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Diversity Within Top Management Teams: The Effects of Diversity Within Boards Towards Managerial Attention on Digital Transformation

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Abstract

Digital transformation (DT) is crucial for firms to stay competitive, yet few fully embrace it. DT goes beyond moving from analogue to digital; it necessitates a complete restructuring of business models, including customer experiences and internal structures. Leadership significantly impacts strategic decision-making, as Hambrick (2007) notes. A board's diversity and composition affect a firm's decisions. Diversity in TMT can enhance innovation and creativity or increase friction and conflicts. While much research exists on these topics, examining managerial focus on DT and TMT diversity using Harrison and Klein's (2007) framework is new. As DT becomes more important, firms must understand TMT diversity's role. I argue that top management's demographic characteristics are positively influenced by diverse education, tenure, and network, with a negative moderating effect of age and gender heterogeneity. This study found that in cumulative DT efforts, there are effects between age and tenure, and gender and network. Age separation decreases tenure's positive effect, and gender separation diminishes the positive effect of diverse networks, suggesting inconsistencies with Hambrick's (2007) theory.

Keywords: Blue's Index; digital transformation; diversity; top management teams; Upper Echelon Theory

1. Introduction

Digital Transformation is redefining the world, affecting individuals, firms and society as a whole (Pasamar et al., 2019; Rachinger et al., 2019). Digital Transformation, or DT, impacts all business sides, from business model innovation to consumer experience and their expectations (Verhoef et al., 2021). The intensifying competitive environments in which firms find themselves, combined with rising expectations of consumers and improving digital technologies, external factors are influencing firms on their road towards digital transformation (Verhoef et al., 2021). The combination of the arrival of Industry 4.0 and the high failure rate of successfully integrating digital transformation resulted in scholars and practitioners asking which components would increase this success rate. Suggesting that digital transformation is the core focus for firms in this era (Hanelt et al., 2020).

As firms are facing the effects of these changing environments, they need to adjust their way of doing business. Hambrick (1984) stated that a Top Management Team (TMT) shapes a firm's strategic choices. TMT's decisions to initiate change within a firm result from their reaction to their internal and external environment, including both opportunities and constraints. The Upper Echelon Theory (UET) by Hambrick (1984) posits that the characteristics of Top Management Team members influence the firms' strategies. For example, the individual characteristics of board members can combine diverse backgrounds, knowledge or experiences which enables the team to address a challenge from a variety of perspectives, which enriches the quality of the proposed solution (Knight et al., 1999). Scholars widely use this theory for researching firm performance and TMT compositions. UET suggests that, depending on the composition of the TMT, it can result in varying interpretations of these opportuni-

I thank Marvin Hanisch for his thoughtful guidance and feedback during this research. A large portion of the data is retrieved from Dr. Marvin Hanisch, the data is subject to revisions and may contain errors. The dictionary used for the CATA analysis was also provided by Dr. Marvin Hanisch. Specifically, I would like to thank Kirsten Huetink, as we have complemented each other wonderfully in conducting our studies.

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ties and constraints. Diversity in demographic characteristics of individual Top Management Team members shapes these interpretations and, consequently, the decisions they make (Hambrick, 1984). Due to the vast variety of metrics which can be used to measure diversity within a team, the outcomes of the prior literature are dual and complex in nature, depending on the used metrics and characteristics researched.

Verhoef et al. (2021) summarized digital transformation to have three phases: digitization (encoding analogue information so that computers can process this information), digitalization (a process used to alter the existing value chain of firms) and digital transformation (firm-wide changes resulting in new business models). Intensifying in between incremental and radical change, and different essentials for every individual stage (Hanelt et al., 2020). One understanding between these phases is that it demands creativity to stimulate firm innovation (Cox & Blake, 1991). These endeavours demand firms to use a multitude of perspectives to find the best qualitative solution for a problem. These perspectives derive from an individual, who tend to flourish in diverse groups (Verhoef et al., 2021).

Harrison and Klein (2007) pose that while diversity in teams has been researched prior, the measures used in these studies are sometimes mixed, leading to incomparable outcomes of studies. Every measure of diversity has, due to it's dual nature pros and cons, so understanding the different kinds is important for firms in order to act accordingly. Variety, separation and disparity are methods proposed to solve this by excluding mixing up the metrics. Separation refers to the differences in opinions or stances among group members, measuring this knowledge on a singular continuous characteristic. Variety is about the different types of knowledge or skills each member brings based on their unique experiences and expertise, enhancing each other in the decision-making process. Disparity denotes the differences in e.g., status among members, like income or hierarchical position variations. Together, these concepts help to understand the multi-faceted nature of diversity in social groups or organizations (Harrison & Klein, 2007). Diversity has a complicated dual nature, depending on the measure and interpretation it could suggest potential different outcomes. Hence for this study, variety (tenure, educational background and network size) is used, as well as separation (age and gender) in order to measure managerial attention to digital transformation.

As digital transformation becomes more critical for firms to stay competitive in the dynamic environment and the respective importance of TMTs during strategic change, this study focuses on diversity within Top Management Teams and their managerial attention towards Digital Transformation (Verhoef et al., 2021). Digital transformation has an effect on all types of firms, improving internal processes, focussing on efficiency, sustainability and effectivity (Hanelt et al., 2020). While there is vast research on TMT composition and Digital Transformation, literature which combines these two distinct topics is relatively scarce. The research question for this study is: *How does diversity in Top Management Teams, including educational backgrounds, tenure and network ties, affect a firm's commitment towards adopting digital transformation? Additionally, how do age and gender differences influence the connection between a board member's background and the success of their change efforts towards Digital Transformation?*

This paper aims to fill the gap and answer these questions by combining Digital Transformation literature with the Upper Echelons Theory. Resulting in an improved understanding of managerial actions and their effects on digital transformation. In addition, the dual nature of diversity research linked with firm innovation and digital transformation leaves the academic community with questions. The findings are constructed around TMT diversity and how this diversity results in strategic decision-making towards digital transformation. For this study, a theoretical model was created to test the diversity within top management teams, specifically educational background, tenure, and network ties. In addition, how do age and gender affect these characteristics concerning managerial attention to DT?

A panel dataset (2005 to 2022) was used with a cross-industry sample of 3,000 of the largest U.S. firms (based on the Russell 3000) to test these aims. Managerial attention towards DT is measured using a CATA scan, counting keywords in 10-K filings of firms per year for every stage of DT. Diversity of TMT is measured using variety (for education, tenure and network) and separation (for age and gender) and this data is retrieved from BoardEx.

Whereas the Top Management Team (TMT) role has been mainly researched via the Upper Echelon Theory, only a few studies look into the growing world of Digital Transformation. In addition, using Harrison and Klein's (2007) suggestion on distinguishing between the various forms of diversity. Answering the call of Verhoef and Bijmolt (2019) for a study focussing on board composition as an influence towards managerial attention on digital transformation. Complemented with Nielsen's (2010) call, this study focuses on the UET in combination with the differences in diversity as presented by Harrison and Klein (2007). Hence, this research will contribute to understanding the individual characteristics, according to Figure 1, and interrelated dynamics and diversity towards the success rate of Digital Transformation within a firm.

2. Theoretical Background & Hypotheses

2.1. Digital Transformation

Digital Transformation is not 'just' an IT initiative anymore but a prerequisite to remaining relevant and competitive in this digitalizing society (Verhoef et al., 2021). Verhoef and Bijmolt (2019, p. 1) defines digital transformation as: "A firm employs digital technologies to develop a new business model that helps to create and appropriate more value for the firm". This definition indicates the complexity of Digital Transformation, splitting it two ways. It (A) redefines the boundaries of firms, stimulating firms to find 'new' ways of doing business, reaching and engaging with customers, as well as (re)structuring internal processes (Furr et al., 2012). Combined with (B) Balancing 'old' and 'new' practices, innovation is paired with digital transformation, while 'traditional' operations are still relevant (Furr et al., 2012). Although a split exists between traditional or 'pre-digital' firms and born-digital firms, digital transformation catalyses both, encouraging them to re-evaluate and overhaul their business models (Chanias et al., 2019).

The split between pre-digital and born-digital firms originates partly through the chronicles of time. Whereas most practitioners are acquainted with IT-enabled innovation, Digital Transformation-enabled innovation is relatively new (Appio et al., 2021; Matarazzo et al., 2021). Considering that this split derived from the effects of 'Industry 4.0'. Industry 4.0 is a (fundamental) shift in manufacturing and production, characterized by the integration of digital technologies, automation, IoT (Internet of Things), and data analytics to create more intelligent and more efficient industrial processes (Savage, 2022). Whereas IT focuses on existing value propositions, DT focuses on (re)defining value propositions (Ferrigno et al., 2023). In addition, the drivers and scope of the processes deviate. IT-enabled innovation focuses on exploitative innovation and improving internal processes and is frequently initiated top-down (Vial, 2019). In contrast, DT responds to external drivers, including technological advancements, in the developing competitive landscape, and consumers' changing demands and behavior (Verhoef et al., 2021). However, both processes are focused on achieving technology-driven change (Besson & Rowe, 2012) and performance improvement (Hanelt et al., 2020). While there is a vast amount of research on IT-enabled innovation, DT differs as they are vastly different, which this study aims to complement to.

