How well can personal network characteristics predict women's ideal family size using machine learning techniques?

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Abstract

Since the dawn of network analysis, several social influence mechanisms fostered by social networks have been identified to impact women's fertility behavior. Earlier studies found that the content and structure of social networks can be a source of helping to raise children (social support), spread the thoughts and ideas of having children (social contagion), spread information about having children (social learning), and enforce pro-natal norms (social pressure). These studies often lack a comprehensive understanding, however, since they usually only test a limited number of network characteristics and often produce poorly generalizable results. This study aimed to overcome these issues with a more holistic and data-driven approach by applying LASSO regression. This Machine Learning technique is a relatively novel method for social science that performs well when the number of variables in statistical models is high relative to the sample size. Furthermore, it identifies which variables are most influential in prediction novel, out-of-sample cases. For the analysis, a unique egocentric dataset is used which included 758 Dutch women, who reported on more than 18.500 relations and information about these relations. The nine models of this study were able to explain between 2% to 11% of the out-of-sample variation. The results indicate that the proportion of kin in a network and the number of strong ties strongly increase the ideal family size of women. Furthermore, whether network members want children or not and the strength of the relationship with these people influenced women's ideal family size. Network members who prefer to have children or close relations with these people, increase the ideal family size. The opposite is true for network members that do not want children. Network density hardly had any impact, which is at odds with earlier studies. The results indicate that machine learning techniques like LASSO regression can provide promising new insights into social science.

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1. Introduction

Starting a family has been an important life goal for people throughout history (Greening & Fefferman, 2014). In evolutionary history, without reliable contraception, this often meant that people had large families (World Health Organization, 1992; Cohen, 1995). At the same time, death rates were also high. This helped to sustain a relative balance in demographics (Cohen, 1995). Of course, there have been declines in the population for different reasons (e.g., war or natural disasters) or inclines due to technological inventions that helped sustain a larger population (e.g., agricultural inventions) (Zhang et al., 2007; Robinson, 2003), but these changes are insignificant compared to the unprecedented decline in the birth rates over the last 200 years. Especially after the second world war, both fertility and death rates declined rapidly in many western countries (Bracher & Santow, 1991). This demographic transition has led to a variety of studies that helped understand which factors impact people's fertility behavior (Saito, 1996; Nozaki, 2017; Keim, Klärner & Bernardi, 2009; Ketzer, 2006).

Two influential theories about this demographic transition exist; the first- and second demographic transition model. The first model suggests that economic, technological, and medical developments caused the mortality rate to decline, followed by a similar decline in birth rates because fewer infants died prematurely (Kirk, 1996). This view changed, however, during the sixties and seventies in Europe with further sudden demographic disruptions in already modernized countries (Caldwell, 1976; Van de Kaa, 2002). Hence the development of the second demographic transition model. The second demographic transition puts a stronger explanatory power on social influence. It describes different mechanisms of how social influence impacts fertility behavior (e.g., the changes in value people attached to having children, attitudes, and norms towards sex and contraception, the importance of marriage as childbearing without being married became more common and accepted, and cohabitation without being married became perceived as normal) (Zaidi & Morgan, 2017). All of these examples reflect changes in values and norms suggesting the importance of social influence on fertility behavior. Since then, scholars have tried to investigate such social influence theories on fertility using diverse methods.

At the same time, the development of theories about social network analysis has expanded, in which network characteristics are used to describe and analyze personal networks (Friedkin & Johnsen, 2011; Gamper, 2022; Luke & Prusascyk, 2021; Perry, Pescosolido, & Borgatti, 2018). Social network analysis has also, though limited, been used to study fertility behavior (Keim, Klämer & Bernardi, 2009; Keim, Klämer & Bernardi, 2013; Kohler, Behrman & Watkins, 2001; Lois & Becker, 2014). Studies have shown the importance of social learning in becoming a parent (Lois & Becker, 2014) and the role of social support in having large families (Dressler, 1985; Gage, 2013; Murphy, 2011; Stulp & Barrett, 2021). These previous studies often lack a comprehensive understanding to what extent network characteristics foster social influence and how this impacts fertility behavior. They typically examine the effect of only a limited number of people in the network and only a few network characteristics on fertility behavior (Kohler, Behrman and Watkins, 2001). Moreover, these studies are often done in small, qualitative studies or in convenience samples (Bernardi, 2003; Bernardi, Keim & Kläner, 2014).

A better understanding of determinants of fertility behavior is important because it helps policymakers to better predict and anticipate future fertility fluctuations (Sear, Lawson, Kaplan & Schenk, 2016). Fertility is central in policies for facilities such as housing, schools and daycare (Botev, 2008). A lack of quality and quantity of such facilities can greatly impact a couple's decision of having children (Nargund, 2009). This is a contributing factor in the increasing number of people that see their wish for children unfulfilled (15%), which can lead to mental and psychological problems (Graham, Hill, Shelley & Taket, 2011). Therefore, a better understanding of the determinants of fertility may also help in combating rising levels of involuntary childlessness, which comes at a significant cost to well-being.

In this study, previous research is advanced on social influence on fertility behavior in three ways. First, the analysis of this study was done on a unique dataset covering a representative sample of Dutch women for whom large personal networks were available. Second, I used a holistic approach by examining multiple mechanisms of social influence by calculating a diverse array of network characteristics all at once. Third, I used machine learning techniques to decide on the most important mechanisms. With these techniques, it can be calculated which network characteristics best predict fertility behavior. This is particularly appropriate for this study because there are many different mechanisms and many different network characteristics that can be included in the statistical models.

2. Theory

This chapter is divided into four sections. The first section describes key elements and concepts from social network analysis and how they influence individual behavior, what social influence in the context of network theory is, and the types of datasets that can be used to extract social network data. The second section elaborates on which network characteristics can be used to measure social influence and what evidence earlier studies have found on how each of these characteristics influences fertility behavior. Moreover, I describe all the mechanisms I consider and the corresponding hypotheses. The third section addresses why I used a data-driven approach instead of the more commonly used theory-driven approach. The fourth section explains the statistical method that is used for this thesis.

2.1.1 Introduction of social networks

Social network analysis is a type of analytical sociology that is meant as a method to understand social facts and the social world. The definition of a social network is a social structure that consists of social actors (nodes) that are connected by relationships (ties) or through other interactions with each other (Robins, 2015). The definition of the nodes and what ties they have depends on the type of research question. Networks in sociology can include social units such as families, schools (classes), companies, or other organizations (Robins, 2015). Network theorists argue that an individual's position within the network and the structure of the network provide opportunities (and constraints) for the individual to be influenced by others (Hedström & Bearman, 2011).

Network data typically comes in two different forms: egocentric networks and sociocentric networks. A sociocentric network is a closed network with clear boundaries (e.g., all firm employees or children in a class) (Goldbeck, 2013). An advantage of socio-centric network data is that it can identify structural patterns of interactions within the defined network boundaries and how this impacts a certain outcome. Here, the emphasis is on the network as a whole. In contrast, in egocentric network data, there is one central node which is called the *ego* (Goldbeck, 2013) that is connected to all other nodes (often referred to as *alters*). In such networks, interest lies in how the personal network shapes the behavior of the ego. I used egocentric network data for this thesis.

2.1.2 Social influence

Social influence describes how people's attitudes, emotions, and behaviors change due to interpersonal influences (Mason, Coney & Smith, 2007; Perry, Pescosolido, & Borgatti, 2018). Social networks foster these processes through their structure and content (Mason, Coney & Smith, 2007). I used Bernardi's definition of social influence for this thesis. According to Bernardi (2003), four distinct mechanisms foster changes because of interpersonal influence. The first mechanism is *social support*, which means the physical or mental assistance one can receive from other people (Bernardi, 2003). The amount of social support can influence people's behavior because it can increase or decrease their opportunities. The second mechanism is *social learning*, which means the process where individuals learn from other people through observation and imitation (Bernardi, 2003). Individuals adjust their behavior on the basis of interactions with other people and the consequences of the experiences these people have. The third mechanism is *social contagion*, which refers to an individual taking over an idea or behavior from someone else (Bernardi, 2003). This is argued to be different from social learning in that social contagion occurs outside conscious thought and deliberation. The fourth mechanism is *social pressure*, which refers to people adjusting their behavior according to dominant social norms or influential people (Bernardi, 2003). This occurs when people seek confirmation or approval from their network of people they perceive as important, or when people avoid particular behaviors when they think this is not in accordance with local norms.

2.1.3 Type of data and the characteristics that are measured

In light of the four mechanisms addressed above, this paragraph continues by discussing the network characteristics that will be examined in this study. Moreover, I will discuss what previous research has found about these network characteristics in relation to fertility. Not every network characteristic can be measured within an egocentric dataset. Therefore, I will only explain network characteristics that can be measured or approximated. The characteristics are divided into alter attributes, ego-alter ties, and alter-alter ties. A distinction between categories is made because each category provides different information on how social influences come about. Alter attributes give insights into the availability and total sum of resources, beliefs, ideas, information, and shared behaviors within the ego's network. How this influences the ego's behavior depends upon the content of the attribute (Steglich, Snijders, & Pearson, 2010). Ego-alter ties capture the strength and function of relationships between the ego and their alters. The strength of relationships impacts how the ego's behavior is influenced by their alters (Aral & Walker, 2014). Alter-alter ties refer to the structure of the network, including the position of the ego within this structure. This captures important social constructs within a network such as power and constraint (Russel, Langham & Hing, 2018).

2.2.1 Composition (alter-attributes)

The composition of a network describes the attributes of the alters in the network (e.g., sex, age, parenthood status). These attributes reflect what content, resources, and opportunities to learn are available in the network (e.g., the number of advisors or babysitters) (Knipschear et al., 1995). Examples of measures of composition are the number of women, the number of alters with children, or the number of alters that do not want children within the ego's network.

Earlier studies about the influence of network composition on fertility behavior indicate the impact it has on fertility outcomes. For example, the study of Stulp & Barrett (2021) offers insights into how kin and friends impact women's fertility behavior through social support, learning, and pressure. They found evidence for the idea that kin were more likely to help with childcare than friends and that friends were more likely to help than non-friends (Stulp & Barrett, 2021). However, increasing the number of kin in the network did not increase the chances to receive more help. Furthermore, more kin in a network also increases the social pressure women experienced to have children (Stulp & Barrett, 2021). Balbo & Barban (2014) also explored the influence of friends on fertility behavior. They found evidence that having children spreads amongst friends, although people were only influenced by friends who had very young children. What is more, Madhavan, Adams & Simon (2003) and Bernardi and Kläner (2014) also examined composition effects and argued that older women in the network cause the ego to be less likely to take up contraceptives and hence have larger families. These older women in the network generally support more traditional family values and are less likely to have taken contraceptives themselves.

While these studies offer convincing examples of how composition matters, they capture only a limited number of compositional elements. This study extends earlier findings by focusing on many different compositional elements (9 in total). An overview of the compositional variables and the hypotheses can be found in Table 1. I also discuss how I believe the compositional element shapes fertility outcomes. For example, a relatively high number of kin in the network is likely to cause higher fertility rates because more kin in the network is associated with stronger family values and more social support (Stulp & Barrett, 2021). Whereas a relatively high number of individuals in the network with higher education likely causes lower fertility rates (Martin, 1995). Achieving a higher education is associated with achieving more self-centered goals and not so much with maintaining traditional family values (Martin, 1995). These expectations are not always straightforward. For example, the number of friends (relative to the number of kin) in the network could be argued to increase anti-natal norms in networks because friends will likely not have the same pro-natal attitudes as kin (Stulp & Barrett, 2021). However, these friends could themselves be pro-natal, and it is unclear whether friends should be expected to be less pro-natal than for instance non-friends.

Table 1: Shows an overview of the compositional variables that are used for this study, the social mechanism per variable, the hypothesis that is tested per variable, and some key sources for every variable.

