MASTER

What makes a creative day?
a diary study investigating effects of internal and external factors on creativity

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What Makes A Creative Day?
A Diary Study Investigating Effects Of Internal And External Factors On Creativity

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in partial fulfilment of the requirements for the degree of

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in Innovation Sciences

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What Makes A Creative Day? A Diary Study Investigating Effects Of Internal And External Factors On Creativity

A.C. Groenewoudt

Abstract

This study investigates which factors explain an individual’s fluctuations in idea generation across days. New ideas were hypothesised to find their origin in identified problems. The link between problems and ideas was proposed to be moderated by two day-level factors: (1) an individual’s access to novel and heterogeneous information through their interactions with (“non-redundant”) others, and (2) an individual’s level of vigour. A diary study was conducted among 31 employees of a Dutch applied university over a period of two weeks. Results show that fluctuations in idea generation across days can be explained by problems that arose during the day. Interactions with non-redundant others had a moderating effect on the link between problems and ideas, whereas the level of vigour had no effect. Results indicate that day-level factors can explain fluctuations in generation of new ideas across days, and imply that an individual’s days can be shaped to stimulate idea generation.

Introduction

Innovation of firms is often based on the successful implementation of new and useful ideas to improve products and processes (Amabile, 1988; Perry-Smith & Shalley, 2003). Employees are an important source for new ideas. Many companies (e.g. Google and Apple) acknowledge the importance of their employees as a source for ideas, and aim to encourage employees to come up with new and useful ideas (“Google for Work”, 2016; Müller, 2010). Ideally, employees can constantly come up with new and useful ideas (Steiber & Alänge, 2013). An employee’s production of new and useful ideas is also termed creativity (Amabile, 1988).

Despite the need for new and useful ideas, employees do not constantly produce new ideas. Several studies showed that an employee is more creative on some days than on other days (Amabile, Barsade, Mueller & Staw, 2005; Binnewies & Wörnlein, 2011). One reason for peaks in creativity may be that, on certain days, employees meet conditions for creativity, whereas other days they do not. Understanding what conditions shape “a creative day” is crucial for firms to be able to stimulate creativity. The aim of this study is to investigate what and how certain factors influence an employee’s creativity across days. In this study, I focus specifically on factors that can explain why employees generate more new ideas on some days than on
In the literature, an individual’s creativity has been argued to be influenced by internal and external factors, such as an employee’s mental state and an employee’s social network (Amabile, 1988; Burt, 2004). These factors derive from two research fields. First, from the research field of organisational psychology, and second, from the field that studies social networks. Although both fields offer alternative explanations for creativity of individuals, it is unclear how the two fields relate to each other. This study integrates factors both from the research fields organisational psychology and the field of social networks. Thereby, this study contributes to a more complete and multidisciplinary understanding of creativity (Zhou & Hoever, 2014). Furthermore, there is little knowledge about the effect of an employee’s social network on fluctuations in creativity across days. This study contributes to the literature by investigating the effects of an employee’s network and interactions on creativity across days; an area that is relatively unexplored (Fu, 2007). The present study proposes a model to explain fluctuation in creativity over time. This model integrates factors deriving from organisational psychology and social network research.

In organisational psychology, one prominent creativity theory is the one by Amabile (1988). She proposed that an individual’s new ideas are the outcome of a creative process. This creative process starts when an individual is exposed to a new problem (Binnewies, Ohly & Sonnentag, 2007). An individual may than start thinking about possible problem solutions, the “new ideas”, for this problem (Amabile, 1988). In an individual’s search for new ideas, multiple factors have been suggested to make the search more or less successful. Amabile suggested that the search may be more successful if an employee is persistent and willing to invest effort in finding new ideas. Feeling vigorous reflects the persistence and willingness of a person to do so (Schaufeli & Bakker, 2002). Therefore, to understand fluctuations in creativity over time, I propose a model that incorporates the starting point for the creative process, the presence of new problems, and an employee’s level of vigour.

More recently, organisational psychology researchers have become more interested in the social side of creativity (Perry-Smith and Shalley, 2003). Scholars have argued that employees are more successful in their search for new ideas if they communicate with others (e.g. colleagues) about current problems (Perry-Smith and Shalley, 2003). Communication with others allows employees to access information relevant to the problem in question, which helps them to develop new ideas. Hence, researchers became interested in the effect of employees’ social networks on creativity (e.g. Perry-Smith, 2006; 2014; Ohly, Kase, & Škerlavaj, 2010); an employee’s network consists of all people with whom an individual interacts (Fu, 2005).

Social network studies originally derive from another research area. Burt (1992) was one of the first
to link an employee’s network to individual performance, including creative performance. Burt (2004) found that employees with certain networks are more creative than others. It is, however, unclear how social networks of employees related to an individual’s internal creative process. Most studies in creativity research have focussed on either psychological or social network factors. Therefore, the proposed model incorporates social network variables as well as psychological factors. In addition, there is little knowledge about the effects of an individual’s network on creativity over time. For this reason, the present study investigates the relationship between social interactions and creativity over time.

In conclusion, this study I propose that fluctuations in creativity over time can be explain by factors deriving from both organisational psychology and the field of social networks. In this study I examine the effects of these factors by conducting a diary study over multiple days.

**Theoretical background**

*Problem identification and idea generation*

Amabile (1988) defined creativity as the production of new and useful ideas. According to Amabile, new ideas are the outcome of a creative process. This study focusses specifically on idea generation. Idea generation refers to a part of the creative process in which an individual recognises to have one or multiple new ideas (Ohly, Kase & Škerlavaj, 2010). In Amabile’s creativity theory, she highlights the importance of “problems” for idea generation, and theorised how problems lead to the generation of new ideas.