According to Verhoef et al. (2021), digital transformation consists of three distinct stages that seamlessly transition into one another, transitioning from IT-enabled innovation towards completed digital transformation: digitization, digitalization and digital transformation. Digitization, the first phase of digital transformation, involves firms converting analogue information into a digital format. It focuses on technical conversion and does not change the value creation process of a firm (Hess et al., 2020; Verhoef et al., 2021). Digitization refers to using digitalized data to improve firm processes or enhance customer experiences with a focus on efficiency. Digital Transformation is the current final state; it refers to a change with a holistic nature that has an influence on the entirety of the organization. It alters the firm's mindset towards innovation-focused processes, referring to culminating new business models (Downes & Nunes, 2016; Matt et al., 2015; Verhoef et al., 2021). While digitization and digitalization typify incremental change, digital transformation is considered radical (Verhoef et al., 2021). Each phase embodies a deeper integration of technology in core business processes and strategy (Verhoef et al., 2021). Demanding firms to collaborate in adapting to change to achieve success reflects a mutual exchange and highlights the importance of fostering ambidexterity within an organization (McAfee & Brynjolfsson, 2017; Rogers, 2016; Venkatraman, 2017). The cumulative efforts of digital transformation, as researched per this study are of interest as they visualize the journey and potential changes that firms need to undergo in their board compositions.

This ambidextrous firm combines the prerequisite of explorative and exploitative innovation to successfully reach Digital Transformation in all its complexity (Henfridsson & Bygstad, 2013). Where exploitation indicates the effective use of current resources, exploration symbolizes the search for new resources (Henfridsson & Bygstad, 2013). Generally, these two strategies do not pair well, and firms tend to separate the two practices within a firm while coordinating them from the executive level (Henfridsson & Bygstad, 2013). Dynamic capabilities enable a firm to fully utilize both procedures (Rindova & Kotha, 2001). Matarazzo et al. (2021) state that dynamic capabilities are the most critical assets of a firm, defining dynamic capabilities as: "higher-level competences that determine the firm's ability to integrate, build and reconfigure internal and external resources/competences to address, and possibly shape, rapidly changing business environments" (Teece, 2012, p. 1395). Dynamic capabilities are different from 'normal' capabilities as they enable a firm to perform essential tasks reconfiguration and are much more difficult to replicate than standard capabilities (Teece, 2012). It relies on a firm's culture, structure and people, and its role is to produce new 'ordinary' capabilities as the environment of a firm changes (Teece, 2007, 2012). Innovation is a combination of two elements: (a) generating new ideas and (b) introducing them as a change (O'Reilly et al., 1989).

Leadership is an essential component of dynamic capabilities. Leaders define the firm's strategic direction, allocate resources, and shape the organizational culture needed to adapt and innovate (Teece, 2012). As DT reshaped the role of IT from supportive to redefining business models, the role of management changed along (Haffke et al., 2016; Lin et al., 2016). Effective leadership is vital for an organization to develop and leverage dynamic capabilities successfully (Matarazzo et al., 2021). He suggested that in order to successfully develop dynamic capabilities, leadership needs to focus on 4 elements: (a) Sensing - Identifying or developing new digital trends, (b) Learning – adapting current capabilities with new knowledge, (c) Integrating - Integrating new knowledge within the firm and (d) Coordinating or asset 'orchestration'. Whereas every firm has its approach to handling these four elements, these clusters state how firms 'create their own capabilities' and make these a result of a sum of the firm's leadership (Fernandez-Vidal et al., 2022; Matarazzo et al., 2021). The demanding role of TMTs in a digital age can be summarized as setting a formal context for DT, leading change while understanding digitalization (Wrede et al., 2020). As TMT members' characteristics influence dynamic capabilities, this study continues to explore the effects of characteristics on developing and maintaining dynamic capabilities.

2.2. Top Management Teams

In 1984, Hambrick and Mason wrote an article that would tremendously affect business scholars. They argue that managers' demographic characteristics shape their values and perceptions. These characteristics, in turn, influence their decisions, affecting the actions executed within an organization (Hambrick et al., 1996). This research suggested that executive management defines their tendencies in strategic decision-making as a combination of their functional characteristics and backgrounds (Carpenter, 2002; Hambrick et al., 1996). When examining the variety within teams, two leading theories are often cited: the information/decision-making viewpoint and the faultline concept, as explored in the work of researchers such as (Lau & Murnighan, 1998; Veltrop et al., 2015; Williams & O'Reilly, 1998). From the angle of the information/decision-making viewpoint, particularly in terms of diversity among board members, it is posited that the heterogeneous nature of a team significantly enhances its ability to make decisions. The Upper Echelon Theory by Hambrick et al. (1996) emphasizes the efforts of an entire team and not an individual CEO, enabling the entire team as strategists and enabling them as they are indicated to be specialized in the maintainment of an operation (Finkelstein & Hambrick, 1996). Contrasting prior research, they considered boards the most influential actors as their decisions impact strategy setting most (Finkelstein & Hambrick, 1996).

These individual characteristics, which ultimately shape a firm's strategic direction, tend to cluster. Whereas homogeneous teams tend to have the same characteristics, leading to similar decisions, they have fewer internal conflicts (Hambrick et al., 1996), faster decision-making processes, and their potential for streamlined decision-making and unified vision stimulate firm performance (Hambrick et al., 1996). Heterogeneous teams tend to have a variety of experiences and perspectives combined within their team. Cox and Blake (1991) argue that combining these characteristics results in innovative thinking and creative problem-solving. This diversity in board composition enables them to detect opportunities from these distinct perspectives, as they have varying knowledge and backgrounds. Outweighing the adverse effects of internal conflicts (Hambrick et al., 1996; Ones et al., 1994). Diversity is essentially a 'double-edged sword' (Hambrick et al., 1996) as diversity has both positive (Kilduff et al., 2000), not significant (e.g. Bunderson and Sutcliffe (2002)) and negative outcomes within academic literature (Timmerman, 2000). Diverse TMTs are believed to enhance innovation and creativity within a firm by creating greater variance and decision-making alternatives (Knight et al., 1999). While their decision-making process might be slower, they are more likely to find solutions for changing environments which are not copied from competitors, ensuring longer lasting competitive advantage (Knight et al., 1999). However, due to these greater variances in the background of the board members, the TMT needs to devote more attention to communicating properly and assimilating information asymmetry as much as possible. People work best if they share similar experiences as well as equivalent beliefs and attitudes (Lawrence, 1997).

In contrast, due to humans tending to stick with their 'own kind', group cohesion within the board decreases, impacting the trust within a TMT (Knight et al., 1999). Finally, the varied backgrounds in a diverse team tend to surface conflicts more readily than in homogeneous teams, where members share similar characteristics and experiences. This commonality in homogeneous groups often streamlines their decision-making process, leading to a higher likelihood of board member agreement (Knight et al., 1999). These board compositions affect a firm's strategic direction, enabling it to focus on innovation (Simons et al., 1999). Looking at these initial differences with regard to diversity in team composition displays the dual and complex nature of diversity research. Due to the different interpretations of diversity research, outcomes can vary per study, which calls for a unified method of interpretating diversity (Harrison & Klein, 2007).

2.3. Diversity within Top Management Teams

Harrison & Klein claimed in 2007 that there is no 'general all applicable diversity measure' and that diversity can be looked at in three ways. They stated that diversity is not a measure of a complete unit on an array of aspects or that diversity belongs to one person in a group. Diversity describes the variation of discrepancies among the members of a unit concerning one standard attribute X, such as tenure, education, gender or pay (Harrison & Klein, 2007). Concluding that diversity is (a) dedicated towards a group and (b) focusing on one specific attribute at a time. Much of the literature regarding diversity surrounds demographic variables and characteristics (Harrison & Klein, 2007), e.g., gender (O'Reilly et al., 1989), tenure (Hambrick et al., 1996) or educational background (Ones et al., 1994).

The different types that they presented were *separation, variety or dispersion.* Separation is classified as a "composition of differences in position towards one another; it is derived from several theories (e.g., attraction-selection-attrition or theory of similarity attraction). The latter can be linked to the quote of Lawrence (1997) above. Variety is a combination of differences derived from information processing, which can be linked to bounded rationality (Harrison & Klein, 2007). Lastly, disparity is a "composition of (vertical) differences in the proportion of socially valued assets, e.g. inequality", which is considered distributive by Harrison and Klein (2007).

On the one hand, one can strive for minimal diversity, e.g. when all members within a team occupy a similar position (separation), belong to the same category (variety) or are on the same level of hierarchy (disparity). Maximized diversity, however, is when members of a team are equally dispersed in terms of, e.g., opinion (separation), are from unique categories (variety) or are different in ranking (e.g. top management team member versus a trainee). (Harrison & Klein, 2007). Separation, as explained by Harrison and Klein (2007), states that reduced separation increases internal integration and trust (Locke & Horowitz, 1990). Resulting in comfortable surroundings with like-minded, agreeable individuals (Harrison & Klein, 2007). However, increased separation (lower similarity) would lead to increased creativity and innovation but with the risk of splitting the group into opposing sub-teams. Variety, according to Harrison and Klein (2007), can result in a "sociocognitive horsepower' (Carpenter, 2002). The members involved have different backgrounds, leading to a creative, solution-oriented team, as everyone has a unique perception of the world. In contrast, it could result in information asymmetry, as the suggestion is there that everyone has the same background and information, failing to discuss information with the entire team (Harrison & Klein, 2007). Disparity, as explained by Harrison and Klein (2007), is a battle between one team member holding the majority of the power within a team (e.g. a CEO in its TMT), resulting in decreased performance as a result of decreased trust or increased deviance within a team (Harrison & Klein, 2007). These contradictions visualize the dual and complex nature of diversity research.

Meanwhile, research into TMTs and their diversity has used numerous personal characteristics (Jackson et al., 2003). This research focuses on the demographic characteristics of TMTs, looking at the variety in educational background, tenure (Hambrick et al., 1996), and network (Matarazzo et al., 2021). And the moderating effects of age- and gender separation towards managerial attention (Konrad & Gutek, 1987). These components create a well-balanced overview of diversity within Top Management teams and are explained in detail in the following sections.