Compositional (alter-attributes) variables			
Variable	Mechanism	Hypothesis	Sources
# Women	Social support	H1.1.1: *More women in ego's network means more support with raising children is available for ego, which increases ego's fertility outcomes.*	Stulp & Barrett (2021)
	Social contagion	*H1.1.2: More women in ego's network means more opportunities for contact with mothers which can increase/decrease emotions towards parenthood, which increases/decreases the ego's fertility outcomes.* [A]	Madhavan, Adams & Simon (2003)
	Social learning	*H1.1.3: More women in ego's network means more opportunities to learn from similar alters about having/not having children, which increases/decreases ego's fertility outcomes.* [A]	Bernardi & Kläner (2014)
# Friends	Social support	H1.2.1: *More friends in ego's network means more support with raising children is available for ego, which increases ego's fertility outcomes.*	Stulp & Barrett (2021)
	Social learning	H1.2.2: *More friends in ego's network means more opportunities to learn about having/not having children, which increases/decreases the ego's fertility outcomes.* [A]	Stulp & Barrett (2021)
	Social pressure	H1.2.3: *More friends in ego's network means more pressure to comply with ingroup fertility norms, which increases/decreases the ego's fertility outcomes.* [A]	Madhavan, Adams & Simon (2003); Bernardi & Kläner (2014)
# Kin	Social support	H1.3.1: *More kin in ego's network means more support with raising children is available for ego, which increases the ego's fertility outcomes.*	Stulp & Barrett, (2021)
	Social contagion	H1.3.2: *More kin in ego's network means more pro-natal ideas spread within the network, which increases the ego's fertility outcomes.*	Bernardi & Kläner (2014)
	Social learning	H1.3.3: *More kin in ego's network means more opportunities within the network to learn about having children, which increases the ego's fertility outcomes.* [A]	Bernardi & Kläner (2014)
	Social pressure	H1.3.4: *More kin in ego's network means more pressure within the network to comply with pro-natal norms, which increases the ego's fertility outcomes.* [A]	Madhavan, Adams & Simon (2003); Bernardi & Kläner (2014)
# Alters with higher education	Social contagion and learning	H1.4: *More educated alters in ego's network means stronger "modern" family values within the network, which decreases the ego's fertility outcomes.*	Martin (1995).
# Alters with child	Social contagion	H1.5.1: *More alters with children in ego's network means more opportunities for contact with young children, which can increase emotions towards parenthood, which increases the ego's fertility outcomes.*	Kuziemko (2006)
	Social learning	H1.5.2: *More alters with children in ego's network means more opportunities to learn about having children, which increases the ego's fertility outcomes.*	Kuziemko (2006)
	Social pressure	H1.5.3: *More alters with children in ego's network means more pressure within the network to comply with pro-natal norms, which increases the ego's fertility outcomes.*	To the best of my knowledge, no previous study has explored this relationship.
# Alters that want a child	Social learning	H1.6: *More alters that want a child in ego's network means more pro-natal ideas spread within the network, which increases ego's fertility outcomes.*	Kuziemko (2006)
# Alters that do not want children	Social learning	H1.7: *More alters that do not want children in ego's network means more anti-natal ideas spread within the network, which decreases the ego's fertility outcomes.*	Kuziemko (2006)

# Alter who offer help	Social support Social learning	H1.8.1: *More alters that offer help raising children in ego's network means more support for raising children within the network, which increases ego's fertility outcomes.* H1.8.2: *More alters that offer help raising children in ego's network means more learning opportunities about raising children within the network, which increases ego's fertility outcomes.*	Bernardi & Kläner (2014) Bernardi & Kläner (2014)
# Talk with alters about having children	Social learning and pressure	H1.9: *More talking with alters about having children means more pro- or anti-natal ideas spread within the network, which increases/decreases the ego's fertility outcomes.* [A]	Kavas & De Jong (2020)

[A.] Increase/decrease depends upon whether the alters want children or not. If the alter prefers having children, then an increase is exacted and vice versa.

2.2.2 Tie strength (ego-alter)

Ego-alter ties describe the relationship between the ego and all the different alters in the network. An important ego-alter characteristic is tie strength, which refers to how close individuals are or how frequently they meet. Strong ties are associated with social support, learning, pressure, and contagion, whereas weak ties are more likely to be associated with social learning (Carolan & Natriello, 2005; Keim, Klärner & Bernardi, 2013; Wellman & Wortley, 1990). In general, ties are stronger when they are older, more (emotionally) intense, and more intimate, when services are more reciprocated, and when contact is more frequent (Granovetter, 1973).

Most strong ties emerge and are maintained within dense and well-defined networks such as family or friendship networks. These networks are well-defined because it is clear who is part of the network. More strong ties within a network make it more likely for alters to adapt their behavior in accordance with ingroup norms. They are interpreted as more reliable and cause more peer pressure. Furthermore, more strong ties within a network are a source of more social support and learning (Kammrath et al., 2020), because individuals are more willing to learn from and receive support from their close alters than from more distant alters (Wellman & Wortley, 1990).

Weak ties mostly exist in less-connected networks or between alters of different networks (e.g., between neighbors, collogues, and teammates). Weak ties cause new (technological) information to spread from outside to inside the networks (e.g., information about contraception, a career, or the cost of children) (Granovetter, 1973).

Some research exists about the importance of tie strength in fertility behavior. More strong ties increase the likelihood of having (more) children because it facilitates *social support, social learning, social pressure, and social contagion* (Kavas & De Jong, 2020; Keim, Klärner & Bernardi, 2013; Sauer & Ellison, 2021). Many western women experience conflicting life goals such as making a career and having children. These women rely on others for (informal) support and care for their children to fulfill both goals (Bernardi and Kläner, 2014).

More strong ties help women with raising children since strong ties are interpreted as more reliable (*social learning*) and are associated with more frequent contact (*social support and contagion*) (Bernardi and Kläner, 2014). More frequent contact provides more opportunities to be emotionally influenced by the fertility behavior of alters (Chartrand & Bargh, 1999). Furthermore, more frequent contact increases the amount of support with raising children. This makes it easier for women to build both a career and start a family because they can allocate more time to investing in their careers (Bernardi and Kläner, 2014; Krämer, Sauer & Ellison, 2021). More strong ties also cause stronger ingroup norms (social pressure). This occurs when people conform to existing (group) norms to avoid conflict or to receive approval. Behavior that aligns with the group norms is enforced with a positive affirmation from network members, whereas the opposite will be punished. Strong ties often exist in close family networks and close family networks cause higher fertility rates (Alesina & Giuliano, 2007).

In addition to strong ties, weak ties are also considered important in fertility behavior, but for different reasons. Research about these types of ties is limited. To the best of my knowledge, the only type of social influence related to weak ties is *social learning* (Keim, Kläner & Bernardi, 2009). Weak ties are key for social learning because they provide new information that is less likely to be obtainable with strong ties (e.g., ideas of not having children or abortion) (Bernardi and Kläner, 2014). I expect that weak ties, through the spreading of novel ideas, cause the ego to want fewer children.

Previous research has clearly shown the importance of tie strength. Often in these studies, the focus was on the strength of one particular tie (e.g., closeness to parents, or partner). In this study, a wide array of tie strength variables are added to the statistical model (12 in total). An overview of all tie strength variables and hypotheses can be found in Table 2. In general, the expectation is that more strong ties in a network lead to higher fertility outcomes for the ego. The exception to this expectation is when more strong ties exist with alters that do not want a child.

Table 2: Shows an overview of the tie strength variables that are used for this study, the social mechanism per variable, the hypothesis that is tested per variable, and some key sources for every variable.

Tie strength (ego alter) variables			
Variable	Mechanism	Hypothesis	Sources
# Average closeness[1]	Social support	H2.1.1: *The closer the egos are with their alters, the more support they have available to raise children, which increases the ego's fertility outcomes.*	Bernardi & Kläner (2014); Sauer & Ellison (2021)
	Social contagion	H2.1.2: *The closer the egos are with their alters, the more opportunities they have to be emotionally influenced, which increases/decreases the ego's fertility outcomes.* [A]	Chartrand & Bargh (1999)
	Social learning	H2.1.3: *The closer the egos are with their alters, the more they can learn about having/not having children from a reliable source, the higher/lower the ego's fertility outcomes.*	Kammrath et al. (2020); Wellman & Wortley (1990)
	Social pressure	H2.1.4: *The closer the egos are with their alters, the more social pressure the ego's experience that stimulates traditional/modern family norms, the higher/lower the ego's fertility outcomes.* [A]	Alesina & Giuliano (2007)
# Average face-to-face contact	Social support	H2.2.1: *The more face-to-face contact the egos had with their alters, the more support they have available to raise children, which increases the ego's fertility outcomes.*	Bernardi & Kläner (2014); Sauer & Ellison, 2021
	Social contagion	H2.2.2: *The more face-to-face contact the egos had with their alters, the more opportunities they have to be emotionally influenced, which increases/decreases the ego's fertility outcomes.* [A]	Chartrand & Bargh (1999)
	Social learning	H2.2.3: *The more face-to-face contact the egos had with their alters, the more they can learn about having/not having children from a reliable source, the higher/lower the ego's fertility outcomes.* [A]	Kammrath et al., (2020); Wellman & Wortley (1990)
	Social pressure	H2.2.4: *The more f*ace-to-face contact *the egos had with their alters, the more social pressure the ego's experiences that stimulates traditional/modern family norms, the higher/lower the ego's fertility outcomes* [A]	Alesina & Giuliano (2007)
# Average non-face-to-face contact	Social support	H2.3.1: *The more non-face-to-face contact the egos had with their alters, the more support they have available on raising children, which increases the ego's fertility outcomes.*	Bernardi & Kläner (2014); Sauer & Ellison, 2021
	Social contagion	H2.3.2: *The more non-face-to-face contact the egos had with their alters, the more opportunities they have to be emotionally influenced, which increases/decreases the ego's fertility outcomes.* [A]	Chartrand & Bargh (1999)
	Social learning	H2.3.3: *The more non-face-to-face contact the egos had with their alters, the more they can learn about having/not having children from a reliable source, the higher/lower the ego's fertility outcomes.* [A]	Kammrath et al. (2020); Wellman & Wortley (1990)
	Social pressure	H2.3.4: *The more non-face-to-face contact the egos had with their alters, the more social pressure ego's experiences that stimulates traditional/modern family norms, the higher/lower the ego's fertility outcomes.* [A]	Alesina & Giuliano (2007)
# Average closeness alters with a child	Social support	*H2.4.1: The closer the egos are with alters with a child, the more support they have available to raise children, which increases the ego's fertility outcomes.*	Bernardi & Kläner (2014); Sauer & Ellison (2021)
	Social contagion	*H2.4.2: The closer the egos are with alters with a child, the more opportunities they have to be emotionally influenced, which increases/decreases ego's fertility outcomes.* [A]	Chartrand & Bargh (1999)
	Social learning	*H2.4.3: The closer egos are with alters with a child, the more opportunities to learn about having children from a reliable source, which increases the ego's fertility outcomes.*	Kammrath et al., (2020); Wellman & Wortley (1990)

[1] The definition of closeness in this study differs from the general definition of closeness within social network analysis (SNA) studies. In short, closeness in SNA is a statistical measurement, where the 'distance' between nodes is calculated. The sum of the length of the shortest paths between every node in a network is calculated. Nodes with shorter paths are more central in these networks. For this study, however, closeness describes the ego-alter relation (i.e., how strong their relation is perceived by the ego).

	Social pressure	*H2.4.4: The closer the egos are with alters with a child, the stronger the traditional family values within the network, which increases the ego's fertility outcomes.*	Alesina & Giuliano (2007)
# Average closeness alters that want a child	Social pressure Social learning	H2.5.1: *The closer the egos are with alter that want children, the more the idea about having children spreads, which increases the ego's fertility outcomes.* *H2.5.2.: The closer egos are with alters that want a child, the more opportunities to learn about having children from a reliable source, which increases the ego's fertility outcomes.*	To the best of my knowledge, no previous study has explored this relationship.
# Average closeness alters that do not want a child	Social pressure Social learning	H2.6.1.: *The closer the egos are with alter that do not want children, the stronger non-natal values within the network, which decreases the ego's fertility outcomes.* *H2.6.2: The closer egos are with alters* that do not want a child*, the more opportunities to learn about having children from a reliable source, which decreases the ego's fertility outcomes.*	To the best of my knowledge, no previous study has explored this relationship.
# Average face-to-face contact alters with child	Social support Social contagion Social learning Social pressure	H2.7.1: *The more face-to-face contact the egos have with alters with children, the more support they have available to raise children, which increases the ego's fertility outcomes.* H2.7.2: *The more face-to-face contact the egos have with alters with children, the more opportunities they have to be emotionally influenced, which increases/decreases the ego's fertility outcomes.* H2.7.3: *The more f*ace-to-face contact the egos have with alters with children*, the more they can learn about having/not having children from a reliable source, the higher/lower the ego's fertility outcomes*. [A] H2.7.4: *The more face-to-face contact the egos have with alters with children, the more social pressure the ego's experience that stimulates traditional/modern family norms, the higher/lower the ego's fertility outcomes.* [A]	Bernardi and Kläner (2014) Sauer & Ellison, 2021 Chartrand & Bargh (1999) Kammrath et al., (2020); Wellman & Wortley (1990) Alesina & Giuliano (2007)
# Average face-to-face contact alters that want a child	Social learning	H2.8: *The more face-to-face contact the egos have with alters that want a child, the more the idea about having children spreads, which increases the ego's fertility outcomes.*	To the best of my knowledge, no previous study has explored this relationship.
# Average face-to-face contact with alters that do not want a child	Social pressure	H2.9: *The more face-to-face contact the egos have with alters that do not. want children, the stronger non-natal values within the network, which decreases the ego's fertility outcomes.*	Keim, Klärner, & Bernardi, (2013).
# Average non-face-to-face alters contact with a child	Social support Social contagion Social learning Social pressure	H2.10.1: *The more non-face-to-face contact the egos have with alters who have children, the more support they have available to raise children, which increases the ego's fertility outcomes.* H2.10.2: *The more non-face-to-face contact the egos have with alters who have children, the more opportunities they have to be emotionally influenced, which increases/decreases the ego's fertility outcomes.* [A] H2.10.3: *The more non-face-to-face contact egos have with alters who have children, the more they can learn about having/not having children from a reliable source, the higher/lower ego's fertility outcomes*. [A] H2.10.4: *The more non-face-to-face contact egos have with alters who have children, the more social pressure ego's experience that stimulates traditional/modern family norms, the higher/lower ego's fertility outcomes*. [A]	Bernardi & Kläner (2014) Sauer & Ellison, 2021 Chartrand & Bargh (1999) Kammrath et al., (2020); Wellman & Wortley (1990) Alesina & Giuliano (2007)
# Average non-face-to-face contact with alters that wants a child	Social pressure	H2.11.1: *The more non-face-to-face contact the egos have with alters that want a child, the more the idea about having children spreads, which increases the ego's fertility outcomes.*	To the best of my knowledge, no previous study has explored this relationship.

