Exploring the relationship between protean and boundaryless career attitudes and affective commitment through the lens of a fuzzy set QCA methodology

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Received November, 2007
Accepted January, 2008

Abstract:

Sweeping changes in employment relationships and organizational structures have challenged traditional career models and gave way to two emerging paradigms to examine professional careers: the protean and the boundaryless career. During the last decades, researchers and practitioners conducted conceptual and empirical research on new career patterns to explore the impact of boundaryless and protean careers upon individual outcomes, such as subjective and objective career success, adaptability and employability. Nevertheless, we have a limited understanding on how new career orientations affect organizational outcomes (such as, for instance, organizational commitment). Therefore, the objective of this research is twofold: (a) first, to determine whether the protean and the boundaryless career attitudes analysed have any kind of impact on employees’ affective commitment; and (b) second, to offer a guideline to use the fuzzy set methodology to enable conducting research about professional careers.

Keywords: professional career attitudes, affective commitment, fuzzy set methodology
Título: Explorando la relación entre las actitudes de carreras proteicas y nómadas y el compromiso afectivo desde la óptica de una metodología basada en lógica difusa

Resumen:

Los cambios sustanciales que se han producido en el marco de las relaciones laborales y en las estructuras organizativas han puesto en tela de juicio el modelo tradicional de carreras profesionales, dando lugar a dos nuevos paradigmas emergentes en el estudio de las carreras profesionales: las carreras proteicas y las carreras nómadas. En las últimas décadas, las investigaciones sobre los nuevos modelos de carreras profesionales han examinado el impacto de las actitudes nómadas y proteicas sobre varios resultados a nivel individual como el éxito subjetivo y objetivo, la adaptabilidad y la empleabilidad. Sin embargo, todavía tenemos una visión restringida sobre la influencia de estas actitudes sobre resultados organizativos como, por ejemplo, el compromiso organizativo. Con el objetivo de profundizar en este tipo de influencias, la investigación se propone: (1) determinar si las actitudes proteicas y nómadas tienen algún impacto sobre el compromiso afectivo de los empleados hacia su organización; y (2) ofrecer una guía de uso de la metodología basada en lógica difusa en las investigaciones sobre carreras profesionales.

Palabras clave: actitudes de carreras proteicas, compromiso afectivo, lógica difusa

1. Introduction

The current highly volatile and unstable organizational environment reshaped the context in which careers are unfolding (Arthur, Inkson, & Pringle, 1999; Eby, Butts, & Lockwood, 2003). Researchers and practitioners highlighted the importance of reconsidering new ways of viewing careers (Arthur & Rousseau, 1996; Hall, 1976, 2002; Hall, 2004), in order to capture its changing nature (Sullivan, 1999).

Career literature distinguishes two new emerging paradigms to examine professional careers – the protean career (Hall, 1976; Hall, 2004) and the
boundaryless career (Arthur & Rousseau, 1996) – that reflect radical changes in employment relationships and organizational structures, driven by globalization, competitive pressures and rapid technological advances. In response to these environmental factors, companies can no longer promise lifetime employment (Cappelli, 1999), and career scholars have argued that employees develop boundaryless careers that are independent from organizational career arrangements, as they transcend physical and psychological boundaries (Arthur & Rousseau, 1996; Sullivan & Arthur, 2006). A distinguishing characteristic of boundaryless careers is that they are not bounded to a single employment setting (Arthur & Rousseau, 1996). While the term “boundaryless” emphasizes the organizational perspective on examining the changing nature of careers, the protean career approaches these new career patterns from an individual perspective (Hall, 1976, 2002; Hall, 2004; Sullivan, 1999) emphasizing self-direction and values-driven predispositions (Briscoe, Hall, & DeMuth, 2006).

In spite of the fact that boundaryless and protean careers have aroused substantial interest, there have been calls for more empirical research on these new career patterns (Eby et al., 2003; Sullivan, 1999). A notable gap in the literature is examining the impact of protean and boundaryless career attitudes upon employees’ organizational commitment. In that sense, protean and boundaryless careers have been mainly analysed from an individual career perspective, examining their impact on individual outcomes, such as adaptability, psychological success and performance (McArdle, Lea, Briscoe, & Hall, 2007; Mirvis & Hall, 1994). Nevertheless, we have a limited understanding on how new career orientations affect organizational outcomes (i.e. such as, for instance, organizational commitment).

This research has two main objectives: (a) first, to detect whether protean and boundaryless career attitudes have any kind of impact on employees’ affective commitment; and (b) second, to offer a guideline for using the fuzzy set methodology in the research on professional careers. The rest of the paper is structured as follows: section 2 offers a review of the existing literature (which is by no means exhaustive) on new career paradigms and their possible relationships with employees’ affective commitment. Section 3 introduces the fuzzy-set QCA methodology in detail, providing an empirical study with examples taken from our sample. Subsequently, section 4 is centred on data analysis and finally section 5 draws a set of conclusions and discusses some of the main findings and limitations.
2. Literature review

Globalization, rapid technological advancements, and emergent reliance on knowledge-intensive professionals and intellectual capabilities (Powell & Snellman, 2004) have challenged traditional career patterns and gave way to new conceptualizations for better capturing the changing nature of careers (Sullivan, 1999).

The psychological contract that contains individuals’ beliefs regarding the terms and conditions of the exchange agreement between themselves and the organizations (Rousseau, 1989) has also been altered and, as a consequence, employees and employers are exploring new patterns of relationships. Under the old relational contract, employees exchanged loyalty and organizational commitment for long-term or lifetime employment. Under the new, transactional contract, employees exchange performance for continuous learning and marketability (Rousseau & Wade-Benzoni, 1995).

The alterations of the psychological contracts have significant implications for both new career patterns and organizational commitment. Individuals are now a less malleable resource for the organization and more active investors of their personal human capital (Gratton & Ghoshal, 2003), for enhancing opportunities for continuous learning, that will further ensure their future marketability. In a context in which individuals perceive organizations as mere vehicles for their careers, we consider that a re-examination of new career orientations and organizational commitment is timely, as it reflects new challenges for individuals and organizations.

Boundaryless and protean careers

As mentioned before, the current unstable and hypercompetitive organizational context gave way to the emergence of two new perspectives on careers: the boundaryless career (Arthur & Rousseau, 1996) and the protean career (Hall, 1976, 2002), that reflect recent changes in the employment relationships and the psychological contract. The traditional career was defined in terms of progressive lineal advancement in one or two organizations and was conceived as evolving through a series of stages (Levinson, 1978; Super, 1957). As opposed to the paternalistic perspective that characterizes traditional careers, boundaryless and protean orientations emphasize the active role of the individual in managing his/
her own career and development, for seizing opportunities for continuous learning, future marketability and psychologically meaningful work.