2.3.1. Educational Background

Education has been positively linked with cognitive orientation and knowledge base (Herrmann & Datta, 2005). Diverse TMTs about educational background are expected to contribute to dealing with uncertainty, a necessity to thrive in an innovative and uncertain environment (Bredthauer et al., 2020; Erhardt et al., 2003). Therefore, these board members have a wide range of skills, perspectives, and domains available during the decision-making process (Wiersema & Bantel, 1993). Different educational backgrounds contribute to a richer board with creativity, a critical attribute for innovative strategies focusing on digital transformation. As these different backgrounds enable individuals to see challenges from different perspectives, enhancing the quality of the solution found. In contrast, a TMT with highly educated directors might face homogeneity within its board. Homogeneous teams tend to have similar demographics. Whereas having higher diversity is linked with higher turnover (Simons et al., 1999). In addition, communication problems increase, e.g., reaching a consensus, negatively impacting firm innovation (Carter & Lorsch, 2004). This type of heterogeneity is a source of conflict (Simons et al., 1999). Concluding that while heterogenous teams might face difficulties in time-constrained situations, their solutions tend to create longer lasting competitive advantages (Teece, 2012).

> **Hypothesis 1:** *There is a positive relationship between the diversity in educational backgrounds of board members and the level of attention towards digital transformation in a firm.*

2.3.2. Tenure

Organizational tenure is the duration of an individual's presence within a firm. Within research, it is considered a sum of relevant knowledge regarding the organization and the function that an individual can find itself in (Gilson et al., 2013). Wiersema & Bantel's study (1993) found that diversity in terms of age, educational backgrounds and tenure influence a firm's attitude towards change. Where age and educational background diversity tend to embrace change, longer tenure suggested an increased resistance towards change. In addition, similar people may find interacting easier, as it provides them with positive reinforcement of their attitudes and beliefs (Tanikawa & Jung, 2016). This contrasts with dissimilarity, in which they consider cooperating a punishment, leading to decreased communication (Williams & O'Reilly, 1998).

Prior research states that older managers are less likely to strategic change performance in comparison to younger managers (Bredthauer et al., 2020). Bantel and Jackson (1989) state that risk-aversion is something that typifies older executives. Bantel and Wiersema (1993) suggest that due to the stage of their career, taking risks might become a career hazard, negatively influencing the financial security needed during their retirement. In contrast to younger managers, according to Bredthauer et al. (2020) who are appealed to strategic changes and are partaking in risk-taking endeavours. Combining these dual perspectives on career creates a positive balance towards firm innovation, using the best of both worlds. Within tenure, heterogeneity refers to a higher likelihood of embracing change as different lengths of experience offer diverse insights (Wiersema & Bantel, 1993).

> **Hypothesis 2**: *There is a positive relationship between board members' diversity in tenure (length of service) and the level of attention towards digital transformation in a firm.*

2.3.3. Network Size

The underlying argument for the complexity of operations is that due to the high information-processing demands of a TMT, diversity works towards relational capital or an extensive network (Matarazzo et al., 2021). To cope with the high complexity of organizations, a broad knowledge base within the team and efficient team processes are necessary (Dezsö & Ross, 2012). The number of network ties available to a TMT increases the cognitive repertoire of board members (Harrison & Klein, 2007). As the size of a network indicates corroborating with a multitude of individuals (Matarazzo et al., 2021). In addition, widespread network ties have been shown to stimulate organization-wide innovation as a value-creation mechanism (Ridwansyah et al., 2023). Having wide networks allows a TMT to spread information, process the information on the horizontal and vertical levels, and eventually stimulate innovation, positively impacting transformational processes such as DT (Clark et al., 2003).

> **Hypothesis 3:** *There is a positive relationship between the diversity in the network sizes of board members and the level of attention towards digital transformation in a firm.*

2.3.4. Age Separation

In an evolving business environment marked by an ageing workforce and a nationwide shortage of skilled junior employees, the qualifications of a firm's workforce are a crucial factor when facing the commitment towards digital transformation (Kunze et al., 2010). The average age of TMTs is considered to be the antecedent of a firm its' performances as it represents a cumulation of knowledge and experience (Bantel & Jackson, 1989; Hambrick & Mason, 1984). Age separation within an organization can present challenges, as suggested by the Faultline Theory, which states that generational differences might create divisions affecting this commitment.

The Faultline theory as proposed by Lau and Murnighan (1998) explores the concept of fault lines in teams. Fault lines, explained as hypothetical dividing lines based on the alignment of multiple demographic variables within a group. The strength of these lines depends on the degree of alignment and influences the group dynamics, including communication, formation of subgroups and potential conflicts. Integrating the dual nature of age diversity and the benefits of having both perspectives in a team as explained in section 2.3.1. Hence, it is hypothesized that age diversity moderates the relationship between educational background, tenure network size and commitment to DT by introducing potential fault lines that may weaken attention and adaptability among directors of different ages (Bredthauer et al., 2020).

> **Hypothesis 4a***: Diversity in age moderates the relationship between educational background and attention toward digital transformation in a firm, resulting in a decreased effect.*

> **Hypothesis 4b**: *Age moderates the relationship between tenure and attention toward digital transformation in a firm, resulting in a decreased effect.*

> **Hypothesis 4c**: *Age moderates the relationship between the Network Size of the different individuals in a board and the attention toward digital transformation in a firm, resulting in a decreased effect.*

2.3.5. Gender Separation

Due to the changing workforce, the relative growth of the number of women (and other minority groups) relative to the number of males in the workforce has been high. Political and societal changes encourage females to participate in the labour market. For example, Denmark forced its firms to install a female -quota (Wolbrecht & Campbell, 2007). In addition, customers are more likely to buy from a firm if the employees of that firm are people they can identify themselves with (Wolbrecht & Campbell, 2007). It would only make sense that the higher levels of management would change along, portraying an example towards the rest of the firm (Rampling, 2012).

However, equal gender diversity in top management teams has not yet been reached. The research found that including females in a TMT has two major strengths: participative decision-making styles and increased sensitivity, positively impacting firm performance and innovation (Rao & Tilt, 2015). In addition, when reaching the threshold of 25% women in a TMT, Abtahi et al. (2023) stated that this increased corporate risk-taking, enhancing innovation. Contrastingly, gender diversity might lead to increased conflict, negatively impacting innovation (O'Reilly). As a result of the dual nature of diversity, situating gender diversity against educational background, tenure and network size is hypothesized to have a moderating negative effect on innovation. Regarding gender diversity,

> **Hypothesis 5a**: *Gender will moderate the relationship between educational background and attention toward digital transformation in a firm resulting in a decreased effect.*

> **Hypothesis 5b**: *Gender will moderate the relationship between tenure and attention toward digital transformation in a firm, resulting in a decreased effect.*

> **Hypothesis 5c**: *Gender will moderate the relationship between the Network Sizes of the different individuals on a board and the attention toward digital transformation in a firm, resulting in a decreased effect.*

In Figure 1, the conceptual model provides an overview of the abovementioned hypotheses.

3. Methods

The following sections explain this study to examine how top management team diversity influences managers' attention towards digital transformation. First, the empirical setting is discussed and aligned with the hypotheses. Second, to ensure validity, the data sample must provide variance among all observations and include all relevant data needed to test the hypotheses. Third, valid measures need to be developed along with the correlating factors of attention. Last, the method needs to include count-distributions focused on within-firm diversity, and an analytical method is described.

3.1. Empirical setting

This research's empirical setting is a dataset comprising data from the 3,000 largest US-listed firms over 18 years (2005 – 2022) and contains all major U.S. industries. The

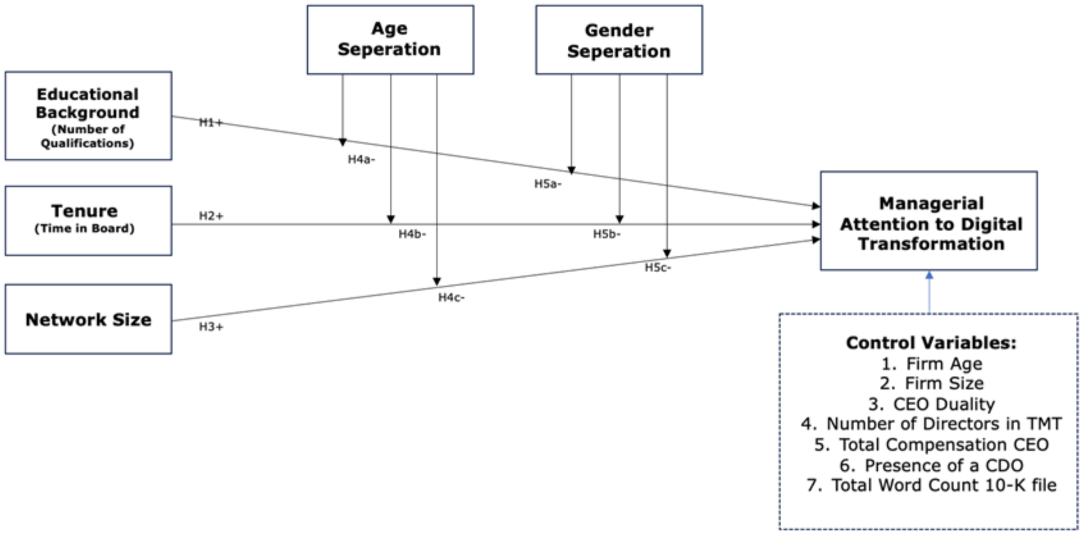

Figure 1: Conceptual Model

fact that the data is cross-industry has several advantages for this study. Verhoef et al. (2021) stated that digital transformation is not solely present in technology industries; rather, it directly affects a wide range of industries and has different maturity levels within each industry. As per these differences, the managerial attention towards digital transformation differs (Chanias et al., 2019). Including these different industries enhances the reliability of the research, as the different maturity levels per sector balance each other out. The research was initiated as a derivative of a custom-made and supervised dataset by Dr. Marvin Hanisch. The data quality within this dataset is relatively high as it has been custom-made for this line of research. Due to the nature of these firms being publicly listed, most information has been available via 10-K filings and/or annual reports.

