The Power of Identification on Deviance

How Does Employees’ Identification With Their Company Influence Their Deviant Behavior at Work, Depending on Tenure?

Semester Thesis

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Abstract

The impact employee's identification with their organization (OID) has on their behavior at work has been studied from different perspectives before. This paper explores its specific positive and negative implications on organizational deviance (OD), the destructive behavior at work that intentionally violates organizational norms. Furthermore, it contributes to the discussion about the moderating effect of tenure, found in previous research, with the findings from an empirical analysis with employee data of an international industrial company. The results revealed that for the same level of identification, employees with longer tenure experienced a stronger effect of reducing deviance than for shorter tenured individuals. However, the study points to the complexities of the relationship depending on different contexts. Additionally, practical implications for management practices are discussed, contributing to the broader understanding of organizational identification and deviance, across different tenure levels.

Keywords: *organizational identification, organizational deviance, work behavior, tenure*

List of Contents

List of Figures

List of Tables

List of Abbreviations

A.	Appendix
Approx.	Approximately
CEHRM	Center for Human Resource Management
E.g.	Exempli gratia ("for example")
Fig.	Figure
HR	Human Resources
I.a.	Inter alias ("among others")
I.e.	Id est ("meaning")
OD	Organizational Deviance
OID	Organizational Identification
Org.	Organizational
p.	Page
pp.	Pages
Resp.	respectively
SCT	Self-Categorization Theory
SIT	Social Identity Theory
t1	Time Period 1
t2	Time Period 2
t3	Time Period 3
UNILU	University of Lucerne

1. Introduction

1.1. Relevance

The importance of organizational identification (OID) in the corporate context has been long established (Mael & Ashforth, 1992). Organizational identification is a specific focus of social identification (Dick, 2005) and describes an individual's "perception of oneness with or belongingness to an organization" (Mael & Ashforth, 1992, p. 104). Hence, organizational identification displays a form of a primary human drive, the need to belong, which humans constantly seek to satisfy (Ferris et al., 2009 ; see Baumeister & Leary, 2007) and, according to Social Identity Theory (Tajfel, 1978), serves the purpose of defining oneself in the social environment.

Multiple studies (e.g. Qiuyun et al., 2020; Ashforth et al., 2008) have identified its impact on organizationally relevant outcomes. Depending on how strongly employees identify themselves with their organization, it can result in either positive, thus desirable or negative, undesirable outcomes for an organization. Strong identification in employees is argued to benefit an organization by e.g. leading to higher job satisfaction (Ashforth et al., 2008; Conroy et al., 2017) or conformity to group norms (Ashforth & Mael, 1989). On the other hand, once an individual is "excessively" identified with its organization (see Dukerich & Kramer, 1998), such that he or she "cannot think of themself as anybody but a member of the organization" (Vadera & Pratt, 2013, p. 178), identification can have undesirable outcomes for the organization, such as e.g. continued commitment to a failing project or not addressing questionable behavior of other organizational members (Ashforth, 2016; Ashforth et al., 2008). The concept and implications of organizational identification should be of everlasting and constant relevance to corporate management, as a company's profitability depends heavily on employee factors (Krekel et al., 2019; see also e.g. Judge et al., 2001; Staw et al., 1994; Strauss, 1968).

Such an employee factor is, organizational deviance, which is to be distinguished from interpersonal deviance and can be defined as the voluntary behavior of employees that violates significant organizational norms and policies, including moral standards (Bennett & Robinson, 2000; Feldman, 1984). Previous literature (e.g. Bennett & Robinson, 2000; Piazza et al., 2024; Vadera & Pratt, 2013) has established that deviant behavior towards an organization can lead to detrimental and costly consequences, such as e.g. reputational damage, sanctions, or hurting the organization's profitability. These negative consequences can create a serious threat to that organization's wellbeing and its survival prospects (e.g. Bennett & Robinson, 2000; Piazza et al., 2024; Qiuyun et al., 2020).

Moreover, several sources (e.g. Ashforth & Mael, 1989; Niu et al., 2022; Umphress et al., 2010; Vadera & Pratt, 2013) argue that an employee's organizational identification influences his or her engagement in deviant behavior specifically, such as e.g. workplace crimes (Vadera & Pratt, 2013). Both, organizational identification as well as organizational deviance, are individual-level variables with potential for collective-level outcomes (Ashforth et al., 2008; see also Haslam & Ellemers, 2005). Besides the previously described organizational relevance and impact of both, identification and deviance, this commonality constitutes the importance of analyzing the relationship between the two constructs.

1.2. Research Gap

The existing literature on organizational identification has been mainly focused on its impact on other organizational constructs such as work commitment, work performance, or individuals' general work behavior (e.g. Ashforth & Mael, 1989; Demir et al., 2014).

Likewise, the literature that focuses on organizational deviance in particular, is often heavily linked to supervisor identification, leadership-style or organizational support (see Ferris et al., 2009; Kark et al., 2003; Niu et al., 2022; Qiuyun et al., 2020), but neglects the specific link to organizational identification. The research that does consider that link, however, does not interpret identification as the influencing variable, but rather as a mediator, between a different (e.g. leadership-related) factor and an individual's work behavior (see e.g. Liu et al., 2021; Qiuyun et al., 2020).

1.3. Contribution

This paper focuses on the specific relationship between organizational identification as the main predictor, and organizational deviance, as the dependent variable, in order to validate and examine their direct relationship in more detail. The goal of using identification as a main predictor instead of as mediator of a different relation, is to move away from previously investigated relationships of organizational factors targeted at an individual (e.g. leadership-style or supervisor identification). Instead, this paper focuses on two variables that target the organization; identification with an organization and deviant behavior towards an organization. That way, this paper contributes with meaningful conclusions and implications about the impact of identification on deviance, on a collective level.

Furthermore, based on the assumption that organizational identification alone, may not drive employees' engagement in deviant behavior (see Umphress et al., 2010), I additionally examine organizational tenure as a moderator of the relationship, for the purpose of enriching the analysis with an additional relevant factor. Organizational tenure refers to the number of years a person has been employed by an organization (Hall & Schneider, 1972). For the relation of tenure with organizational identification previous research (e.g. Decoster et al., 2013; Hall et al., 1970; Mael & Ashforth, 1992; Riketta, 2005) generally suggests a positive association. However, for tenure's relation with organizational deviance, I found conflicting results (e.g. Hameed et al., 2013; Kim, 2018). Hence, this paper contributes to organizational studies about identification and deviance, by examining their relationship in a sample of 139 white-collar employees of an international industrial company and adds to the discussion about the effect of tenure with insights regarding its moderating role within this sample.

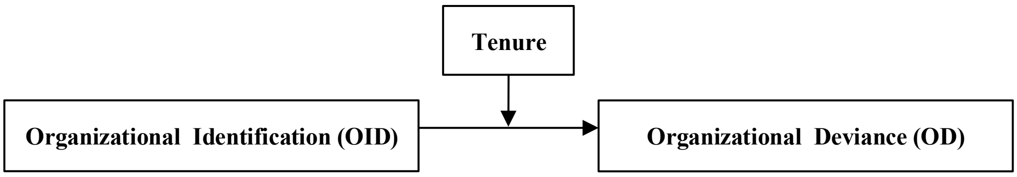


Fig.1. Research Model (c.f. Hayes, 2018)

1.4. Approach

In doing this, first, I review relevant literature for a theoretical background about organizational identification, organizational deviance and the role of tenure, to then develop the hypotheses. For the empirical analysis of my hypotheses I use employee data from an industrial organization. The third part of this paper is dedicated to the detailed description of the empirical methods and data used for this analysis. In the fourth section, I present the obtained results using descriptive statistics and a multiple linear regression analysis. To measure the relevant variables, I used validated reliable scales (Mael and Ashforth, 1992; Bennett and Robinson, 2000). Finally, the last section of this paper concludes and discusses the theoretical and empirical findings, as well as draws relevant implications for theory and practice, mentions the limitations of this paper and makes suggestions for future research.

2. Theoretical Background

2.1. Theoretical Perspectives on Organizational Identification

Organizational Identification (OID) has been studied from multiple perspectives before (e.g. Ashforth & Mael, 1989; Dukerich & Kramer, 1998; Tajfel, 1978). A lot of empirical work (e.g. Liu et al., 2021; Mael & Ashforth, 1992; Qiuyun et al., 2020, Vadera & Pratt, 2013) has proven the impact of an individual's organizational identification on the organization.

2.1.1. Organizational Identification and its Related Constructs

According to Social Identity Theory (SIT) (Tajfel, 1978) and Self-Categorization Theory (Turner, 1999), it is given that humans tend to classify themselves and others into several social categories, in order to "locate or define [themselves] in the social environment" (Mael & Ashforth, 1989, p. 21). This puts forward the definition of social identification, the classification of oneself into social categories: "Social identification is the perception of oneness with or belongingness to some human aggregate" (Ashforth & Mael, 1989, p. 21).
Van Dick (2005) states that the concept of social identification has four dimensions: a cognitive, an affective, an evaluative, and a behavioral one, as well as different foci (e.g., career, work group, organization, occupation). Writing from an economic viewpoint, in this paper, I investigate the organizational focus of social identification. In that sense, organizational identification can be defined as an individual's "perception of oneness with or belongingness to an organization" (Mael & Ashforth, 1992, p. 104). For a broader overview of the history and conceptualization of organizational identification, see e.g. Edwards (2005).

SIT and SCT (Tajfel & Turner, 1986) agree that social, and thus, organizational identification have a cognitive and evaluative dimension. This means that, to identify, individuals need to view themselves as "psychologically intertwined with the fate [of the organization]" (Ashforth & Mael, 1989, p. 21), hence, be aware of their membership (cognitive), as well as connect this awareness to some value connotations (evaluative) (Ashforth et al., 2008).
On the other hand, Ashforth and Mael (1989) apply Social Identity Theory on the organization and agree with the cognitive part, but disagree with the evaluative part by advocating that the incorporation of values is part of internalization ("I believe", p. XX), a construct that is to be distinguished from identification ("I am", p. XX). They (Ashforth & Mael, 1989) clarify this view by stating that a person accepting the organization he or she works for as a definition of self, does not necessarily include him or her accepting and agreeing with the values and attitudes of that organization. Contrary to some literature on SIT, Ashforth and Mael (1989, 1992)

additionally argue that organizational identification has no affective and no behavioral dimension. According to that view, affect (e.g. loyalty to the organization) and behavior (e.g. effort on behalf of the organization) should rather be considered as related constructs, which can influence or be caused by organizational identification (Ashforth & Mael, 1989, Ashforth et al., 2008).

Another construct similar to identification with an organization is identification with an individual (Ashforth & Mael, 1989), e.g. supervisor identification (Johnson & Umphress, 2019). The difference lies within its purpose: While identification with an organization is argued to be based on the desire for self-definition, identification with a person, also called "classical identification" (Kelman, 1961, p. 63), is based on the desire or attempt to gain the qualities of and emulate the other person (Ashforth & Mael, 1989). However, despite the argued distinction of both identification forms, researchers suggest they are complementary for self-definition (Ashforth & Mael, 1989; c.f. Johnson & Umphress, 2019), as an individual often upholds multiple identities simultaneously (see e.g. Ashforth et al., 2008).

Furthermore, organizational commitment is also a related concept, often confused or equated with organizational identification (e.g. Ashforth et al., 2008; van Dick, 2005). However, Ashforth and Mael (1989) argue that the characteristics of commitment include internalization, behavioral intentions, and affect. This definition negates its interchangeability with organizational identification and rather postulates the differentiation of both concepts (Ashforth & Mael, 1989; van Dick, 2005), as well as the possibility for one impacting the other (Ashforth et al., 2008).

2.1.2. Why Does Organizational Identification Matter?

There is consensus in existing literature on identification (Conroy et al., 2017; van Dick, 2005), about it being a natural construct, or, in other words, a “root construct” (Ashforth et al., 2008, p. 326). This is, because it fulfills multiple basic human needs (Conroy et al., 2017; van Dick, 2005), e.g. the need to belong (Baumeister & Leary, 2007). Ashforth et al. (2008) argue that every social “entity needs to have a sense of who or what it is (...)” (p. 326), therefore, “every employee needs something to identify with (...)” (van Dick, 2005, pp. 172).

For an organization, this implies that when its members do not identify with the organization they work for, they will seek identification within other categories, which could be counter-productive to the organization’s goals (van Dick, 2005).