A boundaryless career is viewed as "independent from, rather than dependent on, traditional career arrangements" (Arthur & Rousseau, 1996: 6), as it transcends the boundaries of a single employment setting, involving both physical (objective) and psychological (subjective) mobility dimensions. Arthur and Rousseau (1996) identified six different meanings of the boundaryless career, arguing that it is a complex concept that, apart from emphasizing inter and intra-organizational mobility, encompasses careers that can be extrapolated to employees’ perceptions of the desirability or instrumentality of increased mobility (Feldman & Ng, 2007). This psychological perspective on mobility includes: (1) career actors that draw validation and marketability from outside the present employer; (2) careers that are sustained by external networks or information; (3) careers that involve an individual rejecting career opportunities for personal or family reasons and (4) careers that are based on the interpretation of the individual, who may perceive a boundaryless future regardless of structural constraints (Arthur & Rousseau, 1996).

Baker and Aldrich (1996) enriched the concept of the boundaryless career, claiming that for a career to be boundaryless it should be high on three career dimensions: number of employers, extent of knowledge accumulation, and the role of personal identity. In other words, besides inter-firm mobility, the accumulation of transferable skills and a high personal identity are important factors in determining whether a career actor is pursuing a boundaryless career.

Similarly, DeFillippi and Arthur (1996) offered a competency-based view of careers claiming that in the context of the boundaryless career, individuals develop a portfolio of career competencies (e.g. knowing-why, knowing-whom and knowing-how) for further enhancing their careers. Drawing on DeFillippi and Arthur (1996), Eby et al. (2003) provided empirical evidence, revealing that “knowing-why”, “knowing-whom” and “knowing-how” competencies are salient predictors of success in the context of a boundaryless career. Moreover, Bird (1996) argued for a re-conceptualization of careers as repositories of knowledge, asserting that a knowledge perspective provides significant insights into the implications of a boundaryless career for both individuals and organizations.

Whereas some authors have approached boundaryless careers uniquely considering physical changes in work arrangements (Jones, 1996; Saxenian, 1996), Sullivan
and Arthur (2006) emphasize the need of viewing mobility as measured along two continua (physical and psychological), in order to bring greater precision to research endeavours. In an extensive review of the empirical research conducted on the changing nature of careers, Sullivan (1999) asserted that “only sixteen studies examined mobility across physical boundaries, whereas only three studies focussed on the relationships across these boundaries” (Sullivan & Arthur, 2006: 21). Recognizing that a boundaryless career attitude is primarily psychological, Briscoe et. al. (2006) provided empirical evidence, supporting for the development of two boundaryless career attitudes: boundaryless mindset and organizational mobility preference.

Briscoe et. al. (2006: 31) defined a boundaryless mindset as an opening-up attitude to the world, asserting that “a person with a high boundaryless attitude towards working relationships across organizational boundaries is comfortable, even enthusiastic about creating and sustaining active relationships beyond organizational boundaries”. It refers to a general attitude of transcending organizational boundaries, by feeling comfortable in interacting with people from different organizations and seeking out opportunities for experiencing new situations that result beneficial for the individual (e.g. providing the opportunity to enhance knowledge and skills). Organizational mobility preference, on the other hand, refers to individuals’ tendency towards organizational embeddedness (Briscoe et al., 2006). Thus, it is concerned with one’s preference for job security, predictability and long-term employment.

Researchers and practitioners argued that in the context of a boundaryless career, individuals develop a specific mindset or approach, called protean orientation, for successfully navigating the current unstable organizational context (Hall, 1976, 2002; Hall, 2004). The term “protean” derives from the Greek god Proteus who had the uncanny ability to change his shape at will in order to avoid oncoming threats. Within the context of a protean career, individuals, rather than their employing organizations, become the architects of their own career, development and vocational destiny. This orientation represents an internally driven and self-directed perspective in managing one’s career that reflects values such as freedom and adaptability (Hall, 1976, 2002). Baruch (2004: 71) described the protean career as: “a contract with oneself, rather than with the organization”, as individuals “take responsibility for transforming their career path, in taking responsibility for their career”. As Hall (2004) and Hall and Chandler (2005)
remarked, the hallmarks of a protean orientation are: freedom and growth, professional commitment, and the attainment of psychological success, through the pursuit of meaningful work and the discovery of a “calling”.

In an extensive research on career self-management, King (2004) argued that taking responsibility for managing one’s career development can deliver positive psychological outcomes, including career and life satisfaction, enhanced self-efficacy and individual well-being, if desired career outcomes are achieved. Moreover, Seibert et al. (2001) and Crant (2000) found that individuals who have a proactive disposition achieve extrinsic career progression and internal satisfaction with their careers. Furthermore, Wrzesniewski and Dutton (2001) and Wrzesniewski et. al. (1997) highlighted the idea of career self-management by means of the concept of “job crafting”, conceiving individuals as proactive and creative identity builders who take opportunities to engage others in ways that change work identity and work meaning.

Drawing on self-determination (Ryan & Deci, 2000) and regulatory focus theory (Higgins, 1998) it can be argued that protean careerists (1) are intrinsically motivated, as they seek out novelty and challenges to extend and exercise their capacities, to explore and to learn and (2) they hold a promotion focus, as they work for the attainment of their ideals.

Briscoe and Hall (2006) identified two protean-career relevant attitudes – self-directed career attitudes and values-driven predispositions, and developed new scales for measuring them. According to the authors, a self-directed person takes an independent and proactive role in managing his or her vocational behaviour, while individuals who hold values-driven attitudes rely on their own values, instead of borrowing external standards, when making career choices.

Briscoe et al (2006) brought empirical evidence for supporting that protean and boundaryless careers are related, but independent constructs. In that sense, a person may enact a career, by taking active responsibility for his or her development, and yet not being inclined at crossing subjective or objective boundaries. At the same time, an individual may display boundaryless attitudes without being internally driven or self-directed. Research found that there was a moderate positive correlation ($r=.34, p<.01$) between the Boundaryless Mindset and the Protean Orientation, suggesting that they are related, but separate, constructs (Hall, 2004).
The new transactional psychological contract is characterized by relatively low levels of loyalty to the organization and employees exhibit organizational commitment as long as the company offers them opportunities for continuous learning that will further enhance their future marketability (Rousseau & Wade-Benzoni, 1995). Thus, a re-examination of organizational commitment is timely, given the changing nature of employment relationships and career patterns.

**Affective and continuance commitment**

Commitment has been defined as “a force that binds an individual to a course of action that is of relevance to one or more targets” (Meyer & Herscovitch, 2001: 301). It has been argued that commitment in the workplace has potential to influence organizational effectiveness and individual well-being (Meyer & Herscovitch, 2001) and it has been examined as potential determinant of focal (i.e. employee turnover (Mowday, Porter, & Steers, 1982)) or discretionary behaviours (i.e. job performance (Meyer, Paunonen, Gellatly, Goffin, & Jackson, 1989; Somers & Birnbaum, 1998); organizational citizenship behaviour (Shore & Wayne, 1993)).

