Service Quality Enhancement in Public Sector A Sem-Pls and FSQCA Analysis of AI, Human Capital, and Digital Innovation

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Abstract. The joint effects of Artificial Intelligence Capability (AIC), Human Capital (HC) and Digital Innovation (DI) on Service Quality (SQ) in public technical organizations are little understood. The purpose of the study is to explore the joint effect of AIC, HC and DI on SQ in public technical organizations. Drawing on the Resource-Based View (RBV), the study adopts a configurational perspective through the Resource-Based View (RBV) and employs a mixed-method approach of PLS-SEM and fsQCA. The results show that all three capabilities contribute to service quality, human capital being the most significant. These capabilities do not operate in isolation, but reinforce each other, especially if aligned. Multiple paths to excellent service performance are found. Overall, the results imply that value creation in digital public services relies on the integration of organizational capabilities rather than on isolated resources, thereby extending RBV from a configurational perspective.

Keywords: Artificial Intelligence Capability, Human Capital, Digital Innovation, Service Quality, Resource-Based View, Configurational Approach, Public Sector.

1 Introduction

The digital transformation in the public sector is no longer just about digitising office work. It has now become a matter of strategically building organisational capabilities that aim at service quality (SQ). Actually, public agencies, particularly those ones that operate in complex and technology-dependent environments, are not only expected to provide services in a timely manner but also to possess qualities such as being able to react quickly, adapting easily and being user-friendly. Also, Artificial Intelligence Capability (AIC), Human Capital (HC) and Digital Innovation (DI) have been recognised as the most important factors of digital transformation. It has been proved that AIC enhances decision-making accuracy, operational efficiency and service reliability. Apart from technological innovation, the successful adoption and implementation of which require HC and DI [1-6]. However, how these capabilities interact in influencing service quality in the case of complex service systems is still quite a mystery. Firstly,

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the previous research mostly treat AIC, HC, and DI as separate entities, thereby ignoring their interrelations. Secondly, the fact that linear and symmetrical analytical methods are the methods of choice has resulted in a very limited understanding of the complexity of capability interactions mainly because these methods are additive and independent in nature. Hence, they are incapable of accounting for the fact that different combinations of capabilities might lead to similar service outcomes.

Such constraints point to a more general theoretical drawback of the resource-based view (RBV). RBV has been extensively utilized to explain the impact of resources and capabilities on organizational performance, but its application has been mostly focused on variance-based reasoning that stresses independent net effects. Such an approach is still inadequate to explain value creation in complex service systems, where results are the result of the interplay and alignment of various capabilities, rather than independent resource impacts. Therefore, it is important to expand RBV towards a configurational viewpoint to explain equifinality, causal asymmetry and the possibility of different routes leading to comparable results.

In this sense, this research conceptualizes AIC, HC and DI as complementing strategic skills whose alignment results in service quality outcomes. AIC is the capacity of the company to use artificial intelligence to enable data-driven decision making and adaptive service delivery. HC is the competency, flexibility and readiness of human resources to enable technology transformation in the digital age. DI is a measure of the organization's ability to reconfigure processes, incorporate digital technology and build novel service models. These capabilities are anticipated to operate in a synergistic and complementary manner inside organizational systems rather than in isolation.

To address the points raised above, this paper resorts to a hybrid method that merges Partial Least Squares Structural Equation Modeling (PLS-SEM) with fuzzy-set Qualitative Comparative Analysis (fsQCA). While PLS-SEM studies the isolated effects or relationships between variables, fsQCA reveals the configurational relationships or different causal pathways, thus giving a more comprehensive picture of both symmetric and asymmetric interactions [7, 8].

Building on these gaps and these considerations in mind, this research intends to study how Artificial Intelligence Capability, Human Capital, and Digital Innovation together affect Service Quality in public technical organizations and which combinations of capabilities lead to high service performance. Conceptually, our paper adds to the Resource-Based View by applying a configurational perspective and by asserting that value generation depends on the fit among capabilities rather than on their separate effects only. On the other hand, this paper reveals data from public technical organizations, a research context hardly covered in the literature before. Besides that, the paper makes a methodological contribution by combining PLS-SEM and fsQCA in order to detect net effects along with complex causal configurations. In addition to that, the paper from a practical point of view supplies information for public sector organizations in designing a well-rounded digital transformation strategy that integrates technology, human and innovation capabilities.