Moreover, the concept of organizational identification helps to predict or understand why people join or voluntarily leave organizations, as well as "why they approach their work (...) and interact with others the way they do" (Ashforth et al., 2008, p. 334).
The description of organizational identification as a basic human need (e.g. Conroy et al., 2017; van Dick, 2005) and as a determinator for the organizational members' behavior (see Ashforth et al., 2008), demonstrates its prevalence and importance to the study of and practical field of organizational contexts.

2.1.3. The Impact of Organizational Identification

The areas of impact are broad for organizational identification, as it is an "individual-level variable [with] a natural connection [to] collective-level (organizationally relevant) outcomes because of its social nature" (Ashforth et al., 2008, p. 336)

Positive Outcomes for the Organization

Organizational members, who identify with their organization are e.g. more likely to behave in a way that aligns with the organization's norms, strategy and identity (Ashforth & Mael, 1989; Qiuyun et al., 2020). In other words, they are less likely to deviate from the behavior the organization defines as appropriate. This means, organizational identification can play a key role when it comes to e.g. better understanding and preventing criminal behavior in organizations (Vadera & Pratt, 2013).
Moreover, van Dick (2005) mentions the importance of organizational identification during times of organizational change, as organizations become more and more diverse and global. He (van Dick, 2005) argues that for core members to stay during organizational change, psychological attachment, e.g. in the form of organizational identification, is key. Or e.g. when previous hierarchies become flat in an organization, employees with strong organizational identification might be less likely to abuse the newly gained responsibility and autonomy, thus will act more in the organization's interest.
Other ways in which organizational identification can have an effect on organizational members, which in turn impacts the organization's overall wellbeing, is e.g. the link between strong organizational identification and better performance, reduced turnover, as well as higher job satisfaction (e.g. Ashforth et al., 2008; c.f. Conroy et al., 2017; van Dick, 2005). Furthermore, strong organizational identification can also increase an employee's commitment to the organization (Ashforth et al., 2008).

Negative Outcomes for the Organization

Despite the optimistic view of the relationship between strong organizational identification and employee behavior in previous literature (Conroy et al., 2017), over the past few decades, researchers (e.g. Avanzi et al., 2012; Caprar et al., 2022; Conroy et al., 2017; Dukerich & Kramer, 1998) have emphasized the negative outcomes of strong organizational identification for the organization's functioning as well. According to Dukerich & Kramer (1998), these come mostly with pathological forms of identification, such as i.a. over-identification or under-identification. Over-identification means an individual "cannot think of themself as anybody but a member of the organization" (Vadera & Pratt, 2013, p. 178), while under-identification describes that they are not able or indifferent to being identified with the organization (see Dukerich & Kramer, 1998). However, because the exact level of "too much" or "insufficient" identification might be a relative term and thus, difficult to measure, this paper will further refer generally to "weak" or "strong" identification.

Potential negative outcomes of having overly strong identified employees could manifest as, e.g. continued commitment to a failing project or resistance to organizational change, as the individuals might feel their identity is threatened by the change (Ashforth, 2016; Ashforth et al., 2008; Conroy et al., 2017). Furthermore, undesirable negative outcomes include e.g. higher tendency to groupthink and not addressing the questionable behavior of other organizational members, thus undermining critical thinking (Ashforth, 2016; Ashforth et al., 2008). Moreover, organizational identification was found to be inversely related to effectiveness and creativity (Ashforth et al., 2008).

2.2. Theoretical Perspectives on Organizational Deviance

2.2.1. Organizational Deviance and its Related Constructs

As previously defined, according to several sources (Bennett & Robinson, 2000; Feldman, 1984), organizational deviance (OD) is the voluntary behavior of employees that violates significant organizational norms and policies, including formal and informal rules but also basic moral standards of the organization. However, a newer source (Piazza et al., 2024), recommends Becker's (1963) labeling theory of deviance, as he points out that these norms and policies are subjective, because what is "right or wrong; ethical or unethical" (Becker, 1963, p. 4) might be judged differently by different society groups. In that sense, deviance would "simply [be] behavior that is labeled as such" (Piazza et al., 2024, p. 250). So, to judge a specific behavior as deviant, it must happen in the context of the specific group or organization that responds to it and the norms and rules they set up.

According to Bennett & Robinson (2000), there are two types of workplace deviance: interpersonal deviance, which is targeted at other members of the organization, and organizational deviance, which is targeted at the organization. They (Bennett & Robinson, 2000) argue, that this qualitative differentiation of targets is relevant, because not only do the deviant acts differ based on the target, but also “individuals prone toward deviance directed at the organization are likely to be different than those individuals prone toward deviance directed at other individuals” (p. 350).
Furthermore, Bennett and Robinson (2000) propose a quantitative differentiation of deviant behavior based on its severity, i.e. that both types of deviance - interpersonal and organizational - can range from minor forms of deviance, such e.g. littering one's work environment, to more serious forms of deviance, e.g. sabotaging equipment.
In this paper, I focus on the deviant behavior towards the organization, rather than towards an individual, as it displays a form of a collective-level outcome, related to organizational identification (see e.g. Liu et al., 2021; Niu et al., 2022; Vadera & Pratt, 2013). However, the distinction of severity will not be taken up further within this scope, as the focal point is not the different levels of deviant behavior, but rather the specific relationship with organizational identification and its implications for corporate contexts.

Merton’s (1957) typology of deviance (see Galperin, 2003; Hanke & Saxberg, 1985), proposes a different categorization that distinguishes destructive from constructive deviance. Individuals tend to violate norms with harmful intention (destructive deviance), when they “do not accept the goals and means of the organization” (Galperin, 2003, p. 157). On the other hand, individuals tend to disobey with beneficial intentions, when they accept the goals, but disagree with the means necessary to attain those goals (Galperin, 2003). An example would be non-compliance with dysfunctional directives (Ashforth & Mael, 1998).
However, in this paper, the understanding of organizational deviance complies with the definition of Robinson and Bennet (2000), which describes it as the “voluntary behavior that violates significant organizational norms and *in so doing* threatens the well-being of an organization, its members, or both” (Galperin, 2003, p. 158). Consequently, this view focuses on the destructive aspects of deviance, as conceptualized by Merton (1957).

Given the above, deviance can only exist when certain group norms and standards, formal or informal, are present. So the question poses itself, why do such norms even exist? Becker (1963) argues that “all social groups make rules and attempt, [...], to enforce them” (p. 1), in order to define the social situations relevant to them and “the kinds of behavior appropriate to them” (p. 1). Consistent with the view of Robinson and Bennet (2000), some sociologists define those processes in a society that “tend to reduce its stability, thus [lessen] its chance of survival” (Becker, 1963, p. 7) as dysfunctional, hence, deviant. Based on this view, for any group or organization to determine what is functional or dysfunctional for them, they need to define what their purpose or goal (function) is (Becker, 1963). So, following this perspective, deviant behavior in a corporate organization are the actions that lead to dysfunctional outcomes for the organization and, consequently, reduce the organization’s stability and survival, by hindering the achievement of its higher-order goal.

Similar and specific conceptualizations of deviance (Galperin, 2003), are e.g. the constructs of workplace or organization-motivated aggression (see Baron and Neuman, 1996; O’Leary-Kelly et al., 1996). However, this paper investigates (destructive) organizational deviance as a higher-order construct, rather than specific manifestations of it. That way, the later derived implications can serve a broader range of organizations and cases.

2.2.2. The Impact of Organizational Deviance

The investigation of the behavioral construct of employee deviance matters on an organizational level because of its potential impact on an organization's overall stability and survival (see Becker, 1963). Existing statistics have shown the pervasiveness of destructive deviance at work, posing a costly problem (Galperin, 2003) and “serious economic threat to organizations” (Bennett & Robinson, 2000, p. 349).
For example, organizational sanctions could arise (Piazza et al., 2024), when employees falsify a business expense receipt or discuss confidential company information with outsiders (Bennett & Robinson, 2000; Galperin, 2003). Potential sanctions can result in reputational damage for an organization, which can lead to further losses and hurt its competitiveness (Bennett & Robinson, 2000; Galperin, 2003; Vadera & Pratt, 2013). For an organization it is therefore key to ensure conformity at the micro-level, i.e. their individual employees’ conformity with the organization’s norms, in order to ensure conformity at the macro-level, i.e. the organization’s compliance with the market rules, for their own survival (Zuckerman, 1999). But even without an organizational scandal affecting the organization's survival immediately, deviant actions,

such as e.g. littering the work environment, illegal drug consumption at work or employees often disregarding the boss's instructions (Bennett & Robinson, 2000), can harm the company's societal-wellbeing, reputation and effectively, its profitability as well (e.g. King & Soule, 2007; Piazza et al., 2024), if competitors, customers or potential employees learn about it.

2.3. Organizational Identification and Organizational Deviance (Hypothesis 1)

After establishing the impact of organizational identification, a basic human need, on employees' behavior (e.g. van Dick, 2005) and having demonstrated the importance of the behavioral construct of organizational deviance for an organization's wellbeing or survival (e.g. Bennett & Robinson, 2000), suggests the relevance of examining the relationship between both constructs (see e.g. Qiuyun et al., 2020). What they have in common and thus, makes them comparable variables for an analysis, is both of them being individual-level variables with potential for collective-level (organizational) outcomes: an individual's identification with the organization and an individual's deviant behavior towards the organization (Ashforth et al., 2008).

According to Ashforth's and Mael's (1989) view, it can be expected that "as organizational identification strengthens, employees adhere to and behave in ways that are consistent with organizational norms" (Umphress et al., 2010, p. 770). This feeds into the assumption that organizational identification is negatively related to destructive behavior that intentionally deviates from the organizational norms. Therefore, I propose that employees who strongly identify with their organization, will be less likely to engage in deviant behavior.

Hypothesis 1: Organizational identification is significantly negatively related to organizational deviance, such that, as organizational identification becomes stronger, organizational deviance diminishes.

2.4. The Moderating Role of Tenure (Hypothesis 2)

Based on the unexpected findings of a study which revealed that organizational identification was not significantly related to constructive deviant behavior, Umphress et al. (2010) suggest that "strong organizational identification (or over-identification) alone may not drive" (p. 775) unethical employee behavior. This raised my assumption that the relationship between organizational identification and any type of organizational deviance (destructive as well) may be more complex. My assumption is supported by Aguinis (2004), who points out that the "first order effect of a main effect relationship" (Umphress et al., 2010, p. 776) can be interpreted as an average effect of this relationship (Aguinis, 2004, pp. 35). This explanation and the approach used by Umphress et al. (2010) suggested that the significance of a relationship may depend on the consideration of additional potentially influential factors. Hence the investigated effect of organizational identification on deviance, may benefit from an analysis of the main relationship for different values of such a factor.

The existing literature advocates the consideration of tenure as a moderating influence in the relation of organizational identification and deviance (e.g. Berry et al., 2007; Qiuyun et al., 2020; Riketta, 2005; Vadera & Pratt, 2013).

Furthermore, Wright and Bonett (2002) advise to distinguish between organizational tenure, job tenure and other forms of tenure (see e.g. Mathieu & Zajac, 1990). In this paper, with the term *tenure,* I refer to organizational tenure, which defines the number of years a person has been employed by an organization (Hall & Schneider, 1972; Kim, 2018).

Although literature (e.g. Decoster et al., 2013; Hall et al., 1970; Mael & Ashforth, 1992; Riketta, 2005) does not quite agree on whether to view tenure as an antecedent or consequence of organizational identification, it acknowledges a positive relation, suggesting that with longer tenure, the strength of organizational identification increases.

However, for the association of tenure with organizational deviance, I found conflicting results, within similar organizational contexts. On the one hand, some researchers (e.g. Hameed et al., 2013; Kim, 2018) state that "initially desirable and positive job behaviors" (Kim, 2018, p. 339) can be expected to decrease over time, as e.g. job boredom or lack of motivation might increase with longer tenure. Moreover, "role conflict and overload among employees was found to decrease their affective commitment and job satisfaction over time" (Kim, 2018, p. 339). This serves as a base for the assumption that with longer tenure, employees might become more likely to engage in negative (deviant) behavior.

On the other hand, human capital theory (Myers et al., 2004), speaks for organizational tenure increasing employees' career development at and connection with the organization. Hence, this view suggests that as organizational tenure increases, members are more likely to feel connected to and show commitment towards their organization (Kim, 2018), since longer tenured employees have had more time to share experiences and adjust to organizational culture (Hameed et al., 2013). Additionally, according to that view, different forms of employee commitment might increase with tenure, due to the advantages that come with long service, such as e.g. seniority, retirement contributions, job security, or more vacation days (Kim, 2018; Wright & Bonett, 2002).