	Social learning	*H2.11.2: The more non-face-to-face contact the ego has with alters that wants a child, the more opportunities to learn about having children from a reliable source, which increases the ego's fertility outcomes.*	
# Average non-face-to-face contact with alters that do not want a child	Social pressure	H2.12: *The more non-face-to-face contact the egos have with alters that do not want children, the stronger non-natal values within the network, which decreases the ego's fertility outcomes.*	To the best of my knowledge, no previous study has explored this relationship.

[A.] If this causes an in- or decrease depends on the ingroup norms. If these norms favor more traditional family values, it will increase the ego's fertility outcomes and vice versa.

2.2.3 Density (alter-alter ties)

Network density refers to the proportion of ties that exist out of all potential ties that can exist within a defined network. The higher the proportion, the higher the density. In ego-centric networks, it is typically the ties between alters excluding ego that are assessed for density. It is generally thought that higher levels of density are related to conformity to norms and peer pressure where the alters influence the ego collectively (Bloodgood et al., 2017; Bienenstock, Bonacich & Oliver, 1990). Alters from a dense network punish other members that do not conform to dominant ingroup norms (Bienenstock, Bonacich & Oliver, 1990). Coordinating punishment is easier for network members within denser networks since they interact more compared to people in lesser dense networks (Lois, 2016). Whether conformity and peer pressure cause an increase or decrease in fertility outcomes depends on the prevailing ingroup norms and the composition of the network (e.g., the number of alters that do not want children). In other words, the composition of the network and ingroup norms cause the direction of the push (i.e., pro- or anti-natal norms), where density accommodates the force of this push.

Earlier studies on the influence of network density on fertility behavior are in accordance with this last statement. Stulp & Barrett (2021), for example, found evidence that density amongst kin increased the perceived pressure of pro-natal behavior the ego experiences (Stulp & Barret, 2021). Higher kin density facilitates more opportunities for the ego to learn about other parents' experiences and knowledge because of the intensity and frequency of contact (Kohler, Behrman & Watkins, 2001). Density adds extra pressure to enforce this norm that is associated with kin. Increased accessibility to social support and information about raising children helps to enforce traditional family norms resulting in increased fertility behavior. Furthermore, the study of Kohler, Behrman & Watkins (2001) found evidence for the influence of ingroup norms on fertility behavior. When there is an ingroup norm that is positive towards contraception within a denser network, it will be more likely that the ego's opinion will become (even) more positive about contraception (Kohler, Behrman & Watkins, 2001).

My expectation as to what impact density will have on fertility behavior depends upon the density among particular groups. For example, higher kin density is associated with traditional family values and is therefore expected to cause an increased ideal family size. Density among alters that do not want a child, on the other hand, would cause a smaller ideal family size. An overview of all density variables and hypotheses can be found in Table 3.

Table 3: Shows an overview of the density variables that are used for this study, the social mechanism per variable, the hypothesis that is tested per variable, and some key sources for every variable.

Density (alter-alter-ties) variables			
Density variable	Mechanism	Hypothesis	Sources
# Density among alters	Social support Social pressure	H3.1.1: *Denser networks provide more support to raise children, which increases the ego's fertility outcomes.* H3.1.4: *Denser networks can apply more pressure to conform to pro- or anti-natal norms, which increases/decreases the ego's fertility outcomes.* [A]	Stulp & Barrett, 2021; Kohler, Behrman & Watkins, 2001 Stulp & Barrett, 2021
# Density among friends	Social support Social pressure	H3.2.1: *Higher density amongst friends within ego's network provides more support to raise children, which increases the ego's fertility outcomes.* H3.2.4: *Higher density amongst friends within ego's network can apply more pressure to conform to pro- or anti-natal norms, which increases/decreases the ego's fertility outcomes.* [A]	To the best of my knowledge, no previous study has explored these relationships.
# Density among alters with children	Social pressure	H3.4: H*igher density amongst alters with children, the more social pressure on ego that stimulates traditional/modern family norms, the higher/lower the ego's fertility outcomes.* [A]	To the best of my knowledge, no previous study has explored this relationship.
# Density among alters that want a child	Social pressure	H3.4: *Higher density amongst alters that want a child, means stronger pro-natal norms within the network, which increases the ego's fertility outcomes.*	To the best of my knowledge, no previous study has explored this relationship.
# Density among alters that do not want a child	Social pressure	H3.5: *Higher density amongst alters that do not want children, means stronger non-natal norms within the network, which decreases the ego's fertility outcomes.*	To the best of my knowledge, no previous study has explored this relationship.
# Density among alters that you can talk to about having children	Social learning Social pressure	H3.6.1: *Higher density amongst alters that the ego can talk to about having children, means that ego can learn more about having/not having children, which increases/decreases the ego's fertility outcomes.* [A] H3.6.2 *Higher density amongst alters that the ego can talk to about having children, means that the ego experiences more social pressure that stimulates traditional/modern family norms, which increases/decreases the ego's fertility outcomes.* [A]	To the best of my knowledge, no previous study has explored these relationships.
# Density among alters that can help you with raising a child	Social support Social learning Social pressure	*H3.7.1: Higher density among alters that can help you raise a child, means they have more support available to raise children, which increases the ego's fertility outcomes.* H3.7.2: *Higher density among alters that can help you with raising a child, means t they can learn more about having children, which increases the ego's fertility outcomes.* H3.7.3 *Higher density amongst alters that the ego can talk to about having children, means they experience more social pressure that stimulates traditional norms, which increases the ego's fertility outcomes.* [A]	To the best of my knowledge, no previous study has explored these relationships.

[A.] Increase/decrease depends on whether the alters want children. If the alters prefer having children, then an increase is exacted and vice versa.

2.3.1 Data-driven approach to studying the social influence on fertility outcomes

This chapter ends by explaining the theory behind the methodological approach in this study. This study uses a data-driven approach instead of the more commonly used theory-driven approach (Maass et al., 2018; Yarkoni & Westfall, 2017).

Data-driven research is an approach to identifying knowledge gaps. It is a type of exploratory research where insights are extracted from the data by using sophisticated analytical techniques and usually relies on large and complex datasets. Data-driven research uses a wider scope that considers more potential causal relations, often a thinner theoretical base and more general expectations instead of clear-cut hypotheses. The advantage of this approach is that it can uncover unknown insights by identifying patterns from the complex analysis of these large datasets. These insights can be used for new studies and theory building (Maass et al., 2018).

Theory-driven research is an approach to identifying research gaps. The scope of this approach is more narrow and begins with clear-cut hypotheses that are based on existing theories and abstract constructs. These hypotheses are tested by analyzing data that is collected for testing these hypotheses. This is followed by drawing theoretical conclusions on the results which help to extend knowledge of existing theories (Maass et al., 2018).

An important element of this study is to fill in knowledge gaps, hence a data-driven approach is used. Therefore, the hypotheses of this study are more general expectations of the effects I expect between the independent and dependent variables (Maass et al., 2018).

2.3.2 Pitfalls of traditional statistical methods and how data-driven techniques can overcome them

Theory-driven research when done properly, is a powerful tool to amass new knowledge and further theorizing. When done improperly, it can produce misleading, incomplete, or questionable findings, which can lead to frail theory building. Furthermore, it may have contributed to the replication crisis that has taken hold in several disciplines including the social sciences (Aerts et al., 2015; Dreber & Johannesson, 2019). In short, the replication crisis refers to the observation that many findings from empirical research do not replicate when studies are repeated (Aerts et al., 2015). Being able to replicate earlier studies is key to validating earlier scientific claims (Dreber & Johannesson, 2019). Various reasons have been proposed to explain the causes of the replication crisis such as the pressure of the publishing culture (Martin & Clarke, 2017) and questionable research practices (Wicherts et al., 2016). However, one of the more important causes is thought to be the improper use of inferential statistics and the heavy reliance on p-values and significance (Wicherts et al., 2016). Data-driven research has been suggested as one solution to overcome this crisis (Yarkoni & Westfall, 2017). Below I will explain three limitations in the common statistical practice that has contributed to the replication crisis, and how a data-driven approach may alleviate these problems.

First, in the traditional theory-driven approach, typically only a limited number of variables are included in the statistical model (Yarkoni & Westfall, 2017). This limitation is often set by the theoretical model (Cash, 2018). Even when these methods are applied well and the analysis indicates strong and significant results, the fitted model can be biased and missing crucial other variables, leading to underfitting (this term refers to statistical models that are too “simple” to accurately capture the underlying structure/complexity of the data, which causes poor predictive performance and high bias) (Hastie et al., 2009).

Machine learning, and LASSO regression in particular (the method I used for this thesis), helps to overcome the issue of underfitting and offers comprehensible output even when many variables are used in the model (Roth, 2004). LASSO regression can include many variables (even more variables than cases, which is not possible in ‘ordinary’ regression), thereby preventing underfitting. Moreover, LASSO regression leads to interpretable models with few variables, because only the strongest variables (in terms of predictive ability) are kept in the model, and variables with little to no influence are excluded (see below for more information on LASSO regression in paragraph 2.3.3.) (Roth, 2004).

Second, a common issue with more traditional statistical models is overfitting (Yarkoni & Westfall, 2017). This occurs when a model becomes too aligned with the training dataset, capturing not only the “true” underlying patterns but also “noise” (i.e., random or irrelevant variations, outliers, or errors) (Hawkins, 2004). The model fits to this “noise” present in the training data, which can lead to poor generalization and predictive performance on new, unseen data (Bisho & Nasrabadi, 2006). This issue is caused by the principles in which these models work. The goal of a statistical model is to minimize the sum of squared errors (SSE; the difference between a model prediction and the real outcome) between its predictions and the actual outcomes in the training sample. However, this can make the model overly attuned to the specific and unique noise of that sample. Since this noise is unique to that sample, it will not occur in a different sample drawn from the same population (that will have different ‘noise’) and therefore produce overly optimistic results (Coolen et al., 2020.

In contrast to traditional statistical models, machine learning models offer techniques to mitigate overfitting. (McNeish, 2015). An important difference between both methods is the way in which the models are validated. Traditional models estimate and validate the model on the same sample of the population, while machine learning models are validated on a different sample Cross-validation is an effective technique used in machine learning to accomplish this without requiring new data. It involves randomly splitting the existing data into 'training' and 'test' sets, where the test set serves as unseen data for validating the model trained on the training set (Ghojogh & Crowley, 2019; Yarkoni & Westfall, 2017; Ranstam & Cook, 2018).

However, this approach comes with the drawback of potentially losing a large proportion of the dataset, as one part is used for training and the other for testing the model. A method that overcomes this issue is k-fold cross-validation (CV), where the training and validation process is repeated several times on the same data. The number of folds, defined as K, determines the number of subsets the data is divided into. The choice of K can be made manually or automatically determined by statistical programs to find the most optimal model. In k-fold CV, each subset or 'fold' is used as a test set once, while the remaining folds are used as training data (see Figure 1). After estimating the model on all folds, the average performance across all folds is measured and quantified.

The advantage of k-fold cross-validation is that it maximizes the utilization of the same sample for training and validation, thereby increasing the amount of data available for both. Moreover, it helps prevent overfitting by optimizing the model's performance on out-of-sample prediction rather than in-sample prediction. In the latter case, variables may have been fine-tuned to specific noise present in the sample (Ghojogh & Crowley, 2019; Ranstam & Cook, 2018). Figure 1 illustrates an example of 5-fold cross-validation.

