

Working Under Distractions

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Abstract

Distractions are pervasive in today’s workplaces, from noisy open-plan offices to digital interruptions. Using an incentivized laboratory experiment, I study the effects of distractions on performance and mental well-being, elicit willingness to pay to avoid distractions, and validate questionnaire items on resilience in working under distractions. I then incorporate these validated items in a representative Dutch survey panel. I obtain four main results. First, despite having little impact on performance in the lab, distractions are detrimental to individuals’ self-reported mental well-being while working. Second, many individuals are willing to pay to eliminate distractions, and this willingness to pay is negatively correlated with the change in mental well-being. Third, individual heterogeneity in the impact of distractions on mental well-being can be captured by questionnaire items. Fourth, resilience to distractions strongly predicts income and job satisfaction in the representative survey data, even conditional on education, sector, and other personality traits.

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1 Introduction

In modern professional settings, employees are exposed to various forms of distractions. They may frequently be interrupted by phone calls, messages, or colleagues, forcing them to switch attention between tasks. Moreover, many people work in open-plan offices or shared workspaces where chatty coworkers create constant auditory distractions. These distractions could negatively affect workers' performance, and even if they manage to maintain performance, this may come at the cost of increased mental effort and lower well-being. At the individual level, willingness to work under distractions and resilience to their negative effects could be valuable skills that are linked to occupational sorting, higher earnings, and faster career advancement.

To study responses to distractions as well as the willingness and ability to handle distractions, I combine data from an incentivized laboratory experiment and a representative Dutch survey panel. In the lab, I expose participants to auditory and task-switching distractions while performing a cognitively demanding task. I find that on average, participants manage to preserve the same level of performance when they work under distractions, however, this comes at the expense of their self-reported mental well-being. I use a price list to elicit willingness to pay to eliminate distractions and find that many participants are willing to pay a substantial share of their earnings to do so. This willingness to pay is negatively correlated with the change in mental well-being when working under distractions.

In the lab questionnaire, I elicit new survey questions to capture participants' resilience in working under distractions. Those who score higher on the combined survey measure experience better self-reported mental well-being when working under distractions. I then ask the same set of survey questions in a representative survey panel and find that a higher score on the survey measure predicts higher income and higher job satisfaction, even when controlling for education level, work sector, and other well-established personality traits.

Finally, motivated by the stereotypical belief that women are better than men at multitasking, I study gender differences in the resilience to distractions. In the lab, I find that women perform equally well and maintain similar levels of mental well-being as men when working under distractions, but they are less willing to pay than men to avoid distractions. They also report similar distraction resilience in the questionnaire both in the lab and in the representative survey panel.

This paper contributes to the literature on task-switching behaviors. Psycholo-

gists have investigated the effect of task-switching on performance, generally documenting negative effects.¹ While most papers in psychology examine task-switching through a series of short, simple, and unincentivized tasks, a few papers in economics study multitasking using longer and more complex tasks. Using a sample of Italian judges, [Coviello et al. \(2010\)](#) find that those who are forced to multitask between many trials take longer to complete them than those who complete similar portfolios of cases sequentially. Similarly, [Buser and Peter \(2012\)](#) find that individuals who are forced to multitask perform significantly worse than those who are forced to work sequentially on a Sudoku and a word-searching task. In contrast to existing multitasking papers that use equally important tasks, I use a main cognitively-demanding task alongside a series of short, secondary tasks. This setup mirrors educational and professional settings where individuals need to focus on a main project while managing less critical tasks such as answering phone calls or responding to emails.²

More recently, psychologists and economists focused on the use of information and communication technologies, and in particular their effects on educational outcomes. University students spend a substantial amount of time on their smartphones, which results in lower GPA and fewer exams passed ([Junco and Cotten, 2012](#); [Amez et al., 2023](#)). Multitasking on laptops ([Sana et al., 2013](#)) or simultaneously managing multiple sources of study information ([Pollard and Courage, 2017](#)) also reduce students' educational performance. On the contrary, removing sources of distraction, for example by banning mobile phones in secondary schools, increases student performance ([Beland and Murphy, 2016](#); [Abrahamsson, 2024](#)) with an exception in Sweden ([Kessel et al., 2020](#)).³ See [Chen and Yan \(2016\)](#) for a more thorough review on how mobile phones affect learning in students. These papers study smartphone distractions where people can choose the timing to check notifications. In this paper, I look at a form of task-switching distraction that is common in the workplace, where

¹Task alteration yields switching-time costs ([Rubinstein et al., 2001](#)) and causes loss of fluency during task performance ([Peifer and Zipp, 2019](#)). See [Monsell \(2003\)](#) for a detailed review on task-switching in the psychology literature.

²[Cai et al. \(2018\)](#) study non-incentivized work interruption in the form of machine breakdowns in a factory production setting. They find that a machine breakdown is associated with a significant reduction in worker productivity on the following day.

³[Beland and Murphy \(2016\)](#) find that a school ban on mobile phones increases performance of the lowest-achieving students in secondary schools in England. Similarly, [Abrahamsson \(2024\)](#) finds that banning smartphones in Norwegian middle schools improves the GPA of girls from low socio-economic backgrounds. On the contrary, a similar mobile phone ban in Swedish secondary schools had no impact on student performance, likely due to structural differences in the use of digital technology as compared to England ([Kessel et al., 2020](#)).

interruptions are externally imposed and need to be dealt with immediately.

Some studies have looked into gender differences in multitasking behavior. More than 50% of people from diverse ethnic backgrounds believe in gender differences in multitasking abilities, of which 80% believe women are better (Szameitat et al., 2015). Experimental results from Stoet et al. (2013) support this belief by showing that women perform as well as or better than men across all tasks while multitasking. However, excessive household interruptions like child care responsibilities make mothers earn 20% less than fathers through slower task completion speed on an on-line labor platform (Adams-Prassl et al., 2023). Only one paper estimates willingness to pay to avoid work pressure including factors like multitasking and deadlines and finds that female workers have a higher willingness to pay (Nagler et al., 2023).

Few papers in economics and psychology have addressed the effect of another common type of distraction in the work environment – auditory distraction – on economic decision making and performance. By randomizing exposure to engine noise during a production task, Dean (2024) finds that an increase in the noise level reduces productivity through the impairment of cognitive functions. In lab experiments, open-plan office noises do not reduce immediate performance in a cognitive task (Sander et al., 2021) but cause participants to remember fewer words in a memory task (Jahncke et al., 2011). See Banbury et al. (2001) for a detailed review of how different types of irrelevant sounds impair cognitive performance from a psychological point of view. In this paper, I distract participants with a conversation of general interest to match the environment of an open-plan office.

Little is known about the effect of task-switching and auditory distractions on mental well-being. In an educational setup, removing distractions through smartphones bans decreases health care take-up for psychological symptoms for girls in Norwegian middle schools (Abrahamsson, 2024). In the work context, Pikos (2017) finds that the introduction of new technologies is associated with increased multitasking behavior, which causes emotional exhaustion and burnout. Similarly, auditory distractions like open-plan office noises reduce psychological well-being (Sander et al., 2021) and make participants feel tired and unmotivated (Jahncke et al., 2011). Using survey and experimental data from Germany, Nagler et al. (2023) find that high work pressure, including increased multitasking and interruptions, is associated with worse (mental) health outcomes, though compensated by higher pay.

Employees have reported a rising frequency of workplace interruptions over the years (Nagler et al., 2023). This study advances our understanding of the effect

of working under different types of distractions on people’s mental well-being and their resilience in working under such conditions. Although I do not find short-run performance effects in the lab, my results suggest that there are negative effects of constant distractions on mental well-being. Lower mental well-being could lead to employee burnout and turnover, which may subsequently affect performance in the long run. My results also suggest that – apart from the average effects of distractions – heterogeneity in the ability and willingness to deal with distractions might be an important source of individual differences in career paths. My new survey measure of distraction resilience is correlated with both income and job satisfaction in nationally representative survey data.

The remainder of this paper is structured as follows. Section 2 explains the experimental design in detail. Section 3 presents the results from the lab and the representative survey. Section 4 concludes.

2 Experimental Design

I use a lab experiment to study how individuals respond to distractions. Participants first fill out a personality questionnaire including questions on resilience in working under distractions and then solve a cognitive task and several small tasks under three treatments: no distraction, auditory distraction, and task-switching distraction. After each round, I elicit their mental well-being by asking how they felt while working on the tasks. In the fourth and final round, I use a price list to elicit their willingness to pay to avoid working under distractions. The experiment ends with a survey that elicits basic demographics. Figure 1 shows an overview of the experiment. Full instructions can be found in Appendix C.

The personality questionnaire at the beginning of the experiment consists of the short 15-item Big Five Inventory (Lang et al., 2011) and 12 additional items. Eight of these additional items measure resilience in working under distractions: "I dislike working in distracting environments", "I can focus well in noisy environments", "I can easily concentrate after being interrupted", "I am good at working on several projects at the same time", "I enjoy working on several projects at the same time", "I have trouble limiting my phone usage", "I constantly check my phone while studying", and "I am easily distracted". Following Dohmen et al. (2011), Buser et al. (2024a), and Buser et al. (2024b), I also include four items to mea-

Figure 1: Overview of the experiment

Part 1:	<u>Personality questionnaire</u> <ul style="list-style-type: none">• 15-item Big Five Inventory• 8 questions on distraction resilience• 4 questions on time pressure preferences, risk preferences, and competitiveness
Part 2:	<u>Real effort cognitive tasks</u> <ul style="list-style-type: none">• Treatment: no distraction, auditory distraction, and task-switching distraction• Rounds 1-3 (baseline): Same task order, exogenous treatment order Mental well-being questions after each round• Round 4 (choice): Treatment and payment chosen by participants• <u>Nonogram</u>: 10 min per round Piece rate payment: 1 point per correctly labeled square Wrongly labeled square auto corrected at a cost of 5 points• <u>Adding numbers</u>: 10 tasks per round Solve each task within 1 min; otherwise a 5-point deduction
Part 3:	<u>Post-experimental survey</u> <ul style="list-style-type: none">• Demographic questions

sure attitudes towards competition, risk-taking, and time pressure, which have been shown to be important predictors of career outcomes. The 15 standard Big Five questions measure five personality traits: agreeableness, conscientiousness, extraversion, neuroticism, and openness. Participants choose the extent to which each statement describes them. Seven options are given: “Strongly Disagree”, “Disagree”, “Slightly Disagree”, “Neutral”, “Slightly Agree”, “Agree”, and “Strongly Agree”. These survey questions on distraction resilience and other personality traits are presented at the beginning of the experiment to ensure participants’ responses are not influenced by their experiences in the subsequent parts of the experiment.