A problem can refer to anything in a product, process, or service that requires improvement (Shalley, Zhou & Oldham, 2004). In general, an individual’s creative process only start when an individual identifies a problem (e.g. Binnewies et al, 2007). The underlying assumption in this starting-mechanism is that an individual is constrained in some way by the problem, and therefore, an individual chooses to solve the problem. As a result, an individual will start searching for new ideas when a new problem has come up. The search for new ideas starts by reactivating, or searching for, knowledge and skills that can help to solve the problem in question (Amabile, 1988). Problem-relevant knowledge and skills consists of any information regarding a product, process, or services that may help to solve the problem in question. Next, the actual generation of new ideas takes place. An individual than generates multiple problem solutions, the actual “new ideas”. New ideas refer to ideas of individuals to improve a product, process or service, thereby solving the problem (Shalley et al., 2004). Following this logic, I suggest that newly identified problems are crucial for idea generation. Over time, employees will generate new ideas when they have identified a problem.

Previous studies have shown that levels of creativity fluctuate over time (e.g. Amabile et al., 2005), and presumably, individual’s levels of idea generation fluctuate over time. Therefore, in this study, I argue
that increased problem identification across days will be related to increased idea generation across. This leads to the following hypothesis.

**Hypothesis 1:** *Daily idea generation is positively related to daily problem identification.*

In the creative process, certain factors have been suggested to make idea generation more or less successful. These factors may provide an additional explanation for fluctuation in idea generation over time. First, idea generation is more successful when individuals are persistent and willing to invest effort in finding a problem solution, because idea generation demands effort and persistence (Amabile, 1988). Second, problem-relevant knowledge has been suggested to make individuals more successful in idea generation (Binnewies et al., 2007).

**Interactions for novel and heterogeneous information**

Amabile’s creativity theory stated problem-relevant knowledge help individuals to come up with new ideas to solve a problem (1988). Interactions with others allow employees to access this problem-relevant knowledge and insights (Binnewies et al., 2007). Communication about a problem problem-relevant topics helps an individual to redefine the problem, and provides direct input for ideas about the solution of the problem (Ohly et al., 2010).

Scholars have argued that especially novel and heterogeneous information is useful for generating new ideas (Campbell, 1960; Simonton, 1999; Burt, 2004). Similar to the evolutionary prospective on creativity (e.g. Simonton, 1999), Burt argued that novel and heterogeneous information allows individuals to combine and compare, often contradictory, information. As a result, they can generate multiple ideas (“variation”), and subsequently, to select the best and most suitable idea (“selection”).

Burt studied networks of employees within a large company. He asked 604 employees to list an idea to improve the supply chain of the company, and with whom they had contacted to validate their idea (2004, p.360). His results showed that interactions with many different people about an idea, and in particular with people who provide an individual access to novel and heterogeneous information, were positively associated with an individual’s ability to come up with a good idea (p.364). Novel and heterogeneous information was theorized to derive often from people who were from an otherwise unconnected group (Burt, 2000). This is because people within one group of people were assumed to share information, whereas people from different groups shared no information. As a result, people from another group can provide novel information to people from another group. If two groups are not connected, there is gap in a network structure between those groups. This gap is also termed ‘structural hole’. Applied to an organisation context, different departments can be considered as such unconnected groups, because departments are, to some
extent, divided from each other (Tushman & Tushman, 1988; Cross, Rice, & Parker, 2001; Cross and Cummings, 2004). Taken together, novel and heterogeneous information often derives from otherwise unconnected groups, and such information is beneficial for good ideas.

Burt developed a measure that indicates to what extent a relationship, or “tie”, with another person connects an individual to an otherwise unconnected group, and thus to novel information (Hanneman & Riddle, 2005). This measure is named “redundancy”. The measure of redundancy can be conceptualised as shown in figure 1. If A is tied to both B and C, and B is tied to C, then A’s tie to B is redundant. This is because A can also access information that B has by asking C (assuming that B and C share information). Presumably, B and C can thus provide similar information. If B and C are not tied, A cannot access information from B through C (and vice versa) and thus ties A-B and A-C are not redundant. The assumption is therefore that A can access different information by interacting with B and C.

Burt’s proposition regarding structural holes has been widely tested among firms and entrepreneurs (Bhagavatula, Elfring, van Tilburg, & van de Bunt, 2010; Stam, Arzlanian, & Elfring, 2014). Less attention has been paid to networks of employees. As discussed in the previous section, Burt found evidence for his hypothesis that people who span structural holes are more creative (2004). Perry-Smith found that scientist with more heterogeneous networks are more creative (2006; 2014). She studied networks of research scientists and found that scientists’ who had many relationships with people from heterogeneous backgrounds were more creative. Scientists’ relationships with people from heterogeneous backgrounds suggested “non-redundant” relationships. This was because heterogeneity of personal networks was calculated as the proportion of others in the network with different functional backgrounds (i.e. electrical engineering, business, etc), indicating heterogeneity in knowledge among people.

Rost (2011) provides evidence that individuals do not always profit from structural holes. She studied networks of 9941 inventors in the German automotive industry and their innovative ideas, measured by the number of patents. She found that networks with few structural holes and few structural holes spanning ties can also be advantages for creating and implementing ideas. Scholars have argued that in dense networks (networks with few structural holes) there is trust among people (Coleman, 1988). Therefore, people are more willing to share valuable information regarding new ideas and help each other to make new ideas a success (Rost, 2011).
I argue that network structures cannot be assumed to be advantageous for various aspects of creativity all that the same time. This would explain why, in the literature, creativity could not be linked to one particular network structure. Network structures most beneficial for generating ideas may be different than for validating ideas or implementing ideas (Ohly et al., 2010).

