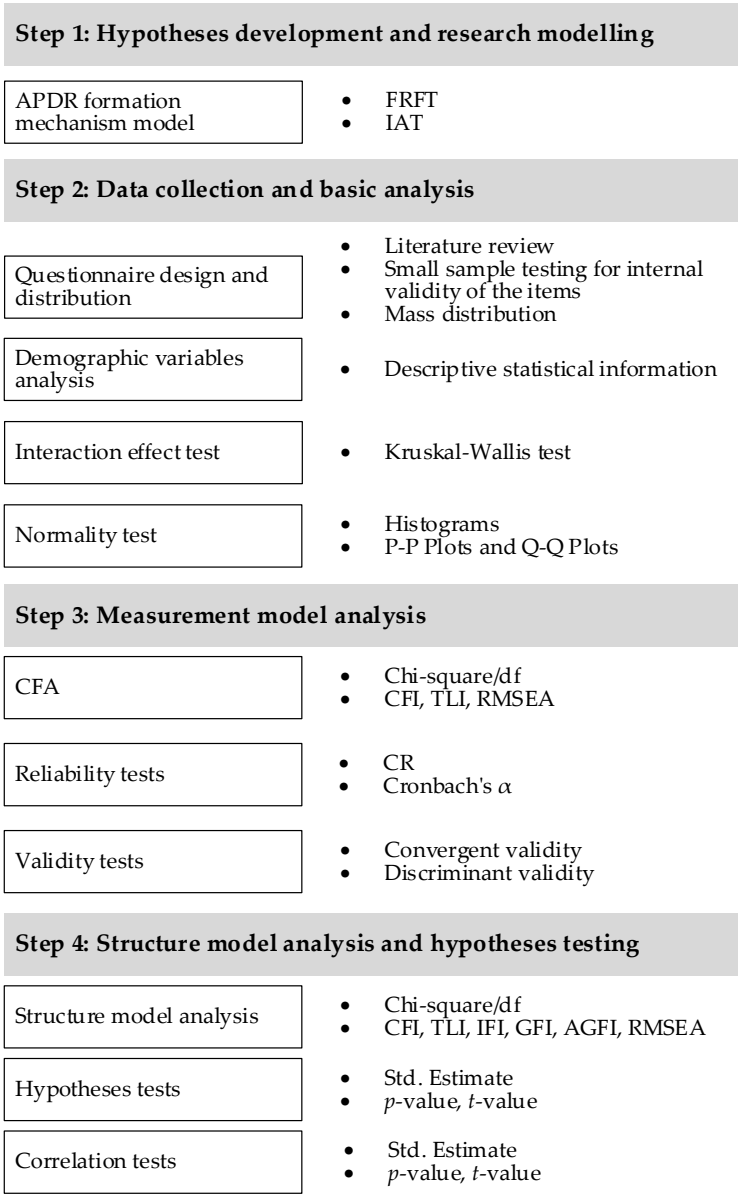


**Figure 2.** Overall research methodology flowchart.

### *3.2. Demographic Variables Analysis*

The descriptive statistical information of the valid sample is shown in Table 2.

Table 2 shows the results of the descriptive statistical information of the valid sample. Respondents were from different types of companies in the construction industry, including developers (29.71%), contractors (27.90%), consultants (26.09%), and others (such as suppliers and inspection agencies, 15.58%). Respondents' job titles included project manager (12.68%), cost manager (21.74%), construction manager (20.65%), safety manager (20.29%), and others (such as engineer and technician, 22.46%). The composition of the respondents is representative of the different stakeholders in the construction project. The project scale and project type in the project information also reflect different types and sizes of projects to some extent. The diverse and balanced composition indicates that the sample is well represented.

**Table 1.** Questionnaire items and factor loading.

| Codes | Questionnaire Items | Source | Std. Factor Loading |
|---|---|---|---|
| EXP1 | Government departments regularly regulate PDR. | [26–38] | 0.797 |
| EXP2 | Project internal regularly supervise PDR. | | 0.794 |
| EXP3 | Affiliated companies regularly supervise PDR. | | 0.857 |
| EXP4 | Public often monitor PDR. | | 0.806 |
| PEN1 | APDR's penalties are very severe. | | 0.833 |
| PEN2 | APDR penalties have impacts on the stakeholders themselves. | | 0.827 |
| PEN3 | APDR penalties have impacts on the project. | | 0.841 |
| PEN4 | APDR penalties have impacts on the affiliated company. | | 0.817 |
| OPP1 | Unclear delineation of data ownership. | | 0.724 |
| OPP2 | Deficiencies in PDR governance mechanisms. | | 0.785 |
| OPP3 | Deficiencies in PDR governance laws and regulations. | | 0.797 |
| OPP4 | Lack of PDR incentives. | | 0.776 |
| ETH1 | Strong digital responsibility atmosphere among project. | | 0.824 |
| ETH2 | Strong digital responsibility atmosphere among affiliated company. | | 0.829 |
| ETH3 | Strong sense of digital responsibility among participants. | | 0.816 |
| ETH4 | Strong sense of digital responsibility among the public. | | 0.832 |
| MOT1 | APDR brings additional benefits to the stakeholders themselves. | | 0.860 |
| MOT2 | APDR can help achieve project appraisal objectives. | | 0.900 |
| MOT3 | APDR can help achieve company appraisal objectives. | | 0.740 |
| INF1 | Information asymmetry between the various stakeholders within the project. | | 0.715 |
| INF2 | Information asymmetry between the project and the affiliated company. | | 0.718 |
| INF3 | Information asymmetry within the project and outside the project. | | 0.715 |
| APDR1 | Frequent data leaks in your project. | | 0.757 |
| APDR2 | Frequent data misuse in your project. | | 0.856 |
| APDR3 | Frequent data falsification in your project. | | 0.835 |
| APDR4 | Frequent data theft in your project. | | 0.723 |