After filling out the questionnaire, participants are introduced to the two types

of cognitive tasks in the main part of the experiment. The first type of task is called the “Nonogram” (see Figure 2). This is the main real-effort cognitive task. Participants have 10 minutes in each round to solve the Nonogram. Each task consists of a 10 by 10 board and each square on the board needs to be colored either green or gray. The number of consecutive green squares in any given row or column must match the sequence of numbers shown at the side or on the top of the board. Two sets of green squares need to be separated by at least one gray square. To color a square, participants need to first click on their preferred color for this square on the right. One point is awarded for each correctly colored square. If a square is colored wrongly, five points will be deducted and the square will flash red then change to the correct color.⁴ Each task has only one unique solution. To determine the correct color of a certain square, participants need to analyze the given information (at the side and on the top) and the already colored squares if there are any. This requires sufficient concentration and cognition, especially when starting a new task or revisiting a partially finished task after an interruption. I choose this task to reduce the likelihood of some participants having previous experience.⁵ If a participant finishes the Nonogram before the time runs out, a new one will appear, in which they can continue earning points.⁶

The second type of task is an adding-numbers task (see Figure 3). This is the interrupting task. Participants have 60 seconds to solve each task, with 10 tasks per round. Each task consists of a 3 by 3 board with nine unique two-digit numbers. The goal is to find the two numbers (out of the nine) that jointly add up to the “target number” displayed on the right side of the screen. Participants can select a number by clicking it. Once clicked, the number turns green. They can click the number again to deselect it. The experimental program proceeds once participants select the correct two numbers or the time runs out. Participants are not rewarded for solving the task but failing to solve it on time results in a five-point deduction.

After reading the instructions and completing the practice tasks,⁷ participants

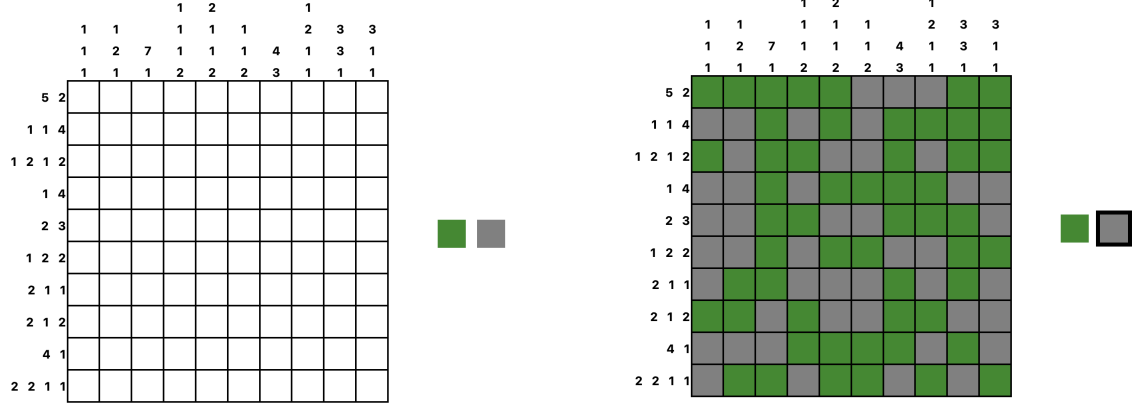
⁴Because a mistake makes it impossible to finish the task correctly and because finding a mistake can be difficult at the later stage of the task, any mistakes are corrected automatically.

⁵This is confirmed by one of the questions asked in the survey at the end of the experiment: “Have you played Nonogram before?”. Only two participants reported playing this game fairly often and more than 80% of the sample had never played it before.

⁶Maximum three Nonogram tasks are given in each round.

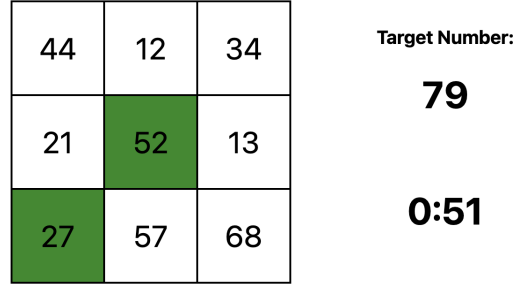
⁷Participants are given 10 minutes to solve a Nonogram and 60 seconds for each of three adding-numbers tasks to familiarize themselves with the task interface. None of the practice tasks are incentivized.

Figure 2: Example of the main cognitive task Nonogram



The figure shows an example of a Nonogram. An empty task is shown on the left and the solved version of this task is on the right.

Figure 3: Example of the interrupting adding-numbers task



play the tasks for four rounds. Prior to the start of the first round, they are informed that one round will be randomly selected for payment. At the end of each round, the final score is converted to money at a rate of 10 points to €1. If the final score for a round is negative, the earnings are 0 for that round.

Three treatments are implemented in the first three round: no distraction, auditory distraction, and task-switching distraction. In the no-distraction treatment, participants solve the Nonogram for 10 minutes, followed by 10 adding-numbers tasks for 60 seconds each. In the auditory-distraction treatment, participants still solve the Nonogram for 10 minutes but a conversation on a topic of general interest (in English) is played in the background at the same time.⁸ After solving the Nonogram

⁸Participants completed the experiment in individual soundproofed rooms. The volume of the

gram for 10 minutes, the conversation stops and participants move on to solve 10 adding-numbers tasks. In the task-switching-distraction treatment, the Nonogram is interrupted at 10 pre-determined moments by the adding-numbers tasks.⁹ Participants have to solve these adding-numbers tasks before resuming the Nonogram.

Participants solve the same sequence of tasks in the same order with the treatment in each round randomly assigned. After finishing all tasks in each round, they see a result page that shows the total score for the Nonogram, the number of solved adding-numbers tasks, the number of points deducted for unsolved adding-numbers tasks, the final score from both tasks, and their payoff for the round.

After each round, participants are asked how they felt while solving the two types of tasks. They choose the extent to which the following statements describe them: “I felt stressed while playing Nonogram (the adding-numbers games)”, “I felt happy while playing Nonogram (the adding-numbers games)”, and “I felt frustrated while playing Nonogram (the adding-numbers games)”. The same seven answer options as in the personality questionnaire are used. These questions aim to elicit participants’ mental well-being while they were solving the tasks under different treatments. For the analyses, I construct a composite mental well-being measure for each type of task under each treatment by taking the average of all three questions. The questions on stress and frustration are reverse coded so that in the composite mental well-being measure, a higher number means better mental well-being while solving the tasks.

In the fourth round, I elicit participants’ willingness to work under the two types of distractions. For each type of distraction, participants make a series of binary choices between solving the Nonogram with distraction and solving the Nonogram without distraction but with points deducted from the final score. The point deduction varies from 0 to 100 points (see Figure 4).¹⁰ In total, participants make 42 decisions, one of which is randomly chosen for implementation. These decisions indicate participants’ willingness to pay to avoid each type of distraction.

After the four rounds, participants reach a final survey that includes basic demographics like age and gender, and whether they have played the Nonogram and other similar puzzle games before. In addition, participants make several choices between a sure amount and a random lottery in which they can receive additional earnings.

conversation was pre-adjusted so they could not hear any sounds from neighboring rooms.

⁹These 10 moments were randomly chosen and were set the same for all participants.

¹⁰When participants select an option for one decision, the remaining decisions are automatically filled in to prevent inconsistent decisions.

Figure 4: Example of the price list in round 4

Round 4 of 4

For each of the following decisions, please indicate which one you would prefer.