The type of network structure that is most beneficial may depend on what resources are required for a particular activity (Bhagavatula et al. 2010). The study by Rooks, Szirma and Sserwanga (2012) suggested that, as a result of multiple uses of networks, solely networks rich in structural holes do not offer the optimum solution. Instead, their study among 697 African entrepreneurs showed that access to various unconnected groups was advantages for accessing new information and spotting opportunities. In contrast, networks with few structural holes, were found to be benefical for implementing new ideas. This suggests that for particular purpose of accessing novel information, important for idea generation, individuals benefit from spanning structural holes. Therefore, I argue that, when individuals need problem-relevant knowledge for new ideas, spanning structural holes is beneficial (Burt, 2004).

As discussed earlier, levels of idea generation across days are hypothesised to be explained by levels of problem identification. When a problem is identified, problem-relevant information helps individuals to generate new ideas for this problem (Amabile, 1988). This information can derive from interactions with others. I argue, therefore, that access to information plays a moderating role in the relationship between problem identification and idea generation. Information deriving from “non-redundant” interactions has a positive effect on this relationship, due to its novel and heterogenic character (Burt, 2004). As people interact with many others every day, I propose that the moderating role of interactions takes place at day-level. This leads to my second hypothesis.

**Hypothesis 2: Interactions with “non-redundant” others have a positive effect on the link between daily problem identification and daily idea generation.**

**Vigour at work**

Generating ideas requires high levels of effort and persistence (Amabile, 1988). This because generating new ideas often entails hard work (Staw, 1995; George & Zhou, 2002). An employee may be more persistent and willing to invest effort in his or her work on some days than on other days.

In a work context, feeling vigorous has been associated with the persistence and willingness to invest effort in finding problem solutions. Vigour has been defined as a high level of energy and mental resilience while working, the willingness to invest effort in one’s work, and persistence when facing difficulties and problems (e.g. Schaufeli, Salanova, Bakker, & Alez-rom, 2002). The definition of vigour suggests that
feeling vigorous is advantages for the search for new ideas. Furthermore, the definition of vigour refers to high levels of energy (Schaufeli et al., 2002). High levels of energy enable individuals approaching work-related problems with energy (Shirom, 2003). This has been suggested to be helpful for generating new problem solutions (Shirom, 2011), and to stimulate creative behaviour at work (Sonnetag & Niesen, 2008).

Vigour has been described as an positive affective state (e.g. Little, Nelson, Wallace, & Johnson, 2011). The proposition that vigour is an affective state concept, implies fluctuations in levels of vigour across days (Sonnetag & Niessen, 2008). In this study, I argue that an individual’s level of vigour across days determines to what extent and individual is willing to invest effort in search for new ideas and is persistent to find problem solutions. I argue, therefore, that vigour is helpful in finding new ideas when an individual has identified problems; the more vigorous an employee feels, the more persistence and willing to invest effort he or she is. As a result, he or she will, when dealing with work-related problem, generate more ideas. Vigour has thus a positive moderating effect on the link between problem identification and idea generation. This leads to my third hypothesis.

_Hypothesis 3: Vigour has a positive effect on the link between daily problem identification and daily idea generation._

Figure 2 shows a graphical representation of the theoretical model, explaining how an individual’s fluctuations in idea generation across days relate to problem identification, interactions with others, and levels of vigour.

![Figure 2. Theoretical model](image)

**Method**

*Participants and procedure*

To test the hypotheses I conducted a diary study among 31 employees of a Dutch applied university for two workweeks. One workday was a national holiday, leaving nine consecutive workdays for the data collection before the employees’ two weeks holiday started. All participants worked at the same department,
where a total of 300 persons were employed. Initially, only employees of one sub-department were approached by e-mail and asked to participate in the study. In total, this sub-department consisted of 90 employees; 34 of them registered for participation (response rate 37.7%). From another sub-department, several persons were asked to participate as well. This group accounted for 13% of the total sample group. Naturally, participation in the study was voluntarily.

From the initial group of 37 employees who registered for participation, 33 participants actually started the contact diary. Two dropped out after one day. The other 31 participants (14 males and 17 females) filled out the contact diary for at least two days ($M = 6.2$), and each day was filled in by resp. 77%, 84%, 68%, 100%, 71%, 55%, 65%, 45%, and 52% of the participants. Not all participants filled out the contact diary for nine days. In many cases this was because people did not work full time (58.6% did not work full-time). In total, I collected data for 191 days, on which a total of 471 interactions were listed. One participant did not fill in the general questionnaire, and therefore, this participant was excluded from analyses that included person-level variables.

Employees were mainly involved in education-related tasks, such as delivering lectures. Participants were involved in similar jobs, which was good for the homogeneity of the sample. It also excluded the possibility that results were influenced by effects job characteristics, such as task autonomy. This was important because such job characteristics, shaped by the organisational context, have been argued to influence whether generating ideas is stimulated or not (Amabile, 1988).

The data collection consisted of three parts: a general survey, a daily survey for nine days, including a contact dairy, and a network survey (Appendix A). Data was collected online, and every day participants could log in with their self-chosen personal code. This allowed me to collect and process data anonymous. The daily survey included questions regarding levels of problem identification, idea generation and vigour. The contact dairy inquired after employees’ interactions with other people during that day (based on the contact diary by Fu, 2005; 2007). Participants filled in the daily survey at the end of each workday. Participants received a reminder by smart-phone and e-mail every workday. In the general questionnaire participants were also asked to fill out questions about personal and job characteristics (e.g. gender, contract hours and years worked in the organisation).

