



# Reframing talent identification as a status-organising process: Examining talent hierarchies through data mining

Sanne Nijs<sup>1</sup>  | Nicky Dries<sup>2,3</sup>  | Véronique Van Vlasselaer<sup>4</sup> | Luc Sels<sup>1</sup>

<sup>1</sup>Department Human Resource Studies, Tilburg University, Tilburg, The Netherlands

<sup>2</sup>Department of Work and Organisation Studies, KU Leuven, Leuven, Belgium

<sup>3</sup>Department of Leadership and Organizational Behaviour, BI Norwegian Business School, Oslo, Norway

<sup>4</sup>SAS, Tervuren, Belgium

## Correspondence

Sanne Nijs, Department Human Resource Studies, Tilburg University, Simon Building, 5000 LE Tilburg, The Netherlands.  
Email: [S.Nijs@uvt.nl](mailto:S.Nijs@uvt.nl)

## Abstract

We examine how peers form talent appraisals of team members, reframing talent identification as a status-organising social process. Using decision trees, we modelled configurations of characteristics and behaviours that predicted dominant versus parallel routes to achieving the status of most talented team member. Across 44 multidisciplinary teams, talent status was most often granted to peers perceived as having both leadership and analytic talent; a STEM degree served a dominant signalling function. Where previous studies assumed that degree operates as a specific status characteristic, we show that a STEM degree operates as a diffuse status characteristic, which predicts status in general. We thus discovered that status hierarchies in teams are also based on the *type* of talent—and not just the *level* of talent—members are perceived to possess. In so doing, we offer a proof of concept of what we call ‘talent hierarchies’ in teams, for future research to build on.

## KEYWORDS

data-mining, decision trees, status, talent hierarchies, talent identification, talent management

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**Practitioner notes****What is currently known about the subject matter?**

- Scholarly literature on talent management mainly focuses on the assessment and emergence of leadership talent and the criteria used for identifying leadership talent.
- Scholarly literature on talent management mainly focuses on the assessment and identification of talent as done by superiors as part of formal talent management programs.

**What our paper adds to the subject matter?**

- In this study, we examine how peers in teams form perceptions of 14 different talents, and extend the talent management literature that has predominantly focussed on leadership talent.
- In this study, we introduce a social perception/status perspective on talent into current academic understandings of talent management—which has heavily relied on the assumption that talent identification is based on the rational assessment of people's strategic contribution to an organisation.
- In this study, we generate more insight into graduate talent management as an understudied strategy to create talent pools.

**Implications of study findings for practitioners**

- Peers are important, but often neglected stakeholders in talent management decisions.
- Peers use different heuristics to assess different types of talents, underlining the importance of asking the 'talent for what?' question when identifying talent.
- Understanding the talent hierarchies that emerge spontaneously among peers in teams can help increase acceptance of sensitive talent management decisions.

## 1 | INTRODUCTION

Organisations today invest significantly in talent identification practices, as they believe that these will support them in detecting and developing the future leaders they need to create competitive advantage (McDonnell et al., 2017). Talent identification procedures involve the assessment of employees' performance and potential, and the subsequent inclusion of high-potential, high-performing employees into the organisation's so-called 'talent pool' (Becker et al., 2009). Determining who should be included in these (typically highly exclusive) talent pools is the key challenge in talent identification (De Boeck et al., 2018). Organisations typically adopt one of three strategies in creating their talent pools: either they identify talented employees within their existing workforce; or they focus primarily on external selection, either through headhunting of senior profiles, or by recruiting 'high-potential' students from respected graduate programs (Clarke & Scurry, 2017).

Although research indicates that all three types of strategies are prevalent (McCracken et al., 2016), the majority of studies to date have focused on talent identification several years after hire. Despite organisations voicing that they need to start identifying high-potentials earlier in their career (McDonnell et al., 2011), much less is known about how organisations should identify talent among young graduates, who have limited work experience. The limited knowledge that is available stems from the emerging literature stream on so-called 'graduate' talent management (TM; Clarke & Scurry, 2017; Muratbekova-Touron et al., 2018). The present study focuses on talent identification among university graduates, thus responding directly to this specific gap in the literature.

As concerns the criteria for talent identification, we see that organisational and academic interest in talent identification accumulates around the assessment of leadership talent (Finkelstein et al., 2018). Typically, organisations focus on a combination of cognitive and social abilities, growth and learning competences, and personality traits to assess which people will most likely be successful in a role with broader responsibilities, higher up in the hierarchy. McDonnell et al. (2016) argued that TM theory and practice place a strong emphasis on leadership talent, while neglecting other key talents that could be of value. This narrow focus on leadership does not align with new ways of working, in which organisations increasingly rely on multidisciplinary, multi-talented and self-steering teams to solve complex problems (Van Der Vegt & Bunderson, 2005).

The status literature might offer a promising way forward here (Bunderson & Barton, 2011). This literature explicitly studies appraisals in team settings, conceptualising status in teams as spontaneously emerging based on group members' assessments of each other's talents. These talent appraisals in turn create status hierarchies between peers where a disproportionate amount of deference and resources are awarded to the lucky few (Bendersky & Pai, 2018; Berger et al., 1992). According to the status literature, the assessment of group members' talents is based on subconscious heuristics that rely on cues—called status characteristics and behaviours—which signal social worth to peers (Blader & Yu, 2017). Bunderson and Barton (2011) theorise that peers do not only confer social worth, and thus status, based on the *level* of talent individuals possess, but also based on the *type* of talents (also called 'talent domains'). More specifically, they suggest that although one can expect a wide variety of talents to be valued in multidisciplinary teams, a certain hierarchy between different types of talents might simultaneously emerge. As such, they claim that in addition to parallel status hierarchies (i.e., the equal social valuation of different types of talents), dominant status hierarchies (i.e., the higher social valuation of some types of talents leading to the most favourable status position) will surface in teams. However, the type of talents that leads to a certain status position in a team is a poorly understood phenomenon.

Surprisingly, the TM literature has widely ignored the social worth peers attribute to different types of talents (McDonnell et al., 2016). The reasons for this absence in the TM literature are: first of all, the narrow focus on leadership talent; second, the tendency to only study talent identification from the perspective of management, based on the incorrect assumption that managers assess talent without consulting peers; third, the use of generic operationalisations of talent without addressing the 'talent for what?' question and; fourth, the use of analytical techniques ill-suited for studying configurations of talent identification cues (Finkelstein et al., 2018; Gallardo-Gallardo et al., 2015; Nijs et al., 2014).

In the present study, we examine the social worth attributed to different types of talents (Gagné, 2004) in multidisciplinary teams by reframing talent identification as a complex status-organising process. We bridge the TM literature and the status literature (Correll & Ridgeway, 2003) to answer the following overarching research question: "*What are the configurations of cues (i.e., status characteristics and status behaviours) peers rely on when assessing and valuing different types of talents in multidisciplinary teams?*" To accurately answer this research question we tackle the following three research aims: first, examine the configurations of status characteristics and behaviours on which peers rely when forming talent perceptions within different talent domains; second, determine the relative value peers attach to status characteristics and behaviours when forming talent perceptions; and third, explore which (combination of) talent domains—signalled by a bundle of cues—ultimately lead to more versus less favourable status positions.

Since our research question focuses on the configurations of cues that determine talent identification, we apply a configurational approach to our data—more specifically, decision tree modelling (White et al., 2020). We selected decision trees for three specific reasons that align with the described research aims and reflect the unique characteristics of this technique compared to parametric techniques. First, decision trees are capable of modelling *n*-way interactions (i.e., beyond typical two- and three-way interactions, based on data-driven patterns), and can thus test how a wide variety of cues configures in the formation of talent perceptions. Second, decision trees generate tree-type structures in which the order of occurrence reflects the relative value attached to cues when forming talent perceptions about peers. Third, decision trees operate according to the principle of equifinality,

meaning that they generate all possible paths (dominant and parallel) to achieving talent status (Witten & Frank, 2005). By using this approach, we can thus explore which (combinations of) talents—signalled by a bundle of cues—lead to the status of most talented team member.

We make three contributions with this paper. First, we advance academic understanding of talent identification by reframing being identified as a 'talent' as a specific form of status (Piazza & Castellucci, 2014). To date, research on talent identification has been overwhelmingly practice rather than theory-driven. We believe that the present study, bridging the status literature and the TM literature, could serve as a solid base for more deductive, theory-driven studies in the future (Chatman & Flynn, 2005).

Second, we empirically investigate the emergence of parallel and dominant status hierarchies in multidisciplinary teams, and how they are formed based on  $n$ -way interactions between status characteristics and behaviours. Although the notion of parallel and dominant intrateam hierarchies is theoretically well-developed in the status literature—referring, in our case, to *different* types of talents that are valued in teams, and those that are valued *most*, respectively (Bunderson & Barton, 2011)—to date there has been very little empirical research on this phenomenon. We also add a new construct to the TM vocabulary, 'talent hierarchies'—that is, the differential appreciation of specific types of talents, translating into certain status positions in teams.

Third, we adopt a data-mining approach to study talent hierarchies in multidisciplinary teams. By applying decision trees (Tan et al., 2006), capable of modelling  $n$ -way interactions, we expand the range of techniques available to management scholars interested in talent identification, status or person-centric research methods more generally (Liu et al., 2011). By adopting a decision tree approach we move away from generic models of talent, instead focussing on different types of talents that can be identified in multidisciplinary teams.