2 Literature Review

This study is grounded on the Resource-Based View (RBV) which states that the performance of an organization is a function of the resources and strategic capabilities they possess. Although RBV is commonly utilized, it has been used via a variance-based strategy that stresses the independent and cumulative impacts of each resource. In the context of complex services, where the value generation is no longer based on single resources, but on the interplay and alignment of several skills, such an approach is increasingly insufficient. With the public sector becoming more digital, this restriction is more tangible since quality of service is very much reliant on an organization's capacity to choreograph the interplay between technology, human resources and innovation.

In light of these constraints, the present research suggests a configurational approach that acknowledges the possibility of equifinality, causal asymmetry, and the availability of alternative paths that might lead to identical organizational results. In this approach, Artificial Intelligence Capability (AIC), human capital (Human Capital / HC) and digital innovation (Digital Innovation / DI) are seen as strategic capabilities that complement each other and collectively determine the quality of services. AIC is the organizational capability to employ artificial intelligence to enable data-driven decision-making, process automation and adaptive service delivery. However, the efficacy of AI technology is more dependent on the degree of integration with organizational processes and human resource capabilities than the degree of adoption [2, 4, 6]. This implies that AIC should be considered as a relational skill within an interconnected resource system.

The human capital (HC) is the main enabler and coordinator of these qualities. HC is not just about technical abilities, but also about digital competence, flexibility and the capacity of the company to keep up with technological progress. The empirical data supports the view that the quality of human resources is a determinant of the success of digital efforts [5, 9]. However, most existing studies still treat HC as a supportive factor, therefore ignoring its significance as a key competence to assess the success of AIC and DI. From a configurational viewpoint, HC is a critical facilitator that amplifies and mediates the effects of other organizational skills.

Digital innovation (DI) is an organization's capacity to reconfigure processes, integrate digital technologies and establish new service models, and is a reflection of dynamic capabilities. Dynamic Capability theory attempts to explain the means by which organizations can adapt to precarious surroundings and improve service delivery through evolution [10]. DI is based on the theory at its core and many studies depict the positive contribution of DI to service performance [3, 11]. Nevertheless, the majority of studies adopt a linear perspective, which does not address the nature of the interaction between DI and other capabilities in delivering outcomes. This calls for a more Integrative approach to the understanding of capacity configuration.

In the conventional paradigm, the service quality is frequently defined as a function of dependability, responsiveness and customer satisfaction from the service quality (SQ) viewpoint. In the digital environment, this concept has expanded to cover system quality, interoperability, usability and data security. However, most of the research still assumes a direct link between service qualities and the obtained outcomes, without examining the structure of the capabilities underpinning the process [12, 13]. Thus quality of service must be reconceptualized not only as an end variable but as a result of the intricate interplay between organizational capabilities.

The Smart Government and data-driven public sector perspectives also emphasize the need for technology integration, governance, and data capabilities to improve service quality. This approach emphasizes the importance of interoperability, smart governance, and user-focused service design [14, 15]. However, such an approach generally presupposes ideal institutional settings and has not properly taken into consideration the practical limits and mismatches of capability that arise in the reality of public organizations. This creates a gap between normative framework and practical reality. Hence, it strengthens the requirement of a configurational approach that can explain how capabilities are genuinely matched in practice.

In general, the literature shows three main limitations. First, past studies usually explore AIC, HC and DI separately without taking into account their relationship. Second, the ubiquity of the linear analytical technique masks the complexity of relationships in combinatorial capabilities. Thirdly, current theoretical frameworks, such as RBV and Dynamic Capability Theory are still constrained in their explanations of the configurative causality and the equifinality principle. The result only partially understands how various capabilities combined impact service quality.

To overcome these restrictions, this research provides a configurational approach that considers service quality as a consequence of the alignment of artificial intelligence capabilities, human capital, and digital innovation. The present research seeks to provide a more holistic and theoretically sound explanation of the way in which organizational capabilities interact in the determination of service quality in public technical organizations by integrating RBV into the configurational logic and using a mixed-method approach through PLS-SEM and fsQCA.