- | | |
|---|---|
| <input type="radio"/> Conversation | <input checked="" type="radio"/> Sequential with 0 point deducted |
| <input type="radio"/> Conversation | <input checked="" type="radio"/> Sequential with 5 points deducted |
| <input type="radio"/> Conversation | <input checked="" type="radio"/> Sequential with 10 points deducted |
| <input type="radio"/> Conversation | <input checked="" type="radio"/> Sequential with 15 points deducted |
| <input type="radio"/> Conversation | <input checked="" type="radio"/> Sequential with 20 points deducted |
| <input checked="" type="radio"/> Conversation | <input type="radio"/> Sequential with 25 points deducted |
| <input checked="" type="radio"/> Conversation | <input type="radio"/> Sequential with 30 points deducted |
| <input checked="" type="radio"/> Conversation | <input type="radio"/> Sequential with 35 points deducted |
| <input checked="" type="radio"/> Conversation | <input type="radio"/> Sequential with 40 points deducted |
| <input checked="" type="radio"/> Conversation | <input type="radio"/> Sequential with 45 points deducted |
| <input checked="" type="radio"/> Conversation | <input type="radio"/> Sequential with 50 points deducted |
| <input checked="" type="radio"/> Conversation | <input type="radio"/> Sequential with 55 points deducted |
| <input checked="" type="radio"/> Conversation | <input type="radio"/> Sequential with 60 points deducted |
| <input checked="" type="radio"/> Conversation | <input type="radio"/> Sequential with 65 points deducted |
| <input checked="" type="radio"/> Conversation | <input type="radio"/> Sequential with 70 points deducted |
| <input checked="" type="radio"/> Conversation | <input type="radio"/> Sequential with 75 points deducted |
| <input checked="" type="radio"/> Conversation | <input type="radio"/> Sequential with 80 points deducted |
| <input checked="" type="radio"/> Conversation | <input type="radio"/> Sequential with 85 points deducted |
| <input checked="" type="radio"/> Conversation | <input type="radio"/> Sequential with 90 points deducted |
| <input checked="" type="radio"/> Conversation | <input type="radio"/> Sequential with 95 points deducted |
| <input checked="" type="radio"/> Conversation | <input type="radio"/> Sequential with 100 points deducted |

Next

The analysis plan was pre-registered in the AEA RCT Registry¹¹ and is reprinted in Appendix B. The experiment was programmed using oTree (Chen et al., 2016) and conducted at the CREED laboratory using the subject pool of the University of Amsterdam in November and December 2023. Based on power calculations reported in the analysis plan, I aimed to collect data from a minimum of 200 participants. In accordance with the analysis plan, I excluded 22 participants who completed all three Nonogram tasks within 10 minutes for at least one treatment,¹² four participants with a very low negative final score for at least one treatment (less than -100 points), three participants who chose the same option for all questions on a particular questionnaire page,¹³ and two participants who tried to turn off the conversation by switching off the computer.¹⁴ After these exclusions, the final sample consists of 217 participants, of whom 54% are female. The average earnings in the experiment were €25.80 including a participation fee of €7.¹⁵

3 Results

I present my results in five sections. In Sections 3.1 and 3.2, I use data from the first three rounds of the experiment to estimate the impact of distractions on performance and mental well-being respectively. In Section 3.3, I use the choice data from round 4 to estimate participants' willingness to pay to avoid working under distractions. I then investigate the relationship between the main experimental outcomes and the survey measure on distraction resilience in Section 3.4. In Section 3.5, I use the representative survey data to study the relationship between the survey questions and realized labor market outcomes.

¹¹<https://www.socialscisceregistry.org/trials/12534>

¹²Eight participants finished all three Nonogram tasks in the task-switching-distraction treatment before time ran out. This prevented one or more adding-numbers tasks from being displayed and caused an application error. These participants were asked to exit the experiment after encountering the error and were compensated based on the performance in the rounds they had completed. Since participants completed the experiment in individual rooms, this did not affect other participants in the same session. 14 participants finished all three tasks in either the no-distraction or auditory-distraction treatments.

¹³This serves as an attention check. Those who chose the same option for all six to eight questions on the same page were very likely not paying attention.

¹⁴This was not stated in the analysis plan since switching off the computer was not expected. After these two incidents happened, students were reminded in the instructions not to press any button on the computer.

¹⁵Two pilot sessions of 38 and 20 participants each were run in the CREED laboratory to finalize the design details and to ensure that there were no technical issues.

Table 1: Effect of distractions on performance

	(1) Total	(2)	(3) Nonogram	(4)	(5) Adding-numbers	(6)
	Earnings	Score	Right	Wrong	Time	Solved
Auditory	-0.083 (0.260)	-1.426 (2.473)	1.467 (1.913)	0.579 (0.383)	-10.354 (7.114)	0.119 (0.170)
Task-switching	-1.069*** (0.259)	-3.569 (2.467)	-1.549 (1.908)	0.404 (0.382)	43.998*** (7.095)	-1.425*** (0.169)
Constant	6.772*** (0.236)	75.184*** (2.249)	128.129*** (1.740)	10.589*** (0.349)	283.182*** (6.469)	8.507*** (0.154)
N	651	651	651	651	651	651

The table shows coefficients from regressions of performance measures on treatment dummies, controlling for task and individual fixed effects. Column (1) uses the total earnings from both types of tasks. Columns (2) to (4) use outcomes for the main cognitive task Nonogram: the final score, the total number of squares that are colored correctly, and the total number of squares that are colored wrongly. Columns (5) and (6) use outcomes for the adding-numbers tasks: total time spent on all 10 tasks in a round and the total number of tasks solved out of 10 under a 60-second limit. Robust standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.1 The impact of distractions on performance

Table 1 presents the average impact of distractions on the performance in the two tasks using the first three rounds. In each column, a different performance outcome is regressed on treatment dummies, controlling for task and individual fixed effects. Column (1) uses total earnings from both types of tasks. On average, participants earn €6.77 in the no-distraction round. Auditory distraction reduces earnings marginally by 8 cents. Meanwhile, the task-switching distraction causes a significant 16% drop in earnings.

To break down the effect on total earnings, I check the impact of distractions on each type of task separately. Columns (2) to (4) use outcomes for the main cognitive task Nonogram: the final score, the total number of squares that are colored correctly, and the total number of squares that are colored wrongly. As compared to working under no distraction, auditory distraction and task-switching distraction barely have any impact on any of the performance measures. This minimal performance effect on the main cognitive task is unexpected since the nature of the Nonogram requires participants to use sufficient cognitive attention. Though they are forced to switch between tasks or listen to a conversation, on average, participants perform similarly

as compared to when there is no distraction.¹⁶

Columns (5) and (6) present the effect of distractions on the performance in the adding-numbers tasks. Column (5) uses the total time taken to solve all 10 adding-numbers tasks and column (6) uses the total number of adding-numbers tasks solved (out of 10) under the 60-second limit. The task-switching-distraction treatment, where participants have to solve the adding-numbers tasks at random moments while solving the Nonogram, significantly hampers performance: participants are 4.4 seconds slower per task and solve 16.8% fewer tasks in total as compared to solving them after the Nonogram sequentially. In the auditory-distraction treatment, the conversation that plays in the background during the Nonogram stops for the adding-numbers tasks. There is no significant effect on either outcome dimension for the adding-numbers tasks.

There is a stereotypical belief that women are better at multitasking than men (Szameitat et al., 2015; Stoet et al., 2013). To study the gender differences in performance, I regress total earnings, the Nonogram score, and the number of adding-numbers tasks solved (out of 10) on a gender dummy, treatment dummies, and the interactions among them. The first three columns in Table 7 in Appendix A present the results. I find no significant gender differences in performance across treatments. Female participants earn marginally more and achieve marginally higher score in the Nonogram than male participants without distractions. However, they earn less and achieve lower score in the Nonogram under auditory and task-switching distractions, though these differences are not statistically significant. This suggests that women and men perform equally well under distractions.

3.2 The impact of distractions on mental well-being

Results from the previous section suggest that individuals manage to maintain the same level of performance under distractions in the short term. However, this could come at the expense of increased stress, reduced enjoyment, and worse mental well-being. These factors are important from an economic perspective because they can

¹⁶A potential issue with the Nonogram is that participants might learn and improve their performance over the course of the experiment. Apart from controlling for task fixed effects in Table 1, another way to address this issue is to use outcomes from the first round only, which amounts to a between-subject randomization of the treatments. Table 6 in Appendix A presents the results using total earnings. The effect of task-switching distraction is consistent with the results in Table 1. Auditory distraction has a positive effect on earnings when only round 1 is used, though this result is statistically significant only at the 10% significance level.

Table 2: Effect of distractions on mental well-being

	(1)	(2)
	Well-being	
	Nonogram	Adding-numbers
Auditory	-0.374*** (0.093)	0.192** (0.089)
Task-switching	-0.632*** (0.093)	-0.292*** (0.088)
Constant	4.595*** (0.085)	3.396*** (0.080)
N	651	651

The table shows coefficients from regressions of the composite mental well-being measure for each type of task on treatment dummies, controlling for task and individual fixed effects. Mental well-being for each type of task is a composite measure constructed by taking the average of the answers to the three questions: “I felt stressed while playing Nonogram (the adding-numbers games)”, “I felt happy while playing Nonogram (the adding-numbers games)”, and “I felt frustrated while playing Nonogram (the adding-numbers games)”. The questions on stress and frustration are reverse coded so that a higher number in the composite measure means better mental well-being while solving the tasks. Robust standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

lead to burnout, which harms individuals both physically and psychologically (Salvagoni et al., 2017) and subsequently damages performance in the long run.

To study the effect of distractions on mental well-being, I regress the composite mental well-being measure for each type of task on treatment dummies, controlling for task and individual fixed effects. Table 2 shows the results. In the main cognitive task Nonogram, participants experience significantly worse mental well-being when they have to solve it in the presence of a conversation or when they are interrupted by adding-numbers tasks relative to solving the Nonogram without distractions. Task-switching distraction is significantly more detrimental to mental well-being than auditory distraction ($p=0.004$, t-test).

In the adding-numbers tasks, the conversation only lasts for ten minutes during the Nonogram and stops for the adding-numbers tasks in the auditory-distraction treatment. After the conversation stops, participants experience better self-reported mental well-being while solving the adding-numbers tasks compared to in the no-distraction treatment. This suggests that a change in environment, from a noisy to a quiet one, contributes to improved mental well-being. In the task-switching treatment, where participants are forced to solve the adding-numbers tasks at random moments while solving the Nonogram, they report worse mental well-being while

solving these adding-numbers tasks compared to solving them sequentially after having completed the Nonogram. Switching between major and minor tasks deteriorates individuals' mental state while solving both tasks.