Despite finding different opinions about the impact of tenure, the arguments advocating a positive relationship between tenure and desirable organizational outcomes seem to be prevailing. Therefore, they lead to the assumption that longer tenure is negatively related to deviant behavior, which was also confirmed in a study by Berry et al. (2007).

Based on the derived assumptions about a positive relationship between tenure and organizational identification (e.g. Riketta, 2005) and tenure's negative relation to deviant behavior (e.g. Berry et al., 2007), I propose the following:

Hypothesis 2: Tenure moderates the relationship between organizational identification and organizational deviance, such that stronger organizational identification reduces organizational deviance more for longer tenured individuals, then for short tenured employees.

3. Methods

3.1. Research Design

The employee data used for the empirical analysis in this paper stems from an industrial organization headquartered in Switzerland and operating internationally. The company's name will remain anonymous throughout this study, hence will further be referred to as Company X. The data was collected by representatives of the University of Lucerne, as part of a joint research project in collaboration with Company X. This research project was funded by an independent party, the Swiss National Science Foundation. The data collection process consisted of virtual interviews as well as three surveys, conducted online and in English within three research cycles over the course of three years: t1 (2021), t2 (2022), t3 (2023).
The employees of Company X participated on an entirely voluntary-basis. For the surveys, the university's representatives used measures previously validated in research (see section 3.3) and combined the answers with information from Company X's HR department.

3.2. Sample and Procedure

The sample considered for this paper consisted of survey participants of the second (t2) and third research cycle (t3) only, as the data from t1 does not contain information on organizational identification and organizational deviance. All surveys were conducted with white-collar workers of Company X, including employees (talents and non-talents) and their supervisors (top- and middle management). Of the overall 593 individuals that participated in the second and/or third survey, I counted 296 participants in t2 and 360 in t3.
To minimize common method bias (Podsakoff et al., 2003), I chose to investigate a time-lagged effect, i.e. the effect of organizational identification in t2 on organizational deviance in t3. In the present study, besides the temporal separation of measurement, I ensure the validity of my conclusions, with data from different sources (raters), by not only including self-reported data from the surveys, but also demographic predictors (age and tenure), provided by the HR Department of Company X. After keeping only the observations without missing values for the relevant time-lagged variables in this study the sample consisted of 147 observations.

Of the 147 participants considered in this sample, around 63% were male and 37% were female (see Appendix 1.1). They were between 25 and 64 years old, with an average age of about 47 years within that group. Tenure ranged from around 1.5 to about 45 years of employment by Company X, with the average tenure of almost 11 years. Around 50% of the individuals are managers, i.e. have direct reports, and about one third of the sample is identified as a talent employee (see Appendix 1.2.). Regarding their nationality, I found a majority of approximately 78% European employees (see Appendix 1.3. & 1.4). Furthermore, the sampled group has a mainly academic background, with nearly 70% having at least a university degree (see Appendix 1.5.).

In conclusion, the chosen sample is appropriate for this study to contribute with a focus on the moderating effect of tenure, as it offers a wide range in regards to age and tenure, as well as a diverse workforce with a multinational character.

To analyze the moderating effect of tenure in the relationship between organizational identification and deviance, I divided tenure into the three groups of short, medium and long tenure (see Hayes, 2018; Preacher et al., 2007), leaning on the method of other researchers (e.g. Hameed et al., 2013; Ng & Feldman, 2011; Wright & Bonett, 2002), using 5-year-intervals (see Appendix 3.1.). To quantify the three tenure groups, I calculated the average tenure for the observations in each group (see Hayes, 2018; Preacher et al., 2007).

Firstly, I used the data set (N = 147) to compute descriptive statistics of all the variables, including their correlations with each other (see section 4.1. and Appendix 4.). Secondly, before conducting the regression, I checked five assumptions for a linear multiple regression (Dalpiaz, 2021). After the necessary adjustments, explained in more detail in Appendix 7, and removing any influential outliers, the new sample size for the regression was N = 139. Therefore, I then adjusted the average tenure values of the three groups to the new sample size (see Appendix 3.2.), displayed in Table 1. Lastly, I conducted the regression analysis in three steps (see Appendix 8.) and complemented the analysis of the moderating effect of tenure with a scatter plot (Fig. 2) portraying separate regression lines for the relationship between organizational identification and deviance for each tenure group.

Table 1. Average Tenure and Number of Observations per Tenure Groups (N = 139).

Tenure Group	***Range[a] (in years)***	***Average Tenure (in years)***	***Observations***
Short Tenure	< 5	2.83	40
Medium Tenure	5 ≤ medium tenure ≤ 10	6.69	40
Long Tenure	> 10	17.68	59
Total			**139**

Note: [a] (see Hameed et al., 2013; Ng & Feldman, 2011; Wright & Bonett, 2002).

3.3. Measures

3.3.1. Predictor Variable - Organizational Identification

A scale (see Appendix 2.1.) of four items devised by Mael and Ashforth (1992), measured the employee’s extent of organizational identification. With a 7-point Likert scale the respondents indicated how much they agreed or disagreed with each statement (*1 = strongly disagree,* to *7 = strongly agree*). A sample item was: “When someone criticizes [Company X], it feels like a personal insult.” (Mael & Ashforth, 1992, p. 122).

3.3.2. Dependent Variable - Organizational Deviance (t3)

The frequency with which participants engaged in deviant behavior towards their organization in the last year, was measured using a twelve-item-scale proposed by Bennett and Robinson (2000) and a 7-point Likert scale (*1 = never,* to *7 = daily*) (see Appendix 2.2). One sample item included e.g. ‘‘Discussed confidential company information with an unauthorized person” (Bennett & Robinson, 2000, p. 360).

3.3.3. Moderator Variable - Organizational Tenure

To obtain the data on the organizational tenure of the participants, a dropdown list with years to choose from was included in the online survey of t2 and aligned with the demographic information provided by the HR department.

3.3.4. Control Variables - Age, Job Satisfaction and Organizational Deviance (t2)

For a reliable regression, I controlled for other variables that could impact the investigated relationship (Bernerth & Aguinis, 2016): age, job satisfaction and organizational deviance(t2). According to previous research (e.g. Aquino & Douglas, 2003; Becker, 2005; Berry et al., 2007; Riketta, 2005) demographic variables, such as age, may influence identification and deviance. As mentioned before, the participants’ age was provided by the HR Department.
Likewise, job satisfaction has been shown to have a strong correlation with organizational identification (e.g. Avanzi et al., 2012; Hall & Schneider, 1972) and with deviant behavior at work (e.g. Judge et al., 2006; Kulas et al., 2007). Participants rated their overall job satisfaction at Company X with two items and a 10-point Likert scale (see Appendix 2.3.).
Lastly, considering the investigated time-lagged effect, for the purpose of eliminating an alternative explanation for the dependent variable in my model (Bernerth & Aguinis, 2016; Podsakoff et al., 2003), I controlled for organizational deviance at t2 as well.

4. Results

4.1. Descriptive Statistics

Means, standard deviations, and interrelations of the variables from for the chosen sample (N = 147) are provided in Table 2. Considering the Likert scales ranged from 1 to 7, organizational deviance takes relatively low mean values (M = 1.34 and 1.42) in both time periods, while the mean organizational identification level (M = 5.29) is relatively high. Regarding the standard deviation, identification (t2) and deviance (t3) both measure low values (SD = 1.09 and 0.44), contrary to age (SD = 10.18) and tenure (SD = 7.33). According to Table 2., organizational identification in t2 and organizational deviance in t3 were, as expected, significantly and negatively related ($r = -0.41$, $p < 0.05$). Tenure correlates negatively with deviance in t2 (r = -0.04), and positively with deviance in t3 (r = 0.13). The correlation between tenure and organizational identification, found in this sample, was positive (r = 0.03). Nevertheless, for both main variables and both time periods the correlation with tenure is not statistically significant. Additionally, Table 2. confirms a significant and strong correlation of organizational deviance (t2), with organizational identification (t2) ($r = -0.38$, $p < 0.05$), as well as with deviance (t3) ($r = 0.71$, $p < 0.05$).

Table 2. Descriptive Statistics and Correlations (N = 147).

	M	*SD*	*1*	*2*	*3*	*4*	*5*	*6*
1. Age (in years)	46.78	10.18	–					
2. Job Satisfaction	7.76	1.54	-.00 [-.16, .16]	*(0.85)*				
3. Org Deviance (t2)	1.42	0.43	-.23 [-.38, -.08]	-.27 [-.42, -.12]	*(0.82)*			
4. Tenure (in years)	10.99	7.33	.36 [.21, .49]	.03 [-.14, .19]	-.04 [-.20, .12]	–		
5. Org. Identification	5.29	1.09	0.19 [.03, .34]	.31 [.16, .45]	-.38* [-.51, -.23]	.03 [-.14, .19]	*(0.84)*	
6. Org. Deviance (t3)	1.34	0.44	-0.22 [-.37, -.06]	-.30 [-.44, -.14]	.71* [.62, .78]	.13 [-.03, .29]	-.41* [-.54, -.27]	*(0.80)*

Note: N = Sample Size, M = Mean, SD = Standard Deviation, Org. = Organizational.
The 95%-Confidence Intervals for the respective correlation coefficients are given in square brackets.

The significance of the correlations between the variables is denoted by * ($p < 0.05$), ** ($p < 0.01$) and *** ($p < 0.001$). (For more details, see Appendix 4.)
Cronbach alpha reliabilities for the non-demographic variables are given in cursive and parentheses along the diagonal. (For the calculation and interpretation, see Appendix 5.)

4.2. Hypothesis Testing

Firstly, before conducting the regression, I checked five assumptions for a linear multiple regression. For two of the five, I was suspicious to accept them as fulfilled, (see Appendix 7.). Consequently, I applied the log-value of organizational deviance (t3), my dependent variable in the regression model, and removed eight influential outliers, which yielded better results in regards to the assumptions. (For details and implications, see Appendix 7.). This resulted in a new sample size of N = 139 and adjusted average tenure values (see Table 1.)

The results from the 3-step hierarchical linear regression analysis are shown in Table 3. It contains the unstandardized values for the correlations (regression coefficients) between the independent variables and the dependent variable, as well as the respective standard deviations (see Appendix 8.). Model 1 tests only the control variables; age, job satisfaction and organizational deviance (t2). For organizational deviance (t2), the coefficient was positive and highly significant (e.g. $\beta = 0.445$, $p < 0.001$, in Model 1) across all models. This indicates that higher levels of deviance at t2 predict higher levels of deviance at t3.
In Model 2, I added the main predictor, organizational identification (t2) and tenure to the regression. Here, the effect on organizational deviance (t3) was negative ($\beta = -0.023$) for organizational identification (t2), as expected, but not statistically significant. Moreover, contrary to the expectations of tenure having a negative effect (see e.g. Berry et al., 2007), in both Models, 2 and 3, the effect on deviance (t3) was positive and highly significant (e.g. $\beta = 0.008$, $p < 0.001$, in Model 2). I note that job satisfaction shows no significant correlation, while age has a significant but weak negative effect on deviance (t2) in Models 2 and 3.
As a final step, Model 3 includes the interaction term for organizational identification and tenure. In Model 3, I found that, when holding the effects of other variables constant, the direct effect of identification (t2) on deviance (t3) became positive, but stayed statistically insignificant, which is unexpected, considering the significant negative correlation initially observed in Table 2. Consequently, the third model rejects Hypothesis 1. The direct positive effect of tenure on deviance (t3), on the other hand, became slightly stronger than before and remained significant ($\beta = 0.030$, $p < 0.01$).
However, regarding the moderating effect of tenure, Table 3. demonstrates that, despite the positive (and partially insignificant) separate effects of tenure and organizational identification

(t2) on deviance (t3) in Model 3, the interaction between organizational identification and tenure had a negative and significant effect (β = -0.004, $p < 0.05$) on organizational deviance, although it is relatively weak. Nevertheless, this indicates that tenure does moderate the relationship between organizational identification and organizational deviance, so that the negative effect of identification on deviance is stronger as tenure increases, which is consistent with Hypothesis 2.

Table 3. Hierarchical Regression Analysis of the Effect on Organizational Deviance (N = 139).