**Table 2.** Basic statistical information of valid questionnaires.

| Variable Dimension | Variable | Group | Frequency | Percentage |
|---|---|---|---|---|
| Respondent information | Sex | Male | 260 | 94.20% |
| | | Female | 16 | 5.80% |
| | Age | <30 years | 68 | 24.64% |
| | | 30–39 years | 81 | 29.35% |
| | | 40–50 years | 65 | 23.55% |
| | | >50 years | 61 | 22.10% |
| | Working experience in construction industry | <5 years | 22 | 7.97% |
| | | 5–10 years | 109 | 39.49% |
| | | 11–20 years | 106 | 38.41% |
| | | >20 years | 38 | 13.77% |
| | Position | Project manager | 35 | 12.68% |
| | | Cost manager | 60 | 21.74% |
| | | Construction manager | 57 | 20.65% |
| | | Safety manager | 56 | 20.29% |
| | | Others | 62 | 22.46% |
| | Company category | Developer | 82 | 29.71% |
| | | Contractor | 77 | 27.90% |
| | | Consultants | 72 | 26.09% |
| | | Others | 43 | 15.58% |

**Table 2.** *Cont.*

| Variable Dimension | Variable | Group | Frequency | Percentage |
|---|---|---|---|---|
| Project information | Project scale (CNY) | <0.1 billion | 29 | 10.51% |
| | | 0.1–1 billion | 83 | 30.07% |
| | | 1–3 billion | 89 | 32.25% |
| | | >3 billion | 70 | 25.36% |
| | Project type | Buildings | 57 | 20.65% |
| | | Municipal | 47 | 17.03% |
| | | Highways | 54 | 19.57% |
| | | Hydropower | 56 | 20.29% |
| | | Others | 61 | 22.10% |

### *3.3. Interaction Effect Test of Demographic Variables*

Since the different backgrounds of the respondents (company category, position, etc.) may lead to intergroup differences in different measurement items, this study used the Kruskal–Wallis test to examine the interaction effects of the demographic variables to rule out their potential effects on the study results, which are shown in Table 3.

**Table 3.** Kruskal–Wallis test results.

| Codes | Sex | Age | Working Experience | Position | Company Category | Project Size | Project Type |
|---|---|---|---|---|---|---|---|
| EXP1 | 0.890 | 0.994 | 0.599 | 0.246 | 0.815 | 0.756 | 0.747 |
| EXP2 | 0.131 | 0.966 | 0.808 | 0.791 | 0.880 | 0.792 | 0.901 |
| EXP3 | 0.479 | 0.899 | 0.539 | 0.461 | 0.598 | 0.296 | 0.166 |
| EXP4 | 0.624 | 0.549 | 0.979 | 0.737 | 0.730 | 0.501 | 0.888 |
| PEN1 | 0.260 | 0.790 | 0.690 | 0.571 | 0.996 | 0.370 | 0.631 |
| PEN2 | 0.986 | 0.838 | 0.881 | 0.169 | 0.341 | 0.462 | 0.470 |
| PEN3 | 0.634 | 0.451 | 0.637 | 0.503 | 0.546 | 0.813 | 0.253 |
| PEN4 | 0.502 | 0.741 | 0.627 | 0.390 | 0.935 | 0.679 | 0.557 |
| OPP1 | 0.145 | 0.747 | 0.621 | 0.425 | 0.748 | 0.330 | 0.301 |
| OPP2 | 0.542 | 0.822 | 0.856 | 0.492 | 0.932 | 0.543 | 0.316 |
| OPP3 | 0.176 | 0.493 | 0.924 | 0.437 | 0.750 | 0.543 | 0.272 |
| OPP4 | 0.997 | 0.891 | 0.873 | 0.543 | 0.338 | 0.905 | 0.642 |
| ETH1 | 0.811 | 0.718 | 0.889 | 0.765 | 0.839 | 0.811 | 0.650 |
| ETH2 | 0.794 | 0.971 | 0.934 | 0.104 | 0.485 | 0.574 | 0.139 |
| ETH3 | 0.121 | 0.530 | 0.466 | 0.906 | 0.331 | 0.825 | 0.393 |
| ETH4 | 0.732 | 0.832 | 0.913 | 0.191 | 0.990 | 0.858 | 0.174 |
| MOT1 | 0.975 | 0.409 | 0.436 | 0.950 | 0.993 | 0.117 | 0.608 |
| MOT2 | 0.802 | 0.698 | 0.778 | 0.962 | 0.786 | 0.666 | 0.936 |
| MOT3 | 0.595 | 0.188 | 0.372 | 0.703 | 0.957 | 0.349 | 0.648 |
| INF1 | 0.726 | 0.376 | 0.286 | 0.673 | 0.315 | 0.489 | 0.455 |
| INF2 | 0.960 | 0.378 | 0.404 | 0.255 | 0.415 | 0.729 | 0.734 |
| INF3 | 0.373 | 0.939 | 0.978 | 0.591 | 0.325 | 0.452 | 0.753 |
| APDR1 | 0.618 | 0.475 | 0.657 | 0.742 | 0.867 | 0.781 | 0.904 |
| APDR2 | 0.559 | 0.802 | 0.900 | 0.862 | 0.873 | 0.531 | 0.766 |
| APDR3 | 0.880 | 0.511 | 0.965 | 0.657 | 0.994 | 0.298 | 0.850 |
| APDR4 | 0.930 | 0.648 | 0.931 | 0.699 | 0.880 | 0.145 | 0.176 |

As shown in Table 3, all Kruskal–Wallis test results have $p$-values greater than 0.05, indicating that there is no interaction effect between the demographic variables and the 26 observable variables at the 0.05 level of significance. Therefore, the effect of the demographic variables on the study results was excluded.

### *3.4. Normality Test*

By checking the histograms, P–P plots, and Q–Q plots, the sample data for the 26 observed variables basically satisfied a normal distribution. Based on this, this study decided to use the maximum likelihood (ML) method for normally distributed data, the most widely used method, for the subsequent parameter estimation and fitting.

## 4. Results

This study used SPSS statistic 26.0 and Amos 28.0 to analyze the model and the sample data. The measurement model analysis is the basis for the structural model analysis, and on the basis of these two analyses, this study tested the research hypotheses.

### *4.1. Measurement Model Analysis*

This study used CFA to verify the validity of the measurement model. The CFA results for different combinations are shown in Table 4.