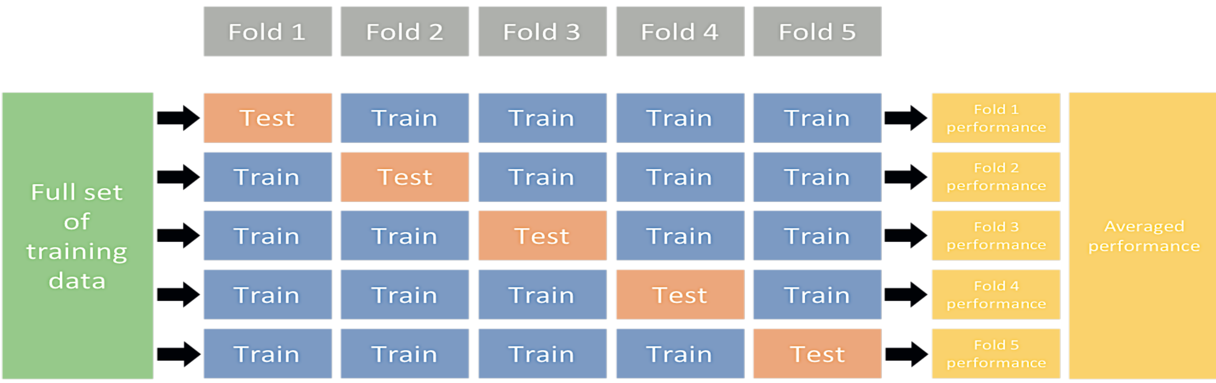

Fig 1. The green block indicates the full sample size. The grey block shows all five folds that were drawn from the full sample size. The orange and blue blocks indicate which data is allocated to train (blue) and test (orange) data. The five small yellow blocks indicate the model performance of the four training and one test set. The large yellow block shows the overall performance of these five estimated folds (Boehmke & Greenwell, 2019).

A third way in which data-driven research may overcome some of the issues of theory-driven research relates to the way most traditional social studies are conducted that facilitate opportunities for “p-hacking” (Wichers et al., 2016). A common way to do statistics is to set up two hypotheses: the null and the alternative. A statistical test aims to assess how probable a given sample result is under the null hypothesis, and when this probability is below a particular threshold (often 0.05), a “significant” result is found and the researcher reports evidence for the alternative hypothesis. Due to many decisions, researchers have to make in data analyses (e.g., restricting sample, removing outliers, choice of statistical technique), finding a p-value below 0.05 is not hard (Simmons, Nelson & Simonsohn, 2011). Given that many journals prefer novel findings (the alternative hypothesis) over null findings (the null hypothesis), researchers may, consciously or not, engage in “p-hacking” to get the desired significant result (Stefan & Schönbrodt, 2023).

Machine learning helps to avoid p-hacking (Hildebrandt, 2018). This is because of the explorative nature of machine learning versus the explanatory nature of more traditional statistical models. Moreover, within machine learning the focus is more on effect size (namely predictive power) rather than on the direction and magnitude of estimates of single variables. Additionally, the step of cross-validation in and of itself prevents p-hacking, because while p-hacking may work on a single sample, it will fail when the p-hacked results need to be used to make predictions in a different sample (Hildebrandt, 2018).

2.3.3 LASSO Regression

There are several branches of data-driven methods. I used LASSO regression, which is a regularization method. This method works similarly to a more ‘traditional’ Ordinary Least Squared error (OLS) equation. OLS models assume there is a linear relation between the independent variables and the dependent variable. Furthermore, it aims to find an equation that minimizes the sum squared error (SSE) between the predicted and the observed outcome. Equation 1 demonstrates the equation of an OLS model.

Equation 1: Ordinary Least Square regression

$$(1)\ Minimize \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

Equation 2: LASSO

$$(2)\ Minimize \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 + \lambda \sum_{j=i}^{\rho} |\, \beta_j \,|$$

LASSO regression adds a penalty term to the equation of OLS (see equation 2). This penalty is a function of the magnitude of the coefficient and effectively constrains the size of the coefficients. This has two advantages. First, it increases the predictive accuracy by resolving the bias-variance tradeoff differently. Traditional OLS is focused on minimizing bias, at the expense of a higher variance. Bias refers to the difference between the average predicted value versus the actual value that the model tries to predict. Models with high bias underfit the data because they are unable to capture the relation between the dependent and independent variables. Variance refers to the variability of a model's predictions for a particular data point. Models with a high variance may focus too much on particular patterns in the training dataset and overfit the data. Models with a low bias but high variance perform well in the training data and poorly in the test data. Both phenomena are depicted in Figures 2 and 3.

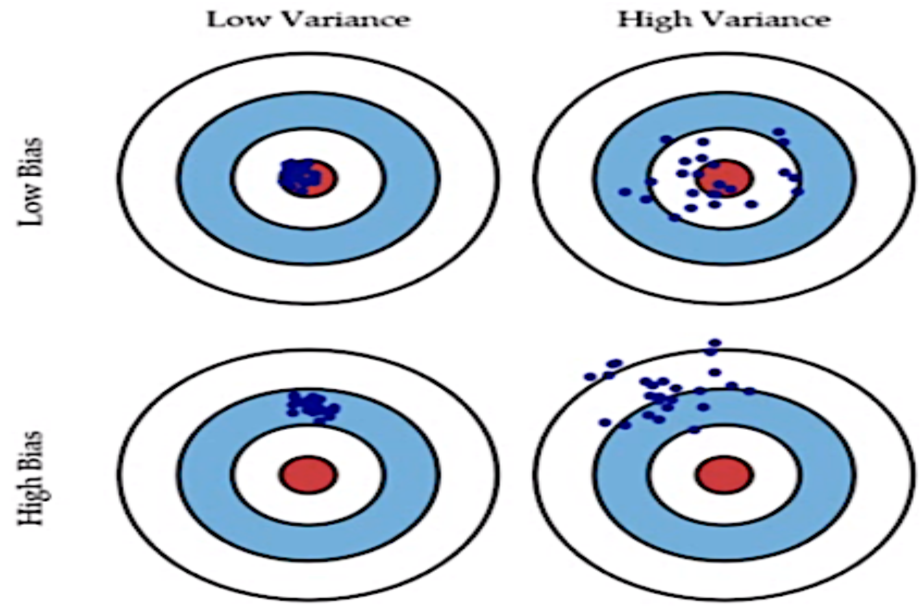

Figure 2: shows an overview of the bias and variance. Models with a high bias cause consistent, but inaccurate prediction. Models with a high variance cause accurate (on average), but inconsistent predictions (Ankitapaunikar, 2018).

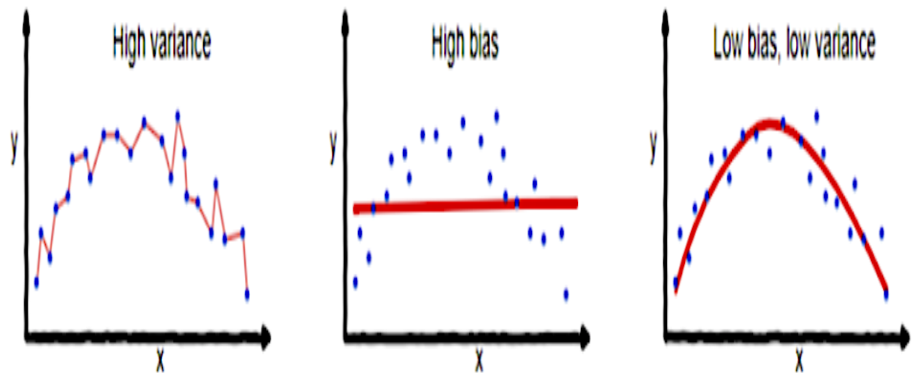

Figure 3: shows three different models. The left model is considered to have low bias but high variance because the model is unlikely to do well in a different sample and one data point has a large effect on model estimates. The model in the middle is said to have low variance and high bias (and can be an example of underfitting); excluding one data point would not change the model much, but the model would do poorly in a different sample because it is under fitted. The model on the right strikes a better balance between bias and variance (Geeksforgeeks, 2023).

Second, incorporating a penalty on the magnitude of coefficients in a regression model helps generate sparse models, which contain fewer variables. Sparse models are easier to interpret compared to models that retain a large number of variables. When the number of independent variables is relatively high compared to the sample size, ordinary least squares (OLS) regression often produces a model with low bias that includes all independent variables (i.e., coefficients are estimated for all variables). However, this also means that variables with high multicollinearity (high correlation among independent variables) are retained in the model, making the interpretation more complicated (Cohen et al., 2013). On the other hand, LASSO regression can handle more variables than cases because the penalty term in the estimation procedure forces some coefficients to be pushed close to zero or exactly zero. As a result, variables with little to no influence on the dependent variable, or those exhibiting high multicollinearity, are filtered out. This leads to a model with a relatively small number of variables that have substantial effects on the predictive ability (Yarkoni & Westfall, 2017). Furthermore, if there is high multicollinearity between variables, LASSO regression tends to select one variable while shrinking the coefficients of others towards zero (Yarkoni & Westfall, 2017). In summary, LASSO regression allows for more interpretable models by retaining a reduced set of variables with relatively larger effects, filtering out variables with little influence or high multicollinearity.

The impact of the penalty on estimates becomes evident in the relationship between the penalty term and the number of estimates pushed to zero, resulting in their exclusion from the final model (Friedman, Hastie & Tibshirani, 2010; Wickham & Grolemund, 2016). This relationship is illustrated in Figure 4, which showcases one of the estimated models from the analysis presented in the results section. The x-axis represents the penalty term (λ; see equation 2), while the y-axis signifies the magnitude of the regression estimate, which can be interpreted as a standardized beta weight. It should be noted that all variables need to be standardized in LASSO regression. Each colored line in the graph represents the estimated magnitude of one independent variable. As the penalty term (λ) increases, more estimates are shrunk towards zero, resulting in the filtering out of these variables from the final model. A low penalty term implies a minimal penalty on the estimated magnitudes, leading to models that resemble ordinary least squares (OLS) regression. Conversely, a high penalty term imposes a substantial penalty on the magnitudes, producing models with no variables. The left dotted line indicates the 'optimal' lambda value, which corresponds to the penalty term that maximizes out-of-sample predictive accuracy. Meanwhile, the right dotted line represents the lambda value within one standard error of the 'optimal' lambda in terms of predictive accuracy.

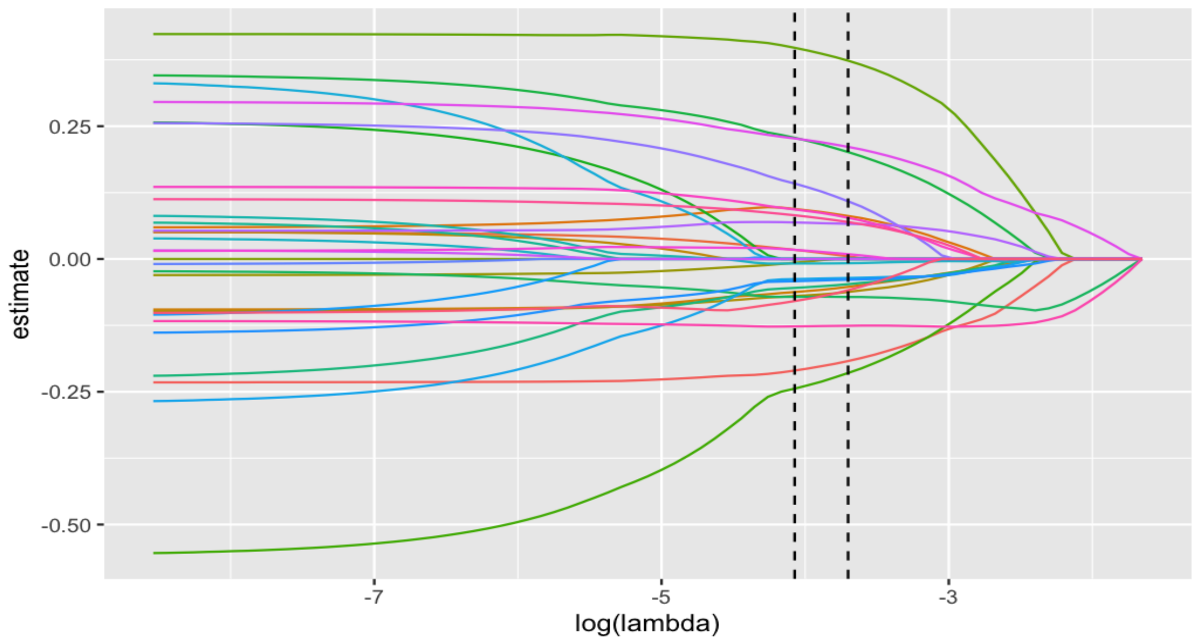

Figure 4: shows an example of the analysis of Model 4D from this study. The x-axis represents the penalty term lambda, the y-axis the magnitude of the estimate, and the colored lines indicate all 31 independent variables that were used in this model. The left dotted line indicates the 'optimal' lambda that leads to the highest out-of-sample predictive accuracy and the right dotted line indicates the lambda that is within one standard error of the 'optimal' lambda in terms of predictive accuracy (see section 2.3.4 for further explanation).