Besides the average effect, I also study gender differences in the effect of distractions on mental well-being. Column (4) in Table 7 in Appendix A presents the results. Under no distraction, female participants experience significantly worse mental well-being. Their mental well-being also declines more under both types of distractions compared to males, but this difference is not statistically significant. The results on the effect of distractions across genders suggest no substantial difference in their ability to handle distractions, both in terms of performance and mental well-being.

3.3 Willingness to pay to avoid distractions

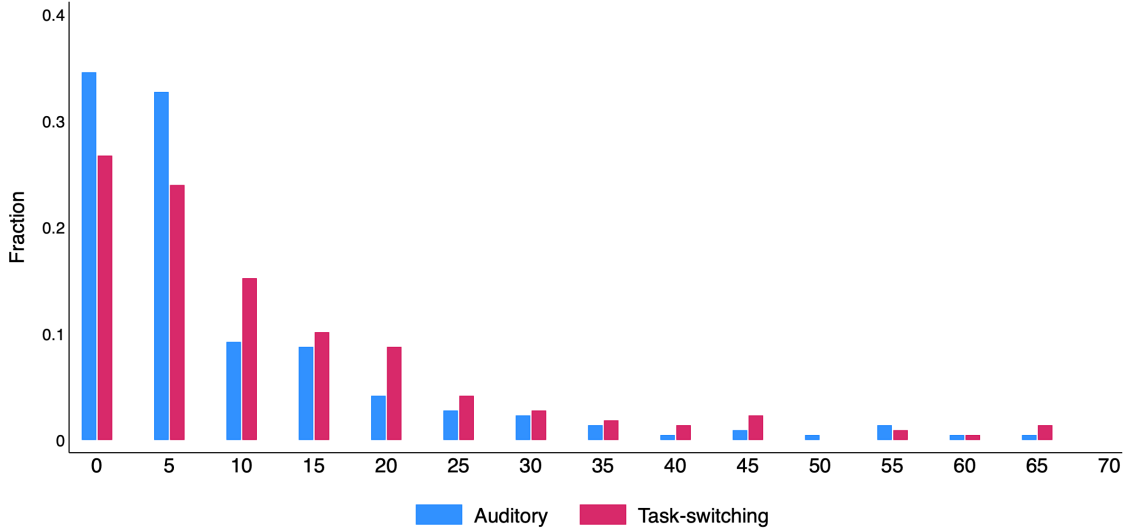
I will now look at how much participants are willing to pay to avoid working under distractions and how their willingness to pay correlates with performance and mental well-being under distractions. In the fourth round, participants choose repeatedly between two options for each type of distraction: solving the Nonogram with the distraction or solving the Nonogram without distraction but with a point deduction varying from 0 to 100 points. The point deduction at which participants switch from choosing no distraction to distraction reflects their willingness to pay (WTP) to avoid each type of distraction. The distribution of WTP is shown in Figure 5.

67% of participants are willing to pay at most 5 points (€0.5) to avoid auditory distraction. Meanwhile, 50% of participants are willing to pay more than 5 points to avoid getting interrupted by small side tasks while working on their main task. The CDF plot in Figure 6 in Appendix A shows that the WTP to avoid task-switching distraction first-order stochastically dominates the WTP to avoid auditory distraction. This is consistent with the previous results showing that task-switching distraction is more detrimental than auditory distraction for both total earnings and self-reported mental well-being.

Table 3 shows the results from regressing the WTP to avoid each type of distraction on mental well-being and total earnings under each treatment, controlling for mental well-being and earnings in the no-distraction treatment.¹⁷ The results show that for both types of distractions, participants who experience a larger decline in

¹⁷Mental well-being for each treatment is the average of all six questions on how participants felt while solving both tasks. The higher the number, the better the mental well-being.

Figure 5: WTP to avoid distractions



The figure shows the distribution of the WTP to avoid each type of distraction. The WTP is the amount of point deduction that makes participants switch from solving the Nonogram without distraction but with point deduction to solving the Nonogram under the specific type of distraction.

mental well-being while working under distractions are willing to pay significantly more to eliminate the distraction, whereas changes in earnings do not play a significant role. This suggests that individuals value their mental well-being more than their earnings or performance.

Table 8 in Appendix A shows the results from regressing the WTP to avoid each type of distraction on a gender dummy. Female participants are willing to pay 40% and 34% less to avoid auditory and task-switching distractions than male participants respectively. This suggests that although males and females are affected by distractions in a similar way, male participants are leaving more money on the table to avoid working under distractions.

3.4 Questionnaire items on distraction resilience

The previous sections show that although distractions do not significantly hamper performance on average, individuals experience worse mental well-being while working under distractions and are willing to pay to avoid being distracted. Beyond these average effects, there might be substantial heterogeneity in how individuals respond to distractions. I will now check whether individual differences in the effects of dis-

Table 3: Relationship between WTP and mental well-being and earnings

	(1)	(2)
	WTP	
	Auditory	Task-switching
Well-being	-0.330*** (0.106)	-0.261*** (0.087)
Earnings	-0.009 (0.082)	-0.062 (0.092)
Well-being no-distraction	✓	✓
Earnings no-distraction	✓	✓
N	217	217

The table shows coefficients from regressions of the willingness to pay to avoid auditory and task-switching distractions on mental well-being and earnings under the specific type of distraction, controlling for mental well-being and earnings in the no-distraction treatment. WTP is the the point deduction that makes participants switch from no distraction to the specific type of distraction. Well-being is the average of all six questions on how participants felt while solving both types of tasks. Earnings is the total earnings from both types of tasks. All dependent and independent variables are standardized. Robust standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Relationship between distraction resilience and experimental outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Auditory			Task-switching		
	Earnings	WTP	Well-being	Earnings	WTP	Well-being
Distraction resilience	0.016 (0.063)	-0.086 (0.066)	0.157*** (0.060)	0.078 (0.060)	0.014 (0.066)	0.136** (0.059)
Earnings no-dist.	✓	✓	✓	✓	✓	✓
Well-being no-dist.	✓	✓	✓	✓	✓	✓
N	217	217	217	217	217	217

The table shows coefficients from regressions of total earnings, willingness to pay, and self-reported mental well-being for each type of distraction on the distraction resilience measure. Distraction resilience is the combined survey measure of resilience in working under distractions and is the first component from the principal component analysis of all eight survey questions. A higher score indicates greater resilience in working under distractions. Please refer to the notes for Table 3 for description of the other variables. All dependent and independent variables are standardized. Robust standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

tractions are correlated with the survey questions. If this is the case, these questions can be used outside the laboratory to measure individuals' skills and preferences for working under distractions.

Figure 7 in Appendix A shows the distributions of answers to the eight survey questions on resilience in working under distractions: "I dislike working in distracting environments", "I can focus well in noisy environments", "I can easily concentrate after being interrupted", "I am good at working on several projects at the same time", "I enjoy working on several projects at the same time", "I have trouble limiting my phone usage", "I constantly check my phone while studying", and "I am easily distracted". The distributions show significant heterogeneity in individuals' resilience in working under distractions. In the remaining analyses, a composite measure is constructed by taking the first component from a principal component analysis of all eight questions. A higher score on this measure indicates a greater self-reported willingness to work under distractions and a higher ability to manage distractions. I will refer to this composite measure as "distraction resilience".¹⁸

Next, I look into the correlations between distraction resilience and three experimental outcomes for each type of distraction: (1) total earnings from both types of tasks; (2) willingness to pay to avoid the distraction as measured by the point deduction at which participants switch from no distraction to the specific type of distraction; and (3) self-reported mental well-being as measured by the average of all six questions on how participants felt while solving both types of tasks. Table 4 shows the results from regressing the three experimental outcomes for each type of distraction on the distraction resilience measure. These regressions control for earnings in the no-distraction treatment in columns (1) and (4), earnings in both the specific distraction treatment and no-distraction treatment in columns (2) and (5), and self-reported mental well-being in the no-distraction treatment in columns (3) and (6). All dependent and independent variables are standardized.

To summarize the results, although distraction resilience does not predict performance effects or willingness to pay to avoid distractions, it is significantly correlated with the change in mental well-being under both auditory and task-switching distractions. Individuals who report being more resilient in working under distractions tend to experience better mental well-being when having to work under such conditions, conditional on well-being in the no-distraction treatment. A one standard

¹⁸Female participants on average rate themselves similarly on the composite survey measure as male participants ($p=0.928$, t -test).

deviation increase in the distraction resilience measure is correlated with a 0.166 and 0.136 standard deviation increase in mental well-being when working under auditory and task-switching distraction respectively.

3.5 Distraction resilience and labor market outcomes in nationally representative survey data

The experimental data show that the combined survey measure for distraction resilience is correlated with the effect of distractions on self-reported mental well-being at the individual level. Previous research has shown that non-cognitive abilities – such as conscientiousness, social skills, willingness to compete, or preferences for working under time pressure – predict labor market outcomes (Mueller and Plug, 2006; Deming, 2017; Buser et al., 2022, 2024b). To test whether willingness and ability to work under distractions is also rewarded in the labor market, I elicit the same set of survey questions in a nationally representative Dutch survey panel.¹⁹ This allows me to link my distraction resilience measure to survey data on monthly income, job satisfaction, education level, occupation, as well as a range of standard personality traits and economic preferences.

Panel A in Table 5 presents results from OLS regressions of standardized gross monthly income on the standardized distraction resilience measure with different sets of controls. Education level is based on six categories defined by Statistics Netherlands. Sector is based on work sector defined by the LISS panel.²⁰ Personality controls include the Big Five personality traits, competitiveness, and risk tolerance.

Column (1) shows that conditional on gender and age, a one standard deviation increase in the combined distraction resilience measure is correlated with a 0.153 standard deviation increase in gross monthly income. After controlling for education level in column (2), the coefficient for distraction resilience barely changes, indicating that the correlation between distraction resilience and gross monthly income is not due to a correlation with education.