**Table 4.** CFA results for different combinations [1].

| Model | $\chi^2$ | df | $\chi^2$/df | CFI | TLI | RMSEA |
|---|---|---|---|---|---|---|
| 7-factor model: EXP, PEN, OPP, ETH, MOT, INF, APDR | 336.67 | 278 | 1.211 | 0.989 | 0.987 | 0.028 |
| 6-factor model: EXP + PEN, OPP, ETH, MOT, INF, APDR | 653.475 | 284 | 2.301 | 0.93 | 0.919 | 0.069 |
| 5-factor model: EXP + PEN, OPP, ETH + MOT, INF, APDR | 899.55 | 289 | 3.113 | 0.884 | 0.869 | 0.088 |
| 4-factor model: EXP + PEN, OPP + ETH + MOT, INF, APDR | 1142.877 | 293 | 3.901 | 0.838 | 0.82 | 0.103 |
| 3-factor model: EXP + PEN, OPP + ETH + MOT + NF, APDR | 1223.579 | 296 | 4.134 | 0.823 | 0.806 | 0.107 |
| 2-factor model: EXP + PEN + OPP + ETH + MOT + INF, APDR | 1318.831 | 298 | 4.426 | 0.806 | 0.788 | 0.112 |
| 1-factor model: EXP + PEN + OPP + ETH + MOT + INF + APDR | 1340.597 | 299 | 4.484 | 0.802 | 0.784 | 0.113 |

[1] Note: $\chi^2$ = chi-square; df = degree of freedom; CFI = comparative fit index; TLI = Tucker–Lewis index; RMSEA = root mean square error of approximation.

As can be seen from Table 4, the 7-factor model has better test results than the other models, indicating that the 7-factor model is more reasonable than the other models. In addition, the low fitness of the 1-factor model also precludes the possibility of common method variance (CMV) in the sample data [41].

Reliability and validity tests are tests of the reliability and validity for the measurement models. Composite reliability (CR) and Cronbach's $\alpha$ are widely used methods for conducting reliability tests. Referring to hair [42], it is suggested that a judgment criterion of 0.7 is used for CR. While Cronbach's $\alpha$ follows Fornell and Larcker [43], Tonglet et al. [44], and Nunnally and Bernstein [45] and uses a threshold of 0.6. Table 5 shows that all the latent variables have CR values greater than 0.7 and all Cronbach's $\alpha$ are greater than 0.6, indicating that the reliability test is passed.

The validity tests for the measurement models were divided into convergent validity and discriminant validity. Average variance extracted (AVE) was used to test the convergent validity. Table 5 shows that the AVE of each latent variable was greater than 0.5, indicating good convergent validity [42,43]. Furthermore, the fact that the correlations (non-diagonal values) between each latent variable were smaller than the corresponding AVE values explains the good discriminant validity of the latent variables [43].

**Table 5.** Measurement validity and construct correlations.

| Latent Variable | CR | Cronbach's $\alpha$ | AVE | Correlation Matrix | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | EXP | PEN | OPP | ETH | MOT | INF | APDR |
| **EXP** | 0.887 | 0.887 | 0.662 | **0.814** | | | | | | |
| **PEN** | 0.898 | 0.898 | 0.688 | 0.655 | **0.829** | | | | | |
| **OPP** | 0.854 | 0.875 | 0.594 | 0.714 | 0.603 | **0.771** | | | | |
| **ETH** | 0.895 | 0.895 | 0.681 | 0.673 | 0.708 | 0.603 | **0.825** | | | |
| **MOT** | 0.874 | 0.869 | 0.699 | 0.689 | 0.629 | 0.637 | 0.652 | **0.836** | | |
| **INF** | 0.759 | 0.759 | 0.512 | 0.703 | 0.577 | 0.669 | 0.577 | 0.598 | **0.716** | |
| **APDR** | 0.872 | 0.925 | 0.632 | 0.697 | 0.761 | 0.706 | 0.759 | 0.757 | 0.678 | **0.795** |

### *4.2. Structure Model Analysis and Hypotheses Testing*

The structural model analysis was carried out based on the proposed model (see Figure 3) and the goodness of fit (GOF) results are shown in Table 6. From Table 6, all the model fitness indices exceeded acceptable standards, of which $\chi^2$/df, CFI, TLI, IFI, and RMSEA met ideal standards. Therefore, this study concluded that the structural model fit was satisfactory.

**Table 6.** GOF test statistics of structural model analysis.

| | $\chi^2$/df | CFI | TLI | IFI | GFI | AGFI | RMSEA |
|---|---|---|---|---|---|---|---|
| Ideal standards | <3 | >0.9 | >0.9 | >0.9 | >0.9 | >0.9 | <0.08 |
| Acceptable standards | <5 | >0.8 | >0.8 | >0.8 | >0.8 | >0.8 | <0.3 |
| Result | 2.562 | 0.914 | 0.903 | 0.915 | 0.844 | 0.810 | 0.075 |

The results of the hypotheses testing, including the standardized estimated coefficients of the paths and their corresponding *p*-values, are summarized in Table 7. From Table 7, all hypothesized paths for the latent variables are supported.

**Table 7.** Results of hypotheses testing.

| Hypotheses | Hypotheses Path | Std. Estimate | *t*-Value | *p*-Value | Results |
|---|---|---|---|---|---|
| H1 | EXP → APDR | −0.5444 | 7.742 | <0.001 | Supported |
| H2 | PEN → APDR | −0.1434 | 2.455 | 0.0141 | Supported |
| H3 | OPP → APDR | 0.2354 | 3.794 | <0.001 | Supported |
| H4 | ETH → APDR | −0.2947 | 4.741 | <0.001 | Supported |
| H5 | MOT → APDR | 0.1926 | 3.177 | 0.0015 | Supported |
| H6 | INF → APDR | 0.2084 | 3.473 | <0.001 | Supported |

It should be noted that while all hypotheses are supported, the level of significance varies between hypotheses.

H1 (EXP to APDR), H3 (OPP to APDR), H4 (ETH to APDR), and H6 (INF to APDR) were accepted at a significance level of 0.001. Both EXP and ETH had significant negative effects on APDR with path coefficients of −0.5444 and −0.2947, respectively. Both OPP and INF had a significant positive effect with path coefficients of 0.2354 and 0.2084, respectively.