## 2 | THEORETICAL FRAMEWORK

A key contribution of the present study is that we reframe being identified as talented as a specific form of status. We thus introduce a social perception perspective on talent (Dominick & Gabriel, 2009) into current academic understanding of TM—which so far has relied strongly on the assumption that talent identification is based on a purely rational assessment of employees' strategic contribution to an occupation, organisation or team (Finkelstein et al., 2018; Huselid & Becker, 2011).

### 2.1 | The meaning of talent

The term 'talent' is most commonly used to refer to an above-average ability—coupled to a specific function, or range of functions—that makes the people who possess it perform better than their peers (Gallardo-Gallardo et al., 2013). Consequently, talent is often equated to excellent performance within a given performance domain (Gagné, 2004). In addition, it is often assumed that natural abilities and aptitudes underlie such excellent performances, and thus form the fundamental building blocks of talent (Gallardo-Gallardo et al., 2013; Silzer & Church, 2009). Similar, but related constructs—most notably expertise—in contrast, place greater emphasis on the prolonged and intense experience that transforms novices into experts through practice (Dreyfus & Dreyfus, 2005; Ericsson et al., 2018). It is believed, however, that people's natural abilities will only become visible when given the opportunity to be developed and expressed (Gagné, 2004). In that sense, talent and its underlying exceptional abilities can only be demonstrated when necessary conditions, such as motivation and interests, are present. In this study, therefore, we adopt the talent definition of Nijs et al. (2014, p. 182): '*Talent refers to systematically developed innate abilities of individuals that are deployed in activities they like, find important, and in which they want to invest energy. It enables individuals to perform excellently in one or more domains of human functioning, operationalised as performing better than other individuals of the same age or experience.*'

Our focus on talent as a central construct fits particularly well with the phenomenon of graduate TM, which is focussed on the identification of talent(s) in a group with particularly little work experience (Clarke & Scurry, 2017; Muratbekova-Touron et al., 2018). Assessments of talents in young graduates, then, offer early indications of who is likely to perform excellently in specific roles and positions later on in their careers, as more specific knowledge and experience is gained.

## 2.2 | Talent identification and status

Status issues permeate organisational life, as the attainment of status is a fundamental motive for organisational actors, and ultimately determines the resources they can marshal in aid of a favoured cause (Chen et al., 2012). Status can be defined as an individual's consensually acknowledged social worth relative to other individuals, as manifested in the differential deference individuals enjoy in the eyes of others (Bendersky & Pai, 2018). Four core features of status distinguish this construct from related constructs such as reputation (which is about being known) and power (which is about being in control) (Cheng et al., 2013). First, status is differentiating, in that it leads to the unequal distribution of privileges such as deference and resources. Second, status is hierarchical, in that it orders actors according to their social worth based on valued characteristics and abilities (Magee & Galinsky, 2008). Third, status is socially constructed, in that it is based on subjective judgements (Piazza & Castellucci, 2014). And fourth, status is consensual, in that it is based on socially agreed-upon judgements (Deepphouse & Suchman, 2008).

Based on these core features, we propose that two basic principles central to TM—workforce differentiation and interpersonal excellence—bridge the constructs of talent and status theoretically (Nijs et al., 2014). First, the principle of workforce differentiation refers to how organisational resources should be distributed among employees. Specifically, organisations are recommended to invest a disproportionate amount of resources where they expect disproportionate returns (Becker et al., 2009). This practice results in a segmentation of the workforce based on the strategic value a given employee is expected to contribute (Boudreau & Ramstad, 2005). Legitimised by its (assumed) disproportionate contributions to team and organisational performance (Aguinis & O'Boyle, 2014), this elite group enjoys increased deference and resources (Aguinis et al., 2016). This corresponds perfectly to the status construct, which entails the granting of membership to a group with distinctive characteristics and abilities, that enjoys positional advantages (Deepphouse & Suchman, 2008). Second, the principle of interpersonal excellence dictates that talent should be operationalised as 'the outstanding mastery of systematically developed abilities and knowledge in at least one field of human activity to a degree that places an individual at least among the top 10% of age peers...' (Gagné, 2004, p. 120). Status, as well, captures hierarchical relations among individuals, with status differences being rooted in relative assessments of individuals compared to referent others (Bendersky & Pai, 2018; Piazza & Castellucci, 2014). Talent is typically evaluated by giving performance ratings to people on a set of predefined domains, which are then forced-ranked to identify top-tier employees (Silzer & Church, 2009).

In conclusion, both status and talent imply hierarchies that reflect the amount of deference and resources individuals receive in comparison to others (Anderson & Kilduff, 2009). While the TM literature so far has only covered formal status-organising processes related to talent identification—since they assume that the talent label is only granted by superiors as part of a formal TM program (Dominick & Gabriel, 2009)—our interest centres around the informal hierarchies that emerge among peers in team settings (Bunderson, 2003). Research largely assumes that managers evaluate employees in isolation. In reality, organisations often base talent assessments on group dialogue and consensus. By assessing how peers informally form consensus on talent perceptions, we could more completely understand talent identification as a differentiating practice in organisations (Doyle et al., 2016).

Peer ratings (i.e., rating the status of each member of a group; Anderson et al., 2001), peer rankings (i.e., ranking members of a group from high to low status; Anderson & Kilduff, 2009), and peer nominations (i.e., identifying the highest-status member of a group; Bunderson, 2003) are the most widely used measures of informal status in the status literature. In order to maximise the parallels with the status construct methodologically, talent identification

was operationalised as the consensus (i.e., status is consensual) that occurred between peers in their perceptions (i.e., status is socially constructed) as to who their most talented team members are.

Since talent identification has not yet been associated with status attainment theoretically, limited knowledge is available on how peers form specific talent perceptions and how this translates into certain status positions in teams. With this study, we aim to explore this topic by studying talent identification as a status-organising process.

## 2.3 | Status-organising processes

Status-organising processes are defined as ‘any process in which evaluations of and beliefs about the characteristics of actors become the basis of observable inequalities in face-to-face social interaction’ (Berger et al., 1980, p. 479). Status-organising processes occur naturally within groups as a direct function of the shared expectations that emerge about each member’s ability to contribute to a focal task (Bendersky & Pai, 2018). As such, status is typically granted to members who are believed to possess superior abilities (Anderson & Kilduff, 2009; Bunderson et al., 2013). From the status literature, we know that observers rely on cues—henceforth referred to as status characteristics and status behaviours—when assessing abilities and making status inferences (Berger et al., 1992). In the TM literature, both conceptual articles looking to define talent (e.g., Nijs et al., 2014) and more ‘practical’ articles (e.g., Silzer & Church, 2009) have emphasised that talent is not a generic concept and refers to the demonstration of superior abilities in a given domain. The educational literature on talent and giftedness distinguishes 14 different talent domains (i.e., type of talents) within which interpersonal excellence can be perceived—that is, linguist, scientist, analyst, technician, creative brain, critical thinker, mediator, speaker, spokesperson, planner, entertainer, leader, business talent and networker (Gagné, 2004; see Appendix S1).

Bunderson and Barton (2011) theoretically proposed that although one can expect a wide variety of (talent) domains to be valued by peers in multidisciplinary teams, a certain hierarchy between these domains will simultaneously surface, leading to the emergence of both parallel and dominant talent hierarchies. We empirically explore if and how status positions are conferred based on talent domains. We build on the status literature to explore how the often subconscious anticipations of a group member’s talents are inferred from characteristics and behaviours the group has come to associate with certain talent domains, and how these talent associations results in a certain status position in the team (Correll & Ridgeway, 2003).

### 2.3.1 | Status characteristics

A widely adopted theory in the status literature is the status characteristics theory (Correll & Ridgeway, 2003). Status characteristics theory implies that talent perceptions will be inferred from socially significant characteristics on which individuals differ, referred to as status characteristics (Bendersky & Pai, 2018). A further distinction is made between diffuse and specific status characteristics.

Diffuse status characteristics are associated with general ability across domains, and can thus be expected to affect status—in our case, the status of most talented team member—more generally. In accordance with the status literature, we will study sex, age, past overall performance and (team)work experience as potential diffuse predictors of the status of most talented team member (Correll & Ridgeway, 2003). Berger et al. (1992) argued that status characteristics theory may apply to a wider range of characteristics than the ones traditionally understood by the theory. Several authors demonstrated that personality may in fact serve similar functions in status-organising processes in teams (i.e., extraversion and dominance positively influenced status while neuroticism negatively influenced status; Anderson et al., 2001; Anderson & Kilduff, 2009). As the review of the status literature indicated that a broad range of status characteristics are believed to potentially influence status attributions (Berger et al., 1992), we also searched the TM literature and giftedness literature for potential determinants of

talent status. A review of existing talent and giftedness models (Finkelstein et al., 2018; Gagné, 2004; Silzer & Church, 2009) yielded the following additional (diffuse) predictors of the status of most talented team member: self-esteem, self-efficacy, self-consciousness, goal orientation and team player attitude. The addition of predictors linked to self-concept fits well with research of Paunova (2017) in which she states that empirical research building on status characteristics theory widely neglects the role self-concepts play in status-organising processes.

Specific status characteristics are associated with ability within a given domain and can be expected to affect status only via specific talent domains. Based on the importance of self-concepts in status organisation processes (Paunova, 2017), we study self-evaluations of one's domain-specific talents as specific status characteristics that are potential drivers of the status of most talented team member. In accordance with the status literature, we also study specialised degree as a specific status characteristic.