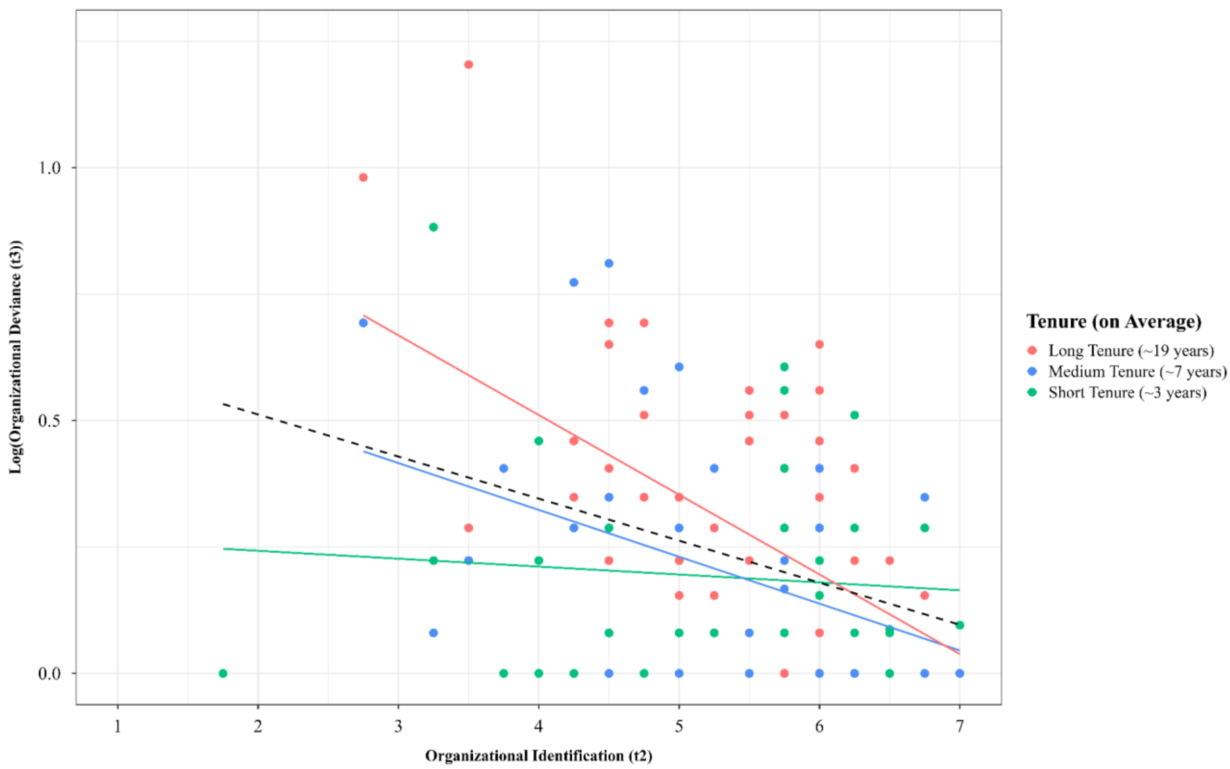
	log(Organizational Deviance (t3))		
Model	***(1)***	***(2)***	***(3)***
(1) Control Variables			
Age (in years)	-0.002 (0.001)	-0.004* (0.001)	-0.003* (0.001)
Job Satisfaction	-0.004 (0.010)	-0.005 (0.010)	-0.002 (0.010)
Org. Deviance (t2)	0.445*** (0.039)	0.415*** (0.038)	0.404*** (0.038)
(2) Main Effect			
Org. Identification		-0.023 (0.014)	0.013 (0.022)
Tenure		0.008*** (0.002)	0.030** (0.010)
(3) Interaction Effect			
Org. Identification*Tenure			-0.004* (0.002)
Constant	-0.273* (0.135)	-0.010 (0.145)	-0.306 (0.171)
Observations	138	138	138
Adj. R^2	0.546	0.597	0.608
RSE	0.162 (df = 134)	0.153 (df = 132)	0.151 (df = 131)

Note: Adj. = Adjusted, RSE = Residual Standard Error, df = Degrees of Freedom, Org. = Organizational.
The values in parentheses represent the standard deviation (SD) of the respective coefficient.
The significance of the regression coefficients is denoted by * ($p < 0.05$), ** ($p < 0.01$) and *** ($p < 0.001$). (For more details, see Appendix 8.2.).

Table 3. additionally shows that the adjusted R^2 value increases from 0.546 to 0.608 and the residual standard error (RSE) decreases slightly from 0.162 to 0.151. This demonstrates that each step increases the model's accuracy in predicting organizational deviance and adds explanatory power. The final model explains a substantial portion (nearly 61%) of the variance in organizational deviance (t3).

For the visual analysis of the moderating effect of tenure, I constructed a scatter plot (Fig. 2.) that depicts a simple model of the relationship between organizational identification (t2) and organizational deviance (t3) for each tenure group (see Table 1.). The figure illustrates that the overall direct relationship between organizational identification and deviance in Company X is negative, when no other control variables are considered. Furthermore, Fig. 2 depicts slightly steeper lines only for the longer tenured group (red), which confirms a stronger negative effect of organizational identification on deviance for longer tenured employees (10+ years). Moreover, there is almost no effect of organizational identification on organizational deviance at all, for the employees with tenure below five years (green).

Fig. 2. Impact of Organizational Identification on Organizational Deviance per Tenure Group (N=139).



Note: The dots indicate the actual values, while the plotted lines represent the estimated regression lines. The dashed black line represents the regression for the simple, averaged effect across all levels of tenure.

5. Discussion

5.1. Key Findings and Theoretical Implications

In this paper, I investigate the time-lagged effect of organizational identification on organizational deviance. Based on Social Identity Theory (Ashforth & Mael, 1989) and further research based on it (e.g. Qiuyun et al., 2020), I argued that an employee's organizational identification is negatively related to the frequency in which they engage in deviant behavior at work. Additionally, I examined the moderating effect of tenure, for which I found conflicting results (e.g. Hameed et al., 2013; Kim, 2018). I further proposed that tenure moderates the relationship between organizational identification and deviance, so that the negative effect intensifies with increasing tenure, i.e. employees with strong organizational identification engage in even less deviant behavior if they also have longer tenure.

The empirical investigation of the employee data from the internationally operating Company X, resulted in a relatively low standard deviation for organizational identification (SD = 1.09) and organizational deviance (SD = 0.43 and 0.44) (see Table 2.). This indicates small variance in how strongly the employees identify with and engage in deviant behavior towards Company X. On the other hand, the tenure standard deviation of around 7 years demonstrates considerable variation of tenure in the sample. Furthermore, the mean organizational identification at Company X (M = 5.29) was considerably high, given the 7-point Likert scale used for the measure. Other studies on employees, with similar sized samples reported similarly high mean values for organizational identification: e.g. M = 3.08 (Liu et al., 2021) and M = 5.18 (Qiuyun et al., 2020), using a 5-point and 6-point Likert scale.

Within the hierarchical regression analysis, before including the interaction term for organizational identification and tenure (see Table 3., Model 2), I found only partial support for Hypothesis 1. Although the observed effect of organizational identification on deviance was negative, as predicted by theory (Ashforth and Mael, 1989) stating that higher organizational identification is associated with lower organizational deviance, the effect was rather weak as well as statistically insignificant. However, once I added the interaction effect of organizational identification and tenure to the final model (see Table 3., Model 3), the direct relation between organizational identification and organizational deviance became positive and remained statistically insignificant, which was unexpected. The positive relation between organizational identification and organizational deviance in Model 3, although statistically insignificant in this analysis, could be explained by the negative effects of over-identification (e.g. Vadera & Pratt, 2013), discussed previously in section 2. Once employees surpass their individual "ideal" level of identification with their organization, they might e.g. refuse to follow new organizational rules as a form of resistance to organizational change (Ashforth et al., 2008; Ashforth, 2016; Conroy et al., 2017) or engage in unethical acts on behalf of the organization (Ashforth et al., 2008; Ashforth, 2016; Conroy et al., 2017; Umphress et al., 2010; Vadera & Pratt, 2013).

Contrary to my expectations about the negative impact of tenure on deviant behavior (see e.g. Berry et al., 2007), Table 3. demonstrated a positive significant effect, indicating that longer tenure is related to increased organizational deviance. This points to the previously found conflicting results in existing literature (see e.g. Hameed et al., 2013; Kim, 2018). The results obtained from the sample of Company X seem to align with the view that tenure is positively related to organizational deviance. This could be due to employees accruing more stress as their workload and responsibilities increase with their tenure (Hameed et al., 2013; Kim, 2018; Ng & Feldman, 2011). The added stress could "reduce their tendency of developing positive attitudes toward organization" (Hameed et al., 2013, p. 106) and thus, indirectly impact their motivation for deviant behavior. Furthermore, Hameed et al. (2013) leans on previous studies that verified e.g. unfavorable perceptions toward work environment and lack of organizational citizenship behavior (Ng & Feldman, 2011) as potential consequences of longer tenure. Moreover, Kim (2018), observed an inverted U-shaped curve for the relationship between organizational tenure and desirable behaviors of employees in the public sector, based on the *honeymoon effect* and the *hangover effect*. With that, Kim (2018) means that newcomers with "relatively low tenure tend to be more willing to devote themselves to the organization, [...] and work for the common good" (p. 339), but the benefits of organizational socialization as well as their job satisfaction may decline after the initial peak.

The results from the regression analysis (see Table 3.), confirm a weak, but significant, negative effect on organizational deviance, for the interaction between organizational identification and tenure. This indicates that the relationship between organizational identification and deviance in this sample is, in fact, different for employees of different tenure levels, i.e. the effect of identification on deviance is moderated by tenure. This is reinforced by Fig. 2, demonstrating that for the same level of organizational identification, longer tenured employees will report lower values of deviance than other employees.

What is unexpected is that the effect of organizational identification is significant and negative only for its interaction with tenure (see Table 3.), which suggests that only the combined effect

of high organizational identification and high tenure reduces deviance. However, according to (Umphress et al., 2010), researchers debate that "replicating interaction effects is not only a rarity but a difficult task" (Umphress et al., 2010, p. 776, e.g. Aguinis, 2002).
What also stands out is that, in this sample, the strongest predictor of future organizational deviance seems to be past deviance, implying that employees of Company X who engaged in deviant behaviors at one point in time (t2) are likely to continue doing so (in t3).

5.2. Practical Implications

The findings of this study suggest that to reduce deviant behavior that threatens the organization (Bennett & Robinson, 2000), management should invest in enhancing employees' identification with the organization. However, considering that strong identification can lead to both, positive and negative outcomes (e.g. Ashforth et al., 2008; Vadera & Pratt, 2013), the insignificant effect for organizational identification alone, as well as the significant moderating effect of tenure found in my analysis, lead to the following conclusion: A deeper understanding of how organizational identification develops and is maintained as employees become more tenured might be essential for maintaining low levels of destructive deviance. In the long-run or in the bigger picture, this ensures effectiveness and survival as a company, as argued by Conroy et al. (2017).

In my study of Company X, results indicate that strong organizational identification, especially in employees with tenure over 10 years, has a more powerful impact on reducing organizational deviance than for other levels of tenure (see Fig. 2). However, assuming that increased tenure will automatically strengthen identification and reduce deviance may be misguided. The correlation between tenure and identification was neither strong nor statistically significant (see Table 2.), and tenure alone influenced deviance positively (see Table 3.). Therefore, management should consistently and consciously ensure organizational identification is strong enough across all employee segments, respectively all tenure levels.

Permanent investment in identification, even for long-tenured employees, might not always be beneficial. While this study did not pinpoint when identification becomes pathological (*over-* or *under-identification*, see Dukerich & Kramer, 1998; Vadera & Pratt, 2013), I argue that maintaining a balanced level of identification is crucial. Managers should continuously monitor identification efforts to establish an ideal level that avoids negative outcomes, such as overcommitment to failing projects, resistance to change, groupthink or unethical behavior on behalf of the organization (Ashforth et al., 2008; Ashforth, 2016; Conroy et al., 2017, Umphress et al., 2010).

Moreover, Ashforth et. al. (2008) suggest that "organizations might not want all of their members to be highly identified because of the costs involved in achieving that identification and the difficulty in releasing them from the organization when their usefulness has been exhausted" (p. 337).

5.3. Limitations and Future Research

The results in Table 2. show noticeably low mean values around 1, for organizational deviance across both time periods, which was measured using a 7-point Likert scale. This might be due to the sample's composition, where over 50% are managers by having one or more direct reports and nearly a third of the sample are identified as talents (see Appendix 1.2.), or because the survey was conducted exclusively among white-collar workers at Company X, which are the employees typically performing managerial or administrative tasks in an office-setting. These participants likely hold higher hierarchical positions at the industrial Company X, which, according to Bowles and Gelfand (2010), tend to evaluate deviance more leniently. The generally low self-reported deviance values in the present sample could also be linked to participants' desire to conform to organizational norms, especially during the talent selection process. Although the use of self-reported data for organizational deviance is generally accepted in research (Ferris et al., 2009), future studies could consider multilevel and cross-level analyses (Quiyun et al., 2020) to reduce the potential risk of self-reported bias.