2.3.4 Estimating the penalty (lambda) in LASSO

Estimating the optimal value of lambda (λ) is crucial, as highlighted in the previous paragraph. I used the K-Fold cross-validation method to accomplish this (Friedman, Hastie & Tibshirani, 2010; Wickham & Grolemund, 2016). I refer to 2.3.3. Pitfalls of traditional statistical methods for a full explanation of this method. In short, this method involves splitting the sample into "training" and "test" data and repeating the process k times. I used ten folds (k = 10) for analysis in this study. The overall model performance was assessed in the training set by calculating the average test performance across all folds, using the Mean Squared Error (MSE) as a measure.

The second step of LASSO regression entails running the models using the lambda values obtained from cross-validation. The lambda selected through this process becomes the LASSO penalty incorporated into the equation. For instance, the value of this λ for model 4D is 0.025. Figure 5 shows an example of the estimation of lambda (for model 4D; see methods). The left-dashed line represents the lambda that leads to the lowest (average) prediction error (a value of 0.025 in this case).

Friedman and colleagues (2010) recommend using the λ that is within one standard error above the optimal lambda as a rule of thumb. Using the 1SE λ increases the bias compared to using the optimal λ, but improves the flexibility of this model (Friedman, Hastie & Tibshirani, 2010). Furthermore, the model performance (measured by MSE) remains strong compared to other λ

values. This 1SE λ is represented by the right dotted line in Figure 5. Figure 5 clearly shows that a higher lambda (some penalty) improves predictive ability relative to a linear regression model (the predictive ability of the lowest model visualized), but that very high lambda (when coefficients are more constrained and more coefficients are pushed toward 0) decreases predictive ability.

After the optimal lambda is found (1SE λ) through cross-validation, a LASSO regression is run with this optimal lambda (resulting in Figure 4). Figures 4 and 5 together demonstrate how LASSO regression produces more sparse models because more variables are filtered from the model without coming at a cost of predictive ability.

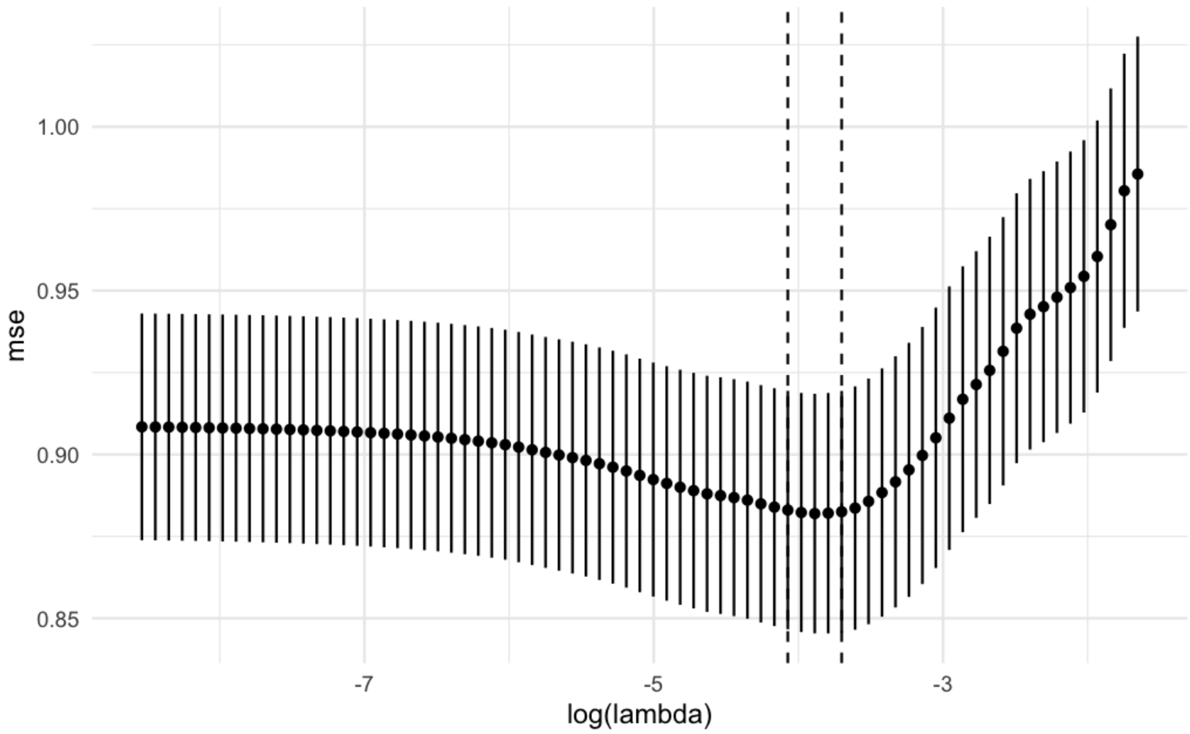

Figure 5: Retrieving the ideal Lambda for model 4D. The two vertical dashed lines are key. The first line shows the optimal λ with the lowest MSE whereas the second dashed line represents the largest value of λ within one SE of the lowest MSE. The value of the minimum $\lambda = 0.025$ and the 1SE $\lambda = 0.191$.

3. Method

The method chapter is divided as follows. First, the description of the research design and procedure of the used dataset is presented. Second, the variables from the analysis are described. And finally, the analytical strategy is described.

3.1 Description of research design and procedure

The dataset used for this study is called "*Social networks and fertility survey*" (Stulp, 2021). This dataset is collected by CentERdata from Tilburg University in The Netherlands through the LISS (Longitudinal Internet Studies for the Social Sciences) panel. A representative probability sample was drawn from households who were registered in The Netherlands by the Central Bureau for Statistics (CBS). Selected households were asked to participate in ten core surveys about an array of topics such as work, education personal values, and more.

Through the LISS panel, researchers can collect their own data within the panel. The dataset I used was designed to study the social influences of personal networks on fertility opinions, ideas, and outcomes. The selected women for the LISS panel (N=1332) were between 18 and 40 years of age. They were approached between the 20th of February and 27th of March in 2018. From this selection, 758 participated and finished the survey. 66 women who did not participate, opened the link to the survey but never finished it. Another 7 women indicated reasons for not participating such as being too busy or on vacation. The rest of the 501 participants gave no reason why they did not participate. There were no demographic differences between participants and non-participants (Stulp, 2020).

Every participant was asked to list exactly 25 people in their network whom they had contact with. The participant is the ego and the listed people are defined as the alters. This means that the dataset consists of 758 networks of 26 people (the ego plus their network of 25 alters). The participants were asked to fill in a variety of questions about the alters such as the number of children they had, what their level of education was, or whether they wanted children.

3.2 Operationalization variables

All variables will be categorized into levels of the ego (respondent), variables about composition (alter attributes), tie strength (ego alter ties), and density (alter-alter ties). This paragraph describes per category (i.e., ego, composition, tie strength, and density) the process of how the corresponding variables were constructed and their descriptive statistics. The process of operation per category and variable is summarized in Table 4 and the descriptive statistics of every variable are presented in Table 5.

Women who did not name 25 alters and that gave problematic answers were removed from the sample (Stulp & Barrett, 2021). Furthermore, respondents that replied to the dependent variable (see below) with “I don’t know” were removed from the sample because the used analytical methods required numerical input. This left 637 respondents. Sample sizes were reduced further by the inclusion of network variables. See section 3.3 The analytical strategy for further consideration of the sample size

Table 4: This table shows an overview of all four categories, the corresponding variables, the question respondents were asked, the answer options they had, and the answers used for this study.

Variable	Question	Answer options survey	Answers used for analysis
# Ideal family size (dependent)	How many children would you like to have? This is including the X children you already have.	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, More than 10 and I don't know	0, 1, 2, 3, 4, 5, 6, 7, 8*
Ego			
# Age	What is your year of birth?	Year of birth	Age is centered around 29
# Has a partner	Do you currently have a partner? By a partner, we mean somebody that you are in a relationship with for over three months. Husbands are also considered partners.	0. No 1. Yes	0. No 1. Yes
# Has children	Do you have children? We mean both your biological children (together with your partner or a previous partner) as well as your stepchildren, adopted children, and foster children.	0. No 1. Yes	0. No 1. Yes
Composition (alter-attributes)			
# Women	Who of these people are men?	1. Men 2. Women	0. Women 1. Men
# Friends	Which of these people do you consider a friend?	1. Is a friend 2. Not a friend	0. Not a friend 1. Is a friend
# Kin	What is your relationship with PERSON A or how do you know him/her? Multiple answers are possible!	1, This is my partner; 2. Father/Mother 3. Brother/Sister 4. Other relative (for example uncle/aunt, cousin) 5. Relative of partner 6. Acquaintance/friend of partner 7. From primary school 8. From high school; 9. From college/university 10. From work 11. From a social activity (sports, hobby, church) 12. Through a mutual acquaintance/friends 13. From the neighborhood 14. Other, namely: ...	0. Non-kin [a] 1. Kin
# Higher educated	What is the highest level of education these people have completed?	1. Primary school or hasn't finished primary school 2. High-school diploma (or a similar diploma) 3. Secondary vocational education (or a similar diploma) 4. Higher vocational education (or a similar diploma) 5. University degree or higher (or a similar diploma)	0. Non-higher education 1. Higher education
# Alters with child	Which of these people have children or are currently expecting a child?	1. "Ja" means has a child or is expecting a child 2. "Nee" means does not have a child.	0. Does not have a child 1. Has a child or is expecting a child
# Alters that want a child	From which individuals do you know that they would like to have children?	1. Would like to have children 2. Don't know whether individual does wants children or not	0. Don't know whether individual wants children or not 1. Would like to have children
# Alters that do not want a child	From which individuals do you know that they would not like to have children?	1. Would not like to have children 2. Don't know whether individual does not want children.	0. Don't know whether an individual does not want children 1. Would not like to have children

# Alters who can help to take care of the child	If you have a child or if you would have child in the future, which of these individuals could you ask for help with the care of the child (for example, by babysitting)?	1. Yes 2. No	1. Yes 0. No
# Talk with alter about children	With whom of these individuals do you discuss having children?	1. Yes 2. No	1. Yes 0. No
Tie strength (ego-alter)			
# Average closeness	How close are you to these people?	1. Very close 2. Close 3. Somewhat close 4. Not close 5. Really not close	1. R Really not close 2. Not close 3. Somewhat close 4. Close 5. Very close
# Average face-to-face contact	How often do you have face-to-face contact with these people?	1. Daily 2. A couple of times per week 3. A couple of times per month 4. About once a month 5. A couple of times per month or less	1.A couple of times per month or less 2. About once a month 3. A couple of times per month 4. A couple of times per week 5. Daily
# Average non-face-to-face contact	How often do you have contact with these people through other ways than face to face, for instance through (mobile) phone, letters, email, chat, sms, and other forms of online and offline communication?	1. Daily 2. A couple of times per week 3. A couple of times per month 4. About once a month 5. A couple of times per month or less	1.A couple of times per month or less 2. About once a month 3. A couple of times per month 4. A couple of times per week 5. Daily
Density (alter-alter)			
# Density	With whom does PERSON X have contact? With contact we mean all forms of contact, including face-to- face contact, contact via (mobile) phone, letters, emails, texts, and other forms of online and offline communication.	PERSON X knows. "2, 3, 5, 15" means that Person X knows alter 2, 3, 5, en 15.	

[a.] non-family (0) consists of nr. 5, 6, 7, 8, 9, 10, 11, 12, 13 and 14. Family (1) consists of nr. 1,2,3 and 4.

[b.] non-higher education (0) consists of 1, 2, and 3. Higher education consists of 4 and 5.

* Eight is the highest number of children that was reported by the respondents.

3.2.1 Ego variables

I created four characteristics about the respondent that were not related to the network. These were the dependent variable 'ideal family size' and the independent variables "*age*", "*having a partner*", and "*has a child*". The three independent variables are chosen because previous research shows they have a strong impact on ideal family size (Delbaere, Verbiest & Tydén, 2020; Ajzen & Klobas, 2013; Sobotka & Beaujouan, 2014). The inclusion of these ego-level variables also allows a quantification of the relative strength of ego variables versus the different network variables. See Table 4 for the operationalization of these four variables.

The average age of the egos is 29 (SD = 1). The proportion of egos who reported being in a relationship is 70%. Out of all the egos, 40% of them reported having at least one child. This aligns with the population of The Netherlands since CBS has reported that 43% reported having children at the age of 30.