### 2.3.2 | Status behaviours

Kunda and Thagard (1996) argued that next to status characteristics, status behaviours influence perceptions formed about individuals within a team. Assertive (non-) verbal behaviours, such as portraying dominance or task confidence are typically perceived as high-status behaviours, as observers tend to assume that the more assertively an actor behaves the more talented he or she must be (Bunderson & Barton, 2011). A wide variety of impression management tactics (i.e., ingratiation, self-promotion, exemplification, intimidation and supplication)—defined as ‘the specific behaviours of an actor directed at creating, maintaining, protecting or otherwise altering an image held by a target audience’ (Bolino et al., 2008, p. 1080)—have been classified as such assertive, high-status behaviours (Turnley & Bolino, 2001) that could affect talent perceptions (Finkelstein et al., 2018). We extend this research by more specifically looking at the influence impression management, as status behaviours, exerts on the formation of dominant and parallel talent hierarchies in a team setting (Bendersky & Pai, 2018).

### 2.3.3 | Organized subset combining

People use a plethora of cues to form judgements about others, resulting in social judgements based on a complex interaction of dimensions (Correll & Ridgeway, 2003). In the status literature, the principle of organised subset combining explains that cues associated with multiple characteristics and behaviours are subconsciously combined in the formation of aggregated appraisals (Berger et al., 1992). The principle of subset combining informed the configurational approach we took to answering our research question, which we brought into practice through the statistical modelling of decision trees (Quinlan, 1986). Tree-based data-mining techniques are particularly well suited to examine how different status characteristics and behaviours (i.e., n-way interactions) interact in predicting the status of most talented team member, as we explain in the Methods. Although useful, traditional parametric methods are not capable of testing the configurations of predictors we are interested in, and do not align with the principle of organised subset combining that is central to the status literature.

## 3 | METHOD

### 3.1 | Sample

Since we specifically respond to the gap in knowledge around graduate TM, data were collected from 238 graduating master in management students—nested in 44 multidisciplinary teams. These students were enrolled in a 6-week business game simulation course at a highly ranked European university in preparation for their entry into

the labour market. Over the 6-week period, each team performed six assignments related to strategy (e.g., conducting a feasibility study), finance (e.g., conducting a company valuation), marketing (e.g., developing a branding strategy), production (e.g., developing an operational planning) entrepreneurship (e.g., presenting a business plan) and HRM (e.g., implementing a reward system) respectively, each with a quantitative (i.e., analysing business choices) and a qualitative (i.e., substantiating business choices) component, thus covering a wide range of talent domains (Gagné, 2004). As each team was running their own fictional company, all teams had the full authority to make decisions and divide tasks and responsibilities as they saw fit.

We opted for a graduate sample for multiple reasons. First of all, the selection of high-potential graduates is a prevalent TM practice, although empirical research on graduate talent identification is lacking (Clarke & Scurry, 2017). Our sample, from a respected graduate program with strict entry requirements, reflects the prime target population of such practices, evidenced by the fact that many of the students had already been offered corporate positions months prior to graduation. Second, it was important for our study that our sample was comprised of a sufficiently large number of teams, all working on a standardised set of tasks. The highly controlled setting of the business game gave us control over team composition and task requirements. This allowed for intensive data collection over a predefined period of time, with highly comparable multidisciplinary teams—a configuration that would be almost impossible to achieve in a corporate setting. These type of management simulations have been successfully used to unravel team dynamics as it provides an unique setting in which differences across teams are minimized (Bunderson et al., 2013; Van der Vegt & Van de Vliert, 2005). Third, it was important that the teams we studied were newly formed (Eddy et al., 2013) as this allowed us to exclude effects of familiarity (Joshi & Knight, 2015).

Students were assigned to 44 teams with a heterogeneous composition in terms of previously obtained undergraduate degree (51.7% of participants held a humanities and social sciences degree; 34.4% a STEM degree and 13.9% a biomedical degree). The sample consisted of 21 teams comprised of 6 members, 20 teams of 5 members and 3 teams of 4 members. Teams were characterised, first, by a high level of skill differentiation, as multidisciplinary was explicitly pursued; second, by a low level of authority differentiation, as formal authority within teams was absent; and third, by a low level of temporal stability, as they worked together, although intensively, for 6 weeks (Hollenbeck et al., 2012). On average, participants were 23.9 years old (ranging from 21 to 36), and 45.8% were female. In line with the demographic make-up of the Master as a whole, ethnic diversity in the sample was very low; only 1% of the students were non-white. Twenty-nine percent of the sample reported having formal work experience prior to enrolling in the Master.

### 3.2 | Data and procedure

Data were collected at two points in time, at the beginning and end of the fifth week of the business game respectively. The response rate was 100% at the first measurement point and 97% at the second, yielding a final sample size of 238 students embedded in 44 teams. By administering our measures at different points in time, using different methods and different types of response scales, we aimed to decrease cognitive load for participants, while reducing the risk of common method bias and minimising priming effects (Podsakoff et al., 2003).

Participants completed a self-report paper-and-pencil questionnaire about their status characteristics and behaviours in the class that kicked off the fifth week of the business game (cf. Anderson et al., 2001; Cornell et al., 1990). This first questionnaire also contained the open-ended item asking who, according to them, was their most talented team member. At the end of the fifth week, all participants received a link to an online 360-degree survey asking them to rate each one of their team members on the 14 talent domains as defined by Gagné (2004) (see Appendix S1). These measures were collected near the end of the Business Game to ensure that peers worked together intensively before assessing each other's talents. Grade point average (GPA) data were archival and obtained from the student administration office.



Peer ratings were used for the outcome variables (i.e., talent perceptions and talent status); archival data were used to capture past performance as a diffuse status characteristic. The status characteristics and status behaviours are measured using self-report, in accordance both with the theoretical arguments raised by Cornell et al. (1990) and with the designs of similar studies conducted in the past (Van der Vegt & Van de Vliert, 2005). Cornell et al. (1990) argued that as self-appraisals are based on a person's experienced history of successes and disappointments in earlier interpersonal interactions, they will greatly influence later interactions with others in group settings and function as cues on which appraisals made by fellow group members will subsequently be based.

### 3.3 | Measures

Unless otherwise indicated, for each measure we used a five-point Likert scale ranging from 1 = completely disagree to 5 = completely agree.

#### 3.3.1 | Status of most talented team member

We asked each participant to nominate one single team member as being, in their eyes, their most talented team member. The relative amount of talent nominations received by team members was used to compute the status variable, which ranged from 0 to 1, with 1 indicating full consensus (cf. Bunderson, 2003). Self-nominations were allowed (and 25 out of 238 study participants nominated themselves), but were not included in the calculation of the outcome variable ( $Y = \text{other-nominations}/(n-1)$ ), as the construct of status is specifically defined as the amount of deference individuals enjoy in the eyes of others (Anderson et al., 2001).

#### 3.3.2 | Peer perceptions of talent

Each participant was rated by all of his or her team members on the 14 talent domains that were based on the work of Gagné (see Appendix S1) and were identified as critical for success in the Business Game by the game developers and coordinators. In line with the principle of interpersonal excellence (Nijs et al., 2014), the 14 talent domains were rated using a slide bar ranging from 0 ('Out of 100 peers, (s)he is the very worst of all in this domain') to 100 ('Out of 100 peers, (s)he is the very best of all in this domain'). Subsequently, the ratings of all team members were averaged out—excluding self-ratings—resulting in 14 scores for each individual, reflecting the peer perceptions of their talents in different talent domains.

#### 3.3.3 | Diffuse status characteristics

Information about sex and age was collected using self-report. *Work experience* was measured as a dummy, and *teamwork experience* was measured using a five-point Likert scale that ranged from 1 = no experience to 5 = extensive experience. GPA was used as a proxy of *past performance* and computed based on the grades participants had attained on every mandatory Advanced Master in Management course they had completed prior to the business game, and was thus perfectly comparable across participants. GPA was measured on a scale of 0 to 20, 20 being the highest possible grade. The *Big 5 personality traits* were measured using a 15-item scale—an abridged and validated version of Shafer's 30-item scale (Langford, 2003). Each trait was measured using three bipolar items on a seven-point scale (e.g., shy-outgoing for extroversion;  $\alpha = 0.83$ ). *Narcissism* was measured using the NPI-16 short measure ( $\alpha = 0.70$ ; Ames et al., 2006), which contains 16 forced dyads (e.g., 'There is a lot that I can learn from other people'

versus 'I am more capable than other people'). Narcissistic answers were added up to compute the final scale score on 10. *Self-esteem* was measured using the 10-item scale ( $\alpha = 0.88$ ) developed by Rosenberg (1965). A sample item is 'I feel that I have a number of good qualities'. General self-efficacy was measured using the eight-item scale ( $\alpha = 0.81$ ) of Chen et al. (2001). A sample item is 'When facing difficult tasks, I am certain that I will accomplish them'. The three facets of *self-consciousness* were measured separately in accordance with Fenigstein et al. (1975): private self-consciousness was measured with a 10-item scale ( $\alpha = 0.73$ ), public self-consciousness with a seven-item scale ( $\alpha = 0.68$ ) and social anxiety with a six-item scale ( $\alpha = 0.77$ ). Sample items, respectively, are 'I am generally attentive to my inner feelings', 'I am concerned about the way I present myself', and 'I feel anxious when I speak in front of a group'. *Goal orientation* was measured based on Van Yperen and Janssen (2002), distinguishing between a mastery and a performance orientation, and measured using an 11-item ( $\alpha = 0.86$ ), and an eight-item scale ( $\alpha = 0.89$ ), respectively. Sample items are 'I feel successful when I acquire new knowledge or learn a new skill by trying hard' (mastery orientation) and 'I feel successful when I accomplish something where others failed' (performance orientation). *Team player attitude* was measured using the 10-item scale ( $\alpha = 0.82$ ) developed by Kline (1999). A sample item is 'My own work is enhanced when I am in a team/group situation'.