3.2. Data Collection and Sample

This study enlarged an already existing panel dataset of the Russell 3000 Index. Several students, including myself, have been working on collecting additional data (2019 – 2022), checking inconsistencies in prior firm data (2017 – 2019), and ensuring completeness of the available documents (e.g., 10-K filings). The dataset provides information from 2005-2022 and includes information on the sector, financial data, shares and stock prices, CEO and CDO information, salary, and digital transformation forms. The data is retrieved from Dr. Marvin Hanisch and consists of public sources, such as annual reports, 10-K filings, letters to shareholders, LinkedIn, About Us pages, Salary.com, and Yahoo Finance. The 10-K file, annual report, letter to shareholders and About Us pages have been converted to (flat) text documents, which helped extract information about managerial attention towards digital transformation. The data may be subject to revisions and may contain errors.

In addition to this collected dataset, Dr. Marvin Hanisch and his students developed the method for the dependent variable (managerial attention). He and his students developed a Computer-Aided Text Analysis (CATA) scan, which analyzed the keywords used in 10-K filings that could be linked to the different stages of digital transformation. This Computer-Aided scan improves the quality of the study, as using CATA for such a study prevents human errors due to fatigue (Short et al., 2018). The list used in this research has not been altered, as this is not considered the focus of this study. A small sample of the words used can be found in Appendix 1.

This research investigates the diversity within top management teams, which was not present in this prior mentioned dataset. Hence, working together with Kirsten Huetink, an additional dataset was created complementing this existing dataset to function as dependent- and moderating variables. The TMT composition data has been retrieved from WRDS, Wharton Research Data Services, and specifically from BoardEx – North America. Two types of data sources have been used from there. Firstly, the Organizational Summary is used to check for the composition of the Top Management Teams and retrieve director IDs corresponding to individual executives, followed by looking up these IDs in the BoardEx – Individual Profile Detail database. These lists have been merged and cleaned prior to analysis.

3.3. Measures

This section gives an overview of the different variables and their measurements used for the hypothesis testing. The independent variable originates from the CATA scan, the dependent and moderating variables originate from WRDS, and the control variables are from the original dataset. Table 2 visualizes all variables used in this study.

3.3.1. Dependent variable.

Managerial attention to digital transformation is measured using CATA on the 10-K filings and relates to the cognitive estimate of paying attention to forms of either digitization, digitalization or digital transformation (Verhoef et al., 2021). This method is derived from prior work linked to the work of Dr. Marvin Hanisch, and the list is created and supervised by him, with no alteration to the keywordlist. The method is a way to quantitatively analyze the different phases of digitalization over a large number of firms/years. It analyses the attention towards DT by counting keywords in 10K filings. The number of keywords counted in the 10K filings indicates the managerial attention towards digital transformation, e.g., a higher number of counted keywords indicated a relatively higher amount of managerial attention.

3.3.2. Independent variable.

Diversity in top management teams is measured using Blue's Index and Separation (Harrison & Klein, 2007). This method consists of five metrics: three are used as independent variables, and two are used as moderating variables. All independent and moderating variables are imported from BoardEx (as outlined in section 3.3). For the independent variables, educational background, tenure, and network size, this study uses Blue's Index. The majority of the diversity research uses *variety* in the field of Upper Echelons (Pasamar et al., 2019).

Blue's Index (BI) is measured by using the number of qualifications each individual TMT member has. This dataset consists of degrees received as Bachelor's, Master's, PhD, MBA, License and Others. After collecting this information, individual dummy variables have been created to categorize this into six categories (0 to 5). Categories are derived from Wiersema and Bantel (1993). Table 1 presents an overview of the categories for the independent variable made.

After ordering this per firm/year, the study uses the proportions of the different categories concerning the total number of qualifications achieved by the sum of board members. These outcomes were squared to calculate the variance, after which this score was summed. This sum was deducted with 1 to retrieve the Blue's Index for Education Level. Afterwards, all dummies were deleted, and only the Blue's Index Score per firm/year was kept and used for calculation.

$$Blau's\ Index = 1 - \Sigma_k\ p_k^2$$

Blue's Index - Tenure is measured using an approach similar to this independent variable. The different categories for time on board are also displayed in Table 1. These categories are based on the time an executive spend within a board and is based on (Wiersema & Bantel, 1993).

Lastly, Blue's Index for Network has been calculated similarly to the previous one. The categories used for this Index are also displayed in Table 1. The used categories are based on the research of Matarazzo et al. (2021).

3.3.3. Moderating variables.

Moderating variables are measured using separation (Harrison & Klein, 2007). Separation is calculated as a Standard Deviation of the included data.

$$Standard\ Deviation = Seperation = \sqrt{\frac{(S_i - S)^2}{n}}$$

Age is calculated first by creating count dummy variables for all the Board Members. After this, a count was done of the total board members per year/firm. Followed by a total sum of the different TMT member's ages (year/firm) was calculated. A mean (year/firm) was derived from that. The different ages of board members were deducted from the mean, squared, and summed to a total. This sum is divided by the total amount of members on each TMT, which is once again squared to derive the standard deviation. All in-between steps were dropped, but the separation age variables (year/firm) were kept as a moderating variable.

$$Separation_{Age} = \sqrt{\frac{\sum_{i=1}^{38}(mean\ age - age_i)^2}{Total\ Age\ dummies}}$$

As gender is considered binary (by the dataset from BoardEx), firstly, (count), dummy variables were produced to derive the total number of board members in a team. Then, dummies were used to derive a total number of men and a total number of women on each team. The amount of male and female board directors was summed, and the proportions of the two genders were calculated (gender/total). Lastly, the proportion of male board members times 1 – the proportion of male board members combined was divided by the total number of board members; this was then squared to derive the standard deviation (or separation as stated by Harrison and Klein (2007)).

$$Separation_{Gender} = \sqrt{\frac{\sum_{i=1}^{38}(Proportion_{males} - proportion_{male_i})^2}{Total\ Director\ Gender}}$$

3.3.4. Control variables.

As prior research states (Verhoef et al., 2021), and assuming that TMT Diversity does not solely determine managerial attention to digital transformation, several control variables are included in this study.

Firm size can impact the likelihood of engaging in innovative activities Wiersema and Bantel (1993). Large firms may have vast resources that can contribute to innovation (O'Reilly et al., 1989). This control variable is calculated by using the number of employees of a firm for any given year.

Firm age. This control variable is calculated by deducting the focal year – the foundation year. As younger firms tend to have a higher likelihood of being a 'born-digital' firm, whereas older firms might have more cumulative resources (Appio et al., 2021).

Total Amount of Board Members: A TMT can consist of as many people as between 1 and 38; the number of board

Table 1: Overview categories used for independent variables

Level of Education	Number of Qualifications	**Level of Tenure**	Time in Board	**Level of Network**	Network size
Category 0	0 number of Qualifications				
Category 1	1 number of Qualifications	Category 1	0 – 2.4 years	Category 1	0 – 250 contacts
Category 2	2 number of Qualifications	Category 2	2.5 - 5.4 years	Category 2	251 – 550 contacts
Category 3	3 number of Qualifications	Category 3	5.5 – 9.4 years	Category 3	551 – 950 contacts
Category 4	4 number of Qualifications	Category 4	9.5 – 15 years	Category 4	951- 1500 contacts
Category 5	≥5 number of Qualifications	Category 5	>15.1 years	Category 5	>1501 contacts

members has been taken into account. This has been calculated by creating a (count) dummy variable and is calculated per firm/year. *As smaller teams may have less trouble communicating all information, a larger team is known for greater variety.* This variable is calculated by counting the different inputs firm/year (Chiang & Lin, 2011; Horwitz & Horwitz, 2007).

CEO compensation as CEO compensation may result in increased discreteness of a CEO (Adams & Ferreira, 2008). It has been calculated as total compensation = salary + stocks + other.

CEO Duality, as DT is a holistic process (Chiang & Lin, 2011), and therefore solely linked to the CEO in terms of functional focus, the duality of a CEO as chairman of a board is taken into account. In addition, this chairman, having complete control, reduces conflict, leading to a higher firm performance (Chiang & Lin, 2011). It functions as a dummy variable derived from the original dataset.

CDO presence is the presence of a Chief Digitalisation Officer in a TMT. The role of the CDO is holistically focussing digital innovation within the firm, making this function fundamentally different as this board member could focus on holistic elements compared to functional board members (Fernandez-Vidal et al., 2022; Fitzgerald et al., 2014; Grossman & Eckel, 2012; Singh & Hess, 2020). This study is considers it a dummy variable as a CDO is expected to act as a digital evangelist (Fernandez-Vidal et al., 2022).

The total number of words in the 10-K file as the dependent variable is derived from the 10-K filings, stating that the number of keywords is the level of managerial attention. This control variable is there to account for differences between the number of words used in the 10-K filings, per year/firm.