H5 (MOT to APDR) was accepted at a significance level of 0.01, implying a significant positive effect of MOT on APDR with a path coefficient of 0.1926.

H2 (PEN to APDR) was accepted at a significance level of 0.05, implying a significant negative effect of PEN on APDR with a path coefficient of −0.1434.

The results of the correlation tests, including the standardized estimated coefficients and *p*-values, are summarized in Table 8. From Table 8, all the correlations are supported at a significance level of 0.001 with standardized correlation coefficients of 0.6536 (PEN and EXP), 0.5159 (OPP and MOT), −0.6522 (ETH and MOT), −0.4857 (OPP and ETH), and 0.4018 (INF and OPP), respectively.

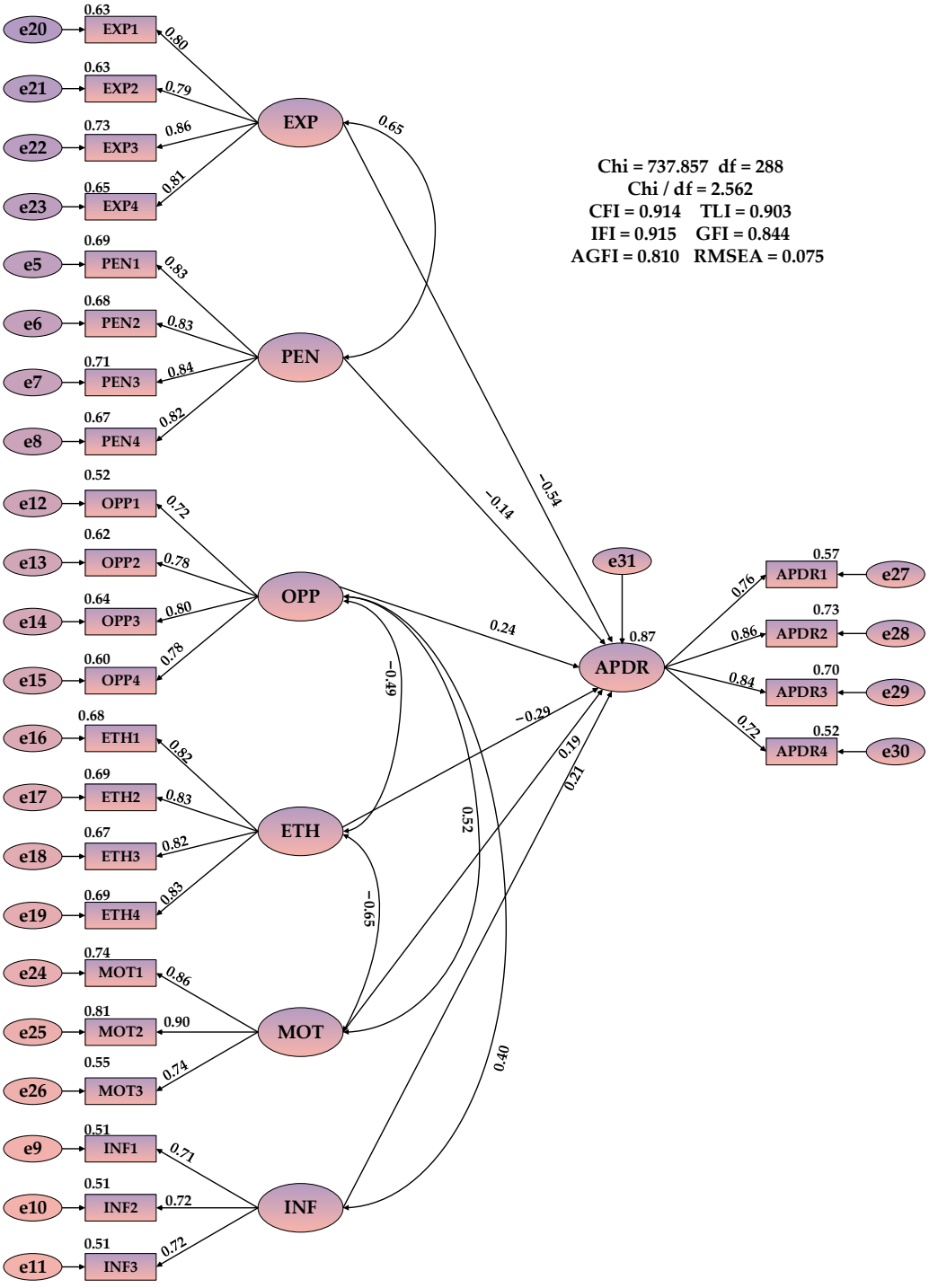


**Figure 3.** GOF test model for structure model analysis.

**Table 8.** Results of correlation testing.

| Correlation | Std. Estimate | *t*-Value | *p*-Value | Results |
|---|---|---|---|---|
| PEN ⟷ EXP | 0.6536 | 7.5797 | <0.001 | Supported |
| OPP ⟷ MOT | 0.5159 | 6.056 | <0.001 | Supported |
| ETH ⟷ MOT | −0.6522 | −7.5926 | <0.001 | Supported |
| OPP ⟷ ETH | −0.4857 | −5.7609 | <0.001 | Supported |
| INF ⟷ OPP | 0.4018 | 4.6701 | <0.001 | Supported |

## 5. Discussion

This study constructs SEM models based on FRFT and IAT to investigate the impact of six latent variables on APDR. The findings reveal that the effects of the six latent variables on APDR are statistically significant. In addition to establishing the validity of FRFT and IAT as a framework for fraud explanation, this study contributes to the existing literature by elucidating the formation mechanism of APDR through empirical research.

The results indicate that exposure probability has a negative impact on APDR, which supports hypothesis H1. In the absence of timely and effective regulatory measures, projects are susceptible to various forms of fraudulent activities, including APDR [46]. Both an empirical study in the Iranian context [47] and a literature-based qualitative study [27] point out that inadequate regulation is one of the main causes of corruption in construction projects. Effective, long-term regulation of project stakeholder responsibilities can substantially mitigate the occurrence of APDRs [48]. These findings not only underscore the importance of well-conceived regulatory measures as a critical anti-corruption strategy [49], but also introduce innovative perspectives on project fraud regulation. Specifically, this study suggests that the responsibility for supervising APDR should not solely rest with government; instead, projects and companies should actively participate in this oversight process [50].