3 Methodology

This study uses a mixed-method approach with a sequential explanatory design that integrates Partial Least Squares Structural Equation Modeling (PLS-SEM) and fuzzy-set Qualitative Comparative Analysis (fsQCA). This approach was chosen because the phenomenon of quality of service in digital systems cannot be adequately explained by just one method. Variance-based models such as SEM are able to explain the direct influence between variables, but are less able to capture the complexity of non-linear and interdependent relationships. Therefore, fsQCA is used as a complement to identify combinations of conditions that produce certain outcomes. In other words, SEM answers "how much influence", while fsQCA answers "how a combination of conditions works together". This mix provides a more comprehensive understanding of the interplay between Artificial Intelligence Capability (AIC), Human Capital (HC), Digital Innovation (DI) and Service Quality (SQ).

This research was conducted at Loka Monitor Spektrum Frekuensi Radio Pangkal Pinang, a public technical agency that heavily depends on digital technology. The choice of this location is purposive because the context is relevant to research based on digital capabilities. Data were collected in March 2026 period from 51 employees who are directly involved in service operations and the use of digital systems. The technique used is saturated sampling, so that the entire population in the organizational unit is used as respondents.

Although the sample size is relatively small, this approach is still valid because the study emphasizes analytical generalization rather than statistical generalization. In addition, PLS-SEM is known to be robust against small samples, and fsQCA is indeed designed for small-N-based analysis. Data were collected using a questionnaire with a 5-point Likert scale. The measurement model is reflective and consists of four constructs: AIC, HC, DI, and SQ, which are adapted from previous research. To provide an overview of the relationship between constructs and indicators, the measurement model is shown in Fig. 1 below.

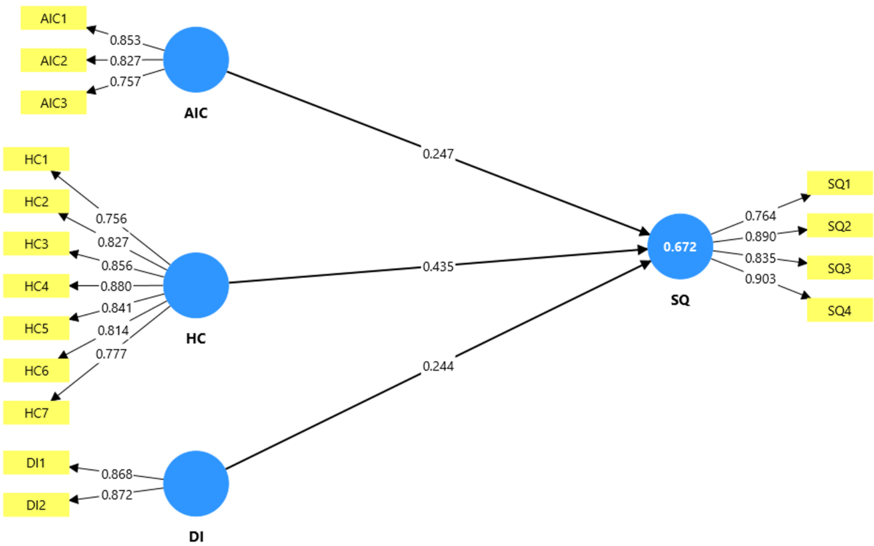

Fig. 1. Outer model.

Before testing the relationship between variables, it is important to ensure that the instrument used is valid and reliable. The results of the analysis show that all indicators have an outer loading value above 0.70. In addition, the Composite Reliability (CR) and Average Variance Extracted (AVE) values also meet the recommended criteria.

The complete results of the validity and reliability testing are presented in Table 1. As can be seen in Table 1, all the constructs have met the required thresholds for reliability and validity. The Composite Reliability values are more than 0.70 and the Average Variance Extracted (AVE) values are more than 0.50. This means that the internal consistency and convergent validity are both good. On the other hand, Human Capital has the highest reliability, which means that its indicators are very consistent with one another. Discriminant validity was assessed using the Heterotrait-Monotrait Ratio (HTMT), as presented in Table 2.

Table. 1. Construct reliability and validity.

	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	AVE
AIC	0,752	0,753	0,854	0,662
DI	0,679	0,679	0,862	0,757
HC	0,920	0,924	0,936	0,677
SQ	0,871	0,883	0,912	0,722

Table 2. Heterotrait monotrait ratio.