The correlation between distraction resilience and income could be either due to people who are better at dealing with distractions choosing different careers or

¹⁹The LISS panel (Longitudinal Internet studies for the Social Sciences) is managed by the non-profit research institute Centerdata (Tilburg University, the Netherlands) and is a representative sample of the Dutch population who participate in monthly surveys.

²⁰The work sectors include agriculture, industry, construction, retail, catering, transport, financial, business, government, education, healthcare, culture/recreation, and other.

performing better within their chosen career. Column (3) shows that controlling for work sector on top of education does not further change the coefficient. This suggests that the correlation between distraction resilience and income is not due to differential sorting but rather due to differential performance within the same sector.

To explore the link between distraction resilience and occupational sorting in more detail, Figure 8 in Appendix A shows the standardized distraction resilience across occupations.²¹ The results indicate that people sort into occupations based on their distraction resilience: the differences across occupations are statistically significant ($p=0.025$, Wald test). Managers, trades people, and business professionals rate themselves the highest on distraction resilience, whereas care workers and clerical workers (including customer service and office workers) rate themselves the lowest on distraction resilience.

A further question of interest is whether the correlation between distraction resilience and income is captured by traditionally measured preferences and personality traits. Table 9 in Appendix A shows the correlations between distraction resilience and other preferences and personality traits measured in the pre-experiment questionnaire. Mental stability has the highest correlation with distraction resilience at 0.43, followed by openness, conscientiousness, and extraversion. After controlling for the full list of traits in column (4) in Table 5, the coefficient for distraction resilience drops by 42 percent but remains statistically significant. To see which specific traits contribute to this reduction, Table 10 in Appendix A shows the coefficients for each preference and personality trait. Competitiveness, extraversion, and stability are highly correlated with standardized gross monthly income.

In line with the laboratory experiment, I also look at whether the combined distraction resilience measure is correlated with realized mental well-being while working. This is proxied by job satisfaction and is measured by the answer to the question “Everything considered, I [am/was] satisfied with my job”. Panel B in Table 5 shows the results from OLS regressions of standardized job satisfaction on the standardized distraction resilience measure, controlling for the same sets of variables as in Panel A. Column (1) shows that conditional on age and gender, a one standard deviation increase in the distraction resilience measure is associated with a 0.206 standard deviation increase in self-reported job satisfaction. The coefficient hardly changes when controlling for education and work sector.

²¹Instead of sector dummies, two-digit ISCO codes are used in this figure. This information is available for a smaller sample.

Table 5: Relationship between distraction resilience and labor market outcomes

	(1)	(2)	(3)	(4)
<i>Panel A: Income</i>				
Distraction resilience	0.153*** (0.023)	0.150*** (0.020)	0.142*** (0.020)	0.089*** (0.023)
Observations	1,843	1,843	1,843	1,843
<i>Panel B: Job satisfaction</i>				
Distraction resilience	0.206*** (0.027)	0.202*** (0.027)	0.204*** (0.027)	0.111*** (0.030)
Observations	1,732	1,732	1,732	1,732
Gender, age	✓	✓	✓	✓
Education level		✓	✓	✓
Sector			✓	✓
Personality				✓

The table shows coefficients from OLS regressions of gross monthly income and job satisfaction on distraction resilience. Job satisfaction is the answer to the survey question: “Everything considered, I [am/was] satisfied with my job”. Distraction resilience is the composite survey measure of resilience in working under distractions and is the first component from a principal component analysis of all eight questions. Age controls include age and age squared. Education level is six dummies for the education categories defined by Statistics Netherlands. Sector dummies are based on work sector defined by the LISS panel. Personality controls include the Big Five personality traits, competitiveness, and risk tolerance. The sample consists of all respondents who are between 25 and 65 years old and for whom all variables are available. All dependent and independent variables are standardized. Robust standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

After additionally controlling for standard personality traits, the coefficient is halved but remains statistically significant. Column (2) in Table 10 in Appendix A shows that among the additional trait measures, only stability is highly correlated with job satisfaction. That is, the relationship between distraction resilience and labor market outcomes is partially captured by mental stability, which is highly correlated with both. But even after controlling for stability, distraction resilience significantly predicts income and job satisfaction.

In terms of gender differences, women rate themselves 0.14 standard deviation lower than men on the distraction resilience measure ($p=0.000$, t-test). Among survey respondents who are similar to the participants in the lab experiment (university students under 25 years old), men and women rate themselves similarly ($p=0.326$,

t-test). Both men and women rate themselves higher as they grow older. This increase is stronger for men and the gender difference becomes statistically significant after around 55 years old (see Figure 9 in Appendix A).

4 Conclusion

People experience many distractions in their everyday work and study life. I use an incentivized laboratory experiment to estimate the effect of two common types of distractions – noise and interruptions – on performance and mental well-being when solving a cognitive task. While I do not find a significant impact of distractions on performance, I show that average mental well-being declines in the presence of either type of distraction as compared to when people work under no distraction. I then use a price list to elicit participants’ willingness to pay to avoid distractions and find that those whose mental well-being is less affected by distractions are willing to pay less to eliminate them. Willingness to pay is, however, not correlated with the effect on performance, suggesting that participants value their mental well-being more than expected earnings.

Extrapolated to a workplace setting, my results suggest that constant distractions have a negative effect on mental well-being while working, likely leading to lower job satisfaction and lower performance in the long run. Given that distractions are common in many careers, being relatively more resilient to them might be a valued skill in the labor market. To test whether heterogeneity in distraction resilience predicts career outcomes, I first show that, in the experimental data, individual differences in the effect of distractions on mental well-being can be captured by a series of simple survey questions that elicit participants’ perception of their ability and preference towards working under distractions. I then elicit the same set of questions in a nationally representative survey panel and find strong correlations between a composite distraction resilience measure and realized labor market outcomes. These correlations are robust to controlling for education, work sector, and standard personality traits. People who are more resilient in working under distractions have a higher monthly income and – in sync with the lab results on mental well-being – higher job satisfaction. People in management positions see themselves as particularly resilient to distractions.

Another contribution of this paper is to test the common belief that women are

better at multitasking than men. I look at gender differences in performance, mental well-being, willingness to pay to avoid distractions, and distraction resilience. I find that women and men are equally good at handling distractions both in terms of performance and mental well-being, but women are indeed willing to pay less to avoid distractions. They also rate themselves similarly on the distraction resilience measure as men when they are young, but rate themselves lower than men with age. This is in contrast to the stereotypical belief: men do not perform worse while multitasking and women do not consistently prefer multitasking more than men.

In summary, my experimental results suggest that distractions in the workplace are a source of stress and lower mental well-being, potentially leading to lower performance or burnout in the long run. My survey results indicate that – from a human capital perspective – working under distractions is a valuable skill and those who are good at dealing with distractions benefit from faster career advancement and higher job satisfaction. The new survey questions can be easily added to any survey by researchers who wish to study the link between distraction resilience and labor market outcomes.

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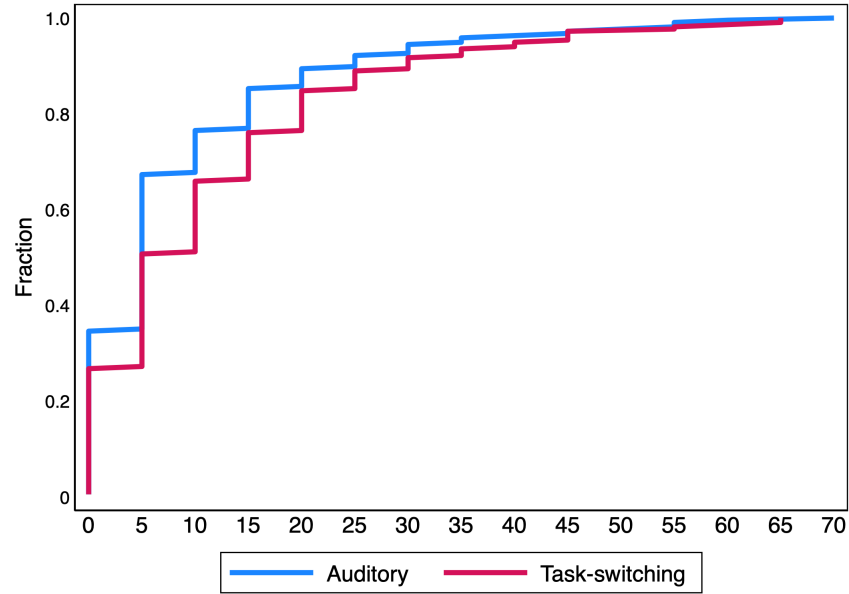
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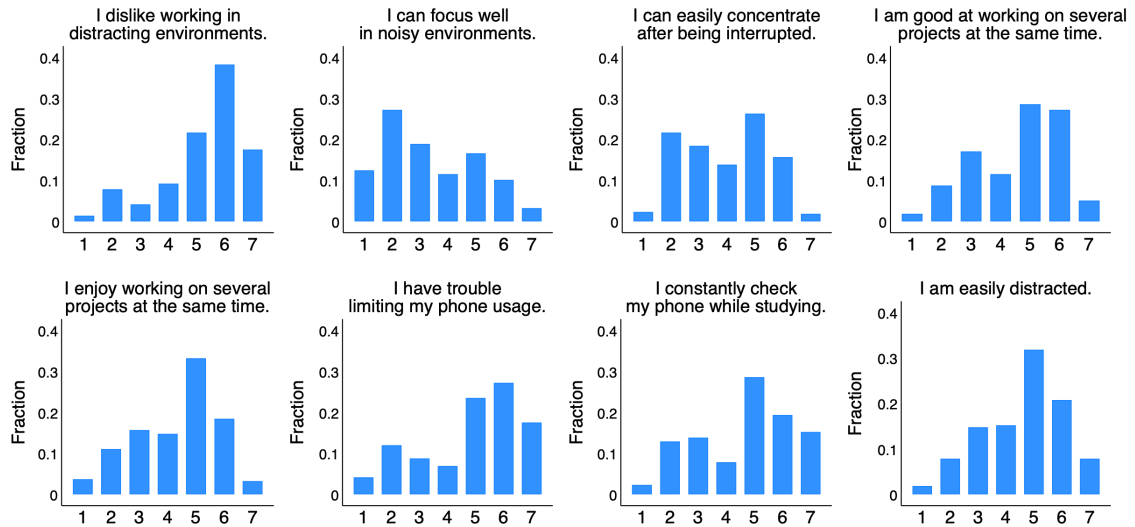
Appendix A: Additional Tables and Figures