Organizational commitment has been conceptualized as a multidimensional construct, encompassing different mind-sets such as affective commitment, continuance commitment and normative commitment (Meyer & Allen, 1991, 1997) that exhibit distinguishable implications on behaviour. From among these components, affective commitment has been chosen as the focus of this study, because research reveals that it has the strongest positive correlation with job performance, organizational citizenship behaviour, intention to stay and attendance (Meyer, Becker, & Vandenberghe, 2004).

Affective commitment develops primarily from positive work experiences and reflects one’s desire to remain in the organization (Meyer & Herscovitch, 2001). Meyer and Allen (1991) defined affective commitment as employee’s emotional attachment to, identification with and involvement in the organization. In essence, Meyer and Allen (1991)’s affective commitment, (i.e. dimension reflecting an affective bond to the organization) is similar to Mayer and Schoorman (1998)’s value commitment and Jaros et al. (1993)’s moral commitment.

Meyer and Herscovitch (2001) proposed that affective commitment develops when individuals (a) become involved (intrinsically motivated, absorbed) in a course of...
action; (b) recognize the value relevance of association with an entity or pursuit of a course of action and/or (c) derive their identity from association with the organization. In other words, strong affective commitment reflects involvement, shared values and identity.

Moreover, drawing on the self-determination theory (Ryan & Deci, 2000) and regulatory focus theory (Higgins, 1998), Meyer et al. (2004) asserted that employees with stronger affective commitment to a target experience greater intrinsic motivation, more autonomous forms of external regulation and a stronger promotion focus (i.e. seeking to achieve the maximum level of accomplishment) in the pursuit of goals of relevance to the target. Hence, it could be argued that employees experiencing high levels of affective commitment to a target are likely to exhibit a certain extent of protean orientation as they work towards the attainment of their ideals, holding values-driven predispositions. Furthermore, as they perceive more autonomous regulation, they are more inclined to develop proactive attitudes and undertake the responsibility of their own vocational development. Nevertheless, these proactive attitudes may include psychological or physical mobility (i.e. boundaryless orientations), in order to pursue opportunities for continuous learning and personal growth, when the current company is not able to provide them. Thus, it can be concluded that in the context of boundaryless and protean careers, employees will exhibit affective commitment as long as they experience a value fit with the employing organization and this in turn fulfils the transactional psychological contract conditions (i.e. providing opportunities for continuous learning and marketability).

Building on the knowledge gleaned on the review of the existing literature, the next section presents an empirical study based on a survey conducted on a sample of students attending business courses, which is aimed at detecting potential relationships between boundaryless and protean career attitudes and affective commitment, using a fuzzy-set QCA methodology.

3. Methodology

Sample

The data of this study was collected from 78 respondents, 35.90% women and 64.01 % men. The respondents were anonymous, and the average age was 25.73 years old. All respondents who volunteered to participate in this study were
students from business courses and should have been working. We asked for that respondents answered about their current employment experience. We recollected the data from paper-and-pencil questionnaires. The respondents were assured that their individual responses would remain confidential and that only a composite summary based on their responses would be utilized.

Method

The Qualitative Comparative Analysis methods use a set-theoretic approach (Ragin, 1987, 2000) that attempts to go beyond the gap situated between the case-oriented approach, which is focused on complexity, and the variable-oriented approach, which is focused on generality. For example, the QCA methods treat cases as wholes like the case-oriented approach. At the same time, these methods also take a broad point of view of the phenomena and transform and analyze the data mathematically, like the variable-oriented approach. Thus, these methods use a language “half-verbal-conceptual and half-mathematical-analytical” (Ragin, 2000: 4).

If we compare the traditional variable-oriented methods and the QCA methods, we can find more differences rather than similarities (Fiss, 2007). On the one hand, the variable-oriented approach assumes that a social phenomenon can be studied as linearity, additive effects, and unifinality. On the other hand, the set-theoretic approach emphasizes the nonlinearity, synergistic effects, and equifinality of these phenomena.

As mentioned before, the traditional statistics methods, based on a correlational approach, study singular causation and linear relationships. This approach analyzes how each causal variable independently affects the outcomes of a phenomenon. In other words, these methods analyze the average net effect of a variable on an outcome. Meanwhile, the QCA methods analyze complex causality and nonlinear relationships. The methods based on a set-theoretic approach permit to analyze synergistic effects that go beyond bivariate interaction effects (Delery & Doty, 1996) and to study under what specific conditions a variable can influence our outcome. These methods allow studying how different elements combine rather than compete to produce an outcome. Furthermore, the correlational approach cannot evaluate the causal relationships, in other words, it cannot assess the necessary and sufficient conditions of an outcome, due to the fact that the correlations are bidirectional.
The QCA methods consider equifinality systems where it is possible reach a final state from different initial conditions and by a variety of different paths (Katz & Khan, 1978). In other words, they propose that different combinations of causes can reach the same optimal outcome. Meanwhile, the traditional multivariate methods, as the multivariate regression analysis, suggest unifinality systems where there is just a single way to obtain a given outcome for all cases. Traditionally, equifinality has been assessed through qualitative research, surveys and factor analysis (Gresov & Drazin, 1997); however, these techniques have different limitations, as that they do not allow to examine an extensive number of different combinations of causal variables, to assess in detail the causality between the causal variables and the outcome, and to identify underlying commonalities (Fiss, 2007). For example, the correlational techniques are not able to identify configurations that are unusual; meanwhile, the techniques based on set-theoretic approach allow us identifying them and assessing their importance in the global model.

Fiss (2007) analyzed deeply the advantages and the limitations of QCA methods in comparison to other techniques such as the multivariate linear analysis, the cluster analysis, the ANOVA, the MANOVA, and the use of deviation scores. The results of this review suggested that there has been a gap between the theory and the empirical methods used in the research of complex social phenomena.

The literature review reveals the existence of two versions of QCA methods: the crisp-set version (cs/QCA) (Ragin, 1987) and the fuzzy-set version (fs/QCA) (Ragin, 2000). The cs/QCA method uses dichotomously measured variables to represent mathematically the causes and the outcome of a social phenomenon. However, the fs/QCA method is grounded in fuzzy-set measurement. In this case, the variables can take values from 0 to 1. Both methods use Boolean algebra in order to identify the combined effects of the causes upon the outcome. Moreover, both methods can be used with veristic and probabilistic approach.