Finally, the average number of children the egos reported is 2.3 (SD = 0.99). To the best of our knowledge, there are no statistics available about the ideal number of children of Dutch women. The NJI (Dutch Institute for Youth) reports that the average number of children Dutch women have is around 1.62, but their ideal family size may differ (Cijfers over geboorte|Nederlands jeugdinsituut, 2023).

3.2.3 Composition (alter-attributes) variables

The first category of network variables is composition. Every variable was modified to a dummy variable where (0) means a negative response and (1) a positive response (see Table 4). The average network value of a particular variable was calculated by the proportion of positive responses. The average for the entire sample (see Table 5) was calculated by the averages of all networks combined.

I will present an example of how the average proportion of kin in a network was calculated. Respondents were asked to indicate for every 25 alters how they know him/her. They could indicate an array of answers (1-14). Answers 2, 3, and 4 indicate this alter was kin and is therefore computed into 1, where the other answer category were recorded as 0. The proportion of kin per network was calculated and included in the statistical models. Table 5 shows the average across all these proportions of kin across networks. This was done for all nine compositional variables. None of these variables had missing values.

3.2.4 Tie strength (ego-alter) variables

The second category of network variables is tie strength. I divided them into three 'core' tie strength variables. The first variable measures the ego's average perception of how close they are to their alters (average closeness). The second and third variables are the average amount of contact (average face-to-face contact and average non-face-to-face contact). The remaining nine variables are a combination of the 'core' tie strength variables and three specific groups of alters (i.e., alter has a child, alter wants a child, and alter does not want a child). The operationalization of these variables can be found under the composition in Table 4. To summarize this, there are four variables of all three 'core' variables (e.g., average closeness, average closeness alters with a child, average closeness alters that want a child and average closeness alters that do not want a child).

The respondent was asked to indicate per 'core' variable how close they thought they were (or how frequent their contact was) with all twenty-five alters in their network (see Table 4 for all questions and answer options). The answer options ranged between one to five and were computed in a way where a higher number indicates a stronger tie. The average closeness of all twenty-five ties between the ego and the alters was calculated per network and included as a variable in the analyses. With the combined variables (e.g., average closeness alters with a child consisting of a combination of a tie strength variable (average closeness) and a compositional variable (alter with a child), the average closeness of the combination tie strength variables was calculated. Again, the average per ego network was calculated followed by an average of all networks. Table 5 presents the average of all tie strength variables across all networks and other descriptive statistics.

The tie strength variables cause a large number of missing values (N = 216). This is caused by the tie strength variables that were combined with "alters that do not want children". Many respondents did not mention any alters who did not want to have children. Tie strength amongst alters who do not have children can only be calculated when the ego reported any alters that did not want to have children.

3.2.5 Density (alter-alter) variables

The final category of network variables was density. The way these variables are constructed is similar to tie strength, but here only one 'core' variable is used (i.e., density). See Table 4 for the question-and-answer options that were used to construct the density variables.

The first variable was density among all others, whereas the other six variables referred to 'density' among friends, among alters with children, among alters that want a child, among alters that do not want a child, among alters that you can talk to about having children and among alters that can help you with raising a child).

I will use "*density among friends*" to demonstrate an example of how density was calculated in combination with other variables. For this variable, all existing ties relative to the possible ties among alters who are indicated as 'friend' within an ego network was calculated. Followed by calculating the average value of all networks. This process was repeated with the remaining density variables.

The density variables caused the largest number of missing values with a total of 379. This was mostly caused by the variable "*Density among alters that do not want a child*" because many respondents did not mention any alters that did not want to have children, and density can only be calculated among two or more alters.

Table 5: Show an overview of the network elements, the variables of these elements, the descriptive statistics of all variables, and the reduction they caused which is defined by N.

Outcome	**Mean (SD) /Proportion**	**Min**	**Max**	**N**
Ideal family size (dependent)	2.3 (1.01)	0	8	637
Ego				
Age 29	29.0 (1.00)	27.27	30.84	637
Ego has a partner (0 = no, 1 = yes)	70% has partner 30% no partner	0	1	637
Ego has a child (0 = no, 1 = yes)	40% Has child 60% has no child	0	1	637
Composition (alter-attributes)				
Women	16.2 (3.14)	6	25	637
Friends	10.5 (5.23)	0	25	637
Kin	9.5 (4.50)	0	23	637
Higher educated	12.0 (6.52)	0	25	637
Alter with a child	10.4 (6.85)	0	25	637
Alter wants child	4.8 (4.67)	0	25	637
Alter does not want a child	1.4 (1.77)	0	23	637
Alter who offer help	9.0 (5.29)	0	25	637
Talk with alter about children	7.1 (5.95)	0	25	637
Tie strength (ego-alter)				
Average closeness	3.5 (0.48)	1.52	5	421
Average face-to-face contact	2.9 (0.60)	1.28	4.8	421
Average non-face-to-face contact	2.8 (0.60)	1.32	5	421
Average closeness alters with a child	3.6 (0.70)	1	5	421
Average closeness alters that want a child	3.8 (0.85)	1	5	421
Average closeness alters that do not want a child	3.4 (1.07)	1	5	421
Average face-to-face contact with alters with a child	2.9 (0.78)	1	5	421
Average face-to-face contact with alters that want a child	3.1 (1.06)	1	5	421
Average face-to-face contact alters that do not want a child	2.8 (1.20)	1	5	421
Average non-face-to-face contact with alters with a child	2.8 (0.79)	1	5	421
Average non-face-to-face contact alters that want a child	3.2 (1.02)	1	5	421
Average non-face-to-face contact with alters that do not want a child	2.6 (1.18)	1	5	421
Density (alter-alter)				
Density among alters	0.7 (0.21)	0.17	1	258
Density among friends	0.3 (0.20)	0	1	258
Density among alters with children	0.4 (0.28)	0	1	258
Density among alters that want a child	0.4 (0.33)	0	1	258
Density among alters that do not want a child	0.4 (0.33)	0	1	258
Density among alters that you can talk to about having children	0.4 (0.29)	0	1	258
Density among alters that can help you with raising a child	0.5 (0.27)	0	1	258

3.3. The analytical strategy

An important aim of this thesis is to identify the predictive ability of the different models, with the further aim of being able to assess what the relative strengths in the predictive ability for the different "blocks" of variables were, contrasting ego variables to composition-, to tie strength- and to density variables. This would allow me to conclude, for example, how important composition variables were relative to ego variables, but also which composition variables particularly mattered. This meant that I ran models with each of the blocks separately (e.g., only ego variables, only compositional variables, only tie strength variables) as well as models where the blocks are all combined.

One problem with this approach is that for some models, as shown in Table 5, the sample sizes varied considerably. Therefore, improvements (or decreases) in predictive ability from the inclusion of different blocks of variables need to be separated from reductions in sample size. To identify if and how strong changes in sample size influenced the predictive effect that every variable had on the dependent variable and the overall strength of the model, nine models were estimated with four different sample sizes (i.e., the four blocks). I will explain each "block" and model after discussing the performance measure. See Table 6 for an overview of the models and blocks.

After evaluating the performance of all nine models, the performance of the strongest model will be highlighted. The results of this model will be used to elaborate on the most important and surprising findings in the results chapter.

All numerical variables were standardized because this is required for LASSO regression. Given that a penalty term occurs on the sum of the absolute magnitudes of the variables, estimates should be on a comparable scale.

Estimating different models in different blocks also meant estimating unique Lambdas per model. Cross-Validation, as explained in 2.3.4, is used twice for each estimated model. First, it is used to obtain the optimal λ (see Figure 5 as an example). Second, LASSO regression is applied using the estimated λ by using cross-validation to obtain an average out-of-sample predictive ability for a particular model. Table 6 shows an overview of every estimated Lambda of all 9 models. Unfortunately, not every model was able to run using the 1SE λ. This is because the estimated value 1SE λ was higher than the optimal Lambda and had a lower predictive ability. For consistency, the optimal λ (with the lowest prediction error) is used for the second step.

Table 6: Shows an overview of every estimated lambda (λ) per model.

	Block 1	**Block 2**	**Block 3**			**Block 4**			
	1A	**2A**	**3A**	**3B**	**3C**	**4A**	**4B**	**4C**	**4D**
Retrieving optimal lambda through CV									
Min.	0.00084	0.01686	0.00684	0.03326	0.04397	0.02291	0.01702	0.01868	0.02051
1SE	0.16801	0.08201	0.19482	0.17751	0.19482	0.13416	0.19124	0.07543	0.19124
Run model in ideal lambda through CV									
Min.	0.00083	0.01851	0.01089	0.03031	0.04397	0.01579	0.01551	0.01551	0.0247

3.4 Comparing the models

I used two ways to compare the quality of each model. First, the performance of every estimated model was judged by comparing the value of cross-validation R^2 of all models. If the R^2 value of two models that included the same variables, but were based on different sample sizes, were similar, this meant that the exclusion of respondents had little effect on the quality of the model. Second, by comparing the coefficients of the variables, and the consistency of the coefficients per variable across different models. If the models based on different sample sizes included similar variables with similar coefficients, this meant that the exclusion of respondents had little effect on the quality of the model. In other words, for both the R^2 and the coefficients, the consistency of the performance is key. I will discuss the performance of the model in the following paragraph.

4. Results

This chapter starts by evaluating the performance across all blocks and models. This is followed by discussing the most important or surprising results of the hypothesis testing.

4.1 Results of the estimations of all four blocks

The following paragraph includes an elaboration of all the blocks, models, and the results of the model performance (see Table 7 for an overview). Every model will be discussed in the order in which they were estimated. Furthermore, the performance of the models that include the same variables, but are based on different numbers of respondents, will be compared. Finally, an overall conclusion will be given on the overall model performance and the consistency of the performance of all models. I refer to Table 8 for an overview of which variables were included in every model. Furthermore, Table 9 in the appendix shows the same overview, but for this table, the coefficients are also included.

4.1.1 Block 1 (ego variables)

The first block only includes the first model, which included three ego variables (see Table 6). The sample size for the first block is defined by the number of missing values from the ego variables. The sample size before filtering for missing values was N = 706. This did not cause a large reduction in respondents (N = 637).

From this sample, model 1 was estimated. I will refer to all models with only the ego variables as the "base" model. The analysis indicated that this model did not perform well compared to other models (CV $R^2 = 0.02$). The variance in the dependent variable that was explained by the ego variables was the lowest across all nine models even though all three variables remained in the model (i.e., the coefficients did not shrink to zero).

4.1.2 Block 2 (variables related to ego and composition)

The second block includes the second model, which consists of the ego and compositional variables. For the estimation of this model, the sample size was defined by the missing values caused by ego and compositional (alter-attributes) variables. This did not impact the sample size compared to block 1 (N = 637). Since composition does not cause a reduction in the sample size, no "base" model was estimated for this block. This "base" model would estimate the same model as model 1.

Model 2 had relatively high predictive ability with a CV R^2 of 0.10), and demonstrated a strong improvement compared to the model performance of model 1. All base variables and five out of nine compositional variables remained in the model (i.e.; see Table 8). Some coefficients had relatively strong effects (e.g., the number of alters that do not want a child with $\hat{\beta} = 0.10$).

4.1.3 Block 3 (variables related to ego, composition, and tie strength)

The third block includes models 3A, 3B, and 3C. Here, the sample size was defined by the missing values caused by ego, composition, and tie strength variables. This caused a relatively large reduction in sample size (N = 421 remaining).

Model 3A consists of the ego variables and was able to explain relatively little variance compared to other models (CV $R^2 = 0.05$). Again, all ego variables remained in the model. This base model seems to perform slightly better compared to model 1 (0.05 versus 0.02), although the same variables are kept in the model and the estimates are very similar.

Model 3B includes the ego and the compositional variables and explained a moderate amount of variance compared to other models (CV $R^2 = 0.07$). Three base variables and four out of nine compositional variables were kept in the model, which were the same variables as model 2 except for the variable the number of alters that the respondent could talk with about children (which was not kept in model 3B). Some variables had relatively strong effects, with the largest coefficient for "*kin*" with $\hat{\beta}$ = 0.13. The performance of this model was similar but slightly lower than that of model 2 (see Table 6). The variables that remained in Model 2 and 3B were similar except for one, and the magnitude of the estimates was comparable.

Model 3C includes the ego, compositional, and tie strength variables. Three base variables, four out of nine compositional variables (the same ones as in model 3B), and two out of twelve tie strength variables were kept in the model (average closeness and average non-face-to-face contact to alters that did not want to have children and the). Although two tie strength variables were kept in the model, adding tie strength variables did not improve the predictive ability relative to model 3B, as also model 3C had a CV R^2 of 0.07. Unsurprisingly, the estimated coefficients of the tie strength variables were low (e.g., the largest tie strength coefficient was average closeness alters that do not want a child ($\hat{\beta}$ = -0.03). Again, the largest coefficient for the compositional variable was "*kin*" ($\hat{\beta}$ = 0.13).