### 3.3.4 | Specific status characteristics

*Domain-specific talents* were measured by having each participant rate him- or herself on the 14 talent domains (i.e., self-perceived talents) defined by Gagné (2004). *Specialised degrees* were operationalised as previously attained undergraduate degree (i.e., a degree in humanities and social sciences, STEM or biomedical sciences).

### 3.3.5 | Status behaviours

Five impression management tactics were measured according to the taxonomy developed by Jones and Pittman (1982; in Turnley & Bolino, 2001). Ingratiation (i.e., using flattery or favour-doing in an attempt to be seen as likeable), self-promotion (i.e., playing up abilities or accomplishments to be seen as competent), exemplification (i.e., going above and beyond the call of duty to appear dedicated), intimidation (i.e., appearing intimidating or threatening to be seen as dangerous) and supplication (i.e., advertising shortcomings to get help or avoid unpleasant tasks) can affect talent perception and, subsequently, talent status (Tetlock & Manstead, 1985).

We asked each participant to indicate how accurately a series of statements described the behaviours they had displayed during the business game. Responses ranged from 1 = very inaccurate to 5 = very accurate. Ingratiation ( $\alpha = 0.69$ ; e.g., 'compliment your group members so they will see you as likeable') and self-promotion ( $\alpha = 0.77$ ; e.g., 'make other group members aware of your unique skills and abilities') were both measured using a four-item subscale. Exemplification ( $\alpha = 0.71$ ; e.g., 'Arrive at group meetings on time and stay until the end in order to look dedicated'), supplication ( $\alpha = 0.71$ ; e.g., 'Try to gain assistance or sympathy from other group members by appearing needy in some area'), and intimidation ( $\alpha = 0.65$ ; e.g., 'Speak strongly or forcefully to get other group members to agree to do the project the way you think it should be done') were measured using a five-item subscale.

## 3.4 | Analyses

### 3.4.1 | Decision trees versus conventional parametric techniques

Parametric techniques typically adopted in the TM field (and the HR field more generally) such as regressions, have so far provided useful insights that have greatly progressed the field. In the present study, however, we adopt an

analytical approach that is much less conventional—decision trees—for three reasons: first, the nature of the research question; second, the maturity of the research topic and third, the overall benefits of working with decision trees.

First, parametric techniques are typically not suited to answer the specific research question of the present study, as they tend to ignore that independent variables interact and form configurations (or bundles) that jointly effect the dependent variable (Martens et al., 2011). By using non-parametric decision trees, we can explore exactly which configurations of cues peers rely on when assessing and valuing different types of talents in teams. Configurational approaches, such as decision trees, are extremely useful when complex causal patterns are at play and when outcomes are expected to be best described in sets of relationships, instead of correlations and net effects. Conventional multivariate regression methods that try to model configurations model these as additive and unifinal effects, and therefore are not able to study the configurations of predictors we are interested in (White et al., 2020).

Second, up until now the information processing underlying specific talent appraisals is a poorly understood phenomenon. As such, this research topic is still in its infancy or in an embryonic stage, as von Krogh et al. (2012) would put it. More explorative methods are well suited to progress an ‘embryonic’ field towards more maturity. Decision trees are an inductive, data-driven approach that helps further explore the implicit and often complex nature of impression formation and talent appraisal.

Third, using decision trees has several benefits as opposed to more traditional regression methods. First of all, decision trees are non-parametric with no assumptions of normality or independence, which facilitates their usage. Second, decision trees are robust with respect to outliers and missing values. Put differently, no outlier detection or missing value handling procedures are needed when using decision trees to analyse the data. Thirdly, decision trees give us easy to interpret models, since every path from the root node to a leaf node can be represented as a simple if-then rule which facilitates interpretation and validation of the patterns found in the data (Baesens, 2014).

### 3.4.2 | The two phases of analysis

Decision trees follow a ‘divide-and-conquer’ strategy that ultimately results in unique paths that stipulate how variables—structured according to their predictive power (i.e., assessment of their value)—are combined (i.e., assessment of their configurations) in multiple ways (i.e., assessment of their equifinality) to achieve a particular outcome. We conducted a two-phase tree-based data-mining analysis using the *rpart* package in R. A ‘tree’ is a decision model with a tree-like structure, containing multiple paths originating from splits in the data based on thresholds of predictor values (see Figures 1–5). Each subsequent split is computed based on the most predictive variable at that point in the tree; variables appearing higher up in a tree should thus be interpreted as more predictive of the outcome than those lower down in a tree (Maimon & Rokach, 2005). Variables that do not occur in a tree do not have any predictive power on its dependent variable (Tan et al., 2006).

In the first phase of our analyses, we took a regression tree approach—used to predict continuous responses (Tan et al., 2006)—to model all possible configurations of the 14 peer perceptions of talents that led to the status of most talented team member. In line with status theory (Piazza & Castellucci, 2014), the status of most talented team member was modelled as a continuous peer consensus variable ranging from 0 to 1. In line with previous studies on informal peer hierarchies (Anderson et al., 2001; Anderson & Kilduff, 2009), only when the relative amount of nominations positively exceeded the mean of our sample with one standard deviation—reflecting high consensus among team members—we considered an individual as ‘truly’ having been attributed the status of the most talented team member (see Figure 1).

In the second phase of our analyses, we took a classification tree approach—used to predict categorical responses (Tan et al., 2006)—to model all possible configurations of the status characteristics and behaviours that predicted the talent perceptions held by peers of their team members for each of the 14 talent domains. In the

Results section, we report the configurations of predictors found for the specific talents that in the first set of analyses were found to be predictive of the status of most talented team member. In line with the principle of interpersonal excellence as a defining feature of talent (Nijs et al., 2014), for each talent, team members were either modelled as 'having' the talent or not in the eyes of peers (see Figures 2–5) based on the cut-offs established in the first set of analyses (Figure 1).

In *rpart*, the performance of tree-based data-mining analyses is typically evaluated using leave-one-out cross-validation (Maimon & Rokach, 2005). Specifically, the data are split into a training set and a test set; the training set contains all observations except for one and the test set contains the one observation left out of the training set. This allows researchers to subsequently compare values predicted by the training model to the actual values in the dataset (Quinlan, 1986). The performance of regression trees is evaluated based on the correlation between actual and predicted values, which in our study was found to be satisfactory, at 0.44 ( $p < 1e-13$ ). The performance of classification trees is evaluated in terms of accuracy, which refers to the amount of observations correctly classified by the tree. Again, accuracy was found to be satisfactory for the different classification trees we modelled (see Figures 2–5)—i.e., 74.79% for leadership talent, 83.19% for analytic talent, 73.95% for business talent and 64.28% for critical thinker talent.

## 4 | RESULTS

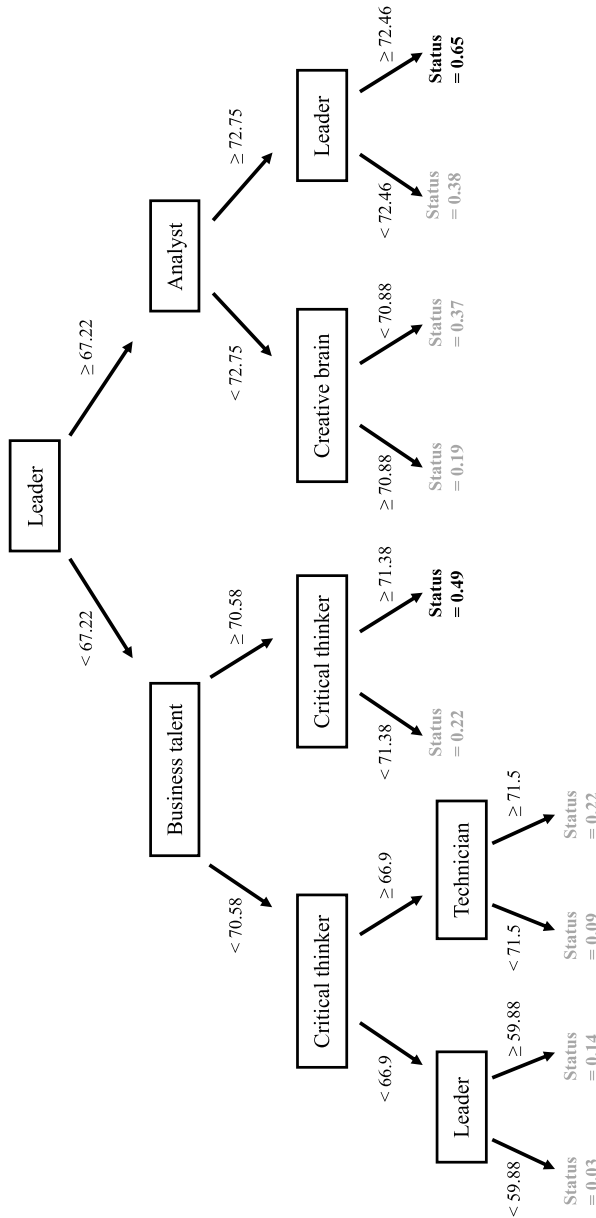
Figure 1 shows the configurations of peer perceptions of the specific talents that were found to be predictive of the status of most talented team member; Figures 2 through 5 show the configurations of the status characteristics and behaviours found, in turn, to predict those perceived talents.<sup>1</sup> In the figures, each predictor is accompanied by a threshold value that functions as a necessary but insufficient condition to obtain the outcome reported at the bottom. The predictive power of each variable is deduced from its relative position in the regression tree, with the highest position indicating the highest predictive power (Maimon & Rokach, 2005).