After the nine consecutive workdays, participants were asked to fill out a network survey, consisting of a network matrix. The network survey was used to construct a measure named “effective network size”. This measurement reflects to what extent participants had non-redundant interactions with the various contacts during one day (Hanneman & Riddle, 2005). It takes into account both the number of interactions and the extent to which a contact was redundant. The network matrix is a tool to map “ego’s” (the focal participant) network. This network included all ego’s “alters” (all persons with whom ego had interacted
over all nine days), and the relationships among those alters. In the network matrix each row represented one alter, and each column represented another ego’s other alters (See for an example Appendix A). Each cell within the matrix represented a relationship between two alters. Participants were asked to fill in all cells. This resulted in a mapped structure of the participant’s ego-network.

Before the actual data collection, they diary survey carefully designed and planned. Diaries provide very accurate information, but are time consuming for participants. In order to develop a feasible diary survey, I conducted interviews and pilot studies. First, sixteen short interviews were conducted, asking interviewees after their work-related problems, ideas, and interactions they had on one day. Second, after designing the diary survey, including the contact diary, a pilot study was conducted. One group (n = 8) filled in the daily survey for one day. After some adaptations, the diary survey was tested for three days by another pilot group (n = 4), from who two were teachers. In addition, during the first days of the diary study many participants were personally asked if they had understood the questions and had been able to fill in the complete diary survey. After the data analysis the results were discussed with two participants.

Measures

General questionnaire

The general questionnaire included control variables gender, and creative self-efficacy (Cronbach’s alpha = .822) (“I am good at finding creative ways to solve problems”) (Tierney 1997). Creative self-efficacy may influence self-ratings of idea generation because people with high creative self-efficacy may in general rate their idea generation higher.

Daily survey

Problem identification. The extent to which individuals identified problems was measured by asking participants the number of work-related problems they had identified during the day, ranging from “0” to “5 or more” (Mean = 1.83). The number of problems identified by participants varied widely across their workdays. The within-person variance ranged from \(SD = 0.00\) to \(SD = 2.53\).

Idea generation. For each day participants were asked to count the number of new ideas they had come up with to solve work-related problems. Idea generation also ranged from “0” to “5 or more” (Mean = 1.63). The within-person variance ranged from \(SD = 0.00\) to \(SD = 2.64\).

Results from conducted interviews implied that the range from 0 - 5 problems and ideas would be sufficient. To ensure participants had sufficient answer possibilities “5 or more” was included. For the
purpose of data analyses “5 or more” rating was later transformed into “6”. This seemed acceptable, especially since this option was rarely selected.

**Vigour.** Vigour was measured by a three item measure on a 5-point Likert-scale (Cronbach’s alpha = .939). Items focussed on experiences on day-level (“Today, I was bursting with energy”). The three item measure was a subset of the initial six item measure (Schaufeli et al., 2002). The within-person variance ranged from $SD = 0.00$ to $SD = 1.20$.

**Contacts.** I used a *contact diary* method using the question “With who did you interact today?” as a name generator. Contact diaries offer a comprehensive approach in order to record information about with which persons participants interact (Fu, 2005). As such, this provides good insights into who is member of a participant’s personal network (Fu, 2007). Contact diaries also yield information about interactions with people with whom participants are not very familiar. This is important since these less familiar persons are been suggested to be likely to provide novel information (Burt, 2004).

Participants were asked to list the interactions with people with whom they had discussed work-related topics. Since contact diaries are time consuming for participants, I set a limit to the number of contacts that could be listed. Participants could list a maximum of four contacts per day (Mean = 2.54, $SD = 0.90$). From conducted interviews prior to the data collection, a limit of four contacts appeared to be both feasible and sufficient. The possibility to list four contacts allowed participants the majority of days to list all work-related interactions: on 66 out of 191 days participants listed the maximum number of contacts. If people had over four work-related interactions, participants were asked to list their most significant interactions. The within-person variance in number of contacts ranged from $SD = 0.00$ to $SD = 1.87$.

Figure 3 gives a graphical representation of the variance in study variables for each person. The boxplots indicate a wide variance in levels of problem identification, idea generation, and number of contacts, both between people and within the different days nested in persons. This confirmed the assumption that there is non-zero variance in study variables.

![Figure 3. Boxplots for problem identification, idea generation and number of contacts for all participants](image)

**Network survey**
Effective network size. The effective size of a network is calculated as the network size minus the redundancy of each tie (Hanneman & Riddle, 2005). For this study the effective network size variable was constructed as a day-level variable. The number of contacts per day served a proxy for network size on day-level. The redundancy was measured in UCINET 6.0. Redundancy indicates the extent to which another person provides access to an otherwise unconnected group, and thus to novel information (“0” = not redundant, “1” = totally redundant) (Burt, 2004). The redundancy measure calculates for each alters in ego’s network, to how many of the other alters this alter is connected. The larger the proportion of others in the network who are tied to this alter, the more “redundant” this alter is (Hanneman & Riddle, 2005). The redundancy of each alter was calculated from the complete ego-network of participants. These complete ego-networks included all alters who participants had listed across all days (M = 15.68). Several participants listed the same alter on multiple days; on average participants listed 1.77 of their alters on multiple days. As a result, the size of complete ego-networks was lower than the total number of contacts listed across all days.

The average effective network size across all days was M = 1.33, and the within-person variance of effective network sizes ranged from SD = 0.05 to SD = 1.48. Figure 4 is an example of a complete network. Each dot represents the persons with whom the participant interacted, the label of each dot indicates on which day the interaction took place.

Data analysis

In a diary study measurements are by definition repeated. The data I gathered is “nested” within participants. I gathered multiple observations for every respondent. This implies that my observations are dependent; observations collected on different days from the same participant are similar to each other. As a result of the hierarchical data structure hypotheses could not be tested with an ordinary least squares regression analysis, since independency among data on the lowest level (day-level) cannot be assumed.
Scores on study variables are to some extent dependent on grouping on the higher level (person-level). In less abstract language: the fact that people differ affects scores of study variables on day-level. To account for the nested data, hypotheses were tested a linear multi-level analysis using STATA 14.0 (Snijders, 2011). A multilevel analysis takes into account the hierarchical structure of the data.