4.1.4 Block 4 (variables related to ego, composition, tie strength, and density)

The fourth block includes models 4A, 4B, 4C, and 4D. Here, the sample size was defined by the missing values caused by ego, composition (alter-attributes), tie strength (ego-alter), and density (alter-alter) variables. This caused the largest reduction in the sample size (N = 258 remaining).

Model 4A contains only ego variables, similar to models 1 and 3A, and was able to explain relatively little to moderate amounts of variance compared to other models (CV R^2 = 0.06). Again, three base variables remained in the model. The coefficients of all base models (including only ego variables) follow a similar pattern. There was one ego variable (having a partner) that did not make it into the model across base models (it was not kept in model 4A), but this variable had the weakest effect in both other models as well. This indicates that the coefficients of all base models follow a similar pattern. This also indicates that the large reduction of respondents did not seem to create a qualitatively different model.

Model 4B includes de ego- and composition variables and was able to explain a moderate amount of variance compared to all other models (CV R^2 = 0.07). All base variables and eight out of nine compositional variables remained in the model (the only composition variable that was not kept was the proportion of higher educated alters; see Table 7). The largest coefficient of $\hat{\beta}$ = -0.16 was "*alters that do not want a child*". The performance of this model was slightly worse compared to model 2, the same as 3B, and it kept more variables in the final model with slightly higher coefficients.

Model 4C includes the ego-, composition- and tie strength variables and was able to explain most variance across all models ($R^2 = 0.11$). All base variables, seven out of nine compositional variables, and six tie strength variables were included in the model. Model 4C kept more variables in the model than 3C and the effects were overall stronger (see Table 8 for the differences in the estimated coefficients). However, most of the variables that remained in 4C in contrast to 3C only predicted a relatively small effect around $\hat{\beta}$ = (-)0.05 (i.e., women, talk with alter about children, average face-to-face contact, average face-to-face contact with alters that do not want a child, average non-face-to-face contact with alters with a child). Three variables had a large difference since they were filtered from 3C, but had a larger than $\hat{\beta}$ = (-)0.10 in 4C (i.e., alter with a child, average closeness, and average closeness with alter that wants a child)

The largest compositional coefficient was "*kin*" ($\hat{\beta} = 0.18$), and the strongest tie strength coefficient was "*average closeness with alters who want a child*" ($\hat{\beta} = 0.20$).

Compared to model 3C, the R^2 of model 4C is higher, (CV $R^2 = 0.11$) more variables are included in the model, and the coefficients are generally larger. No coefficients are in different directions across these two models, and the largest coefficients are designated for similar variables. This suggests that the difference in sample between blocks 3 and 4 leads to somewhat different results, although not substantively different conclusions.

Model 4D is the only model that includes compositional-, tie strength- and density variables. The analysis indicates that this model was able to explain a relatively high amount of variance compared to all models (CV $R^2 = 0.09$). All base variables, seven out of nine compositional variables, seven tie strength variables, and four density variables were included in the model. The largest compositional coefficient was "*kin*" ($\hat{\beta} = 0.21$). The strongest effect for tie strength was "*average closeness alters that want a child*" ($\hat{\beta} = 0.20$). "*Density among alters with children*" was the largest density coefficient ($\hat{\beta} = 0.08$).

The complete model 4D performed well relative to the other models, but less than model 4C which did not include density variables. Furthermore, the values of the coefficients of both the composition and tie strength variables are similar to those from model 3C. I will focus on explaining the most important results of the final model (4D) in paragraph 4.3.

Table 6: Shows which model is estimated per "block", what the sample size was for all models that are estimated per "block", which category of variables is used per model, what the R^2 was per model, and the proportion of variables that were included in the model. See Table 8 in the appendix for an overview of all coefficients per model

Block N = 706	**Block 1**[I] N = 637	**Block 2**[II] N = 637	**Block 3**[III] N = 421	**Block 4**[V] N = 258
Ego 3 variables	**Model 1.** $R^2 = 0.02$ 100%	NA[*]	**Model 3A.** $R^2 = 0.05$ 100%	**Model 4A.** $R^2 = 0.06$ 75%
Ego + composition (alter-attributes) 13 variables		**Model 2.** $R^2 = 0.10$ 55%	**Model 3B.** $R^2 = 0.07$ 44%	**Model 4B.** $R^2 = 0.07$ 89%
Ego + composition (alter-attributes) + tie strength (ego-alter) 25 variables			**Model 3C.** $R^2 = 0.07$ 29%	**Model 4C.** $R^2 = 0.11$ 67%
Ego + composition (alter-attributes) + tie strength (ego-alter) + density (alter-alter) 31 variables				**Model 4D.** $R^2 = 0.09$ 63%

I. The sample size of block 1 is defined by the number of missing values from the ego variables.
II. The sample size of block 2 is defined by the number of missing values from the composition variables.
III. The sample size of block 3 is defined by the number of missing values from the tie strength variables.
V. The sample size of block 4 is defined by the number of missing values from the density variables.
*. This model was not estimated because defining the missing values by composition did not mean extra missing values compared to the Ego variables. This means that this model would have been the same as model 1 since it would include the same variables and N as model 1.

4.2 Overall conclusion model performance and consistency across all four blocks and nine models

Overall model performance across nine models is small to moderate and results are relatively consistent, with CV R^2 values between 0.02 and 0.11. Furthermore, the analysis of the models showed that a substantial fraction of estimated coefficients was (moderately) large, which I consider to be larger than $\hat{\beta}$ = (-) 0.10. A total of 72 variables were used to estimate six models that included predicting variables. Twenty had a coefficient larger than $\hat{\beta}$ = (-)0.10, eight larger than $\hat{\beta}$ = (-)0.15, and four larger than $\hat{\beta}$ = (-)0.20.

The magnitude of the estimated coefficients where overall fairly consistent across all models. The largest differences in coefficients were observed for variables in block 4 compared to the other blocks. Models in block 4 also retained more variables (see Table 6), and coefficients tended to be higher. Some examples of this are the variables "*women*", "*alters with a child*", "*average closeness*" and "*average closeness to alters that want a child*", where the increase of the coefficients ranged between $\hat{\beta}$ = 0.05 to $\hat{\beta}$ = 0.21. The majority of the variables remained more or less the same, however. A complete overview of all coefficients of the predicting variables can be found in Table 8 in the appendix.

The likely reason why block 4 is different from the other blocks is that there was a large reduction in sample size in block 4 (see Table 5). This was because certain density variables could only be calculated when there were two or more alters present. For example, "*density among kin*" could only be calculated when at least three kin were in the network. Given that we calculated density for kin, this meant that our selected sample has at least three of each of those alters in their network. This may be a different sample of the population than a sample that also included people with fewer than three in some of those groups.

Across models, the most important variables are "*kin*", "*alters with a child*", "*alters that want or do not want a child*", "*average closeness*", "*average closeness with alters that want a child*", "*average closeness alters that do not want a child*", and "*density among alters that want a child*". These variables performed most consistently (i.e., were retained in a majority of the models that were used) and had the strongest effect on fertility behavior (i.e., had an effect of at least around (-)0.10.

4.3 Results of the model that explored the impact of the largest number of variables (model 4D)

This chapter continues by discussing the most important, interesting, and surprising results per network category, also in relation to the hypotheses (see Tables 1 to 3). I will focus on the results of the estimation of model 4D since this is the most complete model that explored the impact of the largest number of variables. Furthermore, this model was among the highest-performing models.

4.3.1 Results composition (alter-attributes)

Composition seems to have the most effect on fertility behavior. More than three-quarters (seven out of nine variables) of the compositional variables made it into the final model. Some compositional variables had a moderately strong effect (e.g., three variables had an effect that was larger than (-)0.10). The strongest predicted effect was "*kin*" with $\hat{\beta}$ = 0.21. This result implies that the more family members women have in their network, the larger their ideal family size. This finding is consistent with all four kin hypotheses. Two other important effects for the compositional variables, although not as strong, were "*alters that do not want a child*" with $\hat{\beta}$ = -0.12 and "*alters that want a child*" with $\hat{\beta}$ = 0.08. The results of both effects suggest that women are influenced by the fertility preferences of their network members. If many network members want to have children, ego prefers to have more children, and if many network members do not want to have children, ego prefers fewer. Both effects align with the hypotheses. The results with respect to "*alters with child*" ($\hat{\beta}$ = 0.11) indicate that when women have more people in their network with children, this increases the number of children they desire. This is consistent with three hypotheses. The final two variables that had a noteworthy effect on fertility outcomes were "*women*" with $\hat{\beta}$ = 0.07 and "*alters that can help*" with $\hat{\beta}$ = 0.07. These effects indicate that when respondents had more women in their networks and when they had more people in their network that could help with raising children, the fertility preferences of respondents were higher. Both findings align with all the hypotheses.

The two variables that were filtered out are "*friends*" and "*higher educated*." It was expected that more friends/higher educated people in a network would result in a lower fertility rate since both are generally not associated with traditional family norms.

4.3.2 Results tie strength (ego-alter)

The tie strength variables had the second most impact. More than half (seven out of twelve variables) of tie strength variables were retained in the final model and two variables had an effect that was larger than (-)0.20. The four "*average closeness*" variables had the most impact whereas the four "*average face-to-face contact*" and "*average non-face-to-face contact*" seemed to have a much smaller impact on fertility behavior. Surprisingly, there seems to be little difference between the influence of the last two variables, because it was expected that face-to-face contact would have a stronger impact on influencing fertility behavior. The most important and strongest tie strength effect found is "*mean average closeness*" with $\hat{\beta}$ = -0.21. This result suggests that women who reported being closer to their network members have a smaller estimated ideal family size (on average and considering the other variables that are included in the model). This aligns with hypotheses 2.1.3 and 2.1.4. Two other important effects were "*average closeness to alters that want a child*" with $\hat{\beta}$ = 0.20 and "*average closeness to alters that do not want a child*" with $\hat{\beta}$ = -0.07. The results of network composition already suggested that if more network members wanted children this influenced egos in the expected direction. Being close to alters that want a child further increases the ideal family size, and being close to alters that do not decrease it. Both findings correspond with the hypotheses.

There were also some effects hypothesized that were not supported by the analyses. Surprisingly, being close to or having frequent contact with alters with children seemed to have very little to no impact. Only "*average non-face-to-face contact with alters with a child*" predicted a small decrease in women's ideal family size ($\hat{\beta}$ = -0.04), whereas "*average closeness to alters with child*" and "*average face-to-face contact with alters with child*" shrank to zero. This could indicate that having children is less contagious compared to ideas and values such as wanting to have children or not as earlier evidence suggests (Bernardi and Kläner, 2014). Furthermore, the average (non)-face-to-face contact variables all had a small or no influence on the ideal family size of women. For example, "*average non-face-to-face contact*

", "*average face-to-face contact with alters with child*", "*average face-to-face contact with alters that want a child*" and "*average non-face-to-face contact with alters that want a child*" all shrank to zero and the largest effect of these variables only had a small coefficient (average face-to-face contact with $\hat{\beta}$ = - 0.05). This implies that feeling close to someone has a stronger influence than the frequency of contact people have.

4.3.3 Results density (alter-alter)

Density had the least impact. More than half of the variables (four out of seven variables) were retained in the final model, but the effects were relatively weak. The estimated effects ranged between (-)0.01 and 0.08. The predicted influence of these variables is relatively weak compared to the previous two categories. The strongest density effect that was found was for "*density amongst alters with children*" with $\hat{\beta}$ = 0.08. This result indicates that increased density among alters with children causes a slight increase in women's ideal family size. This result corresponds with the hypothesis. Two other small effects that were found were "*density among alters that you can talk to about having children*" with $\hat{\beta}$ = -0.06 and "*density amongst alters whom you can help with raising children*" with $\hat{\beta}$ = -0.05. Both results do not correspond with the hypotheses.

Three variables that shrank to zero were "*density among alters*", "*density among alters that want a child*" and "*density among alters that do not want a child*". Evidence for the compositional effects of "*alters that want a child*" and "*alters that do not want children*" (see results of network composition) suggested that whether alters wanted children or not had an impact on women's fertility behavior. The findings on these density variables suggest that density does not increase or decrease the strength of this influence.