By analyzing a time-lagged effect in this study, for the reasons of avoiding common method bias (Podsakoff et al., 2003) and eliminating the risk of reverse causality (see Appendix 6), this statistical method results in some limitations nevertheless, as it offers only limited possible interpretations of the causality between the study variables (Qiuyun et al., 2020).
Additionally, collecting data with repeating measurements over the course of several years increases the risk of missing data and a reduced sample size, due to survey participants dropping out of the study (Podsakoff et al., 2003). This becomes evident in this study, as the sample size of N = 296 in t2 and N = 360 in t3, diminished to N = 147 after keeping only the usable observations for the time-lagged investigation (see section 3.).

Another limitation of the statistical procedure applied in this study stems from not fully meeting the assumptions of a linear multiple regression (see Appendix 7.). Despite adjustments to optimize the variance of residuals, the model still did not fully satisfy homoscedasticity. As a result, the standard errors and p-values of the regression coefficients might be slightly inaccurate, requiring cautious interpretation of predictor significance and hypothesis testing. However, the regression coefficients themselves are likely still unbiased. Future studies might improve reliability by using heteroskedasticity-robust standard errors or bootstrapping methods (see Preacher et al., 2007).

The relatively small sample size available for the present study could also result from collecting data from a single company. While providing valuable insights into organizational identification, workplace deviance and tenure within Company X, it restricts the broader applicability of the findings. Future studies might consider larger samples for broader implications, but this could introduce unnecessary complexity. I argue that a broader understanding of organizational constructs can emerge from multiple smaller studies across different industries. Despite the small sample size, this paper contributes to existing literature by offering insights into the relationship between organizational identification and deviance, with the specific focus on tenure as a moderator, among white-collar employees in a global industrial company, relevant to similar industries and contexts.

Another limitation, could be the division of tenure into the three groups of short, medium and long (see section 3). While the method used in this paper (short for < 5 years, medium for ≥ 5 and ≤ 10 years, long for > 10 years) is based on the grouping method applied by several other researchers (e.g. Hameed et al., 2013; Ng & Feldman, 2011; Wright & Bonett, 2002), it accounts for unequal sized tenure-groups (see Table 1.). This could affect the outcome and thus, interpretation of the moderating effect of tenure in this sample. Future research, investigating a moderating or mediating effect of tenure, thus, could consider different ways to divide tenure into relevant groups. Alternatives according to Hayes (2018) are a standard deviation below the mean, the mean, and a standard deviation above the mean or the 16th, 50th and 84th percentile of the distribution of the continuous values.

Additionally, the analysis in this paper was limited by the inclusion of only three control variables, due to the relatively small sample size: age, organizational deviance in t2, and job satisfaction. However, the rather small coefficients for the main effect and the interaction effect (see Table 3.), point to the complexity of the relationship examined and indicate that the effect of organizational identification on deviance might depend on multiple factors, besides tenure and the considered control variables. Future studies, analyzing the effect of organizational identification on organizational deviance, may benefit from controlling for more variables with potential influence, such as e.g. education (Qiuyun et al., 2020), supervisor identification (Ashforth et al., 2008; Johnson & Umphress, 2019), or other types of tenure, such as job tenure (see Mathieu & Zajac, 1990; Wright & Bonett, 2002).

Furthermore, the analysis of organizational identfication’s impact on deviant behavior at work could be enriched by expanding the definition of deviance to include both destructive (Bennett & Robinson, 2000) and constructive deviance (Hanke & Saxberg, 1985). Constructive deviance refers to the voluntary violation of norms with the intent to benefit the organization and its members (Galperin, 2003; Niu et al., 2022). As Ashforth and Mael (1998) note, such behaviors may include innovative actions or challenging dysfunctional directives (see also Galperin, 2003). This suggests that organizational deviance is not always undesirable. The relationship between organizational identification and deviance may be more nuanced, as reducing deviant behavior might not benefit the organization if it involves constructive deviance. Low levels of constructive deviance might impede organizational progress and adaptability in a changing environment (Galperin, 2003; Niu et al., 2022).

5.4. Conclusion

In conclusion, this study highlights the relationship between organizational identification and organizational deviance, revealing that tenure has a significant moderating effect. The findings suggest that longer-tenured employees with strong organizational identification are less likely to engage in deviant actions, though pathological levels of identification such as e.g. over-identification (Dukerich & Kramer, 1998) can lead to undesirable outcomes of low organizational deviance. The study contributes to the understanding of how tenure influences the impact of organizational identification on behavior, providing valuable insights for management strategies aimed at fostering desirable organizational behavior for organizational profitability and well-being.

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Appendix

A.1. Appendix 1: Sample Details

A.1.1. Gender Distribution of the Sample (N = 147)

Gender	Counts	Percentage
Male	93	63.26530612244900
Female	54	36.734693877551000

A.1.2. Talent and Manager Distribution in the Sample (N = 147)

Talents:

t	Talent	Counts	Percentage
t2	**no**	106	72.10884353741500
	yes	41	27.89115646258500
t3	**no**	105	71.42857142857140
	yes	42	28.57142857142860

Direct Reports:

t	Counts	Percentage
t2	77	52.38095238095240
t3	75	51.02040816326530

A.1.3. Nationality Distribution of the Sample (N = 147)

Continents	Counts	Percentage
Europe	112	78.32167832167830
America	30	20.97902097902100
Asia	1	0.6993006993006990

Countries	Counts	Percentage
Switzerland	36	25.174825174825200
United States	24	16.783216783216800
Italy	22	15.384615384615400
Belgium	21	14.685314685314700
Czech Republic	17	11.888111888111900
Germany	9	6.293706293706290
Brazil	6	4.195804195804200
Netherlands	2	1.3986013986014000
Austria	1	0.6993006993006990
China	1	0.6993006993006990
France	1	0.6993006993006990
Portugal	1	0.6993006993006990
Slovenia	1	0.6993006993006990
Spain	1	0.6993006993006990

A.1.4. Nationality Distribution of the European Participants in the Sample (N = 112)

Countries (EU)	Counts	Percentage
Switzerland	36	32.142857142857100
Italy	22	19.642857142857100
Belgium	21	18.75
Czech Republic	17	15.178571428571400
Germany	9	8.035714285714290
Netherlands	2	1.7857142857142900
Austria	1	0.8928571428571430
France	1	0.8928571428571430
Portugal	1	0.8928571428571430
Slovenia	1	0.8928571428571430
Spain	1	0.8928571428571430

A.1.5. Education Distribution of the Sample (N = 147)

Education Type	Counts	Percentage
University – Master Degree or higher	66	45.51724137931040
University – Bachelor Degree	36	24.82758620689660
High school	33	22.758620689655200
Apprenticeship/Vocational Education	10	6.896551724137930

A.2. Appendix 2: Item Scales

The single items for the measures of the non-demographic variables of the present study, organizational identification, organizational deviance and job satisfaction, are presented below. (Despite what may be indicated in the original sources of, in this paper, a 7-point Likert-type scale was used for the measures of both main variables, OID and OD.)
Furthermore, I note that all the questions in the surveys (except for tenure and age) the participants also had the option of choosing "NO ANSWER" or leaving a question unanswered (empty).

A.2.1. All Scale Items of the Measure for Organizational Identification (Mael & Ashforth, 1992, p. 122)

Organizational identification

[1 = Strongly agree; 5 = Strongly disagree]

1 When someone criticizes (name of school), it feels like a personal insult.
2 I am very interested in what others think about (name of school).
3 When I talk about this school, I usually say 'we' rather than 'they'.
4 This school's successes are my successes.
5 When someone praises this school, it feels like a personal compliment.
6 If a story in the media criticized the school, I would feel embarrassed.

For the measure of organizational identification in this study, only four items (item 1, 3, 4 and 5) of this 6-item scale were selected and the word "school" was replaced by "Company X" in the surveys.
For this measure, the 7-point Likert scale, used in the survey, ranged from *1 = strongly disagree, 2 = disagree, 3 = somewhat disagree, 4 = neither agree nor disagree, 5 = somewhat agree, 6 = agree,* to *7 = strongly agree.*

A.2.2. All Scale Items of the Measure for (Organizational) Deviance (Bennett & Robinson, 2000, p. 360)

Final Interpersonal and Organizational Deviance Scale Items

Measure
Interpersonal Deviance
Made fun of someone at work
Said something hurtful to someone at work
Made an ethnic, religious, or racial remark at work
Cursed at someone at work
Played a mean prank on someone at work
Acted rudely toward someone at work
Publicly embarrassed someone at work
Organizational Deviance
Taken property from work without permission
Spent too much time fantasizing or daydreaming instead of working
Falsified a receipt to get reimbursed for more money than you spent on business expenses
Taken an additional or longer break than is acceptable at your workplace
Come in late to work without permission
Littered your work environment
Neglected to follow your boss's instructions
Intentionally worked slower than you could have worked
Discussed confidential company information with an unauthorized person
Used an illegal drug or consumed alcohol on the job
Put little effort into your work
Dragged out work in order to get overtime

For this measure, the full Likert scale, used in the survey, consisted of *1 = once a year, 2 = once a year, 3 = twice a year, 4 = several times a year, 5 = monthly, 6 = weekly* and *7 = daily.*

A.2.3. All Scale Items of the Measure for Job Satisfaction used in the Survey

1. On the whole, how satisfied are you with your work?
2. All in all, how satisfied are you with your career at Company X?

For this measure, the Likert scale in the survey ranged from *1 = not at all satisfied,* to *10 = completely satisfied*.

A.3. Appendix 3: Tenure Groups

This section contains the R-code used to divide the tenure values of the sample into three groups, long, medium and short tenure, based on the division used in other studies (e.g. Hameed et al., 2013, Ng & Feldman, 2011; Wright & Bonett, 2002). The output returned on R is denoted by "##".

A.3.1. Tenure Groups for Descriptive Statistics (N = 147)

```
#Dividing the continuous tenure values into three groups and adding a new column
(tenure_mod) to the data set

data_Zahlen_t23_timelagged_new <- data_Zahlen_t23_timelagged %>%
  mutate(tenure_mod = case_when(
    tenure > 0 & tenure < 5 ~ "short tenure",
    tenure >= 5 & tenure <= 10 ~ "medium tenure",
    tenure > 10 ~ "long tenure"
  ))

#Calculate the average tenure for each tenure group

mean_long_tenure <-
mean(data_Zahlen_t23_timelagged_new$tenure[data_Zahlen_t23_timelagged_new$tenure_mo
d == "long tenure"], na.rm = TRUE)

print(mean_long_tenure)
## [1] 19.14769

mean_medium_tenure  <-
mean(data_Zahlen_t23_timelagged_new$tenure[data_Zahlen_t23_timelagged_new$tenure_mo
d == "medium tenure"], na.rm = TRUE)

print(mean_medium_tenure)
## [1] 6.663656

mean_short_tenure  <-
mean(data_Zahlen_t23_timelagged_new$tenure[data_Zahlen_t23_timelagged_new$tenure_mo
d == "short tenure"], na.rm = TRUE)

print(mean_short_tenure)
## [1] 2.796816

#Add a column (tenure_group_average) to the data set with respective averages

data_Zahlen_t23_timelagged_new <- data_Zahlen_t23_timelagged_new %>%
  mutate(tenure_group_average = case_when(
    tenure_mod == "short tenure" ~ 19.14769,
    tenure_mod == "medium tenure" ~ 6.663656,
    tenure_mod == "long tenure" ~ 2.796816
  ))
```

Table A.1. Average Tenure and Number of Observations per Tenure Groups (N = 139).

Tenure Group	***Range[a] (in years)***	***Average Tenure (in years)***	***Observations***
Short Tenure	< 5	2.80	42
Medium Tenure	≥ 5 medium tenure ≤10	6.66	41
Long Tenure	> 10	19.15	64
Total			**147**

Note: [a] (see Hameed et al., 2013; Ng & Feldman, 2011; Wright & Bonett, 2002).