3.4. Analytical Method

To test the hypotheses, Stata17.0 was used. The dataset contains observations for the years 2005-2022, and panel analysis was used. As the dependent variable, managerial attention towards digital transformation is a continuous variable. A frequency distribution of the dependent variable, as displayed in Appendix 2, is used to check the model for skewness to decide on one of these tests. Looking at Figure 3, the frequency distribution is highly right-skewed, concluding that an OLS model is unsuitable. And as the values are count variables and only contain non-negative values, the best test would be either a Poisson or negative binomial regression (Gardner, 1995). In addition, the variance in the model exceeds the mean value (See appendix 2), leading to the assumption of an over-dispersion within the model, concluding that a Poisson model is not suited either (Hausman & Taylor, 1981).

To test the robustness of the study, a VIF test was used to test for multicollinearity (See Appendix 2). These results where below the rules of thumb threshold of 4 for VIF (O'Brien, 2007), suggesting the lack of presence for multicollinearity in variables within the analysis. This lack of multicollinearity makes this a suitable study for the negative binomial regression model. As this research focuses on diversity within boards, a fixed effect is proposed. The Hausman test was used within Stata to validate this decision (Hausman & Taylor, 1981). After testing both effects, the test indicated that using a fixed effects model for this study is relevant. These fixed effects help us focus on diversity while controlling for potential endogeneity and unobserved heterogeneity across firms.

In total, 44 models are created, consisting of the sum of the processes of the DT *main model* and the different stages *of DT, as seen in the Extensive model* (see table 5). The remaining models are linked with the interaction effects in order to test for the interaction effects, they have been calculated per phase and per interaction variable, after which these outcomes have been combined and inserted in their respective models, as displayed in table 4 and 5.

Table 2: Overview Measures

Variable Type	Variable Name	Measure
Dependent Variable	Managerial attention to Digital Transformation	Total (sum) keyword counts for clusters (D1) digitization, (D2) digitalization, and (D3) digital transformation, as well as a sum of efforts (Appendix A)
Independent Variables	Educational Background	Blau's Index for Number of Qualifications
	Tenure - Time in Board	Blau's Index for time on the board
	Network size	Blau's Index for Network Size
Moderating Variables	Separation - Age	Separation (SD) of Age within a Board
	Separation - Gender	Separation (SD) of Gender within a Board
Control Variables	Age of the Firm	Age of the firm (year - foundation year)
	Size of the Firm	Number of Employees
	CEO Duality	Is the CEO of the Board also chairman - Dummy Variable
	CEO Board member Total Compensation	Total Compensation of the TMT (Base Salary, Stocks + other)
	Presence of CDO	Dummy variable for the presence of a CDO within a Board
	Total Count of Words	Total count of words within 10-k filings
Fixed effects	Year	Controlled for fixed effects

4. Results

In this section, the results following the statistical tests are displayed. Firstly, an overview of the general statistics and the correlations are provided. Secondly, the outcomes of the negative binomial regressions for the different hypotheses are displayed.

4.1. Descriptive Statistics and Correlations

Table 3 gives a summary of the descriptive statistics and the correlation between the different variables used in the model. In total, 18,791 observations contain values for all variables. The average firm age is 55,98 years, and it has approximately 2.609.000 employees. The boards have approximately 9,75 directors. CEOs are more likely to also be chairman of the board (average 1,56); the board is likely to have no CDO (average <0,5).

When looking at the diversity within the board, the Blue Index on the educational background, tenure, and network size are relatively left-skewed (mean = 0,62, mean = 0,60, and mean = 0,55). This indicates that on average, TMTs tend to be more varied. Whereas separation – gender is right-skewed (0,10), indicating that boards tend to consist of more people of the same gender as indicated by less separation.

This table 3 presents the total number of keywords per stage of DT/year. Digitization has been detected on average 43.05 times, digitalization 24.13 times, and digital transformation 2.29 times firm/year. These stages have a cumulative mean of 69.47 keywords per 10-k file.

As expected, there are significant correlations between the dependent variable and the three separate stages, with digitization (r =0.50), digitalization (r = 0.29), and Digital Transformation (r = 0,93). Moreover, Blue's Index Scores for the Number of Qualifications correlate with the dependent variable (r = 0-0,03, r= - 0,01 (not significant), r= 0,05, and r= 0.03). Interestingly, it does not correlate significantly with all phases, assuming that the number of qualifications might be less impactful for the individual stages but essential for the overall cumulative efforts toward DT. In addition, Blue's Index score for Time on Board (r = -0,06, r=-0,05 r=-0,05 and r = 0,07) all significantly correlate respectively with the three stages and SUM of digitalization, suggesting that on the one side, longer tenure might lead to more comprehension of DT, but as it negatively correlates with the other dependent variables, might lead to increased resistance to change. Lastly, Blau's Index for the Network size (r = -0.21, r =-0.18, r=-0.11 and r=0.23) are all correlated towards the dependent variables, indicating that network size might hinder the individual stages of DT but has a positive impact on the cumulative efforts towards DT.

The independent Blau's Index (BI) variables are correlating with the dependent variables. Firstly, BI tenure with BI educational background (r = 0.08), indicating a weak positive effect of a diverse tenure on the educational background on managerial attention. Secondly, BI network size with BI education (r = 0.04) and BI tenure (r = 0.05), suggesting that network sizes positively influences educational background and tenure. Next, the moderating variables correlate significantly with the dependent variable, albeit weakly. In addition, age separation correlates positively with BI Education (r = 0,03) and BI tenure (r = 0.10) but negatively with network size (r = -0.28). Gender separation positively correlates with BI education (r = 0.04) and BI tenure (r = 0.08) but not with BI network size.

Lastly, the control variables correlate significantly with the dependent and independent variables, but since these correlation coefficients are relatively small, no issues regarding multicollinearity are expected. Several interesting elements were analyzed in the control variables. Firm age negatively correlates with all different stages of DT (r=-0.18, r=-0.13, r=-0.09, r=-0.18), suggesting that older firms may reach lower levels of DT. Firm age positively correlates with the independent- and moderating variables, indicating that older firms may have more diverse boards. The size of a firm has a slight positive correlation with the dependent variables (r = 0.01, r=0.08, r=0.03, r=0.04) but negatively correlates with BI network size (r =-0.28), suggesting that larger companies have (relatively) smaller networks in comparison to their size. CEO duality negatively correlates with the dependent variables, indicating that firms where the CEO also serves as a chairman are less likely to participate in DT-related efforts. The number of Directors has weak but mixed significant correlation outcomes (r = -0.06, r=0.03, r=-0.01, r=-0.03) towards the dependent variables, which could be explained as a greater number of directors, negatively impact managerial attention (excluding digitalization). The correlation of the number of directors towards the BI education (r = 0.14), BI tenure (r= 0.29) and the Separation variables (Age – r = 0.33 & gender r = 0.29) is relatively strong for this model, suggesting that a greater number of directors enhances the possibility of diversity within teams. CEO compensation correlations with the variables are generally weak, suggesting no relation between the stages of DT and compensation. The presence of a CDO correlates positively with the later stages of DT (excluding digitization) (Digitalization r = 0.06, DT r=0.02, SUM r=0.03). The total amount of words in a 10-K file positively correlates with all dependent variables (r= 0.07, r=0.11, r=0.09, r=0.1), concluding that more comprehensive 10-K filings seem more involved with DT. Which could be due to the information density of the reports, addressing topics in more detail.

4.2. Regression Results and Hypothesis Testing

Table 4 presents the Negative Binomial Regression results to test the hypotheses in section 2. The total amount of models used to compile this table is 44. In this section, the main model, which includes a sum of the three phases of digitization, will be examined using a fixed-effects method, the number of observations, and the number of firms that decline per stage. Table 5 provides an overview of the three different stages of digitization and their respective outcomes. The natures of the three different stages differ. However, this study aims to look at the firms in their totality with regard to DT, hence, this section will discuss the outcomes based on the proposed hypothesis. As stated in the literature section, and uses the primary model analysis, complemented with the extended regression model, as this has an overview of the individual stages.

The number of observations for this model is 18,791. In the lower sections of the table, there are independent fit models- using the Akaike & Bayesian information criterion (AIC, BIC), as well as the log-likelihood. Although the BIC indicator is above the threshold ($\Delta i > 10$), the AIC and the log-likelihood estimators (from now on LL) decrease from model 4.1 (AIC = 197,199; LL =-98,591) to model 4.4 (AIC = 193,758; LL -96,860), indicating that there is minimal loss of information and a model which improves from basics towards a complete model (Burnham & Anderson, 2004). This trend has been seen for all the different individual stages of D; digitization 1.1 (AIC = 178,567; LL = -89,274) to 1.4 (AIC = 174,872; LL = -87,417), digitalization 2.1 to 2.4 (AIC = 157,112; LL = -78,548) to 2.4 (AIC = 154,597; LL = -77,280), and digital transformation 3.1 (AIC = 56,368; LL =-28,176) to 3.4 (AIC = 54,731; LL = 27,342). These results suggest that every final model of the different stages is most adequate.

The regression has been split into the three Digital Transformation stages and a cumulative model. In this section, the model numbers correspond with the model of the different stages 1.1 to 1.4 is linked with digitization, model 2.1 to 2.4 with digitalization, and 3.1 to 3.4 with Digital Transformation as stated in Table 5. As displayed in Table 4, the main model contains models 4.1 to 4.4. This section first discusses the individual stages of DT, followed by an interpretation of the SUM DT efforts.

Hypothesis 1: *A positive relationship exists between diversity in the number of educational qualifications and the level of attention towards DT in a firm.* Contrary to this hypothesis, the regression results across models 1.1 to 2.4 are non-significant coefficients. However, for the Digital Transformation stage, an increase in diversity in the number of qualifications is associated with a decrease in attention towards managerial attention. There is a non-significant effect for the sum of DT efforts, concluding that the hypothesis cannot be supported.