The multi-level analysis involved testing multiple consecutive models. First, a null model was specified. The null model contains intercepts only; no predicting variables were included. The null model was used to calculate the interclass correlation (ICC). The ICC calculates what proportion the total variability in idea generation could be attributed to the fact that people differ (Maas & Hox, 2005). This is calculated with the formula $\rho = \frac{\sigma^2_u}{\sigma^2_u + \sigma^2_e}$. The null model also acted as a baseline for making comparisons of improvement in model fit. Stepwise, all predictor variables were entered into the model. For each predictor in the model, I tested whether this variable contributed significantly to predicting variance in the dependent variable idea generation (table III and IV). In addition, for each consecutive model I checked whether the model fit had improved significantly compared to the previous model (table II). If $-2\text{LogLikelihood}(\Delta \chi^2)$ had improved significantly, I tested how much variance was explained ($R^2$ in tables III and IV).

The first step in the multilevel analysis adding the null model. Next, in model 1 control variables were entered. This model tested if control variables could predict in variability of idea generation, additional to the variability that was attributable to differences in persons in itself. Next, model 2 included predictor variable problem identification, and model 3 included the remaining predictor variables. Finally, model 4 also included interactions terms, allowing me to test for the moderating effects of vigour and effective network size, as predicted in the hypotheses. Entering all interaction terms into the same model resulted in unstable parameter estimates. This might be due to high correlations between interaction terms. (Table 1 shows all means, standard deviations and correlations for all study variables). Instead, I entered interaction terms into separate models (resp. model 4a, 4b, and 4c), which is a common strategy to deal with this type of problem (Dormann et al., 2013). Table II contains the estimates for predicting idea generation of the individual variables included in each model.

| Table I. Means, standard deviations and correlations for study variables |
|-----------------------|-------|-------|-------|-------|-------|-------|-------|-------|
| Variables             | Mean  | SD    | 1     | 2     | 3     | 4     | 5     | 6     |
| 1. Problem identification | 1.83  | 1.74  |       |       |       |       |       |       |
| 2. Idea generation    | 1.63  | 1.64  | .682**|       |       |       |       |       |
| 3. Number of contacts | 2.47  | 1.39  | .569**| .533**|       |       |       |       |
| 4. Effective network size | 1.33  | 1.07  | .495**| .558**| .724**|       |       |       |
| 5. Vigour             | 3.69  | 0.94  | .096  | .085  | .169  | .284**|       |       |
| 6. Gender             | 1.47  | -.130 | -.126 | .053  | -.343 | -.329 |       |       |
| 7. Creative self-efficacy | 3.83  | 0.62  | .399**| .537**| .450  | .447**| -.098 | -.005 |
Notes: correlations are on day-level, averaged across all days \( (n = 185) \), except for the correlations marked with \( * \) \( (n=30) \). Gender was coded 1 for male and 2 for female.

**Results**

Table I presents means, standard deviations and correlations of all studied variables. Before testing the hypotheses, I inspected the temporal patterns for day-level variables. Figure 5 represents these temporal patterns; for each work day the means of study variables across all participants were calculated. Temporal patterns may occur as a result of weekly patterns. During interviews employees mentioned that, for example, Monday morning were usually scheduled for meetings, and on Thursday many employees worked from home. Figure 1 shows a diagram of the mean scores for study variables over time. A one-way ANOVA was conducted to test for significant differences of study variables scores across days (problem identification: \( F(8, 176) = .62, p = .762 \); idea generation \( F(8, 177) = .805, p = .60 \); interactions \( F(8, 182) = 1.761, p = .087 \); vigour \( F(8, 178) = .55, p = .819 \); effective network size: \( F(8, 182) = 87, p = .554 \)). These results indicate that variance in study variables is not attributable to the day data was collected.

![Figure 5. Over time fluctuation for study variables](image)

**Multi-level analysis**

Before testing the hypotheses, the null model and model 1 were analysed. The null model indicated that 31.3% (ICC = .313) of the total variance in idea generation was attributable to variations among persons, whereas non was attributable to variations between days (ICC = .000) (table II). Model 1 showed that control variable creative self-efficacy indeed predicted idea generation ratings \( (B = .564, t(180) = 3.56, p < .01) \). Model 1 also significantly improved the model fit: \( \Delta -2LL = 17.30 \) \( (p = < 0.01; R^2 = .40) \).

Hypothesis 1 stated that daily problem identification (PI) is positively related to daily idea generation. To test hypothesis 1 problem identification was entered into model 1. The results of the analysis (model 2) showed a significant effect of problem identification on idea generation \( (B = .384, t(177) = 11.33, p < \)
.01) which contributed significantly to the proportion of the variance explained in idea generation ($\Delta -2LL = 100.67, p < 0.01; R^2 = .58$). This result provides support for hypothesis 1.

Hypothesis 2 predicted a moderating effect effective network size on the problem identification – idea generation link. I tested both the moderating effect of contacts with others, regardless their redundancy, and effective network size, as these two variables are related (see method section). Moreover, as shown in table I, these variables also strongly correlate ($r = .724, p < 0.01$). I tested the effect of both variables to avoid inaccurate interpreting results; attributing effects of effective network size to redundancy, instead of network size on itself. First, I simultaneously tested the independent effects of number of contacts and effective network size on idea generation by entering these variables into model 1 as independent variables. Both number of contacts and effective network size contributed significantly to explaining variance in idea generation (number of contacts: $B = .316, t(178) = 3.36, p = .001$; effective network size $B = .217, t(178) = 2.03, p = .044$), which improved the model fit significantly compared to model 1 ($\Delta -2LL = 49.07, p < 0.01$).