A.3.2. Tenure Groups for Regression Analysis (N = 139) (see Table 1.)

```
#re-calculate tenure group averages in smaller sample after removing outliers

mean_long_tenure <-
mean(data_Zahlen_t23_timelagged_new_clean$tenure[data_Zahlen_t23_timelagged_new_cle
an$tenure_mod == "long tenure"], na.rm = TRUE)
print(mean_long_tenure)

## [1] 18.90673

mean_medium_tenure<-
mean(data_Zahlen_t23_timelagged_new_clean$tenure[data_Zahlen_t23_timelagged_new_cle
an$tenure_mod == "medium tenure"], na.rm = TRUE)
print(mean_medium_tenure)

## [1] 6.690437

mean_short_tenure <-
mean(data_Zahlen_t23_timelagged_new_clean$tenure[data_Zahlen_t23_timelagged_new_cle
an$tenure_mod == "short tenure"], na.rm = TRUE)
print(mean_short_tenure)

## [1] 2.831573

#Add column to data set with respective averages

data_Zahlen_t23_timelagged_new_clean <- data_Zahlen_t23_timelagged_new_clean %>%
  mutate(tenure_group_average = case_when(
    tenure_mod == "short tenure" ~ 2.831573,
    tenure_mod == "medium tenure" ~ 6.690437,
    tenure_mod == "long tenure" ~ 18.90673
  ))
```

A4. Appendix 4: Descriptive Statistics (see Table 2.)

A.4.1. Descriptive Statistics

For the mean and standard deviation of job satisfaction and organizational deviance (in t2), one observation was excluded from the calculation, as this participant did not supply an answer (NA) for these two variables in the survey.

A.4.1. Correlation Matrix

```
#Correlation Matrix

correlation_matrix_timelagged <- cor(data_Zahlen_t23_timelagged_new[, c("age",
"satisfaction_t2", "orgdev_t2", "tenure_group_average", "orgid_t2",
"orgdeviance_t3")], use = "complete.obs")
print(correlation_matrix_timelagged)
##                                age satisfaction_t2   orgdev_t2
## age                   1.0000000000   -0.0006455937 -0.23368788
## satisfaction_t2      -0.0006455937    1.0000000000 -0.27394316
## orgdev_t2            -0.2336878761   -0.2739431631  1.00000000
## tenure_group_average  0.3569159811    0.0275005502 -0.04005296
## orgid_t2              0.1923005771    0.3130104811 -0.37867206
## orgdeviance_t3       -0.2163542725   -0.2964508181  0.71155549
##                      tenure_group_average    orgid_t2 orgdeviance_t3
## age                            0.35691598  0.19230058     -0.2163543
## satisfaction_t2                0.02750055  0.31301048     -0.2964508
## orgdev_t2                     -0.04005296 -0.37867206      0.7115555
## tenure_group_average           1.00000000  0.02734281      0.1303856
## orgid_t2                       0.02734281  1.00000000     -0.4135381
## orgdeviance_t3                 0.13038559 -0.41353807      1.0000000
```

```
#p-values for statistical significance of correlations

significance_corr <- rcorr(as.matrix(correlation_matrix_timelagged[, c("age",
"satisfaction_t2", "orgdev_t2", "tenure_group_average", "orgid_t2",
"orgdeviance_t3")], use = "complete.obs"))

p_values <- significance_corr$P #extract p values of correlation matrix

print(p_values)
##                            age satisfaction_t2   orgdev_t2 tenure_group_average
## age                         NA      0.92458640 0.173367314            0.3478682
## satisfaction_t2      0.9245864              NA 0.120910897            0.7536676
## orgdev_t2            0.1733673      0.12091090          NA            0.6318977
## tenure_group_average 0.3478682      0.75366763 0.631897707                   NA
## orgid_t2             0.4794615      0.20511538 0.032966648            0.8652925
## orgdeviance_t3       0.2117606      0.09566232 0.004913687            0.8772524
##                        orgid_t2 orgdeviance_t3
## age                  0.47946154    0.211760583
## satisfaction_t2      0.20511538    0.095662322
## orgdev_t2            0.03296665    0.004913687
## tenure_group_average 0.86529249    0.877252405
## orgid_t2                     NA    0.019174233
## orgdeviance_t3       0.01917423             NA
```

```r
#Fisher's Z Transformation for Confidence intervals

compute_ci <- function(r, n, conf.level = 0.95) {
  # Fisher's z transformation
  z <- 0.5 * log((1 + r) / (1 - r))
  # Standard error of z
  SE_z <- 1 / sqrt(n - 3)
  # Critical value for 95% confidence
  z_critical <- qnorm(1 - (1 - conf.level) / 2)
  # Confidence interval in z-scale
  z_lower <- z - z_critical * SE_z
  z_upper <- z + z_critical * SE_z
  # Transform back to r scale
  r_lower <- (exp(2 * z_lower) - 1) / (exp(2 * z_lower) + 1)
  r_upper <- (exp(2 * z_upper) - 1) / (exp(2 * z_upper) + 1)
  return(c(lower = r_lower, upper = r_upper))
}

# Function to apply compute_ci to a correlation matrix
correlation_ci <- function(correlation_matrix_timelagged, n) {
  # Create matrices for confidence intervals
  ci_lower <- matrix(NA, nrow = nrow(correlation_matrix_timelagged), ncol =
ncol(correlation_matrix_timelagged))
  ci_upper <- matrix(NA, nrow = nrow(correlation_matrix_timelagged), ncol =
ncol(correlation_matrix_timelagged))

  # Compute confidence intervals for each pair
  for (i in 1:nrow(correlation_matrix_timelagged)) {
    for (j in 1:ncol(correlation_matrix_timelagged)) {
      if (i != j) {  # Skip the diagonal
        ci <- compute_ci(correlation_matrix_timelagged[i, j], n)
        ci_lower[i, j] <- ci["lower"]
        ci_upper[i, j] <- ci["upper"]
      }
    }
  }

  list(lower = ci_lower, upper = ci_upper)
}

sample_size <- 147

# Compute confidence intervals
result <- correlation_ci(correlation_matrix_timelagged, sample_size)

# Print lower and upper bounds
print(result$lower)
##             [,1]       [,2]       [,3]        [,4]        [,5]        [,6]
## [1,]          NA -0.1625219 -0.3811609  0.20698263  0.03138435 -0.36544729
## [2,] -0.16252190         NA -0.4173281 -0.13499375  0.15918372 -0.43735400
## [3,] -0.38116089 -0.4173281         NA -0.20064520 -0.50934050  0.62122486
## [4,]  0.20698263 -0.1349938 -0.2006452          NA -0.13514873 -0.03218712
## [5,]  0.03138435  0.1591837 -0.5093405 -0.13514873          NA -0.53932412
## [6,] -0.36544729 -0.4373540  0.6212249 -0.03218712 -0.53932412          NA

print(result$upper)
##             [,1]       [,2]        [,3]      [,4]       [,5]        [,6]
## [1,]          NA  0.1612645 -0.07461756 0.4904688  0.3435000 -0.05643779
## [2,]  0.16126455         NA -0.11724985 0.1885544  0.4519990 -0.14134096
## [3,] -0.07461756 -0.1172499          NA 0.1226355 -0.2309362  0.78322441
```

```
## [4,]  0.49046885  0.1885544  0.12263553        NA  0.1884021  0.28623684
## [5,]  0.34349996  0.4519990 -0.23093619 0.1884021         NA -0.26970100
## [6,] -0.05643779 -0.1413410  0.78322441 0.2862368 -0.2697010          NA
```

A.5. Appendix 5: Cronbach's Alpha Results

I assessed the reliability of the scales used to measure the non-demographic variables using Cronbach's (1951) alpha and presented the respective values in Table 2.

A.5.1. Calculation of Cronbach's Alpha in R

For Job Satisfaction (t2):

```
## Reliability analysis
## Call: alpha(x = data_Zahlen_t23_timelagged_new[, c("satisfaction1_t2",
##     "satisfaction2_t2")])
##
##   raw_alpha std.alpha G6(smc) average_r S/N   ase mean  sd median_r
##       0.85      0.86    0.75      0.75   6 0.024  7.8 1.6     0.75
##
##     95% confidence boundaries
##          lower alpha upper
## Feldt     0.80  0.85  0.89
## Duhachek  0.81  0.85  0.90
##
##  Reliability if an item is dropped:
##                  raw_alpha std.alpha G6(smc) average_r S/N alpha se var.r med.r
## satisfaction1_t2      0.67      0.75    0.56      0.75   3       NA     0  0.75
## satisfaction2_t2      0.83      0.75    0.56      0.75   3       NA     0  0.75
##
```

For Organizational Deviance (t2):

```
## Reliability analysis
## Call: alpha(x = data_Zahlen_t23_timelagged_new[, c("deviance8_t2",
##     "deviance9_t2", "deviance10_t2", "deviance11_t2", "deviance12_t2",
##     "deviance13_t2", "deviance14_t2", "deviance15_t2", "deviance16_t2",
##     "deviance17_t2", "deviance18_t2", "deviance19_t2")])
##
##   raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd median_r
##       0.82      0.86    0.89      0.34 6.1 0.021  1.6 0.75     0.32
##
##     95% confidence boundaries
##          lower alpha upper
## Feldt     0.78  0.82  0.86
## Duhachek  0.78  0.82  0.87
##
##  Reliability if an item is dropped:
##               raw_alpha std.alpha G6(smc) average_r S/N alpha se var.r med.r
## deviance8_t2       0.81      0.83    0.87      0.31 5.0    0.023 0.021  0.28
## deviance9_t2       0.82      0.86    0.88      0.35 6.0    0.022 0.022  0.33
## deviance10_t2      0.81      0.85    0.88      0.34 5.6    0.023 0.023  0.32
## deviance11_t2      0.81      0.85    0.88      0.35 5.9    0.023 0.022  0.33
## deviance12_t2      0.82      0.86    0.88      0.35 5.9    0.022 0.022  0.34
## deviance13_t2      0.81      0.85    0.88      0.34 5.5    0.023 0.024  0.32
## deviance14_t2      0.82      0.86    0.89      0.35 6.0    0.022 0.022  0.35
## deviance15_t2      0.80      0.84    0.87      0.33 5.4    0.024 0.024  0.31
## deviance16_t2      0.81      0.84    0.86      0.32 5.2    0.023 0.015  0.32
```

```
## deviance17_t2      0.81      0.84    0.86      0.32 5.2    0.023 0.015  0.32
## deviance18_t2      0.81      0.85    0.87      0.33 5.5    0.023 0.022  0.32
## deviance19_t2      0.81      0.85    0.87      0.33 5.5    0.023 0.021  0.32
##
```

For Organizational Identification (t2):

```
## Reliability analysis
## Call: alpha(x = data_Zahlen_t23_timelagged_new[, c("orgid1_t2", "orgid2_t2",
##     "orgid3_t2", "orgid4_t2")])
##
##   raw_alpha std.alpha G6(smc) average_r S/N   ase mean  sd median_r
##       0.84      0.84    0.82      0.57 5.4 0.022  5.3 1.1     0.57
##
##     95% confidence boundaries
##          lower alpha upper
## Feldt     0.79  0.84  0.87
## Duhachek  0.79  0.84  0.88
##
##  Reliability if an item is dropped:
##           raw_alpha std.alpha G6(smc) average_r S/N alpha se   var.r med.r
## orgid1_t2      0.82      0.82    0.77      0.60 4.6    0.026 0.01414  0.57
## orgid2_t2      0.80      0.82    0.78      0.60 4.6    0.028 0.01663  0.60
## orgid3_t2      0.80      0.80    0.73      0.58 4.1    0.028 0.00034  0.57
## orgid4_t2      0.75      0.76    0.68      0.52 3.2    0.034 0.00198  0.51
##
```

For Organizational Deviance (t3):

```
## Reliability analysis
## Call: alpha(x = data_Zahlen_t23_timelagged_new[, c("deviance8_t3",
##     "deviance9_t3", "deviance10_t3", "deviance11_t3", "deviance12_t3",
##     "deviance13_t3", "deviance14_t3", "deviance15_t3", "deviance16_t3",
##     "deviance17_t3", "deviance18_t3", "deviance19_t3")])
##
##   raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd median_r
##        0.8       0.8    0.84      0.26 4.1 0.021  1.4 0.46     0.26
##
##     95% confidence boundaries
##          lower alpha upper
## Feldt     0.74   0.8  0.84
## Duhachek  0.75   0.8  0.84
##
##  Reliability if an item is dropped:
##               raw_alpha std.alpha G6(smc) average_r S/N alpha se var.r med.r
## deviance8_t3       0.78      0.80    0.82      0.26 3.9    0.022 0.024  0.27
## deviance9_t3       0.76      0.78    0.81      0.24 3.5    0.026 0.023  0.23
## deviance10_t3      0.80      0.81    0.84      0.28 4.4    0.021 0.023  0.28
## deviance11_t3      0.78      0.79    0.82      0.25 3.7    0.023 0.024  0.25
## deviance12_t3      0.78      0.80    0.83      0.26 3.9    0.023 0.025  0.26
## deviance13_t3      0.79      0.79    0.83      0.26 3.8    0.022 0.028  0.25
## deviance14_t3      0.76      0.78    0.81      0.24 3.5    0.024 0.023  0.23
## deviance15_t3      0.76      0.77    0.81      0.23 3.4    0.025 0.023  0.23
## deviance16_t3      0.78      0.79    0.83      0.25 3.7    0.022 0.027  0.23
## deviance17_t3      0.80      0.81    0.85      0.28 4.3    0.021 0.023  0.27
## deviance18_t3      0.79      0.79    0.83      0.26 3.9    0.021 0.028  0.26
```

```
## deviance19_t3      0.77      0.78    0.82      0.24 3.5    0.023 0.026  0.25
##
```

A.5.2. Interpretation of Cronbach's Alpha

I interpreted the calculated Cronbach's (1951) alpha values according to Streiner (2003). In the present analysis (see Table 2.), the scales showed excellent internal consistency, with Cronbach's alpha reliabilities between 0.80 and 0.85.