Hypothesis 2: *There is a positive relationship between board members' diversity in tenure (length of service) and the level of attention towards digital transformation in a firm*. H2 predicts a positive relationship. However, since the first two phases of DT do not have significant results, DT has a negative significant correlation (model 3.3 b =-0.2183, p<0.01). For the SUM of DT efforts, the outcome in model 4.2 (b = -0.02; not significant) and 4.3 (b = - 0.0598; p < 0.1) is negative and significant, indicating a negative relationship between the level of managerial attention, further disproving Hypothesis 2.

Hypothesis 3: *There is a positive relationship between the diversity in the network sizes of board members and the level of attention towards digital transformation in a firm.* H3 predicts a positive relation, but the different models consistently show a strong negative relationship. The most substantial negative significant effect is seen during Digital Transformation in model 3.1 (b = -0.3283; p<0.01). For the sum of DT efforts, models 4.2 to 4.4 have strong negative relationships between the SUM and BI Network size, all significant at the 0.001 level (-0,17, -0,16, -0,16). These results are contradictory to H3, which predicted a positive relationship.

Hypothesis 4a*: Diversity in age moderates the relationship between the number of Qualifications and the attention toward digital transformation in a firm, resulting in a negative moderating effect.* The interaction is not significant in the dig-

Table 3: Descriptive statistics

		Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Dependent Variables																				
(1)	Digitization	43.05	70.78	0	990	1															
(2)	Digitalisation	24.13	39.52	0	660	0.50***	1														
(3)	Digital Transformation	2.29	10.48	0	404	0.29***	0.32***	1													
(4)	Cumulative SUM DT	69.47	100.83	0	1482	0.93***	0.77***	0.44***	1												
	Independent Variables																				
(5)	BI - Educational Background	0.62	0.12	0	0.83	-0.03***	-0.01	-0.05***	0.3***	1											
(6)	BI - Tenure	0.61	0.19	0	0.80	-0.06***	-0.05***	-0.05***	0.07***	0.08***	1					P					
(7)	BI - Network Size	0.55	0.20	0	0.80	-0.21***	-0.18***	-0.11***	0.23***	0.04***	0.05***	1									
	Moderating Variables																				
(8)	Age Separation	1.82	1.65	0.00	20.51	0.04***	0.05***	0.03***	0.05***	0.03***	0.10***	-0.28***	1								
(9)	Gender Separation	0.10	0.06	0.00	0.35	0.06***	0.07***	0.04***	0.08***	0.00	0.19***	-0.16***	0.09***	1							
	Control Variables																				
(10)	Age of the Firm	55.98	44.30	0	239	-0.18***	-0.13***	-0.09***	-0.18***	0.06***	0.24***	-0.10***	0.11***	0.14***	1						
(11)	Size of the Company (in 1,000,000)	26.09	90.08	0	2925	0.01	0.08***	0.03***	0.04***	0.03***	0.09***	-0.28***	0.16***	0.1***	0.07***	1					
(12)	Dummy - CEO duality	1.56	0.5	1	2	-0.10***	-0.05***	-0.03***	-0.1***	-0.01	0.06***	-0.07***	0.06***	0.00	0.1***	0.01	1				
(13)	Number of Directors on a Board	9.75	2.48	1	33	-0.06***	0.03***	-0.01	-0.03***	0.14***	0.29***	-0.2***	0.33***	0.19***	0.32***	0.2***	0.03***	1			
(14)	Total Compensation CEO	53.41	4127.04	0	563802.28	0.00	0.02***	0.00	0.01	0.00	0.00	-0.01	0.00	0.01	-0.01	0.01	0.01	0.01	1		
(15)	Dummy - Presence CDO	0.02	0.13	0	1	0.01	0.06***	0.02***	0.03***	0.00	0.03***	-0.01***	0.04***	0.06***	0.06***	0.05***	-0.03***	0.08***	0.00	1	
(16)	Total Amount of Words in 10-K (in 1,000)	61.03	31.61	1.5	1150.25	0.07***	0.11***	0.09***	0.1***	0.00	-0.03***	-0.11***	0.07***	0.09***	0.02***	0.00	0.00	0.19***	0.01	0.08	1

Note: N=18,791, significance level at ***p<.01, **p<.05, *p<.10.

itization phase but is negatively significant in the Digitization phase (Model 2.3; b =-0.10131; $p < 0.05$), indicating that the predicted moderating effect is present in this phase of DT. For the SUM of DT efforts, there is no significant interaction in model 4.3 (b = -0.003; $p > 0.05$). From these results, we can conclude that there is support for the individual phase *digitization* but not for the SUM of DT efforts.

Hypothesis 4b: *Age moderates the relationship between the time on a board and the attention toward digital transformation in a firm, resulting in a negative moderating effect.* H4B predicts a negative relation, and the interaction terms are significant across all phases of DT. Most vital in the digitization model 1.3 (b = -0.1273; $p<0.001$), but also present digitalization (b = -0.0999; $p <0.05$) and most robust in Digital Transformation (b=-0.1534; $p <0.01$). DT efforts, the interaction effort is positive and significant in model 4.3 (b = 0.0187; $p < 0.01$), contrasting the predicted negative moderating effect. Hypothesis 4C is therefore not supported.

Hypothesis 4c: *Age moderates the relationship between the network size of the different individuals in a board and the attention toward digital transformation in a firm, resulting in a negative moderating effect.* H4C predicts a negative relation, but there are positive significant outcomes in digitization and digital transformation (b = 0.249; $p<0.001$ and b =0.0186; $p<0.1$). For the SUM of For the SUM of DT efforts, the interaction term is negative and significant (b = -0.1185; $p< 0.01$), indicating that age indeed negatively moderates the relationship between time on board and attention towards cumulative Digital Transformation efforts. This supports Hypothesis 4B.

Hypothesis 5a: *Gender moderates the relationship between the number of Qualifications and the attention toward digital transformation in a firm, resulting in a negative moderating effect.* H5A predicts a negative relation, and the interaction terms are negative across all DT stages. The only significant negative interaction term is in model 3.4 (b = -0.0375; $p<0.1$). For the SUM of DT efforts, model 4.4 is negative and significant (b = -0,012; $p <0.1$), concluding that hypothesis 5A is supported for the cumulative efforts towards DT, and that a larger separation in gender within a board decreases the impact of the positive effect of diversity in educational background.

Hypothesis 5b: *Gender moderates the relationship between the time on a board and the attention toward digital transformation in a firm, resulting in a negative moderating effect.* H5B predicts a negative relation, and the significant outcomes relevant to this hypothesis are in model 1.4 (b = 0.0795; $p< 0.05$) and 2.4 (b = 0.1819, $p < 0.01$), indicating a negative significant relationship for the stages digitization and digitalization. For the SUM of DT efforts, there is no significant interaction effect in model 4.4. This is supported for the individual stages (digitization and digitalization), but the hypothesis (5B) is not supported.

Hypothesis 5c: *Gender moderates the relationship between the Network Sizes of the different individuals on a board and the attention toward digital transformation in a firm, resulting in a negative moderating effect.* H5c predicts a negative relation, and the interaction terms are negative and significant across all individual stages of DT (b = -0.0318; $p <0.01$, b = -0.0380; $p < 0.01$ and b = -0.0359; $p <0.1$). For the SUM of DT efforts, model 4.4 states that the interaction effect is negative and significant (b = 0.0358; $p < 0.01$), supporting hypothesis 5C. Concluding that a larger separation in gender, decreases the impact of the diversity in network size with respect to managerial attention.

An interpretation of the control variables leads to the following observations. The age of the firm is negatively associated with the four distinct models (1.1 to 4.4); the strongest effects are observed in the digital transformation stage (model 3.4 b = -0.2448; $p <0.001$). The size of a firm is positively associated with attention across all individual stages; the level of significance varies between strongest in the digital transformation phase (b = 0.063; $p <0.01$) and weakest in the SUM model (model 4.1 b = 0.0177; $p < 0.001$). CEO duality is negatively associated with all four models of DT, suggesting that firms where the CEO is also chair, might be less attentive to DT efforts (model 4.1; b = -0.1403; $p <0.001$). The number of directors in a TMT has mixed effects across the DT stages. However, model 4.4 is negative and significant (b = - 0.029; $p < 0.001$), indicating that a larger board size might be associated with a decreased focus on DT efforts.

The compensation of the CEO has a weak positive effect on digitalization (model 2.1 b = 0.007; $p <0.05$) but not on other stages. A CDO is positively associated with all models and is most vital in the Digital Transformation stage (model 3.1; b = 0.8227; $p <0.001$). The word count in a 10-K file shows a consistent positive relationship with attention to DT efforts across all individual stages of DT (b = 0.7; $p < 0.001$ in model 4.4).

To interpret the marginal effects, 6 estimated marginal effect plots with 95% Confidence Intervals (Cis; shaded areas) are visualized in Figure 2. These 6 plots are relevant to the main model, the remaining 18 models (linked to the individual stages) can be found in Appendix 3. The plots visualize the two moderating variables (separation) interacting with the independent variables (Blau's Index). These marginal effect plots have three systemic percentiles visualized: 5^{th} percentile, 50^{th} percentile (median), and 95^{th} percentile (Mize, 2019). These systemic percentiles correspond with colors presented in the figure; red lines visualize low levels of separation, green lines average levels, and blue lines have high levels of separation. Highly overlapping Cis indicate no moderating effect, whereas non-overlapping areas indicate a significant difference. As visualized in Figure 2, there are several outcomes which have non-overlapping moderating effects. Including gender and tenure; gender and network size; gender and educational background as well as age and network size (when low). This indicates that the moderation effect of the stated interactions have a significant effect on the independent variables, intensifying when separation increases.