Figure 6: CDF of willingness to pay to avoid distractions



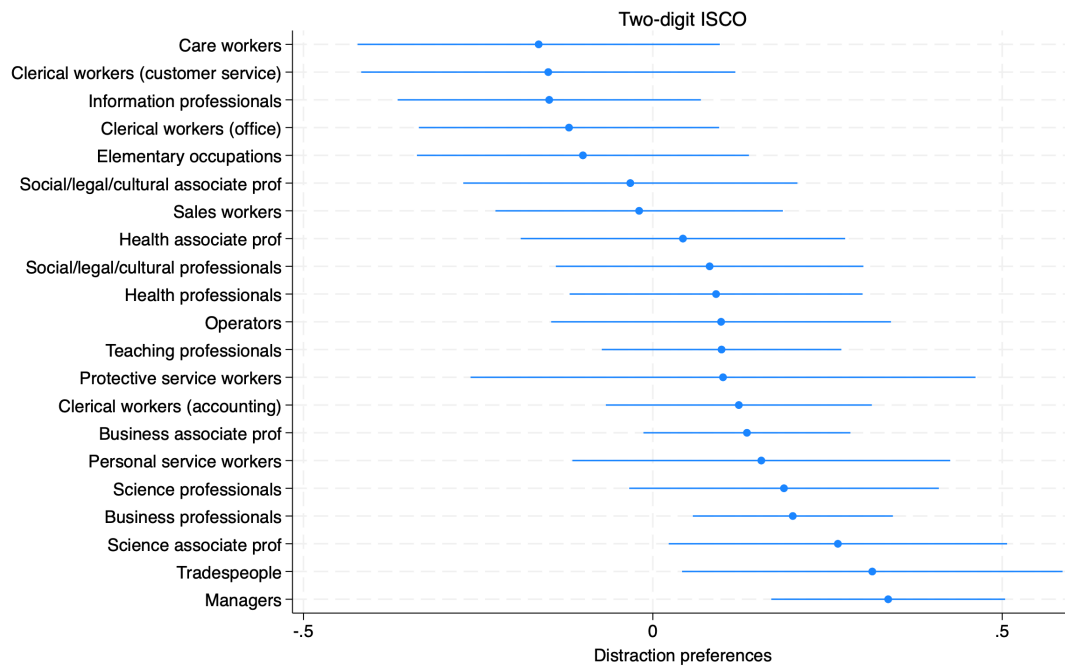
The figure shows the cumulative density functions (CDFs) for the willingness to pay to avoid being distracted by each type of distraction.

Figure 7: Distributions of answers to survey questions



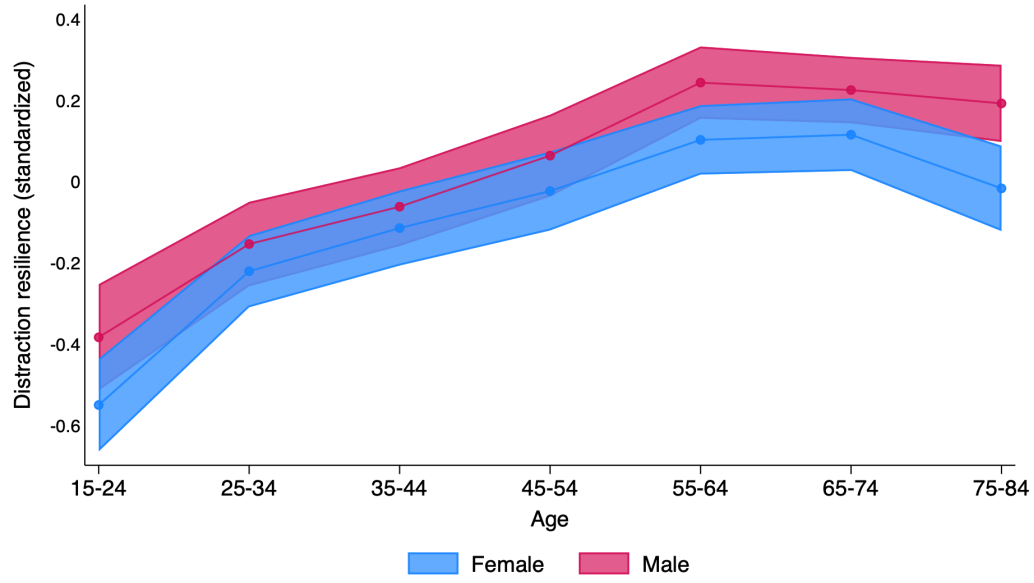
The figure shows the distributions of answers to the eight survey questions on resilience in working under distractions in the lab experiment. Seven answer options are given: from 1 (“Strongly Disagree”) to 7 (“Strongly Agree”).

Figure 8: Distraction resilience across occupations (LISS panel)



The graph shows the average standardized distraction resilience measure across occupations while controlling for gender, age, age squared, and education level. The sample consists of all respondents who are between 25 and 65 years old and for whom all variables are available. Occupations are based as much as possible on the two-digit international standard for classification of occupations (ISCO) level. The following changes were made to ensure a sufficient number of observations in each cell: all managerial occupations were combined into a single category; information technicians were grouped with science technicians; armed forces personnel were grouped with protective workers; people in agricultural occupations were dropped from the sample; all crafts and trades were combined into a single category; all operators and drivers were grouped into a single category; all cleaners and laborers were grouped into a single category. Error bars show 95-percent confidence intervals based on robust standard errors.

Figure 9: Distribution of distraction resilience by gender and age (LISS panel)



The figure shows the distribution of distraction resilience by gender and age. Distraction resilience is the standardized first component from a principal component analysis on all eight survey questions. The shaded areas represent 95% confidence intervals.

Table 6: Effect of distractions on earnings (using round 1 only)

	Earnings
Auditory	1.196* (0.608)
Task-switching	-1.186* (0.678)
Constant	6.444*** (0.411)
N	217

The table shows coefficients from regressions of earnings on the two types of distractions using the first round only. Robust standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Gender differences in performance

	(1) Total Earnings	(2) Nonogram Score	(3) Adding-numbers Solved	(4) Mental Well-being
Female	0.156 (0.571)	3.103 (5.524)	-0.308 (0.192)	-0.432*** (0.134)
Aud	0.310 (0.358)	1.926 (3.552)	0.235* (0.124)	-0.032 (0.107)
TS	-0.996*** (0.355)	-2.671 (3.352)	-1.459*** (0.304)	-0.442*** (0.105)
Female×aud	-0.732 (0.484)	-6.235 (4.720)	-0.217 (0.183)	-0.110 (0.132)
Female×TS	-0.135 (0.502)	-1.660 (4.755)	0.063 (0.400)	-0.037 (0.136)
Constant	6.686*** (0.418)	73.503*** (4.005)	8.671*** (0.167)	4.228*** (0.111)
N	651	651	651	651

The table shows coefficients from regressions of performance measures on a gender dummy, treatment dummies, and the interactions among them. Please refer to the notes for Table 1 and Table 4 for detailed description of the variables. Robust standard errors are shown in parentheses and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Gender differences in willingness to pay to avoid distractions

	(1) Auditory	(2) Task-switching
Female	-4.441** (1.741)	-4.963*** (1.898)
Constant	11.150*** (1.587)	14.450*** (1.618)
N	217	217

The table shows coefficients from regressions of the willingness to pay to avoid working under each type of distraction on a gender dummy. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Correlations between distraction resilience and other preference measures and personality traits (LISS panel)

	Dist.	Risk	Comp.	Extr.	Agr.	Cons.	Sta.	Open.
Distraction resilience	1.000							
Risk tolerance	-0.102	1.000						
Competitiveness	-0.050	0.545	1.000					
Extraversion	0.241	-0.033	0.036	1.000				
Agreeableness	0.105	-0.187	-0.205	0.344	1.000			
Conscientiousness	0.261	-0.216	-0.128	0.155	0.311	1.000		
Stability	0.421	-0.207	-0.150	0.281	0.105	0.290	1.000	
Openness	0.246	0.004	0.068	0.310	0.290	0.274	0.182	1.000

The table shows correlations between distraction resilience, risk preference, competitiveness, extraversion, agreeableness, conscientiousness, stability, and openness.