The cs/QCA methods use binary values (membership/non-membership). This approach has a wide variety of limitations due to the fact that many phenomena can stay in intermediate levels of membership. For example, an employee’s level of commitment is not always fully in or fully out. His/her commitment level can take different values between these two opposite positions. The fs/QCA method has been recently developed to solve this problem. With this approach, we can use
memberships scores ranging from binary values to continuous scores (Ragin, 2000), allowing researches to develop their constructs. Table 1 shows three examples of fuzzy-set. The first column reflects the most basic fuzzy-set with only two values, which is equivalent to a crisp-set. The second column shows a five-value fuzzy set, while the last column displays a “continuous” fuzzy-set. The researches can further divide the fuzzy-set, depending on the necessities of the research.

<table>
<thead>
<tr>
<th>Two-Value Fuzzy Set (Crisp Set)</th>
<th>Five-Value Fuzzy Set</th>
<th>“Continuous” Fuzzy Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>1: fully in</td>
<td>1: fully in</td>
<td>1: fully in</td>
</tr>
<tr>
<td>0.75: more in than out</td>
<td>0.75: more in than out</td>
<td>Numeric scores between 0.5 and 1</td>
</tr>
<tr>
<td>0.5: crossover: neither in nor out</td>
<td>0.5: crossover: neither in nor out</td>
<td>0.5: crossover: neither in nor out</td>
</tr>
<tr>
<td>0.25: more out than in</td>
<td>Numeric scores between 0 and 0.5</td>
<td></td>
</tr>
<tr>
<td>0: fully out</td>
<td>0: fully out</td>
<td>0: fully out</td>
</tr>
</tbody>
</table>

Table 1. “Crisp versus Fuzzy Sets”. Source: Ragin (2000: 156)

Operators on Boolean algebra

In the Boolean algebra, we can find different operations; however, in the crisp-set and fuzzy-set QCA methods we will use only three operations: negation, logical and, and logical or. These operations are the grounds of these techniques.

Negation

The first and simpler operator is the negation. In cs/QCA methods, the operator negation switches membership scores from “1” to “0” and from “0” to “1”. For example, the negation of the variable A if its membership score is “high” will be “low”. In fs/QCA methods, the operator negation is calculated subtracting the membership of the variable from 1.

\[ \sim A \rightarrow Z = 1 - A \]

Equation 1. "Logical Negation"

The symbol “\~” means negation and the symbol “\rightarrow” means logical implication. So, we read the previous expression as “negation of A implies Z”. For example, if a person has a membership score of 0.78 in A, we will have a membership score of 0.22 in Z.
**Logical AND**

The operator AND represents the intersection of two or more variables. In cs/QCA methods, the membership score of the outcome will be “high” only when all causal variables are “high”. In the rest of the cases, the membership score will be “low”. In the fs/score, we calculate the membership score of the outcome taking the minimum value of the membership scores of the causal variables, as follows:

\[
A \cdot B \rightarrow Z = \text{MIN} \{A, B\}
\]

Equation 2. “Logical AND”

The symbol “:\:” means logical AND, and the symbol “\:\:” means logical implication. So, we read the previous expression as “\:\: A and B implies Z\:\:”. For example, if the membership score of A is 0.35 and the membership score of B is 0.75, the membership score of Z will be the minimum of A and B, so 0.35.

**Logical OR**

The operator OR represents the union of two or more variables. In cs/QCA methods, the membership score of the outcome will be “high” when any causal variable is “high”. In the rest of the cases, the membership score will be “low”. In the fs/score, we calculate the membership score of the outcome taking the maximum value of the membership scores of the causal variables, as follows:

\[
A + B \rightarrow Z = \text{MAX} \{A, B\}
\]

Equation 3. “Logical OR”

The symbol “\:+” means logical OR, and the symbol “\:\:” means logical implication. So, we read the previous expression as “\:\: A or B implies Z\:\:”. For example, if the membership score of A is 0.35 and the membership score of B is 0.75, the membership score of Z will be the maximum of A and B, so 0.75.

**4. Analysis and results**

The analysis of our empirical study, based on a fuzzy-set QCA method, has been structured in three steps:

- Building fuzzy set
• Analyzing Necessary Conditions

• Analyzing Sufficient Conditions

In the following sections, we will develop this method in order to answer the research question of this paper. Moreover, Table 2 shows the general guidelines to apply when using QCA methods.

<table>
<thead>
<tr>
<th>Principle</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>To make a &quot;reasonable&quot; use of QCA (DeMeur &amp; Rihoux, 2002)</td>
</tr>
<tr>
<td>2</td>
<td>To draw on the different functions of the software</td>
</tr>
<tr>
<td>3</td>
<td>Technical and reference concepts should be used with precision</td>
</tr>
<tr>
<td>4</td>
<td>Do not forget the fundamental configurational logic of QCA</td>
</tr>
<tr>
<td>5</td>
<td>Do not use QCA in a mechanical manner</td>
</tr>
<tr>
<td>6</td>
<td>To be careful in the interpretation of the solution of a truth table</td>
</tr>
<tr>
<td>7</td>
<td>No researcher should become a &quot;QCA monomaniac&quot;</td>
</tr>
</tbody>
</table>

Table 2. "General guidelines". Source: (Ragin & Rihoux, 2004)

Constructing fuzzy set

The first step in the fs/QCA method is to build a fuzzy set, a task that involves two steps: establishing empirical indicators for the fuzzy set, and calibrating the fuzzy set (Kvist, 2007).

Establishing empirical indicators

In this research, we are studying the relationships and the configurations of protean and boundaries careers into the affective commitment of the workers of a firm. Thus, we have measured the following constructs: Self-Directed (SD), Value-Driven (VD), Boundaryless mindset (BM), Organizational Mobility Preference (OMP) and Affective Commitment (AC). These were assessed using Briscoe et al. (2006) ‘s protean and boundaryless career attitudes scales and Meyer and Allen (1997)’s affective commitment scale.

Calibrating the fuzzy set

The following step is the calibration that consists in translating the empirical evidence into membership scores of the causal variables and the outcome variable (Verkuilen, 2005). This step is crucial in this method because well constructed fuzzy sets are the key to the useful fuzzy set analysis. The calibration allows us to link the precision of the quantitative variables to the scientific knowledge of the qualitative variables. In other words, it reveals how the data of the empirical
evidence reflects theoretical evidences. Social researches have mainly developed procedures to evaluate the positions of cases in distribution ("more versus less"); however they have not created measures based in substantive and theoretical knowledge ("a lot versus a little") (Ragin, forthcoming). This fact is due to the fact that quantitative methods are insensitive to calibration.