The findings suggest that the penalty strength has a negative impact on APDR, offering support for hypothesis H2. When penalties for APDR are excessively lenient, project stakeholders may not perceive a sufficient deterrent and may continue engaging in APDR. It is important to note that while inadequate penalties can indeed contribute to corruption [46], there is no linear relationship between the severity of penalties and the efficacy of fraud management [51]. Increased penalties do not invariably lead to a reduction in fraudulent activities [52]. Nevertheless, it is evident that monetary penalties are more effective deterrents than non-monetary sanctions [53].

Hypothesis H3 is supported by the significant positive influence of opportunity on APDR. The existing system on PDR governance is very poor or even missing, thereby facilitating APDR by project stakeholders. The prevailing ambiguity surrounding project data ownership poses a formidable challenge in ascribing responsibility to these stakeholders. Consequently, it creates opportunities for APDR while impeding the full realization of the benefits derived from the digital transformation of construction projects [54]. These findings resonate with analogous results observed in the examination of the alienation of project environmental responsibility within Chinese megaprojects [18]. Moreover, these findings underscore the efficacy of institutional design in regulating stakeholder conduct [55].

The findings suggest a negative impact of digital ethics on APDR, providing support for hypothesis H4. APDR, inherently unethical, necessitates project stakeholders to transcend their ethical constraints for its implementation. This outcome reaffirms the crucial role of the ethical climate in shaping stakeholders' ethical conduct [56]. Additionally, it highlights the negative effect between stakeholders' ethical sense and unethical behavior [57].

The findings reveal a positive impact of alienation motivation on APDR, corroborating hypothesis H5. Project stakeholders' inclination to implement APDR strengthens when it promises additional financial benefits. APDR, by offering stakeholders a means to alleviate pressure from projects, companies, or society, prompts them to reconsider the complete implementation of PDR. Consequently, the practical needs associated with alienation motivation may lead to a proliferation of stakeholder APDR. On the one hand, the results affirm that project stakeholders are susceptible to fraudulent activities when driven by financial incentives [58], suggesting a nuanced connection between greed and fraud [59]. On the other hand, this study also verifies that project stakeholders might engage in fraudulent activities under external pressures [60].

The findings suggest a positive impact of information asymmetry on APDR, lending support to hypothesis 6 (H6). Information asymmetry empowers project stakeholders to select strategies that primarily serve their individual interests, even if these strategies may

not align with the overall project objectives. It creates objective conditions for the proliferation of APDR [61]. To counter this trend, enhancing transparency in the process of project data utilization and implementing robust mechanisms for information disclosure [62] can effectively mitigate APDR [63]. These results not only directly substantiate prior research, which indicated that stakeholders tend to pursue short-term profit-driven behaviors in the presence of information asymmetry [64], but they also concurrently confirm the positive impact of information disclosure on the overall project performance [65].

## 6. Conclusions, Implications, and Future Research

### *6.1. Conclusions*

As the digital transformation of projects continues, the challenges posed by APDR are becoming increasingly serious. However, the causes of APDR are still unclear. Consequently, this study adopts the perspectives of FRFT and IAT to elucidate the influential factors and unravel the formation mechanisms of APDR. This is achieved through the construction of a model encompassing six latent variables. The empirical validation of this model is conducted using data obtained from 276 practitioners engaged in Chinese construction projects. The investigation unveils compelling insights. Firstly, based on the new empirical evidence of information asymmetry on APDR, this study emphasizes that information asymmetry has a positive effect on the proliferation of APDR. More notably, exposure probability and penalty strength have an inhibitory effect on APDR. This implies that the government and project regulators should increase the frequency of regulation and penalty strength of APDR to better inhibit its occurrence. In addition, opportunity, ethics, and motivation also have significant effects on APDR. These revelations imply that, beyond nurturing a culture of digital responsibility among stakeholders, governments and project regulators can also take measures to improve the effectiveness of APDR governance by addressing institutional deficiencies and suppressing motivation. This study not only provides new research ideas for further research and enrichment of PDR theory, but also provides some important insights and implementation bases for governments and project regulators to govern APDR.

### *6.2. Implications*

#### 6.2.1. Theoretical Implications

APDR governance is an important component of PDR; however, it is evident that the existing body of research in this domain is far from comprehensive. Currently, we possess limited insights into the influencing factors of APDR, while its formation mechanisms still remain unknown. This study represents the first attempt to study APDR and its antecedent configurations, providing preliminary answers to these questions. The contributions of our study to the existing literature are summarized as follows.

Firstly, our study enriched the research related to APDR from FRFT and IAT. We combined FRFT, IAT, and the existing literature to summarize the influential variables of APDR into six. The complex relationships of the six influencing variables for APDR are demonstrated using SEM, and the paths and path coefficients of each influencing variable are identified, filling the gaps in the existing research. Through the fraud perspective, it not only provides a new path of research ideas for the further research of PDR theory, but also expands the application of fraud theory.

Secondly, there is a lack of a well-established and systematic framework to explain the formation mechanism of alienation in construction projects. This study focused on empirically investigating the formation mechanism of APDR, acting as a contribution to the current knowledge of APDR and PDR.

#### 6.2.2. Practical Implications

The prevalence of APDR is on the rise, posing a hindrance to the authentic digital transformation of projects. Meanwhile, it is worth noting that data governance has emerged as a critical factor in environmental, social, and governance (ESG) considerations [66]. In

this context, APDR governance assumes a pivotal role in enhancing data governance. The outcomes of this study also hold significant practical implications for the domain of APDR governance.

Initially, a comprehensive comprehension of the six latent variables and their observed variables contributes to facilitating the development of targeted measures and policies by projects, construction companies, and governments. These measures aim to inhibit APDR and promote PDR. Our findings underscore that APDR is generated by a combination of conditions in which controlling or eliminating one condition alone does not effectively inhibit APDR. Thus, this study presents a more realistic view, emphasizing that effective governance measures should not rely solely on individual conditions but rather necessitate a combination of governance strategies to more effectively curtail APDR.