Table 10: Relationship between distraction resilience and gross monthly income and job satisfaction (detailed)

	(1) Income	(2) Job satisfaction
Distraction resilience	0.089*** (0.023)	0.111*** (0.030)
Risk tolerance	-0.021 (0.024)	-0.010 (0.030)
Competitiveness	0.115*** (0.026)	0.010 (0.027)
Extraversion	0.070*** (0.022)	0.042 (0.027)
Agreeableness	0.016 (0.022)	0.046 (0.030)
Conscientiousness	0.030 (0.021)	0.037 (0.028)
Stability	0.072*** (0.021)	0.170*** (0.030)
Openness	-0.004 (0.023)	0.009 (0.030)
Gender, age	✓	✓
Education level	✓	✓
Sector	✓	✓
Observations	1,843	1,732

The table shows coefficients from OLS regressions of gross monthly income and job satisfaction on the combined distraction resilience measure and personality traits, controlling for gender, age, education level, and work sector. Please refer to the notes for Table 5 for detailed description of the variables. The sample consists of all respondents who are between 25 and 65 years old and for whom all variables are available. All dependent and independent variables are standardized. Robust standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix B: Pre-Analysis Plan

In this section, I reproduce the pre-analysis plan (as registered on the AEA registry at <https://www.socialscienceregistry.org/trials/12534>). Note that the pre-analysis plan only applies to the analysis of the online laboratory experiment, and not the analysis of the nationally representative survey.

Main goal of the study

1. To study the effect of different types of distractions on performance in a cognitive task
2. To study individual heterogeneity in ability to handle distractions
3. To elicit willingness to pay to avoid being distracted

Sample restrictions

We will exclude participants based on the following criteria for our main analysis:

1. Dropping out of the experiment partway through.
2. Finishing all three games in the baseline round before time runs out (this is to remove those who are very good at this game).
3. Finishing at least one round with a very low negative final score (this is to remove those who randomly click through the experiment).
4. Questionnaire variables: participants who select the same option (e.g., “Strongly Agree”) for all questions on a particular questionnaire page.

Analysis

a) Analysis of average effect:

We will use data from the first three rounds to estimate the average impact of distractions on performance of the main cognitive task. We will regress the number of points participants receive in each round on distraction-type dummies controlling for subject dummies and game number dummies, with standard errors clustered at the participant level.

We will then check whether the effect is due to change in percentage of games attempted or change in number of mistakes made by looking at other outcome variables like total number of correct squares, wrong squares, and attempted squares.

We will also look at the impact of distractions on the speed of solving the games. To do so, we will make use of the time taken between the two moves before and after interruption and the time taken between the equivalent moves in the no distraction round and the auditory distraction round. (For example, if the interruption happens after the 10th move, we will use the time between 9th and 10th move and that between 10th and 11th move. Similarly, we will take the time between 9th and 10th move and that 10th and 11th move in the no distraction and auditory distraction round.) We will regress the time taken between moves on distraction-type dummy, controlling for subject and game fixed effect with standard errors clustered at the participant level.

b) Individual heterogeneity in ability to handle distractions:

Before playing the games, participants will fill out a questionnaire that measures their personality traits. We will add multiple items on their attitudes towards being interrupted while working and their attitudes towards multitasking. We will regress performance measures in the rounds with interruptions on the questionnaire measures at the subject level, controlling for personality traits and their performance without distractions.

We will also look at gender differences in the impact of the two types of distractions.

c) Individual preferences for working under distractions:

We are interested in participants' average preferences for working under distractions, whether they are averse to or prefer distractions in their work. We are also interested in which types of participants are averse to and which types prefer distractions. We will construct a choice measure by taking the switching point in the price list for the two types of distractions (the number of points that a participant is willing to give up to switch from being distracted to not being distracted). The preference measure will be constructed from the choice measure by subtracting the switching point just mentioned from the switching point that would maximize expected payoff based on

performance in the first three rounds.

To study individual heterogeneity in preferences for working under different types of distractions, we will regress the choice measure and the preference measure on performance under the specific type of distraction, questionnaire measures (attitudes towards working under distractions), and personality traits at the subject level, controlling for performance under no distractions. We will also study gender differences in the willingness to pay to avoid distractions and preferences for working under distractions.

Power calculations

We can calculate the minimum sample size using the one-sample mean test. In a pilot experiment to test for level of difficulty of the games, to have a 5% change in points earned in part (a) where we are interested in the effect of distractions on performance, a sample size of 200 is required for a power level of 0.8.

Appendix C: Experimental Instructions

The experiment was programmed with oTree (Chen et al., 2016) and conducted in the communication lab of the CREED laboratory using the subject pool from University of Amsterdam in November and December 2023. There were 29 sessions with a total of 217 participants of which 117 are female and 100 are male. Below are the instructions used for the experiment.

Introduction

Thank you for taking part in this study. It will take approximately an hour. You will receive a €7 participation fee with a chance to earn additional money during the study depending on your performance.

If you have any questions, please press the button on the wall on your left.

The study starts with a short questionnaire followed by a main part in which you will play a game for 4 rounds. One of the 4 rounds will be randomly selected for payment. The study ends with a survey in which you can earn additional money.

If you are unable to make it to the end of the study, you will only receive the €7 participation fee.

You will not be asked for any personal information. The data we collect is fully anonymous. In case you have any questions regarding the data we collect, please contact the university's Data Protection Officer at fg@uva.nl.

This study complies with General Data Protection Regulation (GDPR).

Please click "Next" if you consent to proceed with the study.

Payment Registration

Before continuing with the study, we need to ask you to provide your IBAN, which we will use to send you your earnings for the study.

Please double-check to make sure that the IBAN you provide is the correct one. You will not be able to change this at a later point. If you fail to provide the correct IBAN, we will not be able to send you your payment. If you provide the correct IBAN, we will transfer your earnings to you within 5 business days. We will delete this number after making the payment.

Please enter your IBAN number here:

1	2	3	4	5	6	7	8	9	0	Delete
Q	W	E	R	T	Y	U	I	O	P	
A	S	D	F	G	H	J	K	L		
Z	X	C	V	B	N	M				

Submit

Questionnaire

Before we explain how you can earn money in the study, we ask you to fill out a short questionnaire. For each item, please select the option that fits you the best.

Questionnaire Page 1/4

How well do the following statements describe your personality?

Question 1

I see myself as someone who gets nervous easily.

Question 2

I dislike working in distracting environments.

Question 3

I see myself as someone who is sometimes rude to others.

Question 4

I am good at working on several projects at the same time.

Question 5

I see myself as someone who does a thorough job.

Question 6

I see myself as someone who enjoys working under time pressure.

Questionnaire Page 2/4

How well do the following statements describe your personality?

Question 7

I see myself as someone who remains calm in tense situations.

Question 8

I can focus well in noisy environments.

Question 9

I see myself as someone who is outgoing, sociable.

Question 10

I see myself as someone who has an active imagination.

Question 11

I enjoy working on several projects at the same time.

Question 12

I see myself as someone who is productive under time pressure.

Questionnaire Page 3/4

How well do the following statements describe your personality?

Question 13

I see myself as someone who worries a lot.

Question 14

I can easily concentrate after being interrupted.

Question 15

I see myself as someone who is reserved.

Question 16

I see myself as someone who is original, comes up with new ideas.

Question 17

I have trouble limiting my phone usage.

Question 18

I see myself as someone who is considerate and kind to almost anyone.

Question 19

I see myself as someone who is competitive.

Questionnaire Page 4/4

How well do the following statements describe your personality?

Question 20

I see myself as someone who is talkative.

Question 21

I see myself as someone who values artistic, aesthetic experiences.

Question 22

I see myself as someone who has a forgiving nature.

Question 23

I constantly check my phone while studying.

Question 24

I see myself as someone who tends to be lazy.

Question 25

I see myself as someone who does things efficiently.

Question 26

I see myself as someone who is willing to take risks.

Question 27

I am easily distracted.

[Seven options were given for each question: "Strongly Disagree", "Disagree", "Slightly Disagree", "Neutral", "Slightly Agree", "Agree", and "Strongly Agree".]

Instructions

Thank you for filling out the questionnaire. We will now explain the instructions of the games. You will be paid for your performance.

You will play two types of games. We will explain the instructions of the first game and give you a practice game followed by the second game.

The first type of game is called Nonogram. The game consists of a 10 by 10 grid and each square in the grid must be colored either green or gray.

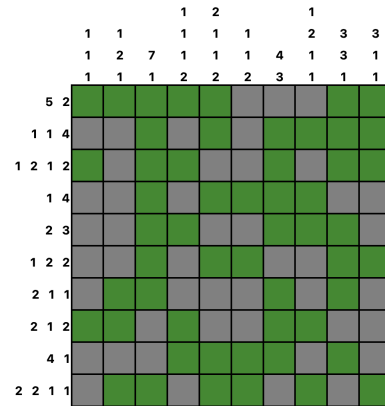
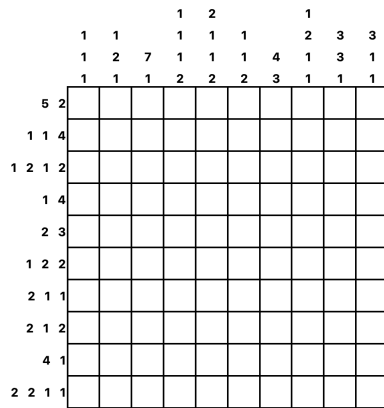
The number of consecutively colored green squares in any given row or column must be in the order of the numbers at the side and on the top.

There has to be at least one gray square in between two sets of green squares.

To color a square, you need to first click on your preferred color for this square on the right. If you color a square wrongly, the square will flash red and then change to the correct color.

Below is an example of a game. A clue of "5 2" means that there are sets of five and two green squares, in this order, with at least one gray square between the two sets. In total there should be three gray squares in this row or column. There is only one unique solution to each game.

You have 10 minutes for the practice game. You will proceed to the next page after you complete the game or the time runs out.



Before we explain how you can earn money in this study, we will give you a practice game for you to familiarize yourself with this game.

Please press the "Next" button to proceed to the practice game.