Figure 1: "Calibration"

The researcher should calibrate the variables based on substantive and theoretical knowledge (social knowledge, collective social scientific knowledge and researcher’s own knowledge). This kind of analysis should specify the chosen
criteria in a transparent way due to the fact the full-membership and full non-membership are qualitative states (Ragin, forthcoming). These criteria should define the meaning of full membership, full non-membership and the point of maximum ambiguity of the conditions and the outcome.

The same variable can be calibrated in different ways. In that sense, figure 1 illustrates four alternatives of calibrating the “Affective Commitment” variable. The first common step for all the alternatives is to decide or to identify the values of full membership, full non-membership and the point of maximum ambiguity (threshold point) of the variable. This criterion has been justified by substantive knowledge. However, we will not include these criteria in the next paragraph as our goal consists only in introducing the different ways to calibrate a variable. Figure 1a defines a full membership when the variable is higher than 25 points, a full non-membership when its value is lower than 10 points, and the point of maximum ambiguity when the value of the variable is between 15 and 20 points. The range between the full membership and the threshold point will be fairly in the set, and the valued between the full non-membership and the threshold point will define as fairly out the set. Figure 1b shows a continuum fuzzy-set. In this situation, the full membership and the full non-membership are defined with the maximum and minimum value of the variable (6 and 30, respectively). The threshold point is situated in the middle of the two ends: 18.

Figure 1c is more complex than the previous ones. In this situation, a full membership is defined when the variable is 30 points. Moreover, the calibration shows a full non-membership when the value of the variable is comprised between 6 and 10 points. The threshold point is situated in the value 18. The degree of membership between the full non-membership and the threshold point increase the linearity. However, we can find two strokes between the full membership and the threshold point. The first one is between the values 18 and 22, and it is lineal. The second one is between 22 and 30, but with a lineal slope which is the double higher than the previous one. The last figure (1d) shows a calibration where the full membership, the full non-membership and the threshold point are the same as in figure 1b. However, this last calibration emphasizes that the change between a high affective commitment and a low affective commitment is very fast. In other words, the degree of the membership changes faster when the variable is near the threshold point than placed on the ends. We have introduced above four ways to calibrate a variable, but there are many others available. It is important to
highlight that the calibration selection depends on the substantive and theoretical knowledge on the social phenomenon subject to study, and not on the personal feelings.

In this research, we have five variables (Self-Directed, Value-Driven, Boundaryless Mindset, Organizational Mobility Preference, and Affective Commitment). The five variables have been developed based on calibration. In these cases, we use a continuum fuzzy-set, containing a full membership when the variable has its maximum value, a full non-membership when the value of the variable is minimum, and the point of maximum ambiguity is the center value between the ends. This strategy is similar to figure 1b. Table 3 illustrates the formula of the degree of membership and its three main values.

<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full membership</td>
<td>$x_{\text{max}}$</td>
</tr>
<tr>
<td>Full non-membership</td>
<td>$x_{\text{min}}$</td>
</tr>
<tr>
<td>Point of maximum ambiguity</td>
<td>$x_{\text{min}} + \frac{x_{\text{max}} - x_{\text{min}}}{2}$</td>
</tr>
<tr>
<td>Degree of membership</td>
<td>$\frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}$</td>
</tr>
</tbody>
</table>

Table 3. "Calibration"

**Necessary conditions**

The QCA methods enable researchers to establish whether a condition or causal variable is necessary for an outcome. In cs/QCA methods, a condition is necessary if it is present in all the instances of an outcome. However, in fs/QCA methods, a condition is necessary for an outcome if its membership score is consistently higher than or equal to the outcome. For example, focusing on the configurations of table 4, we check that the condition 1 is necessary because it appears in all the configurations where the outcome is high, although there are other instances where the condition is high and its outcome is low.

<table>
<thead>
<tr>
<th>Name</th>
<th>Condition 1</th>
<th>Condition 2</th>
<th>Condition 3</th>
<th>Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configuration 1</td>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>Configuration 2</td>
<td>High</td>
<td>High</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Configuration 3</td>
<td>High</td>
<td>High</td>
<td>High</td>
<td>Low</td>
</tr>
</tbody>
</table>

Table 4. "Example of necessary condition in cs/QCA"

Table 5 shows an equivalent example of table 4 in a fs/QCA analysis. We check that the degree of membership of the condition 1 is always higher or equal than
the outcome for all configurations: $0.7 \geq 0.7$; $0.8 \geq 0.6$; and $0.4 \geq 0.2$ respectively. So, the condition 1 is a necessary condition for the outcome.

<table>
<thead>
<tr>
<th>Name</th>
<th>Condition 1</th>
<th>Condition 2</th>
<th>Condition 3</th>
<th>Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configuration 1</td>
<td>0.7</td>
<td>0.2</td>
<td>0.8</td>
<td>0.7</td>
</tr>
<tr>
<td>Configuration 2</td>
<td>0.8</td>
<td>0.9</td>
<td>0.5</td>
<td>0.6</td>
</tr>
<tr>
<td>Configuration 3</td>
<td>0.4</td>
<td>0.5</td>
<td>0.7</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Table 5. "Example of necessary condition in fs/QCA". Source: Owned

The fastest and easiest way to evaluate if a condition is necessary is to create a graphical representation between the condition and the outcome, where we expect that the points appear in the lower-triangular plot of the graphic. Traditionally, researchers have studied only the cases where the conditions and the outcome were positive or high. However, evaluating what happens with the negation of the conditions and the negation of the outcome can provide useful information about the causality of the studied phenomenon. For example, it is as important to evaluate if a condition is necessary to an outcome, as well as if the lack of this condition is also necessary to the same outcome. Figure 2 illustrates an example of necessary condition.

Figure 2: "Necessary Condition"
Consistency and coverage

As mentioned before, a cause is necessary condition when all instances are represented in the lower-triangular plot, but unfortunately the perfect social phenomena do not exist. It is very usual that we find necessary conditions where most instances fall in the lower-triangle plot, but a few appear in the upper triangle. At this point, one question rises: how can we evaluate if a condition is necessary knowing that the social phenomenon, which is being studied, is not completely perfect and predictable? Ragin (2006) proposes two descriptive measures the consistency and the coverage for evaluating the strength of the empirical support for theoretical arguments describing set relations.