Secondly, in the practice of PDR governance, PDR is not only ethically driven to perform, but is also tempted by the profit to alienate. Therefore, it is not only necessary to develop a sound PDR implementation program, but also to inhibit alienation from the reverse direction. Increasing the frequency of regulation, moderately increasing the penalty strength, improving governance systems, fostering digital responsibility, increasing the transparency of data use, and moderately reducing work pressure are all effective disincentives to inhibit APDR.

### *6.3. Limitations and Future Research*

Despite the contribution of this study, there are still some limitations and open questions that need further research. Firstly, this study empirically investigates APDR and its influencing factors through questionnaires to explain the microscopic formation mechanism of APDR, and future studies can focus on the macroscopic formation mechanism of APDR. Secondly, this study focuses on the APDR phenomenon in China, a single country context which may diminish the applicability and persuasiveness, and future studies can examine the APDR phenomenon in more countries to discover and compare different APDR formation mechanisms. Thirdly, construction projects remain a hybrid concept, and APDR may be formed by different mechanisms for projects with different attributes (e.g., PPP projects, public projects, private projects) and different sizes (e.g., mega projects and micro projects). It is fascinating to study and compare APDR for a particular type of segment or multiple segments. Finally, future research will introduce additional theories to enrich the explanation of the drivers of APDR.

**Author Contributions:** Conceptualization, J.G.; software, J.G.; formal analysis, J.G. and F.G.; data curation, F.G.; writing—original draft preparation, J.G.; writing—review and editing, F.G.; supervision, F.G.; project administration, F.G. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was supported by National Natural Science Foundation of China (Grant No: 71440009).

**Data Availability Statement:** The data presented in this study are available on reasonable request from the corresponding author. The data are not publicly available due to further research.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Liviniuk, T. Construction's Dark Data Problem. Available online: https://www.trilliumgroup.io/post/constructions-dark-data-problem (accessed on 12 June 2023).
2. Weber-Lewerenz, B. Corporate Digital Responsibility in Construction Engineering: Ethical Principles in Dealing with Digitization and AI. *IJRLEDM* **2020**, *2*, 32–49. [CrossRef]
3. Wang, G.; Zhou, K.; Wang, D.; Wu, G.; Xie, J. Tensions in Governing Megaprojects: How Different Types of Ties Shape Project Relationship Quality? *Int. J. Proj. Manag.* **2021**, *39*, 799–814. [CrossRef]
4. Gavejian, J.C.; Lazzarotti, J.J. Construction Industry: Data Security Considerations. Available online: https://www.jacksonlewis.com/publication/construction-industry-data-security-considerations (accessed on 12 June 2023).