Figure 1 is to be understood as a regression tree that models the talent perceptions predictive of the status as most talented team member on a continuous scale from 0 to 1, representing the degree of consensus among team members. As we applied the criterion of receiving a relative number of peer nominations higher than one standard deviation above the mean ( $M = 0.19$ ;  $SD = 0.25$ ;  $Y \geq 0.43$ ) only 28 out of 238 participants, were identified as 'talents' by their team members (indicated in bold in Figure 1). This outcome of our data-driven approach corresponds almost perfectly to the 10% cut-off typically recommended in the practitioner literature (Silzer & Church, 2009).

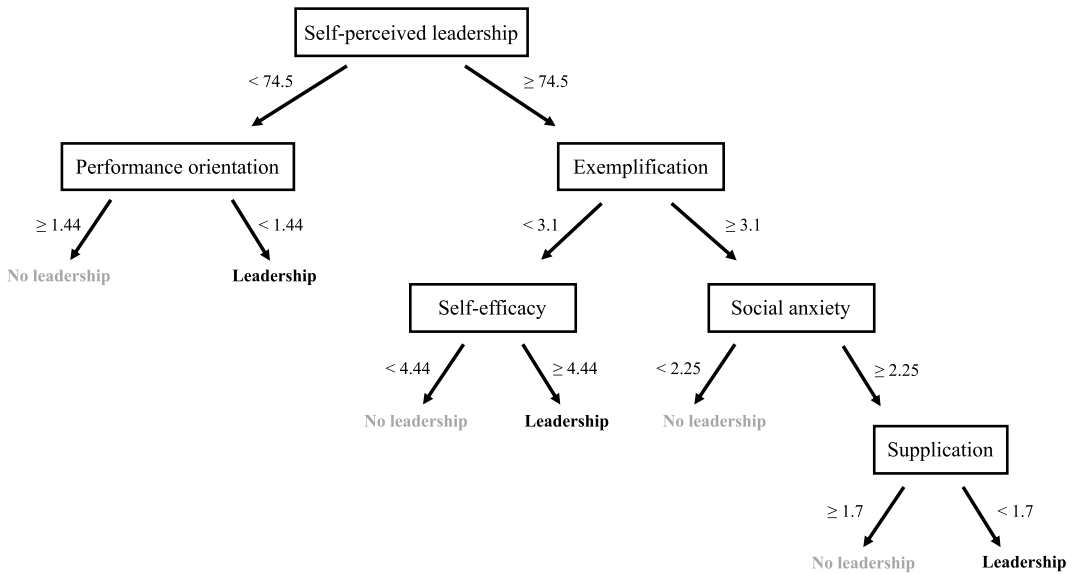
Figures 2 through 5 show the configurations of the status characteristics and behaviours that were found to be predictive of perceived leadership, analytic, business and critical thinker talent in our subsequent classification tree analyses. For each talent, team members were either modelled as 'having' the talent or not in the eyes of peers based on the cut-offs found in the regression tree analyses (Figure 1).

Overall, self-perceived leadership talent was the best predictor of being seen as having leadership talent by peers (Figure 2), while holding a STEM degree was the best predictor of being seen as having analytic talent (Figure 3) and business talent (Figure 4). Perceived critical thinker talent was best predicted by GPA (Figure 5). The fact that holding a STEM degree was the best predictor of perceived business talent was interesting because there is no specific reason to assume that the SKAs acquired in a STEM education would be more proximally associated with this talent domain than the other degree fields. This was a first indication that in our study, holding a STEM degree functioned as a diffuse rather than a specific status characteristic. Another interesting finding was that self-perceived talent was only predictive of talent as perceived by peers for the leadership and the analytic talent domain, but not for the business talent or critical thinker domain.

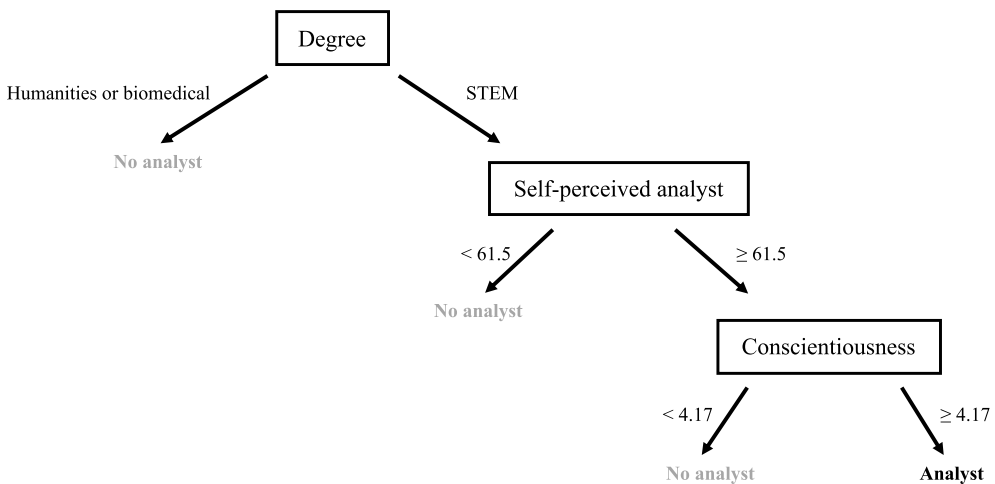
Table 1 consolidates the findings of our two-phase data-mining analysis—represented in Figures 1 through 5—into a single overview table. Taken together, we found evidence for 11 equifinal pathways leading to the



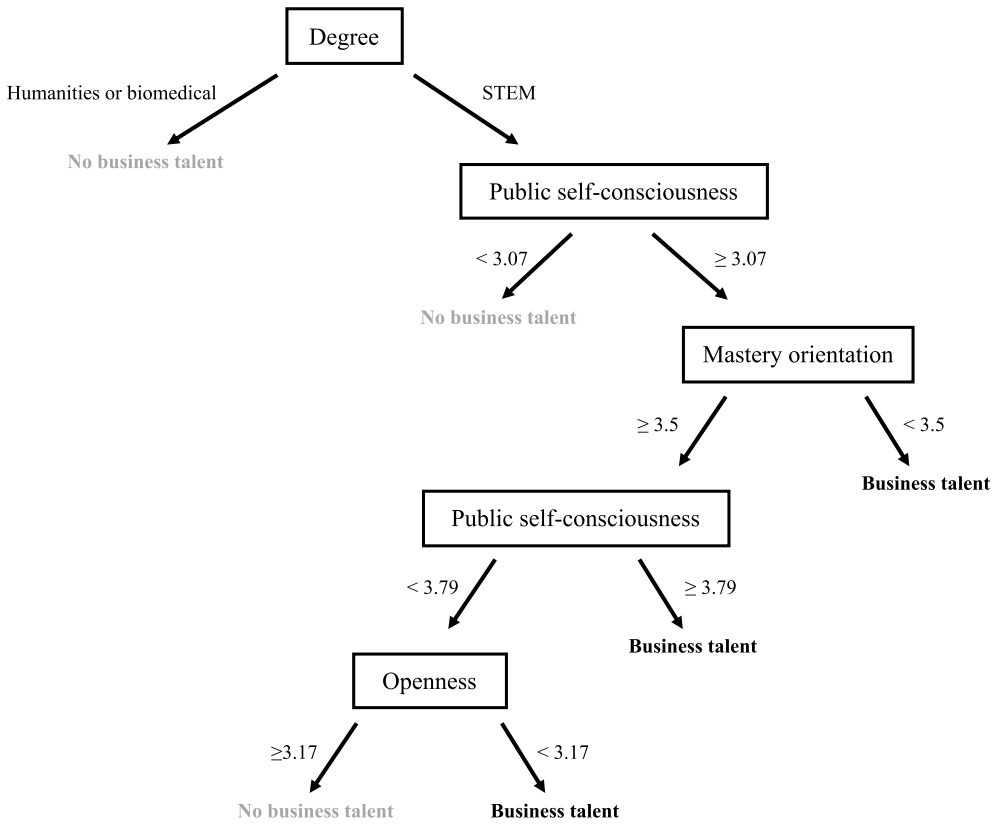
**FIGURE 1** Configurations of peer perceptions of the (different types of) talents that were found to be predictive of the status of most talented team member (regression tree analysis). This figure is to be understood as a regression tree that models the talent perceptions predictive of the status as most talented team member on a continuous scale from 0 to 1, representing the degree of consensus among team members. Being perceived as both a leader ( $X \geq 72.46$  with  $M = 58.50$  and  $SD = 12.48$  on a 100-point scale) and an analyst ( $X \geq 72.75$  with  $M = 62.16$  and  $SD = 14.39$  on a 100-point scale) resulted in the highest consensus among peers—this is, 65%—as to who their most talented team member was ( $Y = 0.65$  with  $M = 0.19$  and  $SD = 0.25$  on a 0 to 1 scale). Alternatively, lower peer ratings on leadership talent ( $X < 67.22$ ) could be compensated by scoring high on perceived business talent ( $X \geq 70.58$  with  $M = 63.68$  and  $SD = 8.96$  on a 100-point scale) while simultaneously being rated as a talented critical thinker ( $X \geq 71.38$  with  $M = 66.25$  and  $SD = 9.19$  on a 100-point scale), at a consensus level of approximately 50% ( $Y = 0.49$  with  $M = 0.19$  and  $SD = 0.25$  on a 0 to 1 scale)