The consistency of a condition by an outcome assesses the degree to which the instances of an outcome agree in displaying the causal condition thought to be necessary. In cs/QCA analysis, we could evaluate the consistency as the percentage the instances where the causal condition is high when the outcome is high. However, to evaluate the consistency in fs/QCA analysis is more complex than in cs/QCA analysis due to the fact that the values of the conditions are not dichotomies. In these situations, we use the following measurement (Kosko, 1993; C. C. Ragin, 2006; Smithson & Verkuilen, 2006):

\[
Consistency_{yi} \leq xi = \frac{\min(x_i,y_i)}{\sum y_i}
\]


where \(y_i\) represents the value of the outcome of the instance \(i\) and \(x_i\) represents the value of the causal condition of the instance \(i\). When all instances are located in the lower-triangle plot, the consistency is 1.0. We will have then the perfect situation of a necessary condition. If we find some instances in the upper-triangle plot but near of the necessity region, the formula returns values close to 1.0. Based on the literature, we will decide if this causal condition is necessary or not. Finally, the consistency is close to 0.0 when there are some instances far from the lower triangle plot. Figure 3 shows three examples where the consistency is perfect, nearly perfect, and low in a necessary analysis.
The coverage of a causal condition by an outcome is a measure of the importance or relevance of this condition as a necessary condition for the outcome. In other words, the coverage measure is fairly comparable to the level of explained variance ($R^2$) in statistics. In cs/QCA analysis, we could evaluate the coverage as the simple percentage the instances where the outcome is high when the causal condition is high. However, we find again a new problem when we are using fs/QCA because the degree of the membership of the causal conditions is continuum. In this situation, Ragin (2006) proposes a new formula that is very similar to the consistency formula. The difference is in the denominator, as follows:

$$Coverage(y_i \leq x_i) = \frac{\sum \min(x_i, y_i)}{\sum x_i}$$


where $y_i$ represents the value of the outcome of the instance $i$ and $x_i$ represents the value of the causal condition of the instance $i$. The coverage is 1.0 when the causal condition and the outcome have the same value. In other words, it occurs when all instances are represented on the limit between the lower-triangle and the upper-triangle plot. If the instances are close the diagonal, the value of the coverage is close to 1.0. In this situation, we understand that the causal condition is closely related to the outcome and the social phenomenon that we are studying. Finally, the coverage is low when the instances are far from the diagonal. In this case, the causal condition is empirically irrelevant or even meaningless necessary condition. For example, when the causal condition is high as when the outcome is high as when the outcome is low. Figure 4 shows three examples where the coverage is perfect, nearly perfect, and respectively low in a necessary analysis.
Necessary conditions for affective commitment

Table 6 shows the results of the necessity analysis of eight causal conditions—the individual conditions in both their original and negated versions. The table illustrates the values of the measurement of consistency and coverage of the eight causal conditions in the outcome affective commitment.

The results indicate that there are only two causal conditions with a consistency equal or higher than 0.5: Self-Directed (SD) and Boundaryless Mindset (BM) with values of 0.9738 and 0.9533 respectively. However, their coverage is lower than 0.8. More exactly, their coverage is 0.6584 and 0.6611 respectively. These values suggest that these causal conditions have little empirical relevance. If we take a lower limit of consistency, we identify the condition Value-Driven (VD) with a consistency value of 0.9064. However, its coverage keeps lower than 0.8. So, we consider that this condition has also a little meaning in this context. The rest of the causal conditions have a low consistency to order to consider it as necessity or a low coverage to contemplate it as relevant.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Consistency</th>
<th>Coverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>SD</td>
<td>0.9738</td>
<td>0.6584</td>
</tr>
<tr>
<td>SD</td>
<td>0.5089</td>
<td>0.9370</td>
</tr>
<tr>
<td>VD</td>
<td>0.9064</td>
<td>0.7148</td>
</tr>
<tr>
<td>VD</td>
<td>0.6591</td>
<td>0.8738</td>
</tr>
<tr>
<td>BM</td>
<td>0.9533</td>
<td>0.6611</td>
</tr>
<tr>
<td>BM</td>
<td>0.5196</td>
<td>0.8954</td>
</tr>
<tr>
<td>OMP</td>
<td>0.7954</td>
<td>0.6780</td>
</tr>
<tr>
<td>OMP</td>
<td>0.7516</td>
<td>0.8852</td>
</tr>
</tbody>
</table>

Table 6. “Consistency and coverage of necessity conditions”

The following steps will try to analyze the sufficient conditions.
**Sufficient conditions**

The research of causal complexity on social phenomena is centered mainly in the sufficient analysis, due to it is rare to find single causal condition that can become necessary or sufficient conditions (Ragin, 2000). A condition or a set of conditions is sufficient for an outcome when the condition or the set of conditions imply the outcome. In cs/QCA analysis, a configuration is sufficient condition if the outcome is always high when the configuration of conditions is high. Again, it is more complex when we are working with fuzzy-set. In fs/QCA, a condition or a set of conditions is sufficient for an outcome if its score is consistently lower than or equal to the outcome. For example, after putting all instances of a research into configurations, we just got the four configurations of the table 7. We observe that the outcome is high only when the condition 1 is high, so the condition 1 is a sufficient condition of the outcome.

Let’s see a similar example for a sufficient test in a fs/QCA analysis. Table 8 is similar to the example of the table 7 but with fuzzy sets. Table 7 shows that the degree of membership of the condition 1 is always lower or equal than the outcome for all configurations: \(0.5 \leq 0.5; 0.6 \leq 0.8; 0.3 \leq 0.3; \) and \(0.1 \leq 0.2\) respectively. The rest of causal conditions do not fulfill this relationship with the outcome. So, the condition 1 is the only sufficient condition of the outcome.

<table>
<thead>
<tr>
<th>Name</th>
<th>Condition 1</th>
<th>Condition 2</th>
<th>Condition 3</th>
<th>Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configuration 1</td>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>Configuration 2</td>
<td>High</td>
<td>High</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Configuration 3</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Configuration 4</td>
<td>Low</td>
<td>High</td>
<td>High</td>
<td>Low</td>
</tr>
</tbody>
</table>

Table 7. “Example of sufficient condition in cs/QCA”

As in the case of a necessary analysis, the graphical representation is an easy, fast and intuitive way to assess the degree of sufficient condition of one or a set of causal conditions. In this kind of analysis, we expect that the points appear in the upper-triangular plot of the graphic.

<table>
<thead>
<tr>
<th>Name</th>
<th>Condition 1</th>
<th>Condition 2</th>
<th>Condition 3</th>
<th>Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configuration 1</td>
<td>0.5</td>
<td>0.2</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>Configuration 2</td>
<td>0.6</td>
<td>0.7</td>
<td>0.9</td>
<td>0.8</td>
</tr>
<tr>
<td>Configuration 3</td>
<td>0.3</td>
<td>0.4</td>
<td>0.2</td>
<td>0.3</td>
</tr>
<tr>
<td>Configuration 4</td>
<td>0.1</td>
<td>0.7</td>
<td>0.6</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Table 8. “Example of sufficient condition in fs/QCA”
Figure 5 shows an example of sufficient condition, where all instances have a higher outcome than the causal condition.