Table. A.2. Interpretation of Cronbach's Alpha according to Streiner (2003).

Cronbach's Alpha (α)	***Internal Consistency***
$80 < \alpha \leq 90$	Excellent
$70 < \alpha < 80$	Good
$60 < \alpha < 70$	Acceptable
$\alpha < 60$	Questionable

A.6. Appendix 6: Robustness Test

To check for reverse causality, first, I conducted a reverse causality test in the initial model. According to the results in R (see below), the regression would show a statistically significant reversed causal effect (β = -0.045, p < 0.1) for the interaction between organizational deviance (t2) and tenure on organizational identification (t2), if both variables are measured in the same time period.

Hence, besides the previously mentioned assumption about potential common method bias (see Podsakoff et al., 2003), these results confirming the risk of reverse causality in my model validate the use of time-lagged data for the following regression.

```
## Call:
## lm(formula = orgid_t2 ~ age + satisfaction_t2 + orgdev_t2 + tenure_group_average
+
##     orgdev_t2 * tenure_group_average, data = data_Zahlen_t23_timelagged_new)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.9920 -0.5507  0.1910  0.7329  1.5250
##
## Coefficients:
##                                 Estimate Std. Error t value   Pr(>|t|)
## (Intercept)                     3.889312   0.801167   4.855 0.00000318 ***
## age                             0.013852   0.008865   1.563    0.12042
## satisfaction_t2                 0.158884   0.055455   2.865    0.00481 **
## orgdev_t2                      -0.293448   0.314501  -0.933    0.35240
## tenure_group_average            0.058522   0.039037   1.499    0.13608
## orgdev_t2:tenure_group_average -0.045088   0.025929  -1.739    0.08424 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.982 on 140 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.2239, Adjusted R-squared:  0.1961
## F-statistic: 8.076 on 5 and 140 DF,  p-value: 0.000001018
```

A.7. Appendix 7: Assumptions of Multiple Linear Regression

There are five assumptions recommended to fulfill before performing a multiple linear regression (Dalpiaz, 2021): First, a linear relationship between the independent variables and the dependent variable. Second, homoscedasticity, a constant variance of the residuals across all levels of the independent variables. Third, the residual errors are independent of each other, i.e. no autocorrelation. Fourth, the residuals are normally distributed. And fifth, the independent variables are not too highly correlated with each other.

To check whether the five assumptions of a multiple linear regression are fulfilled, I run several tests on R on the simple regression model. In R, the model is denoted as:

```
#Model: y ~ control variables + X + M + X*M
model <- lm(orgdeviance_t3 ~ age + satisfaction_t2 + orgdev_t2 + orgid_t2 +
tenure_group_average + orgid_t2*tenure_group_average , data
=data_Zahlen_t23_timelagged_new)
```

Later, a log-transformation to the model will be necessary, which is covered in more detail in section A.6.2. Additionally to checking the assumptions, I will look for "unusual observations" in the data, as advised by Dalpiaz (2021, p. 282).

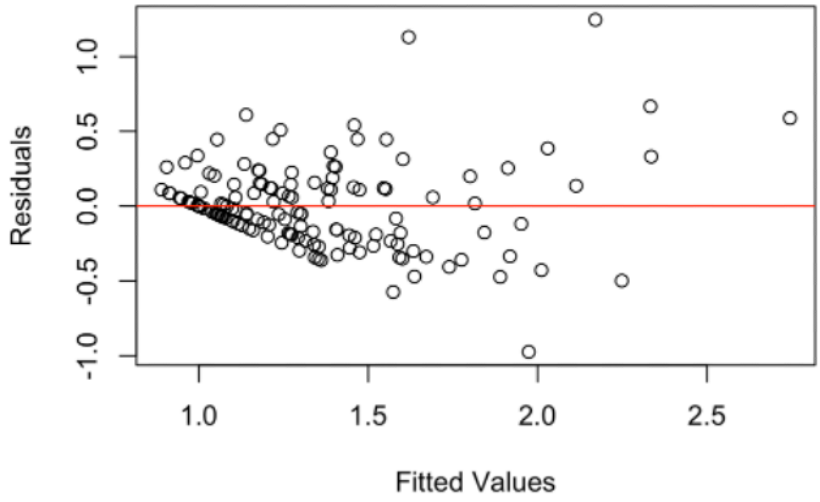
A.7.1. Linearity

To check for linearity, the fitted values can be plotted against the residuals (Dalpiaz, 2021). According to Dalpiaz (2021), "At any fitted value, the mean of the residuals should be roughly 0. If this is the case, the linearity assumption is valid." (p. 266).

The resulting plot is depicted in Fig. A.1. and shows that for any fitted value, the residuals seem to be roughly centered around the red horizontal line, where y = 0. Hence, the linearity assumption is fulfilled.

```
plot(model$fitted.values, model$residuals, xlab = "Fitted Values", ylab =
"Residuals")
abline(h = 0, col = "red")
```

Fig. A.1. Fitted vs. Residuals Plot of the Initial Regression Model.



However, what stands out in Fig. A.1. is that, for the larger fitted values, the spread of the residuals is much bigger. This results in a pattern, i.e. the points seem to be distributed in a subtle "horizontal-V"-shape, which might be problematic considering the following assumption.

A.7.2. Constant Variance of Residuals (Homoscedasticity)

To check for homoscedasticity, in other words constant variance of the residuals, Dalpiaz (2021) recommends the studentized Breusch-Pagan test. A big p-value would indicate homoscedasticity, while a small p-value would indicate heteroskedasticity, non-constant variance.

After running this test on my model in R, the output suggests that there is evidence of heteroskedasticity, by returning a small p-value (see below). This was also visible in the pattern observed in Fig. A.1. Hence, the second assumption of homoscedasticity is not fulfilled within the present model.

```
bptest(model)
##
##  studentized Breusch-Pagan test
##
## data:  model
## BP = 32.207, df = 6, p-value = 0.00001489
```

In the case of large variance, Dalpiaz (2021) recommends to apply a variance stabilizing transformation to the regression model, such as log(Y). Hence, the new transformed model is denoted by:

```
#Log-Model: log(y) ~ control variables + X + M + X*M
model_log <- lm(log(orgdeviance_t3) ~ age + satisfaction_t2 + orgdev_t2 + orgid_t2
+ tenure_group_average + orgid_t2*tenure_group_average, data =
data_Zahlen_t23_timelagged_new)
```

However, the results (see below) regarding the Homoscedasticity-test with the new log-model were still not satisfactory, as the new p-value was still relatively small.

```
bptest(model_log)
##
##  studentized Breusch-Pagan test
##
## data:  model_log
## BP = 17.756, df = 6, p-value = 0.006873
```

Additionally, Dalpiaz (2021) suggests removing the outliers, the points that don't fit the model well, since they can have a large effect on the model. To identify the outlying observations and measure their influence, I apply the Cook's Distance method (Dalpiaz 2021). According to the output in R (see below), my log-transformed regression model still has 8 influential observations.

```
model_log_cd = cooks.distance(model_log)
sum(model_log_cd > 4 / length(model_log_cd))

## [1] 8
```

Then, I removed them from the data set, which reduced the sample size to N = 139, for which I re-calculated the tenure group averages (see Appendix 3.2.). The new transformed and clean model, that will further be used for the analysis in this paper (corresponds to Model 3, see Appendix 8), is denoted by:

```
#Final log-model without outliers & with adjusted tenure group averages:

model_log_fix = lm(log(orgdeviance_t3) ~ age + satisfaction_t2 + orgdev_t2 +
orgid_t2 + tenure_group_average + orgid_t2*tenure_group_average , data =
data_Zahlen_t23_timelagged_new_clean)
```

This time, running the studentized Breusch-Pagan test for the final model, returns much better results (see below). The p-value ($p \approx 0.060$) became substantially bigger, compared to before ($p \approx 0.000$ and 0.007), indicating an improved variance of the residuals now.

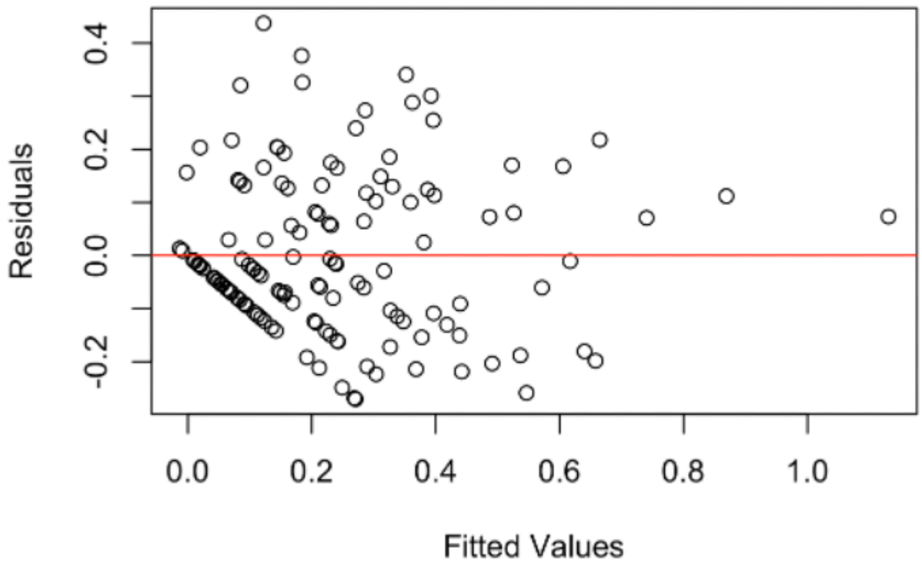
```
bptest(model_log_fix)
##
##  studentized Breusch-Pagan test
##
## data:  model_log_fix
## BP = 12.108, df = 6, p-value = 0.05961
```

Moreover, plotting the new fitted values against the residuals in Fig. A.2. shows that the points seem to be much more randomly distributed and there is now less of an obvious pattern. Furthermore, considering the significantly lower y-axis limits in Fig. A.2., I note that the overall range of variance is considerably smaller now (between -0.3 and 0.4; range of 0.7) compared to before (between -1.2 and 1.2; range of 2.4). This indicates that the transformed model without outliers, has a better fit for the regression examined in the scope of this paper. Nevertheless, the data points seem to be rather left skewed, which, despite the improved picture, leaves a bit of uncertainty regarding the acceptance of the homoscedasticity-assumption as fulfilled.

But, besides that, in Fig. A.2., the residuals remain roughly centered around the horizontal reference line, at y = 0, which reinforces the presence of linearity, the first assumption initially confirmed in section A.7.1.

```
plot(model_log_fix$fitted.values, model_log_fix$residuals, xlab = "Fitted Values",
ylab = "Residuals")
abline(h = 0, col = "red")
```

Fig. A.2. Fitted vs. Residuals Plot of the Transformed Regression Model without Outliers.



A.7.3. Independence of Residual Errors

The Durbin-Watson test is suited to check for the independence of residual errors. A d-value close to 2, signifies no autocorrelation among the residuals of a regression.