**FIGURE 2** Configurations of the status characteristics and behaviours that were found to be predictive of peer perceptions of leadership talent (classification tree analysis). This figure represents the classification tree that models the status characteristics and behaviours that were predictive of the absence ( $Y < 72.46$ ) or presence ( $Y \geq 72.46$ ) of leadership talent as rated by peers. Perceived leadership talent was, in order of importance, predicted by self-perceived leadership ( $X \geq 74.5$  with  $M = 64.73$  and  $SD = 16.98$  on a 100-point scale), exemplification ( $X \geq 3.1$  with  $M = 2.72$  and  $SD = 0.60$  on a five-point scale), social anxiety ( $X \geq 2.25$  with  $M = 2.75$  and  $SD = 0.74$  on a five-point scale), and supplication ( $X < 1.7$  with  $M = 1.88$  and  $SD = 0.54$  on a five-point scale); or by self-perceived leadership ( $X \geq 74.5$  with  $M = 64.73$  and  $SD = 16.98$  on a 100-point scale), exemplification ( $X < 3.1$  with  $M = 2.72$  and  $SD = 0.60$  on a five-point scale), and self-efficacy ( $X \geq 4.4$  with  $M = 3.65$  and  $SD = 0.51$  on a five-point scale); or by self-perceived leadership ( $X < 74.5$  with  $M = 64.73$  and  $SD = 16.98$  on a 100-point scale), and performance orientation ( $X < 1.44$  with  $M = 3.04$  and  $SD = 0.80$  on a five-point scale)

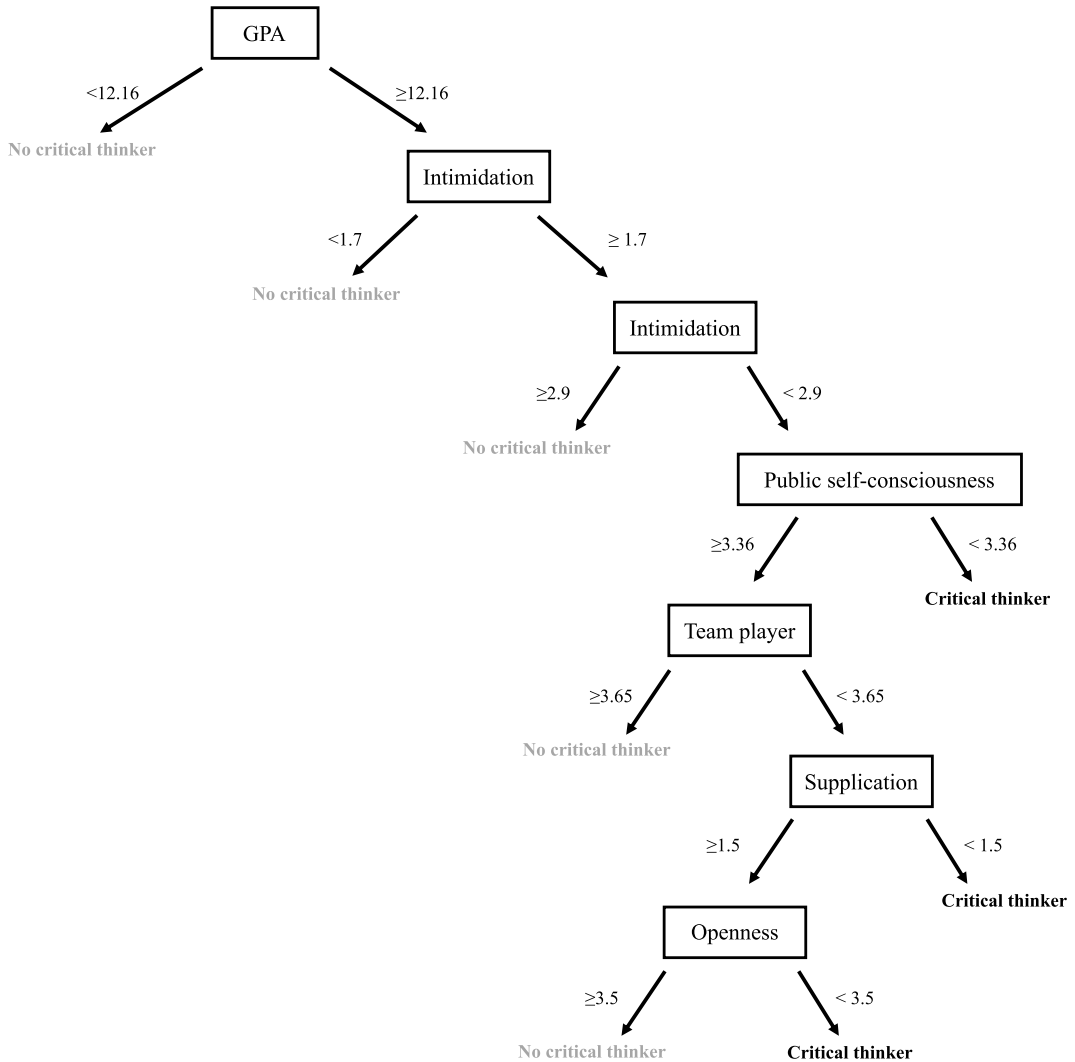


**FIGURE 3** Configurations of the status characteristics and behaviours that were found to be predictive of peer perceptions of analytic talent (classification tree analysis). This figure represents the classification tree that models the status characteristics and behaviours that were predictive of the absence ( $Y < 72.75$  on 100) or presence ( $Y \geq 72.75$  on 100) of analytic talent as rated by peers. Perceived analytic talent was, in order of importance, predicted by attained degree (a STEM degree as opposed to a humanities or biomedical degree), self-perceived analytic ability ( $X \geq 61.5$  with  $M = 58.06$  and  $SD = 23.23$  on a 100-point scale), and conscientiousness ( $X \geq 4.17$  with  $M = 5.26$  and  $SD = 0.93$  on a seven-point scale)



**FIGURE 4** Configurations of the status characteristics and behaviours that were found to be predictive of peer perceptions of business talent (classification tree analysis). This figure represents the classification tree that models the status characteristics and behaviours that were predictive of the absence ( $Y < 70.58$  on 100) or presence ( $Y \geq 70.58$  on 100) of business talent as rated by peers. Perceived business talent was, in order of importance, predicted by attained degree (i.e., a STEM degree as opposed to a humanities or biomedical degree), public self-consciousness ( $X \geq 3.07$  with  $M = 3.42$  and  $SD = 0.58$  on a five-point scale), mastery orientation ( $X < 3.5$  with  $M = 3.86$  and  $SD = 0.51$  on a five-point scale); or by attained degree (i.e., a STEM degree as opposed to a humanities or biomedical degree), public self-consciousness ( $X \geq 3.07$  with  $M = 3.42$  and  $SD = 0.58$  on a five-point scale), mastery orientation ( $X \geq 3.5$  with  $M = 3.86$  and  $SD = 0.51$  on a five-point scale), public self-consciousness ( $X \geq 3.79$  with  $M = 3.42$  and  $SD = 0.58$  on a five-point scale); or by attained degree (i.e., a STEM degree as opposed to a humanities or biomedical degree), public self-consciousness ( $X \geq 3.07$  with  $M = 3.42$  and  $SD = 0.58$  on a five-point scale), mastery orientation ( $X \geq 3.5$  with  $M = 3.86$  and  $SD = 0.51$  on a five-point scale), public self-consciousness ( $X < 3.79$  with  $M = 3.42$  and  $SD = 0.58$  on a five-point scale), and openness to experience ( $X < 3.17$  with  $M = 4.17$  and  $SD = 1.24$  on a seven-point scale)

status of most talented team member. Although multiple talent domains (i.e., leader, analyst, business and critical thinker) were highly valued by peers in our sample of 44 multidisciplinary teams, the status of most talented team member was most often granted to peers perceived as having both leadership and analytic talent. Therefore, we must conclude that in multidisciplinary teams, there is indeed a hierarchy between talents, and that leadership and analytic talent are most valued by peers (Bunderson & Barton, 2011). In keeping with the principle of organised subset combining, the status of most talented team member was only granted to an individual when all conditions specified in one of the 11 equifinal pathways were simultaneously met (Berger et al., 1992; Correll & Ridgeway, 2003). Looking at Table 1, we see that the dominant configurations—that is, those leading to the highest consensus as to who the most talented team member is



**FIGURE 5** Configurations of the status characteristics and behaviours that were found to be predictive of peer perceptions of critical thinker talent (classification tree analysis). This figure represents the classification tree that models the characteristics and behaviours that were predictive of the absence ( $Y < 71.38$  on 100) or presence ( $Y \geq 71.38$  on 100) of critical thinker talent as rated by peers. Perceived critical thinker talent was, in order of importance, predicted by GPA ( $X \geq 12.16$  with  $M = 12.85$  and  $SD = 2.66$  on 20), intimidation ( $1.7 \leq X < 2.9$  with  $M = 2.23$  and  $SD = 0.62$  on a 5-point scale), and public self-consciousness ( $X < 3.36$  with  $M = 3.42$  and  $SD = 0.58$  on a five-point scale); or by GPA ( $X \geq 12.16$ , with  $M = 12.85$  and  $SD = 2.66$  on 20), intimidation ( $1.7 \leq X < 2.9$  with  $M = 2.23$  and  $SD = 0.62$  on a five-point scale), public self-consciousness ( $X \geq 3.36$  with  $M = 3.42$  and  $SD = 0.58$  on a five-point scale), team player attitude ( $X < 3.65$  with  $M = 3.43$  and  $SD = 0.54$  on a five-point scale), and supplication ( $X < 1.5$  with  $M = 1.88$  and  $SD = 0.54$  on five-point scale); or by GPA ( $X \geq 12.16$ , with  $M = 12.85$  and  $SD = 2.66$  on 20), intimidation ( $1.7 \leq X < 2.9$  with  $M = 2.23$  and  $SD = 0.62$  on a five-point scale), public self-consciousness ( $X \geq 3.36$  with  $M = 3.42$  and  $SD = 0.58$  on a five-point scale), team player attitude ( $X < 3.65$  with  $M = 3.43$  and  $SD = 0.54$  on a five-point scale), supplication ( $X \geq 1.5$  with  $M = 1.88$  and  $SD = 0.54$  on five-point scale), and openness to experience ( $X < 3.5$  with  $M = 4.17$  and  $SD = 1.24$  on seven-point scale)

(i.e., paths 1–3)—contain relatively more specific status characteristics as predictors of status than the parallel configurations characterised by lower consensus, which contain relatively more diffuse status characteristics (i.e., paths 4–11).