![Sufficient Condition](image)

**Figure 5. “Sufficient Condition”**

**Consistency and coverage**

But, what does happen when not all instances fall in the upper-triangular plot? The answer is easy. We can use the same two descriptive measures that we have introduced in the necessary analysis: consistency and coverage. However, the meaning of these measurements slightly different, as it is the way to compute them. The consistency of a condition by an outcome assesses the degree to which the cases sharing a given condition or combination of conditions agree in displaying the studied outcome. In cs/QCA analysis, we could evaluate the consistency as the percentage of the instances where the outcome is high when the causal condition is high. However, it is more complex to evaluate the consistency in fs/QCA analysis than in cs/QCA analysis. The consistency of sufficient conditions is calculated as follows:

\[
\text{Consistency}(x_i \leq y_i) = \frac{\sum \text{min}(x_i, y_i)}{\sum x_i}
\]


where \(y_i\) represents the value of the outcome of the instance \(i\) and \(x_i\) represents the value of the causal condition of the instance \(i\). We get a perfect consistency, that is
1.0, when all instances are displayed in the upper-triangle plot. The meaning of this value is that all instances support this sufficient condition. Nevertheless, the social phenomena are rarely perfect. Moreover, it is likely that small mistakes occur when collecting the data. So, it is usual to observe some instances in the lower-triangle plot, yet not too far from the sufficiency region. In these situations, we would have consistencies with values close to 1.0. Finally, the formula returns values close to 0.0 when there are some instances far from the upper-triangle plot.

In complex social phenomena where equifinality exists, the sufficiency analysis can provide one or more sufficient conditions. We can assess the consistency of each sufficient condition and the consistency of the whole sum of the sufficient conditions. Figure 6 shows three examples where the consistency is perfect, nearly perfect, and respectively low in a sufficient analysis.

![Figure 6. "Consistency of Sufficient Conditions"](image)

The coverage of a causal condition by an outcome is a measure of the importance or relevance of this condition as a sufficient condition for the outcome. This measurement assesses the level of the explained sufficient condition. In cs/QCA analysis, we evaluate the coverage as the percentage the instances of a sufficient condition compared to the number of instances of the rest of sufficient conditions. So, we have as many measurements of coverage as sufficient conditions. This is different in fs/QCA analysis where the degree of the membership of the conditions is not dichotomic. In this situation, we use the following formula:

\[
Coverage(x_i \leq y_i) = \frac{\sum \min(x_i, y_i)}{\sum y_i}
\]

where $y_i$ represents the value of the outcome of the instance $i$ and $x_i$ represents the value of the causal condition of the instance $i$. You can check that (1) the formula of consistency of a necessary condition has the same structure as the measurement of coverage of a sufficient condition and (2) the formula of consistency of a sufficient condition has the same structure as the coverage measurement of a necessary condition.

The formula of coverage returns 1.0 when the causal condition and the outcome have the same value. This value means that the sufficient condition explains the outcome perfectly and completely. However, it is unusual to find the perfect coverage in social science. Graphically, we can observe this relation when all instances are located on the limit between the lower-triangle and the upper-triangle plot. It is more usual to find the instances close this limit. In this situation, the coverage is near 1.0. The meaning of this value is that the sufficient condition explains the outcome but there are other causes of minor importance that can complete the explanation. Finally, the coverage is low when the instances are far from the diagonal. In this case, the measurement tells us that there are other causes that explain the outcome, but that the causal condition that we are studying also can be important.

![Figure 7. "Coverage in Sufficient Conditions"

We can assess the coverage of each sufficient condition separately or the coverage of the sum of all sufficient conditions. The first measurements inform us about the degree of explanations of each sufficient condition, while that the second one advise us about the degree of the explanation of the whole model. It is important to remark that the coverage and the consistency of the whole model are not the sum of the coverage and consistency of the causal conditions. Figure 7 shows three
examples where the coverage is perfect, nearly perfect, and respectively low in a sufficiency analysis.

**Sufficient conditions for affective commitment**

The sufficient analysis is more complex and longer than the necessity analysis. This process is explained in the following section. The sufficiency analysis can be structured in two steps: the creation of a truth table and the application of a reduction procedure.

**Truth table and reduction procedure**

The following method uses Boolean logic to identify the minimal list of configurations that determine the truth condition of the observed cases.

**Truth table**

The first step of this process is to create a truth table that lists all possible configurations of the causal conditions of the social phenomenon that we are studying. The number of configurations is $2^k$ where $k$ is the number of causal conditions. In our research, we have four causal conditions (Self-Directed, Value-Driven, Boundaryless Mindset, and Organizational Mobility Preference), and thus we have 16 ($2^4$) configurations in the truth table (see table 9).

The observed cases are classified into the truth table based on a crisp set approach. The causal conditions with a membership higher than 0.5 are assessed as high; the rest of conditions are considered as low. Moreover, the truth table shows the number of cases or instances of every configuration, the number of cases or instances with an outcome higher than 0.5 of every configuration, and the consistency of every configuration. The configurations without cases are called “remainders”.

Now, we have obtained all possible combinations of causal conditions or configurations. The following step is to decide which configurations have a high outcome, which combinations of causal conditions are associated to a low outcome, and which configurations are remainders. Ragin (forthcoming) proposes two measurements to assess them: the frequency threshold of a configuration and its consistency. The frequency threshold indicates the minimum number of cases with an outcome higher than 0.5 to consider it “not remainder”. When the number of
cases is small, the frequency threshold should be 1 or 2. In the rest of cases, the frequency threshold depends on the researcher criterion.

<table>
<thead>
<tr>
<th>SD</th>
<th>VD</th>
<th>BM</th>
<th>OMP</th>
<th>N of Instances</th>
<th>N of Instances &gt;0.5</th>
<th>Consistency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>0</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
<td>0</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>Low</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>0</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>0</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>Low</td>
<td>0</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>Low</td>
<td>High</td>
<td>High</td>
<td>Low</td>
<td>1</td>
<td>1</td>
<td>0.9366</td>
</tr>
<tr>
<td>High</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>0</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>0</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>1</td>
<td>1</td>
<td>0.9329</td>
</tr>
<tr>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>High</td>
<td>9</td>
<td>9</td>
<td>0.8717</td>
</tr>
<tr>
<td>High</td>
<td>High</td>
<td>Low</td>
<td>Low</td>
<td>3</td>
<td>3</td>
<td>0.9224</td>
</tr>
<tr>
<td>High</td>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>2</td>
<td>1</td>
<td>0.8920</td>
</tr>
<tr>
<td>High</td>
<td>High</td>
<td>High</td>
<td>Low</td>
<td>16</td>
<td>12</td>
<td>0.9166</td>
</tr>
<tr>
<td>High</td>
<td>High</td>
<td>High</td>
<td>High</td>
<td>46</td>
<td>36</td>
<td>0.7508</td>
</tr>
</tbody>
</table>

Table 9. “Truth table”

At this moment, the researcher must decide if they want to find the most complex solution or the most parsimonious one. In the first option, we consider that the remainders are equivalent to the cases with a low outcome. In the second one, we treat the remainders according to the research. In some situations, we will consider the remainder as a case with a high outcome, and in others as a case with a low outcome. In our research, we have taken a frequency threshold of two, considering the configurations with 0 and 1 case as remainders. As regards the consistency, the research takes two thresholds: 0.9 and 0.85.