Instructions

The second type of game is called adding numbers game. Every game consists of a board with nine different numbers. Your task is to find the two numbers (out of the nine) that jointly add up to a "target number". You can select a number by clicking it. Once clicked, the number will turn green. To deselect a number, you can simply click it again.

You have 60 seconds for each game. You will move on after you have selected the correct two numbers or the time runs out.

Here is an example of a game. The two selected numbers (52 and 27) add up to the target number of 79. There is only one unique solution to each game.

44	12	34
21	52	13
27	57	68

Target Number:

79

0:51

We will give you three practice games for you to familiarize yourself with this game.

Please press the "Next" button to proceed to the practice games.

Instructions

You are now almost ready to start playing the games. You will play the games for 4 rounds.

As in the practice games, you will have 10 minutes in each round to play Nonogram and 60 seconds for each adding numbers game. We will now explain how you can earn money in the games.

For Nonogram, you will earn 1 point for each correctly colored square. If you color a square wrongly, 5 points will be deducted. As in the practice game, the square will flash red and then change to the correct color.

If you finish a Nonogram, a new one will appear, in which you can continue earning points. There is no additional bonus for finishing a game. Only the final points matter for your payment.

For the adding numbers games, you will not be rewarded with points for solving the game. However, if you cannot solve a game within 60 seconds, 5 points will be deducted. You will move on after solving the game or when the time runs out. You will solve 10 adding numbers games in each round.

At the end of each round, the final score will be converted to money at a rate of 10 points to €1. If the final score for a round is negative, your earnings will be 0 for that round.

At the end of the study, 1 of the 4 rounds will be randomly selected for payment. You will receive the earnings for that round.

Please press the "Next" button to continue.

Round 1-3

[The treatment in Round 1-3 is randomized. The following screenshots show the rounds with the treatment order: task-switching distraction, no distraction, and auditory distraction. The result and survey pages are shown after each round.]

Round 1

You are now in Round 1.

In this round, you will play Nonogram for 10 minutes and 10 adding numbers games for 60 seconds each.

The adding numbers games will interrupt Nonogram at random moments. The timer for Nonogram will pause while you solve the adding numbers games.

Nonogram will resume once you solve the adding numbers game within 60 seconds. If you cannot solve it within 60 seconds, Nonogram will still resume but 5 points will be deducted.

Please press "Next" to continue.

Result

This is the end of this round.

Your total score from Nonogram is 145.

You solved 9 out of 10 adding numbers games on time.

Therefore 5 points are deducted.

Your final score for this round is 140.

Your payoff for this round is €14.0.

Please press "Next" to continue.

Next

Survey

How well do the following statements describe you while playing the games?

Question 1

I felt stressed while playing Nonogram.

Question 2

I felt happy while playing Nonogram.

Question 3

I felt frustrated while playing Nonogram.

Question 4

I felt stressed while playing the adding numbers games.

Question 5

I felt happy while playing the adding numbers games.

Question 6

I felt frustrated while playing the adding numbers games.

[Seven options were given for each question: "Strongly Disagree", "Disagree", "Slightly Disagree", "Neutral", "Slightly Agree", "Agree", and "Strongly Agree".]

Round 2 of 4

You are now in Round 2.

In this round, you will first play Nonogram for 10 minutes. After that, you will play 10 adding numbers games for 60 seconds each. 5 points will be deducted if you cannot solve an adding numbers game within 60 seconds.

Please press "Next" to continue.

Round 3 of 4

You are now in Round 3.

In this round, you will play Nonogram for 10 minutes followed by 10 adding numbers games for 60 seconds each. 5 points will be deducted if you cannot solve an adding numbers game within 60 seconds.

A conversation will be played over the speakers while you play Nonogram. The volume is already set. Please do not press any buttons on the computer.

Please press "Next" to continue.

Round 4 of 4

You have now arrived at the final round (Round 4). In this round, you will still play Nonogram for 10 minutes and 10 adding numbers games for 60 seconds each. The difference compared to previous rounds is that this time you will be able to choose the format of the games.

In particular, you will be asked to make several decisions between two payment options. Depending on the decision, the first option in each decision is either to play Nonogram with adding numbers games interrupting at random moments (this option will be called "Interruptions" hereafter) or to play Nonogram with a conversation playing in the background (this option will be called "Conversation" hereafter).

The second option is to play Nonogram for 10 minutes followed by 10 adding numbers games for 60 seconds each (this option will be called "Sequential" hereafter). If you choose the second option, you will have a certain number of points deducted from the final score. The number of points deducted varies across the decisions.

After you have made all decisions, one decision will be randomly selected. Your payment in Round 4 will then be determined according to the payment option you chose in this decision. As before, 5 points will be deducted for each wrongly labeled square in Nonogram and 5 points will be deducted for each adding numbers game that is not solved within 60 seconds.

Please press the "Next" button to proceed to making the decisions.

Round 4 of 4

On the following page, you will choose between playing Nonogram with adding numbers games interrupting at random moments ("**Interruptions**") and playing Nonogram followed by the adding numbers games ("**Sequential**") but with points deducted from the final score.

Please press the "Next" button to proceed to making the decisions.

Round 4 of 4

For each of the following decisions, please indicate which one you would prefer.

- | | |
|-------------------------------------|---|
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 0 point deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 5 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 10 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 15 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 20 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 25 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 30 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 35 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 40 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 45 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 50 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 55 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 60 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 65 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 70 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 75 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 80 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 85 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 90 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 95 points deducted |
| <input type="radio"/> Interruptions | <input type="radio"/> Sequential with 100 points deducted |

Next

Round 4 of 4

On the next page, you will choose between playing Nonogram with a conversation playing in the background followed by adding numbers games ("**Conversation**") and playing Nonogram without a conversation playing in the background followed by adding numbers games ("**Sequential**") but with points deducted from the final score.

The conversation that will be played is not related to the conversation in the past rounds.

Please press the "Next" button to proceed to making the decisions.

Round 4 of 4

The following decision has been chosen for payment:

Interruptions

Sequential with 20 points deducted

You chose: Sequential with 20 points deducted

Next

Round 4 of 4

According to your choice, you will first play Nonogram for 10 minutes. After that, you will play 10 adding numbers games for 60 seconds each. 5 points will be deducted if you cannot solve an adding numbers game within 60 seconds.

20 points will be deducted from the final score once you finish all the games.

Please press "Next" to continue.

Next

Result

This is the end of this round.

Your total score from Nonogram is 216.

You solved 10 out of 10 adding numbers games on time.

Therefore no point is deducted.

You chose Sequential with 20 points deducted over Interruptions.

Your final score for this round is 196.

Your payoff for this round is €19.6.

Please press "Next" to continue.

Next

Survey

This is almost the end of the study. We now ask you to fill out a short survey in which you have the chance to earn additional money.

Survey

On the next page, you will make 11 decisions between a sure amount of €4 and a random lottery between €2 and €6 with changing probabilities.

After you have made all decisions, one decision will be randomly selected. Your additional earnings will then be determined according to the option you chose in this decision.

Survey

For each of the following decisions, please indicate which one you would prefer.

- | | |
|---|---|
| <input type="radio"/> Receiving €4 for sure | <input type="radio"/> 0% probability of receiving €6 and 100% probability of receiving €2 |
| <input type="radio"/> Receiving €4 for sure | <input type="radio"/> 10% probability of receiving €6 and 90% probability of receiving €2 |
| <input type="radio"/> Receiving €4 for sure | <input type="radio"/> 20% probability of receiving €6 and 80% probability of receiving €2 |
| <input type="radio"/> Receiving €4 for sure | <input type="radio"/> 30% probability of receiving €6 and 70% probability of receiving €2 |
| <input type="radio"/> Receiving €4 for sure | <input type="radio"/> 40% probability of receiving €6 and 60% probability of receiving €2 |
| <input type="radio"/> Receiving €4 for sure | <input type="radio"/> 50% probability of receiving €6 and 50% probability of receiving €2 |
| <input type="radio"/> Receiving €4 for sure | <input type="radio"/> 60% probability of receiving €6 and 40% probability of receiving €2 |
| <input type="radio"/> Receiving €4 for sure | <input type="radio"/> 70% probability of receiving €6 and 30% probability of receiving €2 |
| <input type="radio"/> Receiving €4 for sure | <input type="radio"/> 80% probability of receiving €6 and 20% probability of receiving €2 |
| <input type="radio"/> Receiving €4 for sure | <input type="radio"/> 90% probability of receiving €6 and 10% probability of receiving €2 |
| <input type="radio"/> Receiving €4 for sure | <input type="radio"/> 100% probability of receiving €6 and 0% probability of receiving €2 |

Next

Survey

What is your age?

What is your gender?

What is your nationality?

What is your first language?

What is your current education level?

What is the language of your study program?

Have you played Nonogram before?

Have you played other similar puzzle games before, for example, Sudoku?

Next

Survey

The following decision has been chosen for payment:

Receiving €4 for sure

10% probability of receiving €6 and 90% probability of receiving €2

You chose: €4 for sure

The additional money you will receive for filling in the survey is €4.

Next

End of Study

You have now finished the study. Please click "Next" to see your payment.

End of Study

Thank you for participating in the study.

Your results for each round were the following:

Round	Final Earnings (€)
1	0
2	19.6
3	0
4	19.6

The computer randomly selected Round 4 for payment.

Your final earnings for this round are €19.6.

Your additional payoff from the previous survey is €4.

Including your participation fee of €7, your total earnings for the study are €30.6.

Your payment will be transferred to your bank account within 5 working days.

Once you press "Next", you can leave the room quietly. Please do not forget any of your personal belongings.

Please press "Next" to end the study.

Next