To conclude, the Blau Index score indicates that this board characteristics, network size, consistently negatively

Table 4: Main Model – Negative Binomial Regression

	Model 4.1	Model 4.2	Model 4.3	Model 4.4
Dependent Variable	Total Sum Keywords Digital Transformation Stages			
Independent Variables				
BI - Educational Background		0.00	-0.00	-0.0009
		(0.01)	(0.01)	(0.0060)
BI - Tenure		-0.01	-0.02*	-0.0598
		(0.01)	(0.01)	(0.0335)
BI - Network Size		-0.17***	-0.16***	-0.1640***
		(0.01)	(0.01)	(0.0064)
Moderating Variables				
Age Separation			0.00	0.0670**
			(0.00)	(0.0249)
Gender Separation			1.22***	0.0495**
			(0.10)	(0.0185)
Interaction Variables				
Interaction effect - Qualifications x Age				-0.0030
				(0.0059)
Interaction effect - Time on Board x Age				-0.1185***
				(0.0356)
Interaction effect - Network Size x Age				0.0187***
				(0.0044)
Interaction effect - Qualifications x Gender				-0.0117*
				(0.0059)
Interaction effect - Time on Board x Gender				0.0486
				(0.0295)
Interaction effect - Network Size x Gender				-0.0358***
				(0.0066)
Control Variables				
Age of the Firm	-0.11***	-0.12***	-0.12***	-0.1248***
	(0.01)	(0.01)	(0.01)	(0.0066)
Size of the Company	0.04***	0.02***	0.02***	0.0177***
	(0.00)	(0.00)	(0.00)	(0.0045)
Dummy - CEO Duality	-0.11***	-0.14***	-0.14***	-0.1403***
	(0.01)	(0.01)	(0.01)	(0.0121)
Number of Directors on a Board	0.01	-0.01*	-0.03***	-0.0289***
	(0.01)	(0.01)	(0.01)	(0.0071)
Total Compensation CEO	0.01	0.01	0.01	0.0052
	(0.01)	(0.01)	(0.01)	(0.0038)
Dummy - Presence CDO	0.17***	0.09*	0.09*	0.0760
	(0.05)	(0.05)	(0.04)	(0.0449)
Total Amount of Words in 10-K	0.08***	0.07***	0.07***	0.0700***
	(0.00)	(0.00)	(0.00)	(0.0040)
Observations	19,036	19,034	18,791	18,791
AIC	197199	196446	193806	193758
BIC	197261	196533	193809	193907
Log-likelihood	-98591	-98212	-96890	-96860

Standard errors in parentheses, significance levels at *** p<0.001, ** p<0.01, * p<0.05 I N = 18,791 impact transformation efforts. This suggests that having a more extensive network may not benefit DT efforts. The moderating variables play a significant role, indicating that demographic diversity within a board can influence how the board impacts DT. The different interaction terms suggest a complex dynamic with varying outcomes. This leaves us to assume that while the board composition can significantly impact the DT efforts, other factors such as the control variables (e.g., firm age, size, leadership structure, and CDO presence and thoroughness of corporate reporting) are also critical.

5. Discussion

5.1. Theoretical Contributions and Implications

This research investigated the role of Top Management Team compositions and their respective levels of diversity (variety and separation) in combination with managerial attention on digital transformation efforts. The aim of this was to understand *when* and *why* managerial attention shifts during the cumulative process of digital transformation. In order to increase understanding of the individual stages, these have been added to this study as well. As addressed in the introduction, the current gap in literature presents opportunities for combining UET with DT, in addition, this study succeeded in advancing literature with regards to distinguishing the effects of the different kinds of diversity, as well as their effects on optimal board composition per phase.

First, intending to advance the Upper Echelon Theory as a framework to look at TMT's, with digital transformation, several inconsistencies have been found when comparing the empirical findings to current the literature. The independent variables, diversity in education, tenure, and network size, do not directly influence managerial attention toward digital transformation. This opposes Hambrick et al. (1996). For diversity in the number of qualifications, the cumulative effects are non-significant, opposing Bredthauer et al. (2020), Erhardt et al. (2003), and Wiersema and Bantel (1993). However, it negatively contributes to the individual stage of digital transformation, which might be due to the holistic and drastic nature of digital transformation (Verhoef et al., 2021). In addition, diversity in tenure negatively correlates with the individual stage of digital transformation, opposing Hambrick et al. (1996), stating that it would positively contribute towards innovation. Due to being a relatively new phenomenon and heterogeneous firms being slower but qualitatively better in their strategic changes, it might be that these phases still need to happen, which would explain the current empirical outcomes (Gilson et al., 2013; Wiersema & Bantel, 1993). Diversity in network size, as proposed by Ridwansyah et al. (2023), does not positively influence attention to digital transformation. This study's empirical outcomes suggest that diversity tends to negatively impact managerial attention during every stage, which might be explained by overstimulation of information, linking the empirical findings to the bounded rationality theory (Clark et al., 2003).

Second, this study further explored the moderating effects of age and gender separation on the demographic diversity. This study hypothesized that the separation would negatively moderate digital transformation while age separation only negatively moderates the digitalization stage in the empirical findings. This might be explained by Rogers' innovation diffusion theory (Oliveira & Martins, 2011), as explained by to digitalization as a threshold (Wonglimpiyarat & Yuberk, 2005). As found in the empirical evidence, age separation negatively moderates tenure, enhancing research on this topic (Bredthauer et al., 2020). In conclusion, age separation about diversity in network size, as found in the study, positively moderates the attention to DT, contradicting the hypothesis suggested in this study (Matarazzo et al., 2020). This could be explained by the decreased need for an extensive network because a diverse team can represent and connect with different elements of the firm (Bantel & Jackson, 1989).

Third, gender separation influencing the diversity in educational has been correctly hypothesized, confirming O'Reilly et al. (1989) research. While gender separation has a negatively moderating impact on diversity in tenure concerning the initial stages of digital transformation (digitization and digital transformation), this study has found no support for the individual stage of digital transformation and the cumulative efforts of DT. The reason for this may relate to the increased conflict of age separation within TMTs (O'Reilly et al., 1989), increasing the time to understand one another, which delayed the current evidence for these later phases of DT (Rao & Tilt, 2015). Gender separation in relation to network sizes is correctly hypothesized, as this has a negative moderating effect on managerial attention to DT. The individual stages, as well as the cumulative efforts, are negative, which could be explained by the decrease for a variety in the number of contacts due to the increased initial diversity within a board (Rao & Tilt, 2015).

5.2. Managerial implications

This study concludes with insights for practitioners. As digital transformation efforts become a necessity of continuous innovation for firms, managers and shareholders might consider re-evaluating the board composition for the different stages of digital transformation and adjust their hiring efforts accordingly. While this research aimed to look at cumulative efforts towards Digital Transformation, several compositions have been found essential for the individual stages, these are described in Table 6. Insights that are applicable across the DT journey consist of the interaction between age and tenure , gender and network, indicating that low age separation in a TMT with longer tenure decreases the amount of managerial attention to DT, and low gender separation and larger networks also decrease the amount of managerial attention to DT. TMTs might use the insights of the different stages in combination with self-reflection of their current stage to focus on their following strategic goals and analyse competitors to explore future strategic goals.