**Reduction procedure**

The reduction procedure allows us to reduce these configurations to most robust and general relationships, and some causal conditions might be dropped out as redundant. The reduction procedure according to Boolean algebra relies upon two operations: absorption and reduction. The absorption operation asserts that when two Boolean expressions that produce the same outcome and that part of one of them is the another one, we can consider the first one as irrelevant and remove it. The following example shows the absorption operation works:

\[ A + A \cdot B = A \rightarrow Z \]

Equation 8. “Reduction procedure: Absorption operation”
On the other hand, the reduction operator says: “If two Boolean expressions differ in only one causal condition yet produce the same outcome, then the causal condition that distinguishes the two expressions can be considered irrelevant and can be removed to create simpler, combined expressions” (Ragin, 1987: 93). We can observe how this operation works in the following example:

\[ A \cdot B + A \cdot \neg B = A \cdot (B + \neg B) = A \cdot (1) = A \rightarrow Z \]

Equation 9. “Reduction procedure: Reduction operation”

Generally, it is easy to use these operators; nevertheless, when we have various causal conditions the situation is more complex. In these situations, we can use the Quine-McCluskey algorithm and Patrick Method that allow us simplifying set-theoretic statements through software.

Results of sufficiency analysis of affective commitment

Table 10 shows the results of the sufficient analysis when the consistency threshold of the truth table is 0.9. In this situation, we observe that there are only two configurations in the truth table where the outcome is high: SD·VD·BM·\neg OMP and SD·VD·\neg BM·\neg OMP. Applying the reduction operation, we get the expression SD·VD·\neg OMP where the coverage and the consistency is 0.7226 and 0.9075, respectively.

<table>
<thead>
<tr>
<th>Configuration</th>
<th>Coverage</th>
<th>Consistency</th>
</tr>
</thead>
<tbody>
<tr>
<td>SD·VD·\neg OMP</td>
<td>0.7226</td>
<td>0.9075</td>
</tr>
<tr>
<td>Global</td>
<td>0.7226</td>
<td>0.9075</td>
</tr>
</tbody>
</table>

Table 10. “Sufficient condition analysis with consistency of 0.9”

If we use 0.85 as a consistency threshold in the truth table, we get different results (see table 11). In these circumstances, we have two configurations to achieve a high outcome (equifinality): SD·VD·\neg OMP and SD·\neg VD·BM·OMP. The first configuration has a higher coverage and consistency. However, the second configuration also has acceptable values in its coverage and consistency. Both configurations are represented in Figure 8.

This model has a higher coverage and a lower consistency than the previous global model (where the consistency threshold was 0.9). In other words, the second final
model with two configurations explains the outcome better than the first model, although with a lower consistency.

<table>
<thead>
<tr>
<th>Configuration</th>
<th>Coverage</th>
<th>Consistency</th>
</tr>
</thead>
<tbody>
<tr>
<td>SD-VD-OMP</td>
<td>0.7226</td>
<td>0.9075</td>
</tr>
<tr>
<td>SD-VD-BM-OMP</td>
<td>0.6111</td>
<td>0.8717</td>
</tr>
<tr>
<td>Global</td>
<td>0.7970</td>
<td>0.8652</td>
</tr>
</tbody>
</table>

Table 11. "Sufficient condition analysis with consistency of 0.85"

5. Conclusions

This research aimed at providing an insight on the impact of holding protean and boundaryless career attitudes upon an organizational outcome (in our case, affective commitment), in a context in which individuals experience less job stability and increased organizational changes (Eby et al., 2003). Moreover, by means of an empirical study, we brought evidence on the usefulness and salience of a fuzzy-set QCA methodology, when conducting research on new career patterns.

As mentioned before, research on new career patterns has analysed protean and boundaryless career attitudes, mainly from the perspective of career actors, examining its impact upon individual outcomes, such as adaptability, psychological success and employability. Therefore, we addressed a notable gap in literature, namely the effects of holding a protean and /or boundaryless career attitude upon
employee’s emotional attachment to, identification with and involvement in the organization. Given the complexity of this relationship, we have chosen to approach it using a fuzzy-set QCA methodology, instead of a traditional statistic method, that is based on a correlational approach and examines singular causation and linear relationships. The fuzzy-set approach allowed us to study how different elements combine rather than compete to produce an outcome, in the sense that it enabled the detection of different configurations that reach the same optimal outcome.

Our findings illustrate that protean and boundaryless career attitudes are important in predicting affective commitment. Considering 0.85 as a consistency threshold in the true table, we obtained two career attitudes configurations that provide high affective commitment (equifinality): SD·VD·¬OMP and SD·¬VD·BM·OMP. The first configuration had a higher coverage and consistency. Nevertheless, the second configuration was also considered valid for having acceptable values in its coverage and consistency. These configurations reflect that individuals high on protean attitudes (values-driven predispositions and self-directed attitudes) exhibit high levels of affective commitment, while they are not inclined towards organizational mobility. Moreover, individuals high on boundaryless attitudes (organizational mobility preference and boundaryless mindset) and who are self-directed in managing their careers and development also experience high levels of attachment and involvement with the organization, with the condition of not holding values-driven predispositions.

The research results provide empirical support for the importance of taking protean and boundaryless attitude toward the career, which not only delivers positive individual outcomes, but also has a positive impact upon the employing organization. These findings highlight the importance for individuals to take active responsibility in managing their careers instead of passively relying on the employing organizations to provide them with a clear career path. Furthermore, this research provides empirical testing for four newly developed scales.

Nevertheless, this research has several limitations. One limitation is related to the characteristics of our sample, as participants were relatively homogenous with respect to age and education level. For this reason, they tended to be high on protean career attitudes, as the majority declared to rely on their own values to direct their careers and take an independent role in managing their vocational
behavior. Therefore, future research might seek samples that are more heterogeneous on these characteristics. An interesting avenue for future research is to consider the combined effects of demographic characteristics and career attitudes upon affective commitment or any other organizational outcomes. Other limitation is related to the commitment mind-set selected, in the sense that we restricted our analysis only to affective commitment. Future research might examine the relationship between boundaryless and protean career attitudes and the other two components of organizational commitment (continuance commitment and normative commitment). This will probably provide a more complex insight upon the mentioned relationship, due to the fact that commitment components are distinguishable from each other and have distinct behavioral consequences.

References