**TABLE 1** Eleven equifinal Configurations of diffuse and specific status characteristics and behaviours leading to the status of most talented team member (path-based visualisation based on a two-phase tree-based data mining analysis)

Performance (GPA)	Diffuse characteristics										Specific characteristics				Behaviours			Peer perceptions of talents			Status
	Conscientiousness	Openness to experience	Self-efficacy	Public self-consciousness	Social anxiety	Mastery orientation	Performance orientation	Team player attitude	STEM degree (0/1)	Leader (self-perceived)	Analyst (self-perceived)	Exemplification	Supplication	Intimidation	Leader	Analyst	Business	Critical thinker	Consensus on the most talented team member		
1. -	≥4.17	-	-	-	≥2.25	-	-	-	1	≥74.5	≥61.5	≥3.1	<1.7	-	≥72.46	≥72.75	-	-	0.65		
2. -	≥4.17	-	≥4.4	-	-	-	-	1	≥74.5	≥61.5	<3.1	-	-	-	≥72.46	≥72.75	-	-	0.65		
3. -	≥4.17	-	-	-	-	-	<1.4	1	<74.5	≥61.5	-	-	-	-	≥72.46	≥72.75	-	-	0.65		
4. ≥12.16	-	-	-	3.07 ≤ X < 3.36	-	<3.5	-	1	-	-	-	-	-	1.7 ≤ X < 2.9	-	-	≥70.58	≥71.38	0.49		
5. ≥12.16	-	-	-	≥3.36	-	<3.5	<3.65	1	-	-	-	<1.5	<1.5	1.7 ≤ X < 2.9	-	-	≥70.58	≥71.38	0.49		
6. ≥12.16	-	<3.5	-	≥3.36	-	<3.5	<3.65	1	-	-	-	≥1.5	≥1.5	1.7 ≤ X < 2.9	-	-	≥70.58	≥71.38	0.49		
7. ≥12.16	-	-	-	≥3.79	-	≥3.5	<3.65	1	-	-	-	<1.5	<1.5	1.7 ≤ X < 2.9	-	-	≥70.58	≥71.38	0.49		
8. ≥12.16	-	<3.5	-	≥3.79	-	≥3.5	<3.65	1	-	-	-	≥1.5	≥1.5	1.7 ≤ X < 2.9	-	-	≥70.58	≥71.38	0.49		
9. ≥12.16	-	<3.17	-	3.07 ≤ X < 3.36	-	≥3.5	-	1	-	-	-	-	-	1.7 ≤ X < 2.9	-	-	≥70.58	≥71.38	0.49		
10. ≥12.16	-	<3.17	-	3.36 ≤ X < 3.79	-	≥3.5	<3.65	1	-	-	-	<1.5	<1.5	1.7 ≤ X < 2.9	-	-	≥70.58	≥71.38	0.49		
11. ≥12.16	-	<3.17	-	3.36 ≤ X < 3.79	-	≥3.5	<3.65	1	-	-	-	≥1.5	≥1.5	1.7 ≤ X < 2.9	-	-	≥70.58	≥71.38	0.49		

## 5 | DISCUSSION

In interpreting our findings, we not only consider the status characteristics and behaviours occurring within the pathways, but also across them. Predictors can fall into one of three categories: first, predictors found in all pathway to status; second, predictors found in multiple pathways to status and third, predictors found in only one pathway to status. The more a predictor recurs across configurations, the more fundamental (i.e., difficult to compensate for by other predictors) it is to achieving the status of most talented team member. Based on status characteristics theory, we would expect specific status characteristics to be present in fewer parallel paths than diffuse status characteristics and status behaviours, as the former are assumed to be predictive of specific talent domains only (Correll & Ridgeway, 2003).

### 5.1 | Talent pathways

#### 5.1.1 | Characteristics and behaviours represented in all pathways

The only predictor that was present in every pathway—and should thus be interpreted as a necessary precondition to achieve ‘talent’ status in the eyes of peers—was holding a degree in STEM. Put differently, in our study only individuals with a STEM degree were identified as talents by way of peer consensus, irrespective of the specific configuration of talent domains leading up to the ultimate status of most talented team member. Although in the status literature it is assumed that a specific degree would operate as a specific status characteristic (Correll & Ridgeway, 2003)—in the sense that it would only be predictive of specific, STEM-related talent domains (most notably, analytical talent)—it actually operated as a diffuse status characteristic that predicted overall status across talent domains. A potential explanation for this finding is the widely publicised link between holding a STEM degree and occupational prestige. Occupational prestige is defined as the consensual ranking of an occupation based on shared societal beliefs of its worthiness and the admiration and respect a particular occupation holds in a society (Treiman, 1977).

Correll and Ridgeway (2003) stated that occupational prestige is often associated with inferences about ability and status of the people in given occupations as a way of legitimising power and status differences between occupations. Consequently, higher ability may have been attributed to those participants in our study holding a STEM degree as these degree programs are associated with entry into the highest-prestige, highest-income occupations in the labour market (Theunissen & Sels, 2014).

#### 5.1.2 | Characteristics and behaviours represented in multiple pathways

Most of the other predictors listed in Table 1 fell under the second category. GPA, self-perceived leadership talent, self-perceived analytic talent, conscientiousness, team player attitude, mastery orientation, intimidation and exemplification were all found to recur across multiple pathways, although looking at Figures 2–5 we must conclude that in most cases they were associated with one specific talent domain only. Self-perceived leadership talent and exemplification were only found in pathways to status that ran through peer-rated leadership talent (see Figure 2); self-perceived analytic talent and conscientiousness were only found in pathways to status that ran through peer-rated analytic talent (see Figure 3); mastery orientation was only found in pathways to status that ran through peer-rated critical thinker talent (see Figure 4); and GPA, intimidation, and (not having a) team player attitude were only found in pathways to status that ran through peer-rated critical thinker talent (see Figure 5). This is an indication that some presumed diffuse status characteristics actually operated as specific status characteristics (Correll & Ridgeway, 2003).

Interestingly, self-perceived talent was only predictive of peer ratings of talent for the leadership and the analytic talent domain, but not for the business or critical thinker domain. A possible explanation is that not all talent domains in the study correspond to equally salient cognitive schemas—and that people's mental models of what leaders or analysts look like are better defined than their mental models of business talent or critical thinkers (Yammarino & Bass, 1991). Consequently, it may have been easier for the participants in our study to both signal and perceive the former compared to the latter types of talent (Cornell et al., 1990).

Openness to experience, public self-consciousness and supplication also recurred across pathways but were associated with more than one talent domain—as one would expect of diffuse status characteristics (Correll & Ridgeway, 2003). Specifically, openness to experience and public self-consciousness were predictive of both perceived business talent (Figure 4) and critical thinker talent (Figure 5); and a low score on supplication (i.e., the only 'negative' impression management tactic; Wayne & Liden, 1995) was predictive of both leadership talent (Figure 2) and critical thinker talent (Figure 5).

### 5.1.3 | Characteristics and behaviours represented in only one pathway

As to the third category of predictors—that is, those more peripheral to the prediction of status—high self-efficacy, medium-high social anxiety and low performance orientation were each found to be predictive of only one, distinct path to status (paths 1–3 in Table 1), in each case running through peer-rated leadership talent (see Figure 2). Our findings for social anxiety and performance orientation were surprising, as one would expect social anxiety to be negatively, and performance orientation to be positively associated with perceived leadership talent. It is possible that, in a teamwork setting, medium-level social anxiety acts as a cue for a leader's sensitivity to his or her environment (Yammarino & Bass, 1991). Alternatively, as leadership talent is the dominant predictor of the status as most talented team member it may be important for this potentially 'threatening' characteristic to be compensated by a more 'humbling' characteristic such as a moderate level of social anxiety (Klimoski & Donahue, 2001). The negative effect of performance orientation may have been caused either by the social desirability of having a mastery orientation (Van Yperen & Janssen, 2002), or by the fact that the teamwork performed by the participants in our study was highly collaborative in nature, while performance orientation measures a person's drive to outperform co-workers (DesJardins et al., 2015).

## 5.2 | Limitations and directions for further research

The current study has three main limitations linked to avenues for further research. First of all, we worked with a student sample, which is typically not an approach taken in HR research. However, in our specific case, working with newly formed, multidisciplinary graduate teams without pre-existing status hierarchies—while keeping the context, content and duration of the teamwork constant—was a deliberate, theory-driven choice (Eddy et al., 2013). Our sample of young graduates had limited to no work experience meaning that the peer assessments were not based on extensive work experience or the accumulation of tacit knowledge throughout a career. Rather, in this study, we focused on the fundamental talents of graduates that might later—with prolonged and intensive training and experience—translate into domain-specific expertise. For organisations, identifying talent in this early stage is a valuable strategy as it allows them to develop graduate hires further in a way they see fit. As we explained in the introduction, graduate recruitment is one of three strategies organisations use to build talent pools, alongside internal identification of high-potential employees and external headhunting for senior profiles (Clarke & Scurry, 2017). Future research could study if and how the cues that signal talent differ, based on the three talent identification strategies organisations can adopt. For instance, talent cues might differ depending on the seniority of the target group, with degree being a more dominant cue for junior talent (as was evident from our findings), while

experience, expertise and tacit knowledge are likely more dominant cues for senior talent. A longitudinal, within-person analysis would allow practitioners and researchers to fully understand (changes in) the value attached to different talent cues over the course of people's careers. In order to better understand the role of degree in talent identification, future research could also look into the talent cues that are dominant in different sectors to see if and how their mental models of talent differ.