Table 5: Extensive Regression Model

Dependent Variable	Model 1.1	Model 1.2	Model 1.3	Model 1.4	Model 2.1	Model 2.2	Model 2.3	Model 2.4	Model 3.1	Model 3.2	Model 3.3	Model 3.4
		Keywords digitization				Keywords Digitalisation				Keywords Digital Transformation		
Independent												
BI - Education		-0.0006	-0.0036	-0.0047		0.0092	0.0063	0.0060		-0.0248*	-0.0287*	-0.0267*
		(0.0063)	(0.0063)	(0.0063)		(0.0062)	(0.0062)	(0.0062)		(0.0124)	(0.0125)	(0.0126)
BI - Tenure		0.0047	-0.0076	-0.0302		-0.0127	-0.0155*	-0.0549		-0.0430**	-0.0507***	-0.2183**
		(0.0073)	(0.0073)	(0.0355)		(0.0071)	(0.0072)	(0.0356)		(0.0136)	(0.0138)	(0.0671)
BI - Network		-0.1825***	-0.1730***	-0.1742***		-0.1406***	-0.1389***	-0.1353***		-0.3283***	-0.3170***	-0.3162***
		(0.0063)	(0.0065)	(0.0067)		(0.0063)	(0.0065)	(0.0068)		(0.0112)	(0.0117)	(0.0123)
Moderating Variables												
Age Separation			0.0062	0.0626*			0.0002	0.0618*			0.0019	0.0847
			(0.0039)	(0.0266)			(0.0040)	(0.0266)			(0.0075)	(0.0511)
Gender Separation			1.7642***	0.1077***			0.6845***	-0.0039			1.7571***	-0.0103
			(0.1035)	(0.0199)			(0.1036)	(0.0194)			(0.2045)	(0.0368)
Interaction Variables												
Qualifications × Age				-0.0019				-0.0131*				0.0045
				(0.0062)				(0.0064)				(0.0119)
Tenure × Age				-0.1273***				-0.0999**				-0.1534*
				(0.0379)				(0.0382)				(0.0737)
Network Size × Age				0.0249***				0.0084				0.0186*
				(0.0046)				(0.0047)				(0.0084)
Education x Gender				-0.0100				-0.0109				-0.0375**
				(0.0063)				(0.0061)				(0.0123)
Tenure × Gender				0.0120				0.0795*				0.1819**
				(0.0315)				(0.0310)				(0.0587)
Network Size × Gender				-0.0318***				-0.0380***				-0.0359**
				(0.0068)				(0.0073)				(0.0122)
Control Variables												
Age of the Firm	-0.0941***	-0.1129***	-0.1174***	-0.1185***	-0.0894	-0.0999***	-0.1009***	-0.1009***	-0.2238***	-0.2406***	-0.2433***	-0.2448***
	(0.0069)	(0.0069)	(0.0069)	(0.0069)	(0.0068)	(0.0069)	(0.0069)	(0.0069)	(0.0142)	(0.0143)	(0.0143)	(0.0144)
Size of the Company	0.0371***	0.0087	0.0062	0.0066	0.0509***	0.0319***	0.0315***	0.0310***	0.0629***	0.0184*	0.0171*	0.0162
	(0.0039)	(0.0050)	(0.0052)	(0.0051)	(0.0035)	(0.0042)	(0.0042)	(0.0042)	(0.0062)	(0.0085)	(0.0087)	(0.0088)
Dummy - CEO duality	-0.1203***	-0.1473***	-0.1560***	-0.1524***	-0.0697	-0.0902***	-0.0933***	-0.0937***	-0.0945***	-0.1522***	-0.1542***	-0.1526***
	(0.0129)	(0.0128)	(0.0128)	(0.0128)	(0.0127)	(0.0126)	(0.0127)	(0.0127)	(0.0250)	(0.0250)	(0.0253)	(0.0253)
Total Directors	0.0085	-0.0170*	-0.0349***	-0.0350***	0.0151*	-0.0028	-0.0115	-0.0118	0.0444***	0.0087	-0.0043	-0.0044
	(0.0068)	(0.0071)	(0.0075)	(0.0075)	(0.0068)	(0.0071)	(0.0075)	(0.0075)	(0.0132)	(0.0141)	(0.0149)	(0.0149)
Total Compensation CEO	0.0049	0.0047	0.0044	0.0043	0.0073*	0.0072*	0.0071*	0.0071*	-0.0053	-0.0066	-0.0069	-0.0069
	(0.0044)	(0.0045)	(0.0044)	(0.0044)	(0.0037)	(0.0036)	(0.0036)	(0.0036)	(0.0136)	(0.0149)	(0.0148)	(0.0148)
Dummy - Presence CDO	0.1804***	0.0887	0.0863	0.0708	0.2015***	0.1379**	0.1392**	0.1229**	0.8277****	0.6446***	0.6442***	0.6304***
	(0.0486)	(0.0474)	(0.0468)	(0.0469)	(0.0478)	(0.0469)	(0.0466)	(0.0467)	(0.0696)	(0.0685)	(0.0684)	(0.0685)
Total words 10 K filing	0.0799***	0.0705***	0.0665***	0.0678***	0.0715***	0.0654***	0.0636***	0.0644***	0.0790****	0.0776***	0.0762***	0.0765***
	(0.0039)	(0.0043)	(0.0045)	(0.0045)	(0.0038)	(0.0040)	(0.0041)	(0.0041)	(0.0059)	(0.0063)	(0.0065)	(0.0065)
Number of Observations	18,791	18,791	18,791	18,791	18,791	18,791	18,791	18,791	18,791	18,791	18,791	18,791
AIC	178567	177420	174916	174872	157112	156646	154632	154597	56368	55564	54745	54721
BIC	178646	177507	175018	175021	157175	156732	154734	154746	56431	55651	54847	54870
Log-likelihood	-89274	-88699	-87445	-87417	-78548	-78312	-77303	-77280	-28176	-27771	-27359	-27342

Standard errors in parentheses, significance levels at *** p<0.001, ** p<0.01, * p<0.05 II Year fixed effects: YES

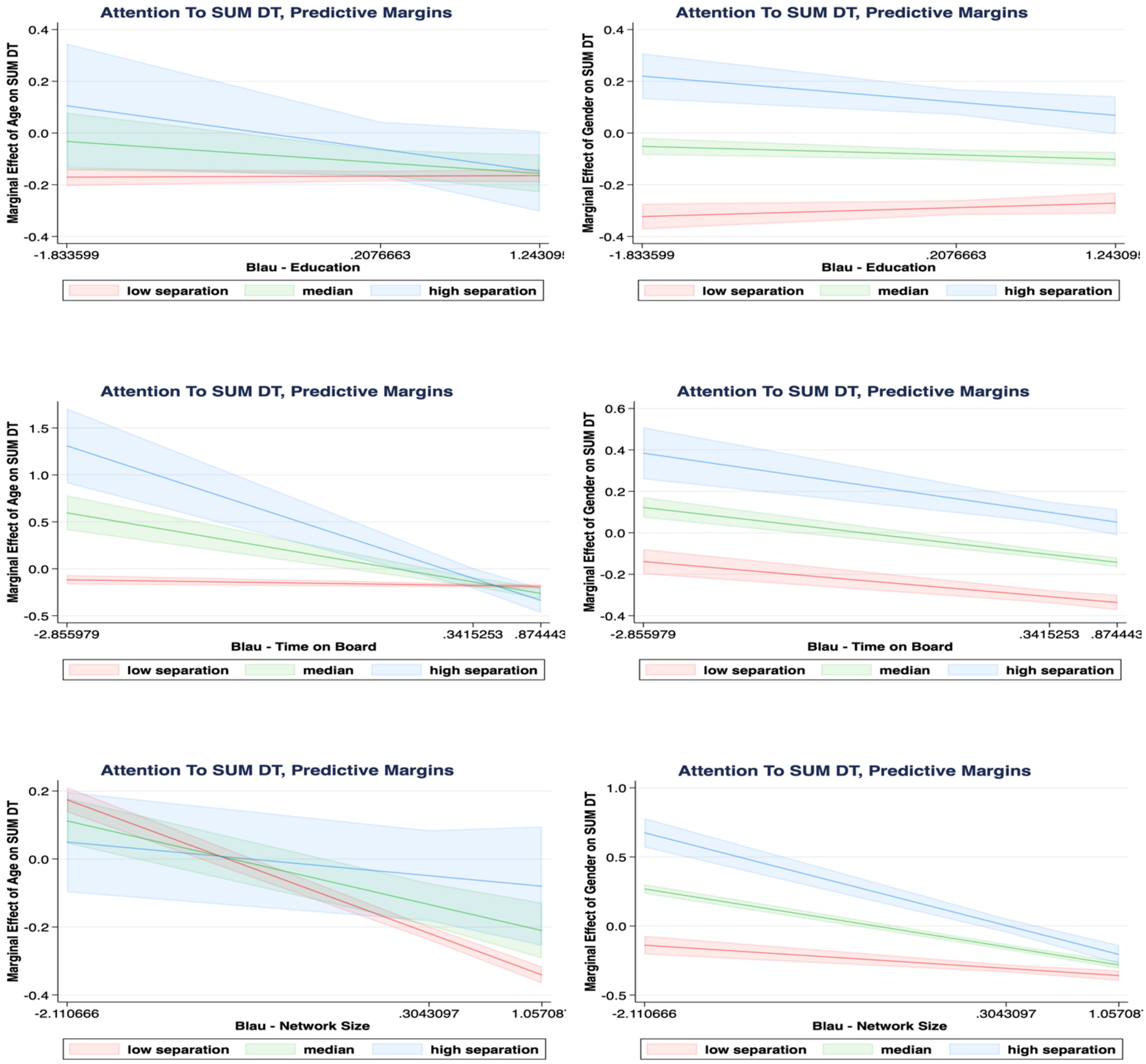

Figure 2: Predicted marginal effects

5.3. Limitations and future research

This study is subject to limitations due to time constraints or human errors but offers promising topics for future research. First, the study focuses on top-performing firms, as they are part of the Russell 3000, potentially leading to a selection bias. Considering this bias, the study's generalizability is limited to the largest firms in the United States. Second, due to the nature of the research, looking at the compositions of boards during the individual phases and the cumulative DT efforts. Third, while the data, supervised by Dr. Marvin Hanisch, is of high quality, the merge with the individual board member information decreased the number of total observations due to lacking information from both datasets. This in combination with manually calculating the Blau's Index scores and separation; while it has been done several times and checked over and over, there might be data points that slipped through. Last, due to the nature of the negative binomial regression, it might have impacted the results of the outcomes.

Future research could be considered to uncover the complex dynamics of Top Management Team compositions. To understand the different board compositions and their effect on managerial attention and the sociological group dynamics that stimulate these mechanisms. For this research, a qualitative approach might be more appropriate. In addition to this, a generalized study, including a larger sample of firms, could be included, including small- and medium-sized firms as well as family-owned firms, to discover if the found effects would be similar in these types of firms.

Table 6: Managerial recommendations

Digitization	Low age separation combined with a similar educational background decreases the managerial attention toward digitization. Low age separation with larger network sizes increases this initial stage of DT. However, low gender separation with longer tenure decreases the managerial attention to digitization.
Digitalization	Low gender separation, in combination with longer tenure, decreases the amount of managerial attention toward Digitalisation.
Digital Transformation	A TMT with similar educational qualifications harms managerial attention to digital transformation. Similarly, low separation of gender and the number of qualifications obtained by a TMT hurts managerial attention. Lastly, low age separation, combined with an extensive network size, positively impacts managerial attention.
The sum of DT Efforts	Larger network sizes hurt managerial attention towards DT in general. In the overall DT efforts, low gender separation combined with a similar number of education qualifications has negatively impact managerial attention to cumulative DT efforts.

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