5. Wang, Y.; Chen, Y.; Wang, W.; Chen, Y.; Jin, M. Revisiting the Relationship Between Contract Governance and Contractors' Opportunistic Behavior in Construction Projects. *IEEE Trans. Eng. Manag.* **2022**, *69*, 2517–2529. [CrossRef]
6. Mihale-Wilson, C.; Hinz, O.; van der Aalst, W.; Weinhardt, C. Corporate Digital Responsibility. *Bus. Inf. Syst. Eng.* **2022**, *64*, 127–132. [CrossRef]
7. Herden, C.J.; Alliu, E.; Cakici, A.; Cormier, T.; Deguelle, C.; Gambhir, S.; Griffiths, C.; Gupta, S.; Kamani, S.R.; Kiratli, Y.-S.; et al. "Corporate Digital Responsibility" New Corporate Responsibilities in the Digital Age. *Nachhalt. Manag. Forum* **2021**, *29*, 13–29. [CrossRef]
8. Lobschat, L.; Mueller, B.; Eggers, F.; Brandimarte, L.; Diefenbach, S.; Kroschke, M.; Wirtz, J. Corporate Digital Responsibility. *J. Bus. Res.* **2021**, *122*, 875–888. [CrossRef]
9. Pearse, J. Socially Irresponsible: How Data Protection Fines from Big Tech and Social Media Platforms Are Eroding Digital Trust. Available online: https://newdigitalage.co/technology/socially-irresponsible-how-data-protection-fines-from-big-tech-and-social-media-platforms-are-eroding-digital-trust/ (accessed on 12 June 2023).
10. Niu, Y. A Study on the Motivation and Governance of Financial Fraud in Listed Companies: A Joint Perspective of Fraud Risk Factor Theory and Game Theory. *Commun. Financ. Account.* **2020**, *12*, 99–103. [CrossRef]
11. Miao, A. A Study on Financial Fraud Governance of Listed Companies Based on Fraud Risk Factor Theory——Taking Erkang Pharmaceutical as an example. *Commun. Financ. Account.* **2020**, *20*, 100–103. [CrossRef]
12. Wang, X.; Zhang, Y. A study of the first illegal delisting case under the new fraud risk factor theory. *Friends Account.* **2020**, *22*, 46–52.
13. Bergh, D.D.; David, J.; Ketchen, J.; Orlandi, I.; Heugens, P.P.M.A.R.; Boyd, B.K. Information Asymmetry in Management Research: Past Accomplishments and Future Opportunities. *J. Manag.* **2019**, *45*, 122–158. [CrossRef]
14. Li, Y.; He, N.; Li, H.; Liu, Z.; Qi, J. Influencing Factors on Inter-Organizational Trust Asymmetry Behavior in Construction Projects: Evidence from China. *ECAM* **2021**, *28*, 308–331. [CrossRef]
15. Armstrong, J.S. Social Irresponsibility in Management. *J. Bus. Res.* **1977**, *5*, 185–213. [CrossRef]
16. Jones, B.; Bowd, R.; Tench, R. Corporate Irresponsibility and Corporate Social Responsibility: Competing Realities. *Soc. Responsib. J.* **2009**, *5*, 300–310. [CrossRef]
17. Clark, T.S.; Grantham, K.N. What CSR Is Not: Corporate Social Irresponsibility. In *Corporate Social Irresponsibility: A Challenging Concept*; Tench, R., Sun, W., Jones, B., Eds.; Critical Studies on Corporate Responsibility, Governance and Sustainability; Emerald Group Publishing Limited: Bingley, UK, 2012; Volume 4, pp. 23–41. ISBN 978-1-78052-999-8.
18. Xie, L.; Xu, T.; Ju, T.; Xia, B. Explaining the Alienation of Megaproject Environmental Responsibility Behavior: A Fuzzy Set Qualitative Comparative Analysis Study in China. *ECAM* **2023**, *30*, 2794–2813. [CrossRef]
19. Zou, W. Analysis of Financial Fraud of Listed Company in China: A Case Study of Dandong Xintai Electric Co., Ltd. *Am. J. Ind. Bus. Manag.* **2016**, *6*, 931–941. [CrossRef]
20. Fan, J.X.; Yu, Z. Prevalence and Risk Factors of Consumer Financial Fraud in China. *J. Fam. Econ. Iss.* **2022**, *43*, 384–396. [CrossRef]
21. Al-Dhubaibi, A.A.S.; Sharaf-Addin, H.H.H. An Analysis of External and Internal Auditors' Use of ISA 240 Red Flags: The Impact of Auditors' Estimation of Fraud Pervasiveness. *Cogent Bus. Manag.* **2022**, *9*, 2118209. [CrossRef]
22. Owusu-Manu, D.-G.; Kukah, A.S.; Boateng, F.; Asumadu, G.; Edwards, D.J. Exploring Strategies to Reduce Moral Hazard and Adverse Selection of Ghanaian Public–Private Partnership (PPP) Construction Projects. *J. Eng. Des. Technol.* **2020**, *19*, 358–372. [CrossRef]
23. French, D.P.; Sutton, S.; Hennings, S.J.; Mitchell, J.; Wareham, N.J.; Griffin, S.; Hardeman, W.; Kinmonth, A.L. The Importance of Affective Beliefs and Attitudes in the Theory of Planned Behavior: Predicting Intention to Increase Physical Activity1. *J. Appl. Soc. Psychol.* **2005**, *35*, 1824–1848. [CrossRef]
24. Zhao, X. Research on Audit Behavior Alienation from the Perspective of Risk-Oriented Audit—A Case Study of Fushun Special Steel Audited by Zhongzhun Certified Public Accountant. Master Thesis, Shanxi University of Finance and Economics, Taiyuan, China, 2023.
25. Zhao, N.; Sheng, Z.; Yan, H. Emission Trading Innovation Mechanism Based on Blockchain. *Chin. J. Popul. Resour. Environ.* **2021**, *19*, 369–376. [CrossRef]
26. Ameyaw, E.E.; Parn, E.; Chan, A.P.C.; Owusu-Manu, D.-G.; Edwards, D.J.; Darko, A. Corrupt Practices in the Construction Industry: Survey of Ghanaian Experience. *J. Manag. Eng.* **2017**, *33*, 05017006. [CrossRef]
27. Owusu, E.K.; Chan, A.P.C.; Shan, M. Causal Factors of Corruption in Construction Project Management: An Overview. *Sci. Eng. Ethics* **2019**, *25*, 1–31. [CrossRef]
28. GIACC Why Corruption Occurs—GIACC. Available online: https://giaccentre.org/why-corruption-occurs/ (accessed on 23 May 2023).
29. Liu, J.; Zhao, X.; Li, Y. Exploring the Factors Inducing Contractors' Unethical Behavior: Case of China. *J. Prof. Issues Eng. Educ. Pract.* **2017**, *143*, 04016023. [CrossRef]
30. Van Fossen, A. Financial Frauds and Pseudo-States in the Pacific Islands. *Crime Law Soc. Change* **2002**, *37*, 357–378. [CrossRef]
31. Chop, R.M.; Silva, M.C. Scientific Fraud: Definitions, Policies, and Implications for Nursing Research. *J. Prof. Nurs.* **1991**, *7*, 166–171. [CrossRef] [PubMed]
32. Liu, J.; Wang, Y.; Wang, Z. Multidimensional Drivers: Exploring Contractor Rule Violations in the Construction Industry. *Eng. Constr. Archit. Manag.* **2023**, *30*, 1496–1518. [CrossRef]