Heterotrait-Monotrait Ratio (HTMT)	
DI ↔ AIC	0,818
HC ↔ AIC	0,748
HC ↔ DI	0,910
SQ ↔ AIC	0,778
SQ ↔ DI	0,913
SQ ↔ HC	0,845

The discriminant validity was tested using HTMT to ensure that each construct had a clear difference. Most values were below the 0.90 threshold, although there was a slight increase in the HC–DI and SQ–DI relationships. In the context of digital transformation, this condition is understandable because the three variables are conceptually closely interrelated. Therefore, these values are still acceptable, especially in exploratory and configurational studies.

Before proceeding to structural analysis, it is necessary to ensure that there is no multicollinearity between indicators. For this reason, the Variance Inflation Factor (VIF) is used. The results of the VIF test are shown in Table 3 below.

Table 3. Value of variance inflation factor.

Indicator	Variance Inflation Factor (VIF)
AIC1	3,411
AIC2	3,250
HC4	5,637
HC6	4,405
SQ1	2,252

Most VIF values are below the 5 limit, so there are no serious problems. Although there are some relatively high values, they are still within the tolerance limit and do not affect the stability of the model.

Once the measurement model is valid, the analysis is proceeded to the structural model. To help understand the relationships between variables, the model results are shown in Fig. 2.

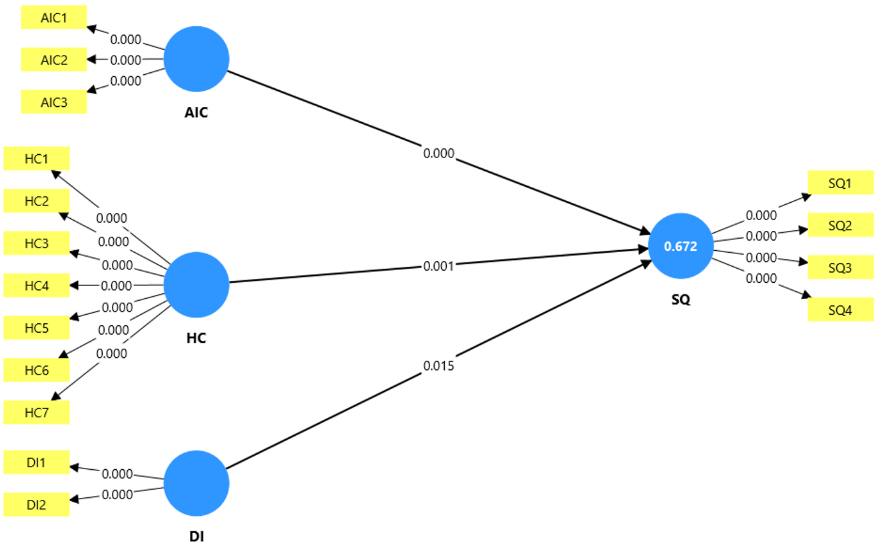

Fig. 2. Path coefficient and R-square value.

As shown in Fig. 2, all hypothesized relationships are statistically significant. The strongest factor that affects Service Quality is Human Capital ($\beta = 0.435$, $p = 0.001$). Next is Artificial Intelligence Capability ($\beta = 0.247$, $p < 0.001$), and then Digital Innovation ($\beta = 0.244$, $p = 0.015$). The R-square value of 0.672 shows that the model explains 67.2% of the differences in service quality, which shows that it has a lot of explanatory power. To add to the SEM-PLS analysis, fsQCA was used to find the pathways that lead to high service quality. To see the contribution of each variable, an effect size (f^2) is used. The results are presented in Table 4.

Table 4. Effect Size (f^2).

Relationships	f^2	Interpretation
AIC ↔ SQ	0,104	Small – Medium
DI ↔ SQ	0,081	Small
HC ↔ SQ	0,239	Medium

These results confirm that Human Capital has the most dominant role in improving service quality. To complete the analysis, the fit model was tested using SRMR and related indices. The results are presented in Table 5.

Table 5. Model fit.

Table of Contents	Value
SRMR	0,110
NFI	0,615

The SRMR value is slightly above the ideal limit, but in PLS-SEM this is still acceptable because the main focus is the model's predictive ability. To understand the more complex relationships, fsQCA analysis was performed. The data were calibrated using three threshold points: 0.95 (full membership), 0.50 (crossover), and 0.05 (full non-membership). The configuration results are shown in Table 6.