Second, due to the individual differences approach we took to predict the attainment of the status of most talented team member, we are not able to make statements about situational factors or boundary conditions (Yammarino & Bass, 1991). Status characteristics theory assumes that status beliefs are widely ingrained at the societal level and are thus quite generalizable across settings. However, there is also evidence that patterns of shared beliefs about the relative value of status cues are contextually embedded in team and organisational culture (Berger et al., 1992). The question left to examine is, then, whether our findings would hold up in teams performing very different sets of tasks (e.g., more creative tasks vs. analytical task; Bunderson & Barton, 2011). Additionally, it would be interesting to see whether our proposition that the predictive effect of holding a STEM degree is caused by its relationship to occupational prestige would hold up in samples of working people, preferably across a range of sectors, organisations, types and duration of teamwork and countries or cultures. Specific measures of occupational prestige could be used to replace degree field (Treiman, 1977). If it is indeed true that some occupations are seen as inherently more prone to talent than others, this has implications for the 'talent for what?' debate held in the TM literature (Silzer & Church, 2009). Aguinis et al. (2016), for instance, distinguished between conductors and insulators of cumulative advantage. They argued that job complexity, job autonomy and productivity ceilings—which could vary across sectors, organisations, occupations and even teams—affects the emergence, identification and proportion of star performers and the cumulative advantages they are capable of generating.

A third limitation is that our design did not allow us to study the interpersonal dynamics influencing status attainment in teams, most notably in-group prototypicality (Gómez et al., 2013) and social affinity (DesJardins et al., 2015; Joshi & Knight, 2015). In fact, we tried to control for prototypicality and affinity effects by working with newly formed teams in which pre-existing status differences were assumed to be minimal. In addition to purely individual cognitive processes, however, interpersonal factors, organisational politics, and existing status hierarchies in organisations, are believed to shape the cognitive processes underlying social judgement (Klimoski & Donahue, 2001).

Self-categorisation theory, for example, states that intrateam status will also depend on group norms (Gómez et al., 2013). In-group prototypicality, then, is defined as the extent to which an individual matches the normative attributes (i.e., attitudes, feelings and behaviours) of a psychologically salient in-group (Hogg et al., 1998). Prototypicality is associated with status due to the essential role prototypical members play in defining and maintaining group identity (Gómez et al., 2013). The extent to which a person matches the prototypical attributes of the in-group can be an important factor in the nomination of the group leader, for instance. Magee and Galinsky (2008) have showed that hierarchies do develop differently depending on the social dimensions most valued in a given context. There has also been research, however, concluding that status is associated with deviation from, rather than conformity with group norms. Bellezza et al. (2014) showed that such deviations, under certain boundary conditions, can be interpreted as a sign of high status. Taken together, these competing findings about intrateam status and norms form a promising avenue for further research on informal talent hierarchies in teams.

Social affinity is another issue that could be linked to talent identification in further research as peers might particularly value it as it contributes to team spirit. Joshi and Knight (2015) developed a dual pathway model of dyadic deference in multidisciplinary teams, driven by task contribution on the one hand and social affinity on the other. In other words, the authors proposed that status can be determined either by perceived talent or by likeability. Whereas their study suggests that task-based deference enhances team performance while affinity-based deference detracts from it, the work of DesJardins et al. (2015) implies that effects on team performance might be contingent upon whether groups work on competitive or cooperative tasks. Further research could test the dual

pathway model and the boundary condition of competitive versus cooperative teamwork as applied to informal talent hierarchies in teams. As social affinity is a function of the relationship between two people, social network or dyadic research methods, such as Social Relations Modeling (Kenny et al., 2006), are particularly well suited to study the effects of interpersonal dynamics on informal talent hierarchies in teams, and how more dyadic forms of hierarchies (also referred to as acyclicity; Bunderson et al., 2016) affect team performance and satisfaction in multi-talented teams. As Doyle et al. (2016) discovered that the magnitude of status differences between team members can differ—conceptualised as status distance—these dyadic methods are particularly promising to detect how talent perceptions might translate into different status relations in a team depending on the peers in question. In a similar vein, peers might develop different status distances with peers based on the perceived complementarity or supplementary of their talents. This research could further the knowledge on interpersonal dynamics on a dyadic level by studying how status attainment is driven by the complementarity of teams members' talents (Van der Vegt, & Van de Vliert, 2005).

### 5.3 | Implications for practice

As many organisations seek to identify talent among young graduates, we are convinced that our results contribute to talent identification practice by exploring an understudied strategy for building talent pools—graduate talent identification (Clarke & Scurry, 2017; Muratbekova-Touron et al., 2018). A key implication of the present paper is that TM practitioners could capitalise on knowledge of informal peer hierarchies, for a host of reasons (Doyle et al., 2016).

First, involving peers in talent identification might increase the transparency and acceptance of talent decisions made (Gelens et al., 2014). Several studies have shown that most organisations today feel forced to keep their TM practices a secret, due to the fact that they are considered sensitive—since a small number of employees is singled out as 'talents' and awarded additional resources (De Boeck et al., 2018). However, organisations often feel uncomfortable with this secrecy, which has been found to compound negative co-worker reactions to elitist talent decisions, as sensitive information tends to leak (Gelens et al., 2014). The knowledge generated by the present study could thus be used to avoid or at least buffer negative co-worker reactions to TM decisions (De Boeck et al., 2018).

Second, actively acknowledging the role of peers as relevant TM stakeholders might support organisations in making more ethical talent identification decisions (Collings, 2014). Too often it is assumed that talent assessments are only reserved for managers. Including a wider range of decision makers, giving them 'voice' in the process, can result in more supported talent decisions.

Third, establishing more heterogeneous talent pools, grounded in multidisciplinary intrateam hierarchies (Bunderson & Barton, 2011) might help promote innovation, diversity and inclusion in TM (Swales, 2013). For instance, there is a tendency towards appreciating leadership as the most 'important' talent—which was also found in the present study—as both organisational and academic interest in TM tends to accumulate around assessments of leadership potential (Nijs et al., 2014). Consequently, employees identified as talents are predominantly young, white males who are perceived as future leaders (Swales, 2013). Maximising team heterogeneity could thus be a strategy to achieve more inclusive and diverse talent pools, something organisations report struggling with. Our study shows that when generic operationalisations of talent—in our case 'who is the most talented team member'—are used, there is a tendency to mainly appreciate a narrow set of talents (e.g., leadership) signalled by a narrow set of dominant cues (i.e., STEM degree), leading to a homogenous talent pool. In contrast, when talent is operationalised more diversely—by acknowledging and naming the different domains people can be talented in—we see that a wider range and combination of talent cues are valued. Organisational decision makers today however often work with generic operationalisations of talent, applying

methods and tools that assess talent in general terms (e.g., the nine-box grid), largely bypassing the 'talent for what?' question.

Our study implies that strategically reflecting about the types of talents that could be valuable for one's organisation—and using specific talent domain operationalisations—opens up much more actionable pathways to more inclusive, diverse talent pools. As an increasing number of organisations are aiming to create more inclusive TM pools, answering the 'talent for what?' question and incorporating this in assessment tools and methods forms a concrete starting point for organisations to make their TM more inclusive. Especially in a team context, it is crucial to assess what type of talents are complementary, with the potential to strengthen rather than weaken each other (i.e., cooperation instead of competition; Groysberg et al., 2011). When organisations do not specify what types of talent they are looking for, TM procedures and methods will be more susceptible to bias and face higher odds of reproducing deeply ingrained beliefs about what talent is (Makarem et al., 2019). By mapping the heuristics that underlie talent assessments, the present study has developed a clearer understanding of the combination of cues that are used when assessing talent, upon which organisations can build to develop assessor training where needed.

## ACKNOWLEDGEMENTS

This research was funded by an FWO project grant from the Research Foundation Flanders (G074418N) and an Internal Funds C1 grant from the KU Leuven (C14/17/014).

## CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

## ORCID

Sanne Nijs  <https://orcid.org/0000-0001-8493-7172>

Nicky Dries  <https://orcid.org/0000-0002-1556-0479>

## ENDNOTE

<sup>1</sup> A correlation table is not provided since this is not customary for data-mining papers. First of all, multi-collinearity between predictors is not an issue in data mining—and linear dependencies between variables non-informative—as this type of analyses model non-linear dependencies between multiple variables in the form of *n*-way interactions (Witten & Frank, 2005). Second, due to the inductive nature of the method our model contains a very large number of variables, difficult to render in a single correlation table. We do report the means and standard deviations for all variables that were found to be predictive of talent perceptions and talent status in the notes of Figures 1–5.

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**How to cite this article:** Nijs, S., Dries, N., Van Vlasselaer, V., & Sels, L. (2022). Reframing talent identification as a status-organising process: Examining talent hierarchies through data mining. *Human Resource Management Journal*, 32(1), 169–193. <https://doi.org/10.1111/1748-8583.12401>