According to the output of the Durbin-Watson test performed in R on my model, the d-value is approximately 1.99, which rules out autocorrelation and confirms the independence of the residual errors in the regression. Thus, the third assumption is fulfilled.

```
dwtest(model_log_fix)
##
##  Durbin-Watson test
##
## data:  model_log_fix
## DW = 1.9897, p-value = 0.4816
## alternative hypothesis: true autocorrelation is greater than 0
```

A.7.4. Normality of Residual Errors

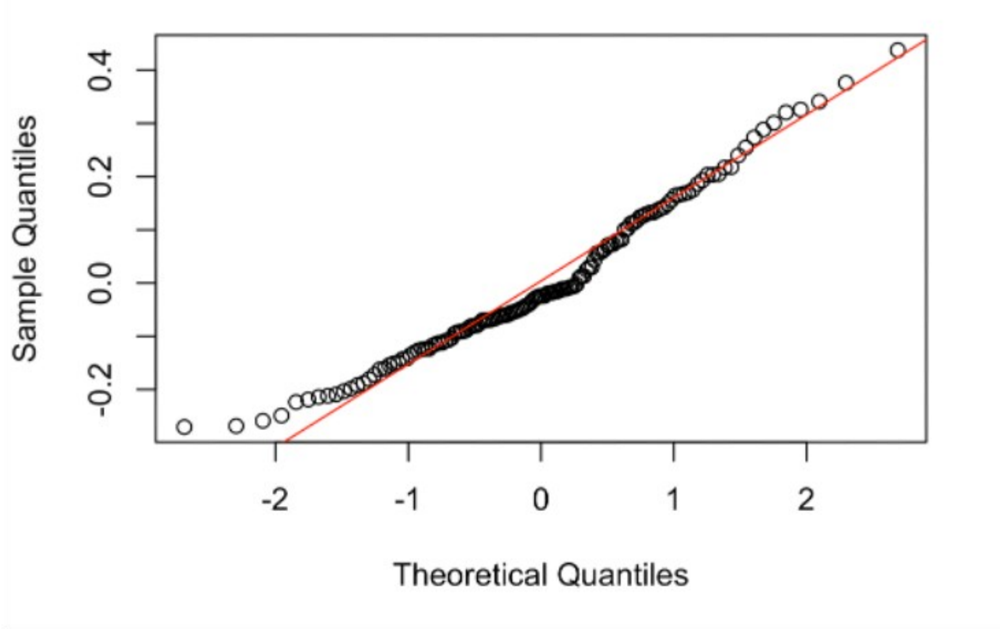
The Shapiro-Wilk test serves to assess the normality of the residuals errors from a regression (Dalpiaz, 2021). The W-value always falls between 0 and 1, with a value closer to 1 and a big p-value suggesting normality.
After running the Shapiro-Wilk test on my final regression model in R, the output indicated conflicting results, with $W \approx 0.970$ being close to 1 and thus, implying a nearly perfectly normal distribution and $p = 0.004104$ implying the opposite by being relatively small.

```
shapiro.test(model_log_fix$residuals)
##
##  Shapiro-Wilk normality test
##
## data:  model_log_fix$residuals
## W = 0.97023, p-value = 0.004104
```

In that case, it is helpful to visually assess the nature of the potential deviation of normality using a Q-Q plot (Dalpiaz, 2021). In the Q-Q plot, if the residuals are normally distributed, the points should roughly follow a straight diagonal reference line.
Given the generated Q-Q-plot in Fig. A.3., I observe a generally close fit to the reference line. However, there are some minor deviations from the red line at both the lower and upper tails of the distribution as well as in the middle, which could be the reason for the sensitivity of the Shapiro-Wilk test that returned a small p-value before. Although the deviations are quite small and overall, the points are closely aligned with the reference line, Fig. A.3. may indicate not a perfectly normal, but only a close to normal distribution of the residual errors.
Additionally considering the relatively low p-value of the Shapiro-Wilk test, I am suspicious to accept the fourth assumption as fulfilled.

```
qqnorm(model_log_fix$residuals)
qqline(model_log_fix$residuals, col = "red")
```

Fig. A.3. Q-Q Plot of the Regression Residuals.



A.7.5. Multicollinearity

Lastly, according to Dalpiaz (2021), the Variance Inflation Factor (VIF) is a measure of how much the variance of the regression estimates is inflated due to multicollinearity with other predictors in the model. VIF-values below 5, indicate that there are no problematic correlations between the predictors (Dalpiaz, 2021).

After running the VIF-test on my regression model in R, I obtained an error message (in red, see below) stating that there are higher-order terms (interactions) in my model, thus, I should consider setting the type as "predictor". This is potentially due to the inclusion of the interaction term *OID*Tenure* in my model. After adjusting the code, the returned VIF-values for all the predictor variables in my regression model were far below 5. Therefore, multicollinearity can be excluded in the present regression model, which fulfills the last assumption.

```
#First Try:

vif(model_log_fix)

## there are higher-order terms (interactions) in this model
## consider setting type = 'predictor'; see ?vif
##
##   age      satisfaction_t2     orgdev_t2     orgid_t2     tenure_group_average
##   1.219373 1.234578            1.319829      2.923069     31.165557
##   orgid_t2:tenure_group_average
##   34.781038
```

```r
#Second Try:

vif(model_log_fix, type = "predictor")
## GVIFs computed for predictors
##                         GVIF Df GVIF^(1/(2*Df))       Interacts With
## age                 1.219373  1        1.104252                   --
## satisfaction_t2     1.234578  1        1.111116                   --
## orgdev_t2           1.319829  1        1.148838                   --
## orgid_t2            1.487888  3        1.068468 tenure_group_average
## tenure_group_average 1.487888  3        1.068468            orgid_t2
##                                                          Other Predictors
## age                 satisfaction_t2, orgdev_t2, orgid_t2, tenure_group_average
## satisfaction_t2                 age, orgdev_t2, orgid_t2, tenure_group_average
## orgdev_t2                 age, satisfaction_t2, orgid_t2, tenure_group_average
## orgid_t2                                  age, satisfaction_t2, orgdev_t2
## tenure_group_average                      age, satisfaction_t2, orgdev_t2
```

A.8. Appendix 8: Regression Models

A.8.1. Regression Equation

$log(Y) = \beta_0 + \beta_1 C_1 + \beta_2 C_2 + \beta_3 C_3 + \beta_4 X + \beta_5 M + \beta_6 (X * M) + u_i$, where

$log(Y)$	=	Logarithmic values of Organizational Deviance (t3) (Dependent Variable)
X	=	Organizational Identification (t2) (Main Predictor)
M	=	Tenure (Moderator Variable)
$(X * M)$	=	Organizational Identification & Tenure (Interaction Term)
C_1	=	Age (Control Variable)
C_2	=	Job Satisfaction (t2) (Control Variable)
C_3	=	Organizational Deviance (t2) (Control Variable)
β_0	=	Intercept
β_i	=	Regression Coefficients
u_i	=	Error Terms

A.8.2. Model Summaries of Hierarchical Regression

Model (1):

```
#Model 1: log(Y) = Control Variables

model1 <- lm(log(orgdeviance_t3) ~ age + satisfaction_t2 + orgdev_t2, data =
data_Zahlen_t23_timelagged_new_clean)

summary(model1)
##
## Call:
## lm(formula = log(orgdeviance_t3) ~ age + satisfaction_t2 + orgdev_t2,
##     data = data_Zahlen_t23_timelagged_new_clean)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.30702 -0.09635 -0.04761  0.11366  0.46665
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)     -0.272717   0.135001  -2.020              0.0454 *
## age             -0.001656   0.001396  -1.187              0.2375
## satisfaction_t2 -0.003737   0.010219  -0.366              0.7152
## orgdev_t2        0.445034   0.038986  11.415 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1624 on 134 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.5559, Adjusted R-squared:  0.5459
## F-statistic:  55.9 on 3 and 134 DF,  p-value: < 0.00000000000000022
```

Model (2):

```
#Model 2: log(Y) = Control Variables + X + M

model2 <- lm(log(orgdeviance_t3) ~ age + satisfaction_t2 + orgdev_t2 + orgid_t2 +
tenure_group_average, data = data_Zahlen_t23_timelagged_new_clean)

summary(model2)
##
## Call:
## lm(formula = log(orgdeviance_t3) ~ age + satisfaction_t2 + orgdev_t2 +
##     orgid_t2 + tenure_group_average, data =
data_Zahlen_t23_timelagged_new_clean)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.31734 -0.10528 -0.03233  0.10365  0.41902
##
## Coefficients:
##                       Estimate Std. Error t value             Pr(>|t|)
## (Intercept)          -0.099809   0.144642  -0.690                0.491
## age                  -0.003488   0.001415  -2.465                0.015 *
## satisfaction_t2      -0.004748   0.009899  -0.480                0.632
## orgdev_t2             0.414548   0.038252  10.837 < 0.0000000000000002 ***
## orgid_t2             -0.023165   0.014143  -1.638                0.104
## tenure_group_average  0.008043   0.001966   4.092            0.0000741 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1529 on 132 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.6119, Adjusted R-squared:  0.5972
## F-statistic: 41.63 on 5 and 132 DF,  p-value: < 0.00000000000000022
```

Model (3):

```
#Model 3: log(Y) = Control Variables + X + M + X*M

model3 <- lm(log(orgdeviance_t3) ~ age + satisfaction_t2 + orgdev_t2 + orgid_t2 +
tenure_group_average + orgid_t2*tenure_group_average , data =
data_Zahlen_t23_timelagged_new_clean)

summary(model3)
##
## Call:
## lm(formula = log(orgdeviance_t3) ~ age + satisfaction_t2 + orgdev_t2 +
##     orgid_t2 + tenure_group_average + orgid_t2 * tenure_group_average,
##     data = data_Zahlen_t23_timelagged_new_clean)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.27059 -0.10151 -0.02449  0.10944  0.43750
##
## Coefficients:
##                                Estimate Std. Error t value             Pr(>|t|)
## (Intercept)                   -0.306089   0.171281  -1.787              0.07624
.
## age                           -0.003299   0.001398  -2.360              0.01973
*
## satisfaction_t2               -0.001937   0.009847  -0.197              0.84438
## orgdev_t2                      0.404135   0.038025  10.628 < 0.0000000000000002
***
## orgid_t2                       0.012545   0.021540   0.582              0.56130
## tenure_group_average           0.029477   0.010042   2.935              0.00393
**
## orgid_t2:tenure_group_average -0.003981   0.001830  -2.175              0.03139
*
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1508 on 131 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.6254, Adjusted R-squared:  0.6083
## F-statistic: 36.46 on 6 and 131 DF,  p-value: < 0.00000000000000022
```

Declaration of the Use of Artificial Intelligence (AI)

During data analysis in R Studio, I used ChatGPT as support while working on the codes needed for the statistical methods used in this paper. I verified the suggestions and output with the step by step indications from Dalpiaz (2021). At times, I also encountered error messages that I could not interpret. I used ChatGPT to find out how to resolve the errors.
I confirm that I have used AI with necessary care and caution, fully disclosed the use of AI, and take full responsibility for the content of this paper.

Prompts

[1] ChatGPT, OpenAI, Aug. 2, 2024. Promt: "In R, how do I count the amount of observations in my data set with the value 2, 4, 6 or 7 in column "participantgroup"? ".

[2] ChatGPT, OpenAI, Aug. 2, 2024. Prompt: "How to delete any observations that have NA in column "orgid_t2" or "orgdeviance_t3"? ".

[3] ChatGPT, OpenAI, Aug. 10, 2024. Prompt: "How do I conduct a fisher's Z transformation in R to determine the confidence intervals of the correlations in a correlation matrix?".

[4] ChatGPT, OpenAI, Aug. 12, 2024. Prompt: "How do I check the independence of the residuals in my model in R?".

[5] ChatGPT, OpenAI, Aug. 12, 2024. Prompt: “When checking for multicollinearity I get this error message. How can I fix it? "there are higher-order terms (interactions) in this model consider setting type = 'predictor'; see ?vif"”

[6] ChatGPT, OpenAI, Aug. 16, 2024. Prompt: “I identified 8 outliers with the cooks distance method. How do I remove them from the data set?”

[7] ChatGPT, OpenAI, Aug. 16, 2024. Prompt: “How can i see which rows ([..]) are the outliers identified with this code: model_log_cd = cooks.distance(model_log)?”

[8] ChatGPT, OpenAI, Aug. 16, 2024. Prompt: “How can I remove rows 3 and 32 from the data set?”

Declaration of Independent Work

I hereby declare that I completed this thesis independently and only used the sources and aids stated. I further declare that I have not previously submitted the thesis to any other institution. I acknowledge that this essay can be checked for plagiarism with the help of electronic tools.

[Place], 07.09.2024 Lara Mühlemann