Table 6. Configuration results from fsQCA

Factors	S1	S2
AIC	●	●
HC	⊗	●
DI	⊗	●
Raw Coverage	0.523	0.581
Unique Coverage	0.162	0.22
Consistency	0.959	0.983
Solution Coverage: 0.744586		
Solution Consistency: 0.970865		

Table 6 shows two different configurations like S1 and S2. The first configuration (S1) shows that AIC alone can provide high service quality, with a raw coverage of 0.523 and a consistency of 0.959. The second configuration (S2) shows that the combination of AIC, HC, and DI provides a stronger pathway, with a higher coverage (0.581) and a consistency (0.983). The overall solution coverage (0.744586) and consistency (0.970865) show that the model reliably explains most high service quality outcomes.

When used together, SEM-PLS and fsQCA can show both linear and configurational relationships. SEM-PLS shows how big each effect is, while fsQCA shows how different capabilities work together to make service better. Together, they give a full picture of how complicated things work in digital public service settings.

4 Discussion

The results of this study show that Artificial Intelligence Capability (AIC), Human Capital (HC), and Digital Innovation (DI) have a significant effect on Service Quality (SQ), with the most dominant factor of Human Capital. This finding can be seen from the results of the structural model which shows that HC has the strongest contribution compared to other variables, as presented in Figure 2 and Table 2, indicating that in the context of technology-based public organizations, the quality of services is not solely determined by technological sophistication, but is highly dependent on the capacity of human resources in managing and implementing these technologies. According to Barney's research in 1991, these findings strengthen and expand the Resource-Based View (RBV) by emphasizing the importance of strategic resources to create organizational excellence [16]. However, unlike the classic RBV approach which tends to place technology as the main source of excellence, the results of this study show that Human Capital plays a role as an orchestrator capability that determines the effectiveness of the use of technology and innovation [5, 10]. Thus, the success of digital transformation in the public sector is determined more by human readiness than by the technology itself.

In addition, the results of the study also clearly show that Artificial Intelligence Capability and Digital Innovation have a positive influence on service quality, even though their contribution is lower than that of Human Capital. The role of AIC in this study can be understood as an enabling capability that improves operational efficiency and service accuracy through the use of data and automation [4, 6]. Meanwhile, according to research Mariani and Bianchi in 2023 stated Digital Innovation serves as a mechanism for organizational adaptation in responding to environmental changes through the development of digital-based processes and services [11]. However, the results of the study show that these two capabilities are not strong enough to produce optimal service quality without the support of Human Capital. This shows that technology and innovation are conditional, where their effectiveness is highly dependent on the competence and readiness of human resources.

The findings based on fsQCA analysis reinforce these results by showing that service quality is not generated by a single factor, but by a combination of capabilities. As shown in Table 6, configurations involving a combination of AIC, HC, and DI result in the most optimal level of service quality over a single condition. This supports a configurational perspective that emphasizes that the relationships between variables are complex, non-linear, and involve multiple causal pathways (equifinality) [17, 18]. Thus, the results of this study show that the variance-based approach alone is not enough to explain the phenomenon of service quality in complex digital systems.

Furthermore, the integration between SEM-PLS and fsQCA provides a more comprehensive understanding of the relationship between capabilities. The SEM results show that Human Capital is the strongest predictor individually, while the fsQCA results show that no single variable is sufficient independently to produce service quality. This difference confirms the difference between net effects and configurational effects, where individual influences do not necessarily reflect the reality of interactions between variables [19]. Thus, this research makes a theoretical contribution by extending RBV towards a configurational perspective that emphasizes the importance of capability alignment in creating organizational value.

In practical terms, the findings of this study provide clear implications for public sector organizations. Digital transformation strategies cannot only focus on technology investments, but must be accompanied by strengthening human resource capacity and developing integrated innovations. Organizations need to develop employees' digital competencies through continuous training, improve the integration of AI-based systems in service processes, and encourage service innovation that is oriented to user needs. Without the alignment of these three capabilities, digital transformation efforts risk not resulting in significant improvements in service quality.

5 Conclusion and Recommendation

The study concludes that the service quality of digital public organizations is the consequence of the interaction of Artificial Intelligence Capabilities, Human Capital and Digital Innovation, with human capital being the most essential aspect. In this sense, digital transformation is not just about technology but it is also about the ability of the organization to combine and coordinate many skills at once. Theoreticaly it highlights the significance to see Resource-Based View from a configurational perspective where value is the result of capabilities interaction and alignment [10, 16] and not their impacts examined separately. This viewpoint helps to develop a more sophisticated understanding of the emergence of value in complex digital service systems [17, 18].