Second, I entered both variables into model 2 (this was resp. “model 3”). Model 3 included thus problem identification as independent predictor, as well as number of contacts and effective network size. Interestingly, as shown in table II, in model 3 number of contacts no longer significantly contributed to the explained variance in idea generation, whereas effective network size was still significant. This suggests that the effect of number of contacts cannot explain a separate part of the variance in idea generation over the other included independent variables. Third, interaction variables (resp. PI x number of contacts, and PI x effective network size) were entered into model 3 (resp. “model 4b” and “model 4c”). Results showed that interaction variable PI x number of contacts had no effect on idea generation ($B = .093, t(173) = 1.33, p = .219$). In contrast, interaction variable PI x effective network size did have a significant effect on idea generation ($B = .108, t(178) = 1.96, p = .049$). Moreover, including this interaction variable also significantly improved the model fit, and the model explained 58 % of the variance in idea generation ($\Delta -2LL = 4.90, p < 0.05; R^2 = .58$). Consequently, hypothesis 3 was confirmed. Furthermore, I inspected whether random slopes would improve the model fit for model 4c. Random effects appeared to have no significant effects on im-

![Figure 6. Linear relationship between idea generation and problem identification](image.png)
provement of the model fit. Figure 6 shows a graphical representation of the effect effective network size on the link between problem identification and idea generation.

Hypothesis 3 stated that vigour had a moderating effect on the link between problem identification and idea generation. First, I checked whether vigour could explain variance in levels of idea generation by entering vigour as an independent predictor for idea generation into model 1. Results showed that vigour was no significant predictor for idea generation ($B = .047, t (179) = 0.56, p = .576$). To test hypothesis 3, I then entered vigour into model 2 (“model 3”), and subsequently, the interaction variable of problem identification and vigour into model 3 (“model 4a”). Results showed that the interaction variable of PI and vigour made no significant contribution to the model ($B = -.060, t (174) = -1.04, p = .297$), and the model fit did not significantly improve compared to model 1 ($\Delta -2LL = 1.36, p > 0.05$). Consequently, hypothesis 3 did not receive support.

Table II. Differences in model fit for predicting idea generation

<table>
<thead>
<tr>
<th>Idea generation</th>
<th>Models</th>
<th>-2Log Likelihood</th>
<th>Df</th>
<th>$\Delta -2LL$ ($=\Delta \chi^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null model (intercept only)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level 1 (person-level) ICC = .313</td>
<td>489.87</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level 2 (day-level) ICC &lt; .000</td>
<td>526.84</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1 (Intercept + controls)</td>
<td>472.57</td>
<td>2</td>
<td>17.30**</td>
<td></td>
</tr>
<tr>
<td>Model 2 (model 1 + PI)</td>
<td>371.90</td>
<td>1</td>
<td>100.67**</td>
<td></td>
</tr>
<tr>
<td>Model 3 (Model 2 + vigour + contacts + effective network size)</td>
<td>356.26</td>
<td>2</td>
<td>15.64**</td>
<td></td>
</tr>
<tr>
<td>Model 4a (Model 3 + PI x vigour)</td>
<td>354.90</td>
<td>1</td>
<td>1.36</td>
<td></td>
</tr>
<tr>
<td>Model 4b (Model 3b + PI x number of contacts)</td>
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<td>1</td>
<td>2.63</td>
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<tr>
<td>Model 4c (Model 3 + PI x effective network size)</td>
<td>351.36</td>
<td>1</td>
<td>4.90*</td>
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</tr>
</tbody>
</table>

Notes: PI = problem identification, * $p < 0.05$, ** $p < 0.01$ (two-tailed)

Table III. Multilevel estimates for predicting idea generation

<table>
<thead>
<tr>
<th>Model</th>
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</thead>
<tbody>
<tr>
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<td>-0.56</td>
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<tr>
<td>Problem identification</td>
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</tr>
<tr>
<td>Vigour</td>
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<td>-0.06</td>
</tr>
<tr>
<td>Interactions</td>
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<td>0.09</td>
</tr>
<tr>
<td>Effective network size</td>
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<tr>
<td>Gender</td>
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</tr>
<tr>
<td>Creative self-efficacy</td>
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<td>0.15</td>
</tr>
<tr>
<td>PI x vigour</td>
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</tr>
<tr>
<td>PI x interactions</td>
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<tr>
<td>PI x effective network size</td>
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</tr>
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</table>

R² | .58 | .59 |
Table IV. Multilevel estimates for predicting idea generation (continue)