Table 7: This table indicates the model, the N, the explained variance (R^2), and which variables were retained in the model

N and model	R^2	Which variables were retained in the model
Model 1 N = 637	0.02	A. Age, Has partner & Has a child
Model 2 N = 637	0.10	A. Age, Has partner & Has a child B. Kin, Alters who want a child, Alter does not want a child, Alter who can help & Talk with partner about children
Model 3A N = 421	0.05	A. Age, Has a partner & Has a child
Model 3B N = 421	0.07	A. Age & Has a child B. Kin, Alter does not want a child, Alter who can help

Model 3C N = 421	0.07	A. Age & Has a child B. Kin, Alters who want a child, Alter does not want a child & Alter who can help C. Average closeness with that do not want a child & Average non-face-to-face contact with alters that do not want a child
Model 4A N = 258	0.06	A. Age & Has a child
Model 4B N = 258	0.06	A. Age, Has partner & Has a child B. Women, Friends, Kin, Alter with a child, Alters who want a child, Alter does not want a child, Alter who can help & Talk with partner about children
Model 4C N = 258	0.11	A. Age, Has partner & Has a child B. Women, Kin, Alter with a child, Alters who want a child, Alter does not want a child, Alter who can help, Talk with partner about children C. Average closeness, Average face-to-face contact, Average closeness alters that want a child, Average closeness alters do not want a child, Average non-face-to-face contact with alters with a child & Average non-face-to-face contact with alters that do not want a child
Model 4D N = 258	0.09	A. Age, Has partner, Has a child B. Women, Kin, Alter with a child, Alters who want a child, Alter does not want a child, Alter who can help & Talk with partner about children C. Average closeness, Average face-to-face contact, Average closeness alters that want a child, Average closeness alters that do not want a child, Average face-to-face alters that do not want a child, Average non-face-to-face contact with alters with a child & Average non-face-to-face contact with alters that do not want a child D. Density among friends, Density among alters with children, Density among alters that you can talk to about having children, Density among alters that can help you with raising a child

A. Base variables
B. Compositional variables (alter-attributes)
C. Tie strength variables (ego-alter)
D. Density variables (alter-alter)

5. Discussion

5.1 Which network characteristics influenced women's behavior most?

The first aim of this research was to identify which network characteristics had the most influence on the ideal family size of women. Overall, I found strong evidence that kin in women's networks was important: women that reported more kin in their network had a higher ideal family size on average (across all models). This was consistent with our hypotheses that were based on previous research that showed that family members enforce more traditional family values (Alesina & Giuliano, 2007; *social pressure*), spread information about raising children that are interpreted as more reliable (Chartrand & Bargh, 1999; *social learning*) and are more likely to help with childcare (Stulp and Barrett, 2021; *social support*). The current analytical strategy does not allow me to conclude why kin is important. However, previous research on the same sample suggests that the importance of kin is explained better by the increased support they provide rather than the increased pressure (Stulp & Barrett, 2021).

Furthermore, I found support for the idea that whether alters want to have children or not, influences women's fertility behavior. Women that reported more people that want children in their network had a higher ideal family size on average (across all models), whereas the opposite effect was found for women who reported more people that do not want children in their network. This aligns with the hypotheses and earlier studies that indicate that more network members with children spread the idea of having children and create an opportunity to learn from their experience (Lois & Becker, 2014; *social pressure, contagion, and learning*). Again, the current analytical strategy does not offer enough insights to conclude which mechanism has the strongest effect on fertility behavior. However, the study of Lois & Becker (2014) points out that an increase in the fertility behavior of women due to people in the network with children is mostly caused by increased learning opportunities about having children.

Surprisingly, I found minimal evidence that friends had any effect on women's fertility behavior. This is surprising since earlier studies suggest that women without children experience pressure from friends to have children (Stulp & Barrett, 2021), are more likely to offer support than non-friends (Stulp & Barrett, 2021), and that childbearing can be contagious within friendship groups (Balbo & Barban, 2014). This could suggest that it is not the number of friends itself is not as important but the number of friends that share the same or different opinions. If women's opinion about the ideal family size already aligns with the opinion of their friends, it is unlikely that the opinion of their friends would cause a shift in their opinion on the ideal family size. Future studies could explore to what extent the difference in opinions between women and their friends makes any difference in influencing women's fertility behavior.

There was also no support for the idea that the level of education of alters was important for women's fertility behavior. The reason why a network effect was expected for the number of women with higher education, is that these women are argued to have a stronger emphasis on achieving individual goals, instead of family-oriented goals (Martin, 1995). Perhaps no effect was found because the fertility preferences of highly-educated women do not differ from those in other educational groups (Monstad, Propper & Salvanes, 2008). It is also possible that the inconsistency with earlier studies is caused by the difference in the statistical approach. The significant findings from earlier studies do not necessarily mean that they have a strong predictive value as well. Moreover, it might be caused by the nature of LASSO regression. LASSO regression filters out the variables that have no influence, which is especially true when adding more variables to the statistical model. Earlier studies only included a limited number of compositional variables (Balbo & Barban, 2014; Madhavan, Adams & Simon, 2003; Martin, 1995) and its effects are not always statistically quantified (i.e., qualitative studies) (Knipschear et al., 1995; Bernardi and Kläner, 2014). Adding more composition variables could have therefore exposed spurious correlations in these earlier studies. This is an interesting topic of interest for future research to explore.

Previous research has shown that the strength of the tie to particular people in the network is also important for social influence and fertility behavior. The strongest tie strength impact on fertility behavior was average closeness. However, the evidence I found does not support the notion that higher levels of average closeness within a network increase the ideal family size. Two out of three models reported that more average closeness decreases women's ideal family size. This could suggest that current societal norms are more self-centered and less about traditional family norms, which is in accordance with the second demographic transition model (Caldwell, 1976; Van de Kaa, 2002). This implies that closer networks would enforce norms that are less concerned with traditional family values. These findings suggest that social pressure is the most important underlying social mechanism that causes a decreased ideal family size.

Also, no evidence was found for the idea that having contact with people with children is contagious (Bernardi and Kläner, 2014), but I did find evidence that having contact with alters that want or do not want children to affect fertility preferences. The evidence of various models indicates that being close to people who want children increases the ideal family size on average, whereas being close to alters that do not want children causes a decrease. This raises the question of why people's opinions on having children seem to be more important than their actual fertility behavior (i.e., having children), particularly because earlier studies suggest that people in the network that have young children are particularly influential on fertility outcomes (Balbo & Barban, 2014). This may be because of my operationalization of the variables. For example, many networks consist of parents of the respondents as well, who will be included as alters in the network with children. It is very unlikely that their fertility behavior is contagious to their daughters. Another explanation is that this study did not take the age of the children into consideration as Balbo & Barban (2014) did.

Density had little impact on women's ideal family size, although some smaller effects were observed. Density among alters with children caused a slight increase in the ideal family size of women. This effect has not been studied previously, although it does correspond with the influence of other forms of density (e.g., among kin and friends) on fertility outcomes. These studies imply that fertility outcomes are associated with the ingroup norms of specific subgroups (Kohler, Behrman & Watkins, 2001; Stulp & Barret, 2021).

Density among alters that you can talk to about having children and density among alters that can help you with raising a child caused a small decrease in ideal family size. I do not have an explanation for why density among these groups of alters would decrease fertility preferences, although it does suggest that tight-knit groups of people are better able to exert influence. Future research could delve into other characteristics of the alters in these tight-knit groups.

5.2 How well does LASSO regression work when applied in social science?

The second aim of this thesis is to explore how well a data-driven approach works in a social science study. I have two reasons to believe that LASSO regression, the Machine Learning method I used, has provided useful insights accompanied by robust and convincing results. First, I believe this method was able to uncover how strong the influence of network characteristics was on women's ideal family size. Furthermore, the findings align in many instances with earlier studies suggesting that this method uncovers phenomena that were also observed in other research (e.g., the number of kin increases the ideal family size of women (Alesina & Giuliano, 2007)) or were able to identify knowledge gaps (e.g., the results of this study suggest that having children might not be contagious whereas Balbo & Barban, 2014 found evidence that it is contagious).

Second, I believe that LASSO regression produced robust and generalizable results. I estimated nine models through four different blocks of sample sizes. I separately ran models with each of the blocks (e.g., only ego variables, only compositional variables, only tie strength variables) as well as models where the blocks of variables were all combined. The variables that were retained in multiple models mostly had a similar influence on fertility behavior across every estimated model. The consistency in these findings gives some confidence that the most important network variables were uncovered.

Although the findings were consistent, it is also notable that the inclusion of many different variables were only able to explain about 10% of the out-of-sample variation. It is difficult to indicate how the findings of this study relate to earlier studies about fertility behavior and outcomes since these topics are not often quantified in terms of predictive ability (Salganik et al., 2020).

In conclusion, I believe that my findings suggest that focusing on predictive ability is a promising method for new insights in social science (Verhagen, 2022). More studies with a similar set-up and method are desired to conclude to what extent data-driven research uncovers patterns that were previously unknown. Additionally, I believe applying LASSO regression and a more traditional method (such as OLS) to the same study is better because it allows comparing how well both methods work in a similar context. It would also demonstrate if and how much better its predictive ability is in comparison to more traditional models.

5.3 Limitations and future research

There are a few limitations in this study that limit generalizability. First, measuring social influence can best be done by measuring the same respondents multiple times over a set period (e.g., over ten years). Changes in behavior or attitude caused by social influence are caused by (repeated) interactions people have over a longer period. Moreover, such longitudinal assessments may allow separating selection (where similar people tend to form networks with similar others) from influence (where people have an influence on others) (Steglich, Snijders, & Pearson, 2010). Therefore, the current approach of assessing network effects on the basis of one cross-sectional sample clearly limits the strength of our conclusions. Therefore, I propose future research can explore using a dataset that is constructed over an extended period of time.
A second limitation is that the effect of many variables were hypothesized through multiple mechanisms. My analysis did not allow investigating which of these mechanisms had the strongest impact. To work around this issue, I compared the results per variable with earlier studies which indicated which mechanism most likely had the strongest effect. Future research could focus on analyses in which the focus is on the combined characteristics of particular alters (e.g., highly educated alters with young children), to get more insights on particular mechanisms.
A third limitation is that respondents only consisted of Dutch women between 18 and 40. The force of social influence may be much greater within countries with a higher fertility rate. Moreover, influence processes may be different for men and women (Golmakani et al., 2015).
A final limitation is that other machine learning techniques are known to have better predictive ability compared to LASSO regression. One example is known as the Random Forest model which includes interactions among the variables. A downside of such models is that they are less easy to interpret. It could be interesting for future research to explore different machine learning techniques in social science studies to investigate if this has any impact on predictive abilities (and why) and whether findings from past studies can be confirmed with other methods.

5.4 Conclusion

This is the first study that has attempted to address the effects of many different network variables simultaneously on fertility behavior using a unique dataset and has helped to better understand how social networks impact fertility behavior. The findings of this study have underpinned the complexity of the puzzle of women's fertility behavior. This thesis contributed to earlier knowledge by expanding what was already known and attempting a novel and more comprehensive approach. A central goal of studies on fertility is that insights will help policymakers make better decisions that will help future parents see their wish to have children fulfilled and sustain a healthy demographic population. The limited ability to predict fertility outcomes from this study suggests that we are not particularly close to this goal yet.

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Appendix

Table 8: Shows an overview of all coefficients per model. The four “base models” are excluded from this overview.

Variables	Coefficients per model					
	Block 2	**Block 3**		**Block 4**		
	2A	**3B**	**3C**	**4B**	**4C**	**4D**
Composition (alter-attributes)						
Women	0	0	0	0.05	0.06	0.07
Friends	0	0	0	- 0.03	0	0
Kin	0.10	0.13	0.12	0.15	0.19	0.21
Higher educated	0	0	0	0	0	0
Alter with a child	0	0	0	0.12	0.09	0.11
Alter wants child	0.10	0.11	0.10	0.07	0.08	0.08
Alter does not want a child	- 0.10	- 0.05	- 0.04	- 0.15	- 0.12	- 0.12
Alter who offer help	0.03	0.01	0.01	0.06	0.11	0.07
Talk with alter about children	0.02	0	0	0.01	0.02	0.01
Tie strength (ego-alter)						
Average closeness			0		- 0.20	- 0.21
Average face-to-face contact			0		-0.06	- 0.05
Average non-face-to-face contact			0		0	0
Average closeness alters with a child			0		0	0
Average closeness alters that want a child			0		0.19	0.20
Average closeness alters that do not want a child			- 0.03		- 0.09	- 0.07
Average face-to-face contact with alters with a child			0		0	0
Average face-to-face contact with alters that want a child			0		0	0
Average face-to-face contact with alters that do not want a child			0		> -0.01	- 0.01
Average non-face-to-face contact with alters with a child			0		- 0.04	- 0.04
Average non-face-to-face contact with alters that want a child			0		0	0
Average non-face-to-face contact with alters that do not want a child			- 0.02		- 0.03	- 0.04
Density composition (alter-alter)						
Density among alters						0
Density among friends						0.01
Density among alters with children						0.08
Density among alters that want a child						0
Density among alters that do not want a child						0
Density among alters that you can talk to about having children						-0.06
Density among alters that can help you with raising a child						-0.05