From a practical standpoint, the findings suggest that the development of integrated capabilities should be prioritized in the design of the public sector organizations' digital transformation strategy. In particular, strengthening of human capital via focused digital competence development is vital to allow the successful application of artificial intelligence in service operations. Simultaneously, organizations require more integrated systems of digital technology across organizational units to guarantee coordination and efficiency, and ongoing service innovation should be stimulated via user participation in service design. Future research should examine comparable configuration possibilities in other organizational settings and at larger scale to enhance the generalizability of these findings.

References

1. Alhosani, K., Alhashmi, S.M.: Opportunities, challenges, and benefits of AI innovation in government services: a review. Discover Artificial Intelligence **4**(1) (2024).
2. Busayo, T., Igbekoyi, O.E., Oluwagbade, O.I., Adewara, Y., Dagunduro, M.E., Boluwaji, Y.: Artificial intelligence and service quality of telecommunication firms in Nigeria. Journal of Economics Finance and Accounting Studies **5**(3), 203–214 (2023).
3. Das, D.K.: Exploring the symbiotic relationship between digital transformation, infrastructure, service delivery, and governance for smart sustainable cities. Smart Cities **7**(2), 806–835 (2024).

4. Dimcheva, G.: Opportunities for application of artificial intelligence in telecommunication projects. Engineering Proceedings 18 (2024). https://doi.org/10.3390/engproc2024070018
5. Nwosu, C.C., Obalum, D.C., Ananti, M.O.: Artificial intelligence in public service and governance in Nigeria. Journal of Governance and Accountability Studies **4**(2), 109–120 (2024).
6. Rana, C., Pardeshi, P.D.R.K.: A research review: AI and data science applications in the telecom industry. IBMRD's Journal of Management & Research, 196–210 (2022).
7. Ahi, A., Sinkovics, N., Sinkovics, R.R.: E-commerce policy and the global economy: a path to more inclusive development? Management International Review **63**(1), 27–56 (2022).
8. Parast, M.M., Safari, A.: Do quality and business excellence models improve quality and operational results in educational organizations? A repeated cross-sectional analysis. Operations Management Research **16**(2), 868–886 (2022).
9. Trabelsi, M.A.: The impact of artificial intelligence on economic development. Journal of Electronic Business & Digital Economics **3**(2), 142–155 (2024).
10. Teece, D.J.: Business models and dynamic capabilities. Long Range Planning **51**(1), 40–49 (2018).
11. Mariani, I., Bianchi, I.: Conceptualising digital transformation in cities: a multi-dimensional framework for the analysis of public sector innovation. Sustainability **15**(11), 8741 (2023).
12. Hodžić, S., Ravšelj, D., Alibegović, D.J.: E-government effectiveness and efficiency in EU-28 and COVID-19. Central European Public Administration Review **19**(1), 159–180 (2021).
13. Maragno, G., Gastaldi, L., Corso, M.: E-government for public values creation: a systematic literature review, 386–397 (2021).
14. Hujran, O., Alarabiat, A., Al-Adwan, A.S., Al-Debei, M.M.: Digitally transforming electronic governments into smart governments: SMARTGOV, an extended maturity model. Information Development **39**(4), 811–834 (2021).
15. Sienkiewicz-Małyjurek, K., Zyzak, B.: Digital technologies in public administration networks: systematic literature review and research avenues. Administration & Society **57**(8–9), 1051–1087 (2025).
16. Barney, J.: Firm resources and sustained competitive advantage. Journal of Management **17**(1), 99–120 (1991).
17. Fiss, P.C.: Building better causal theories: a fuzzy set approach to typologies in organization research. Academy of Management Journal **54**(2), 393–420 (2011).
18. Ragin, C.C.: Redesigning social inquiry: fuzzy sets and beyond. University of Chicago Press (2008). https://press.uchicago.edu/ucp/books/book/chicago/R/bo5971406.html
19. Misangyi, V.F., Greckhamer, T., Furnari, S., Fiss, P.C., Crilly, D., Aguilera, R.V.: Embracing causal complexity: the emergence of a neo-configurational perspective. Journal of Management **43**(1), 255–282 (2017).