<table>
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<th>Variables</th>
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<th>SE</th>
<th>t</th>
<th>Model</th>
<th>B</th>
<th>SE</th>
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<th>Model</th>
<th>B</th>
<th>SE</th>
<th>t</th>
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<tr>
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<td>0.56</td>
<td>-1.03</td>
<td>4b</td>
<td>-0.71</td>
<td>0.58</td>
<td>-1.23</td>
<td>4c</td>
<td>-0.71</td>
<td>0.57</td>
<td>-1.26</td>
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<tr>
<td>Problem identification</td>
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<td>0.56</td>
<td>0.06</td>
<td>8.86**</td>
<td></td>
<td>0.50</td>
<td>0.08</td>
<td>6.36**</td>
<td></td>
<td>0.49</td>
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<td>6.82**</td>
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<td></td>
<td>-0.02</td>
<td>0.06</td>
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<td></td>
<td>-0.03</td>
<td>0.06</td>
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<td>0.09</td>
<td>0.84</td>
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<td>0.14</td>
<td>0.10</td>
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<td>0.16</td>
<td>0.09</td>
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<td>Effective network size</td>
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<td>0.09</td>
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<td></td>
<td>0.19</td>
<td>0.09</td>
<td>2.01*</td>
<td></td>
<td>0.16</td>
<td>0.10</td>
<td>1.68</td>
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<tr>
<td>Gender</td>
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<td>0.01</td>
<td>0.17</td>
<td>0.07</td>
<td></td>
<td>0.02</td>
<td>0.17</td>
<td>0.10</td>
<td></td>
<td>0.01</td>
<td>0.17</td>
<td>0.08</td>
</tr>
<tr>
<td>Creative self-efficacy</td>
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<td>0.15</td>
<td>0.13</td>
<td>1.14</td>
<td></td>
<td>0.17</td>
<td>0.14</td>
<td>1.25</td>
<td></td>
<td>0.17</td>
<td>0.13</td>
<td>1.28</td>
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<tr>
<td>PI x vigour</td>
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<td>-0.06</td>
<td>0.05</td>
<td>-1.07</td>
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<td>0.09</td>
<td>0.07</td>
<td>1.33</td>
<td></td>
<td>0.11</td>
<td>0.06</td>
<td>1.96*</td>
</tr>
<tr>
<td>PI x interactions</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
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<td>PI x effective network size</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td></td>
<td>.58</td>
<td></td>
<td></td>
<td>.56</td>
<td></td>
<td></td>
<td></td>
<td>.58</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

n of observations: 181

Notes: PI = problem identification, * p < 0.05, ** p < 0.01 (two-tailed)

Additional analyses

In contrast to the prediction, vigour did not moderate the effect of problem identification on idea generation. Interestingly, vigour significantly predicted the number of interactions (\(B = 0.20, t (185) = 2.02, p = 0.043\)) and the effective network size (\(B = 0.16, t(185) = 2.91, p = 0.004\)), and explained a significant proportion of variance in both variables (resp. \(R^2 = 0.11\) and \(R^2 = 0.13\)). (See also Table V and VI). As this analyses were only to explore possible effects, these multilevel models (one to predict number of interactions and one to predict effective network size) only included the null model and vigour. Results imply vigour has an indirect effect on idea generation through interactions and effective network size.

Table V. Differences in model fit for predicting number of contacts and effective network size

<table>
<thead>
<tr>
<th>Models</th>
<th>Number of contacts</th>
<th>Effective network size</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-2Log Likelihood</td>
<td>Df</td>
</tr>
<tr>
<td>Null model (intercept only)</td>
<td>455.22</td>
<td>506.87</td>
</tr>
<tr>
<td>Level 1 (person-level)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1 (null model + vigour)</td>
<td>435.60</td>
<td>1</td>
</tr>
</tbody>
</table>

Notes: * p < 0.05, ** p < 0.01 (two-tailed)

Table VI. Multilevel estimates for predicting number of contacts and effective network size

<table>
<thead>
<tr>
<th>Variables</th>
<th>Number of contacts</th>
<th>Effective network size</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>SE</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.04</td>
<td>0.11</td>
</tr>
<tr>
<td>Vigour</td>
<td>0.16</td>
<td>0.08</td>
</tr>
</tbody>
</table>

R² | .11    | .13

Notes: * p < 0.05, ** p < 0.01 (two-tailed)
Discussion and conclusion

The aim of this study was to examine which factors explained an individual’s fluctuations in levels of idea generation across days. I hypothesized that idea generation is a result of problems that require ideas as a solution, and that this relationship was moderated by two factors. The first factor was an individual’s level of vigour; the second was the extent to which individuals had access to novel and heterogeneous information. To test the hypothesis, I used data from employees working for a Dutch applied university collected over nine subsequent days.

Findings from the present study provide evidence for the hypothesis that idea generation across days can be explained by problem identification. This implies that problems identified during the day trigger individuals to generate new ideas. This suggests that problems indeed create a specific need for new ideas. Results also showed that, when exposed to problems, individuals particularly generate new ideas when they interact with others who provide access to novel and heterogeneous information. Novel and heterogeneous information was theorized to derive from “non-redundant” others. The number of interactions by itself did not moderate the effect of problem identification on idea generation. This confirmed that redundancy of ties is important in the problem-idea link, and provides evidence for proposed role of novel and heterogeneous information on idea generation.

Furthermore, findings from the present study support the assumption that network variables cannot only explain creativity in general, but also on day-level. The day-level approach is particularly interesting since data showed large fluctuations in the number of interactions and effective network sizes across days. Also in other research fields this day-level approach for network studies might be interesting.

Vigour was the second variable for which a moderating effect was hypothesised. Contrary to my predictions I found no moderating effect of vigour on the link between problem identification and idea generation. Interestingly, feeling vigorous is correlated with the number of interactions and effective network size. This suggests that vigour has an indirect effect on idea generation. Feeling vigorous is needed to interact with others, and thus results in larger effective network size. This, in turn, may have a positive effect on idea generation. Hence, vigour may play a role in interactions because meeting someone may cost effort. Participants mentioned that especially interactions with colleagues from other departments required more effort than interactions with colleagues from the same department. This was because colleagues from other departments worked in other parts of the building, and interacting with them often required employees to plan a meeting or to walk to the other part of the building. Future research may investigate the effect of feeling vigorous on interactions, and whether vigour indeed has an indirect positive effect on idea generation. Perhaps, the role of vigour in the theoretical model should be adapted.

Results showed thus that vigour had no direct effect on the problem identification- idea generation link, but vigour did have an effect on effective network sizes, thereby possibly indirectly affecting this link.
Psychological and network factors may thus be intertwined rather than contradicting. This finding underlines the importance of integrating psychological and social network research for a better understanding of creativity (Zhou and Hoever, 2014).