33. Deng, X.; Wang, Y.; Zhang, Q.; Huang, J.X.; Cui, J. Analysis of Fraud Risk in Public Construction Projects in China. *Public Money Manag.* **2014**, *34*, 51–58. [CrossRef]
34. Van Den Heuvel, G. The Parliamentary Enquiry on Fraud in the Dutch Construction Industry Collusion as Concept between Corruption and State-Corporate Crime. *Crime Law Soc. Change* **2005**, *44*, 133–151. [CrossRef]
35. Welsh, D.T.; Ordonez, L.D. The Dark Side of Consecutive High Performance Goals: Linking Goal Setting, Depletion, and Unethical Behavior. *Organ. Behav. Hum. Decis. Process.* **2014**, *123*, 79–89. [CrossRef]
36. Mitchell, M.S.; Baer, M.D.; Ambrose, M.L.; Folger, R.; Palmer, N.F. Cheating Under Pressure: A Self-Protection Model of Workplace Cheating Behavior. *J. Appl. Psychol.* **2018**, *103*, 54–73. [CrossRef]
37. Robertson, D.C.; Rymon, T. Purchasing Agents' Deceptive Behavior: A Randomized Response Technique Study. *Bus. Ethics Q.* **2001**, *11*, 455–479. [CrossRef]
38. Rivers, L.; Dempsey, T.; Mitchell, J.; Gibbs, C. Environmental Regulation and Enforcement: Structures, Processes and the Use of Data for Fraud Detection. *J. Environ. Assess. Policy Manag.* **2015**, *17*, 1550033. [CrossRef]
39. Yildirim, V.Y. Homework Process in Higher Education Scale (HPHES): A Validity and Reliability Study. *Int. J. Assess. Tools Educ.* **2021**, *8*, 120–134. [CrossRef]
40. Mac Donald, K.; Rezania, D.; Baker, R. A Grounded Theory Examination of Project Managers' Accountability. *Int. J. Proj. Manag.* **2020**, *38*, 27–35. [CrossRef]
41. Kock, F.; Berbekova, A.; Assaf, A.G. Understanding and Managing the Threat of Common Method Bias: Detection, Prevention and Control. *Tour. Manag.* **2021**, *86*, 104330. [CrossRef]
42. Hair, J.F. (Ed.) *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 2nd ed.; Sage: Los Angeles, CA, USA, 2017; ISBN 978-1-4833-7744-5.
43. Fornell, C.; Larcker, D.F. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *J. Mark. Res.* **1981**, *18*, 39–50. [CrossRef]
44. Tonglet, M.; Phillips, P.S.; Read, A.D. Using the Theory of Planned Behaviour to Investigate the Determinants of Recycling Behaviour: A Case Study from Brixworth, UK. *Resour. Conserv. Recycl.* **2004**, *41*, 191–214. [CrossRef]
45. Nunnally, J.C.; Bernstein, I.H. *Psychometric Theory*, 3rd ed.; McGraw-Hill Series in Psychology; McGraw-Hill: New York, NY, USA, 1994; ISBN 978-0-07-047849-7.
46. Le, Y.; Shan, M.; Chan, A.P.C.; Hu, Y. Investigating the Causal Relationships between Causes of and Vulnerabilities to Corruption in the Chinese Public Construction Sector. *J. Constr. Eng. Manag.* **2014**, *140*, 05014007. [CrossRef]
47. Kim, S.Y.; Rad, K.G. Exploratory Factor Analysis of the Causes of Corruption in Iranian Construction Projects. *KSCE J. Civ. Environ. Eng. Res.* **2018**, *38*, 369–376. [CrossRef]
48. Zhang, B.; Le, Y.; Xia, B.; Skitmore, M. Causes of Business-to-Government Corruption in the Tendering Process in China. *J. Manag. Eng.* **2017**, *33*, 05016022. [CrossRef]
49. Owusu, E.K.; Chan, A.P.C.; DeGraft, O.-M.; Ameyaw, E.E.; Robert, O.-K. Contemporary Review of Anti-Corruption Measures in Construction Project Management. *Proj. Manag. J.* **2019**, *50*, 40–56. [CrossRef]
50. Durach, F.; Brgoanu, A.; Nastasiu, C. Tackling Disinformation: EU Regulation of the Digital Space. *Rom. J. Eur. Aff.* **2020**, *20*, 5–20.
51. Farrar, J.; King, T. To Punish or Not to Punish? The Impact of Tax Fraud Punishment on Observers' Tax Compliance. *J. Bus. Ethics* **2023**, *183*, 289–311. [CrossRef]
52. Kwan, C. Causes, Typologies, and Deterrence of Fraud Crime in the United Kingdom: Lessons for Reform of Fraud Prevention in the South Korea. *J. Soc. Sci.* **2010**, *36*, 143–164. [CrossRef]
53. Wang, Y.; Ashton, J.K.; Jaafar, A. Money Shouts! How Effective Are Punishments for Accounting Fraud? *Br. Account. Rev.* **2019**, *51*, 100824. [CrossRef]
54. Fadler, M.; Legner, C. Data Ownership Revisited: Clarifying Data Accountabilities in Times of Big Data and Analytics. *J. Bus. Anal.* **2022**, *5*, 123–139. [CrossRef]
55. Okafor, O.N.; Adebisi, F.A.; Opara, M.; Okafor, C.B. Deployment of Whistleblowing as an Accountability Mechanism to Curb Corruption and Fraud in a Developing Democracy. *AAAJ* **2020**, *33*, 1335–1366. [CrossRef]
56. Al Halbusi, H.; Ruiz-Palomino, P.; Morales-Sánchez, R.; Abdel Fattah, F.A.M. Managerial Ethical Leadership, Ethical Climate and Employee Ethical Behavior: Does Moral Attentiveness Matter? *Ethics Behav.* **2021**, *31*, 604–627. [CrossRef]
57. Feng, Z.; Keng-Highberger, F.; Li, H.; Savani, K. Implicit Morality Theories: Employees' Beliefs About the Malleability of Moral Character Shape Their Workplace Behaviors. *J. Bus. Ethics* **2023**, *184*, 193–216. [CrossRef]
58. Yan, J.; Li, X.; Shi, Y.; Sun, S.; Wang, H. The Effect of Intention Analysis-Based Fraud Detection Systems in Repeated Supply Chain Quality Inspection: A Context of Learning and Contract. *Inf. Manag.* **2020**, *57*, 103177. [CrossRef]
59. Tunley, M. Need, Greed or Opportunity? An Examination of Who Commits Benefit Fraud and Why They Do It. *Secur. J.* **2011**, *24*, 302–319. [CrossRef]
60. He, Q.; Wang, Z.; Wang, G.; Xie, J.; Chen, Z. The Dark Side of Environmental Sustainability in Projects: Unraveling Greenwashing Behaviors. *Proj. Manag. J.* **2022**, *53*, 349–366. [CrossRef]
61. Chen, Y.; Wang, G.; He, Y.; Zhang, H. Greenwashing Behaviors in Construction Projects: There Is an Elephant in the Room! *Environ. Sci. Pollut. Res.* **2022**, *29*, 64597–64621. [CrossRef]
62. Peng, J.; Tu, G.; Liu, Y.; Zhang, H.; Leng, B. The Integration Role of Governmental Information Disclosure Platform: An Evolutionary Game Analysis of Corporate Environmental Monitoring Data Fraud. *Kybernetes* **2019**, *49*, 1347–1379. [CrossRef]

63. Lehtinen, J.; Locatelli, G.; Sainati, T.; Artto, K.; Evans, B. The Grand Challenge: Effective Anti-Corruption Measures in Projects. *Int. J. Proj. Manag.* **2022**, *40*, 347–361. [CrossRef]
64. Hörisch, J. Take the Money and Run? Implementation and Disclosure of Environmentally-Oriented Crowdfunding Projects. *J. Clean. Prod.* **2019**, *223*, 127–135. [CrossRef]
65. Wang, S.; Wang, H.; Wang, J.; Yang, F. Does Environmental Information Disclosure Contribute to Improve Firm Financial Performance? An Examination of the Underlying Mechanism. *Sci. Total Environ.* **2020**, *714*, 136855. [CrossRef]
66. Jarzebowski, M. Data Governance: The Next Big ESG Controversy. Available online: https://www.forbes.com/sites/forbesfinancecouncil/2021/02/04/data-governance-the-next-big-esg-controversy/ (accessed on 11 June 2023).