The effects of internal and external factors on idea generation may vary across persons. Due to small sample sizes, no person-level variables were included in the multi-level analysis to predict idea generation (with exception of the control variables). Possibly, person-level could explain individual differences in the effects of internal and external factors on idea generation. For example, an individual’s motivation has been suggested to play an important role in how willing an employee is to search for problem solutions (Amabile, 1988). Highly motivated employees may more actively search for new ideas. Also personality and behavioural variables have been suggested to affect an individual’s social network structure, thereby potentially affecting the access an individual has to novel information (Forret and Dougherty, 2001; Sasavova et al., 2010; Vissa, 2012). Including person-level variables may be an interesting scope for future research, and may contribute to a more in depth understanding about idea generation.

**Practical implications**

In business context, producing new and useful ideas is important for employees because it helps them to do well in their job. Moreover, employees’ new and useful ideas contribute to the firm’s performance since their ideas contribute to a firms’ ability to outperform their competitors and to find sustainable solutions.

The results from this study help us to understand why individuals generate more ideas on some days than on others. Insights from this study may be used to help individuals to generate more new ideas. Results imply that individuals can shape their own day to enhance idea generation by identifying important problems. Paying extra attention to sub-optimal parts of products, processes, and services may help them to identify problems. When problems have been identified, employees may deliberately search for novel and heterogeneous information regarding the problem in question. Employees may, for example, plan meetings with persons who can provide such information.

Firms can stimulate their employees’ idea generation as well. For example, by stimulating interactions among people who can give each other novel problem-relevant information. For instance, by organising organisation-wide events or even events inviting external parties.

**Limitations**

An obvious limitation of this study is the small sample size. In practice, 30 is the smallest acceptable number according to Kreft and De Leeuw (1998). To some extent, this study compensates for the limited
number of participants by the large number of days (n = 9) (Maas and Hox, 2005; Ohly, Sonnentag, et al., 2010). A small sample size has implications for the power and generalizability of this study. The complexity of the established relationships, and in particular the highly significant effects, reduced the concerns regarding the limited sample size (Spector, 2006). Moreover, results showed substantial differences among participants in levels of i.e. idea generation, vigour, age, contract hours, and levels of pro-activity increasing the likelihood that results are representable for all employees in similar jobs.

Another limitation is that this study relied exclusively on self-reported data, which has drawbacks. Firstly, self-reported data are often perceived as subjective, although alternative measurements may not necessarily be better. For vigour, self-reporting is the most straightforward measurement since this variable taps into personal psychological states. Also for problem identification and idea generation other alternative measurements may not necessarily provide better insight in these variables. Shalley et al. (2004), for example, indicated that “sometimes employees are best suited for self-report creativity because they are the ones who are aware of the subtle things that they do in their jobs that make them creative” (p. 495). Moreover, since problems and ideas were measured in the same way, this controlled to some extent for the effect that some people count events different than others. Secondly, another drawback of self-reported data is that reporting problems and ideas may be difficult for participants. In contrast to initial doubts, participants indicated that counting problems, ideas and the number of work-related interactions was feasible. During the data collection participants appeared to have little trouble counting problems and ideas. (It also led to enthusiastic reactions “I had another good idea just now!”). Also the within-people variety in those variables indicated that people can make a clear distinction between higher or lower numbers of problems and ideas. This study, however, does not take into account that some problems and ideas are more substantial than others. Hence, how good or creative an idea was, was not taken into account. Future research may include a self-reporting measurements for the size of a problem or idea.

Another limitation is that the conducted multi-level analyses assumed no overlap in networks of ego’s, or at least that the overlap is negligible (Snijders, Sreen, and Zwaagstra, 1995). After comparing names and initials filled in for all interactions, the network overlap was estimated on approximately 20%. This percentage is not negligible. In situation of high network overlap, the Bayesian approach offers an alternative for the normal multi-level analysis (Bowne, Goldstein, & Rasbach, 2001). Applied to network context, this approach takes into account that each alter can affect multiple egos. One study that used the Bayesian approach, was the study by Schweinberg and Snijder (2003). For their study they collected data to map the network of members from one particular group, and interactions among them. In the present study, however, no data was collected regarding the complete network of all employees of the department in question. Participants were free to use any name or initials for their contacts. As a result, it is unknown
whether alters belong to networks of multiple participants. (The 20% is thus only an estimation). Consequently, a similar approach as exemplified by the study by Schweinberg and Snijder would have been very difficult to conduct.

Furthermore, ego-networks measured for this study give an incomplete insight in the actual, much more complex, network among alters. Ego-network in this study only included 1-step away alters. Alters of alters may, however, be tied to each other, and this affects levels of redundancy of alters.
References


Appendix A: Survey items

Diary survey
Problem identification and idea generation
Today I was exposed to a work-related problem. If yes, how many problems?
Today I came up with a work-related idea or problem solution. If yes, how many ideas?

Vigour
Today I felt strong and vigorous.
Today I was very resilient, mentally.
Today I was bursting with energy.

Interactions
With who did you have work-related interaction today? (If more than 4, please list the four most significant interactions).

General questionnaire
Creative self-efficacy
I feel that I am good at generating novel ideas.
I have confidence in my ability to solve problems creatively.
I have a knack for further developing the ideas of others.
I am good at finding creative ways to solve problems.

Network matrix

<table>
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<tr>
<th></th>
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<th>2</th>
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</tr>
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<tbody>
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<td>Person 1</td>
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</tr>
<tr>
<td>Person 2</td>
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</tr>
<tr>
<td>Person 3</td>
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<td>Person 4</td>
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