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Marko Slavković [1]
Milan Stamenković
Marina Milanović
Stefan Sretenović

DIRECTION FOR REMOTE SENSING SUPPORTIVE ROLE IN REMOTE WORKING: CART ALGORITHM APPLICATION FOR MONITORING AND SELF-DISCIPLINE DETERMINATION

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Abstract: *In previous years, remote working has become an important and widely applied business practice that has attracted the attention of academic researchers, especially in the field of social sciences. The purpose of the study is to identify, through the analysis of monitoring and self-discipline during remote working, the possibilities of applying remote sensing to improve the existing practice. The study participants were employees with a remote working status, and the sample counts a total of 227 valid surveys. The CART algorithm was deployed to analyze the acceptance of monitoring and the level of self-discipline during remote working. Results indicate generally less acceptance of direct monitoring, as well as self-discipline of remote workers. Life circumstances play an important role in accepting monitoring and achieving self-discipline. The study offers insight into how the remote sensing can contribute to the improvement of remote working and generally provides guidelines for the interdisciplinary relationship of remote sensing and social sciences.*

Keywords: *remote sensing, remote working, monitoring, self-discipline.*

1. Introduction

Remote working was initially created as a result of job redesign in the practice of human resources management (Reina et al., 2022) with the aim of increasing motivation and improving work-life balance. The pandemic of COVID-19 has altered working conditions and the context of completing job tasks. Due to the prevention of the spread of the virus and the measures implemented by numerous countries around the world, remote working has become practically the only option for the completion of tasks at remote workplaces by employees. The increasing popularity of remote working during the COVID-19 pandemic has prompted a plethora of academic studies aimed at developing practical guidelines for managing remote working in novel circumstances. This became especially important due to the fact that for a large number of companies such a form of work was the only solution for the continuity of business operations.

Numerous previous studies have shown that remote working has had significant positive effects on work-related outcomes. Kondratowicz et al. (2022) examined the relationship between remote working and job

[1] Corresponding author: Marko Slavković
Email: mslavkovic@kg.ac.rs

satisfaction, as well as the effect of remote working on the quality of life of employees during the COVID-19 pandemic. The results showed that remote working has a positive impact on job satisfaction, as well as general satisfaction with the life of employees. Slavković et al. (2022) found that remote working has a positive impact on work engagement. Studies that focused on productivity showed that employees were more productive when working remotely compared to working in the office (Tleuken et al., 2022).

Despite this, previous studies have identified a number of negative effects associated with remote working. According to Bellmann and Hübler (2020), remote working negatively impacts work-life balance. Due to the blurring of the lines between private and professional life, remote working has a negative impact on employee job satisfaction. Toscano and Zappalà (2020) stated that employee productivity decreased during remote working. Tsen et al. (2021) indicate that remote working influences employees' intention to leave an organization due to role conflicts between work and personal life. Wang et al. (2020) indicate that remote working can negatively impact the emotional and psychological health of employees in a variety of ways.

The loneliness of employees (Lowman, 2021; Becker et al., 2022) management control and monitoring employees from a distance (Delfino & van der Kolk, 2021), self-discipline of employees who work from remote places (Adekoya et al., 2022), and negative impact on work-life balance (Bellmann & Hübler, 2020) have been identified as significant problems of remote work. Despite numerous researches, there are still many dilemmas and open questions: to what extent are employees ready to accept direct monitoring during remote work, how to control the performance of employees who work from remote workplaces, how to control the work of remote employees, to should employee control be discreet or direct, how to overcome the problem of employee loneliness, how to ensure employee work engagement, how to recognize employee exhaustion without direct contact, whether the working conditions (temperature, air quality, noise, etc.) are good enough for performance of work and how similar they are to conditions in the office, how to determine the state of health of employees, how to determine the effective working time achieved by an individual during one working day, and the like. Remote sensing data and their analysis are recognized as a tool that can contribute to solving the above problems.

The diverse possibilities of remote sensing, which are utilized in different scientific disciplines where their application has been validated and the outcomes confirmed, provide an impetus for study in the social sciences and the deployment of an interdisciplinary approach. Fundamentally, remote sensing and social science have very distinct methodological and practical approaches, making their integration challenging (Taubenbock et al., 2009). National Research Council (1998) argued that the integration of remote sensing and the social sciences is fraught with numerous challenges and obstacles, but that the use of remotely sensed data in the study of social phenomena is feasible and constitutes a promising research avenue. Particular emphasis should be placed on sociological, economic, and anthropological issues in the social sciences, and remote working incorporates all of the above, so supporting our study. According to Hall (2010), remote sensing is a fine blend of science, technology, and art that permits acquiring information about an observed object or subject from a distance. Digital cameras, various types of detectors, and human visual systems are listed as examples of systems that enable the collecting of diverse data and information from remote locations and exhibit the features of a remote sensing system. One of the main reasons for the limited usage of remote sensing in social research is the scepticism of social researchers regarding the applicability of remotely sensed data to their field of study (Taubenbock et al., 2009). The major cause for the aforementioned may be attributed to a lack of understanding of the methods for collecting and analyzing remotely sensed data. The wider public and social scientists have access to the level of development of remote sensing with a certain time lag, although professionals are always extremely well informed about achievements and innovations in remote sensing.

The relationship between remote sensing and human activity or behaviour has been the subject of a number of previous researches. In their study, Zhao et al. (2019) emphasized the importance and potential applications of remote sensing data obtained through satellite remote sensing of night-time light to the monitoring of social events, human behaviour, and related effects such as pollution, energy consumption, armed conflicts, urbanization, and others. Anugraha and Chu's (2018) study on anticipating human behaviour in a large urban area relied on two types of publicly available data: social sensing data and remote sensing data. By analyzing the data using the decision tree technique, predictions of the effects of human behaviour in traffic were obtained. A study by Taubenbock et al. (2009) indicates the relevance of socioeconomic factors of the observed population in risk assessment and urban planning, with the integration of remote sensing data and social science providing the foundation for value-added outcomes. Intentions of human behaviour that are reflected through the choice of household location in relation to climate change were analyzed through a study that combined remote sensing data and human behavioural processes (Galvin et al., 2001). Using an integrated approach to analysis, a deeper comprehension of this interacting process may be possible, according to the study. In addition to the aforementioned studies aimed at evaluating or forecasting human behaviour in the short or long term, Lee et al. (2023) revealed the use of remote sensing data to the identification of working conditions and the significance of such factors to the execution of work. The focus of the research was radiation and metrological conditions and their impact on employees of different ages. The aforementioned studies point to numerous spheres of human activity, behaviour and work that can be subject to the successful application of remote sensing data. On the other hand, the high level of focus of the discipline on topic-oriented journals and the lesser dispersion of articles in other publications are noted as one of the obstacles to the increased application of remote sensing in the aforementioned researches (Hall, 2010).

The preceding demonstrates that remote working falls primarily within the field of social sciences, and that research focuses primarily on social interactions, outcomes, and context. Nonetheless, some of the aforementioned social categories are directly or indirectly associated with remote sensing, particularly in the monitoring and self-discipline domains of remote work. In addition, there is a substantial research gap concerning the management of working conditions during remote work. Remote sensing can make a significant contribution to the development and improvement of remote working practices in this domain. Through the analysis of monitoring and self-discipline during remote work, the objective is to identify a domain in which remote sensing can contribute to increasing the efficiency of remote working while simultaneously achieving positive social effects. Our study is predicated on the assumption that remote sensing can contribute to the fact that remote workplaces can be designed to be a suitable alternative to offices, with benefits for both employees and companies.

2. Materials and Methods

The data used for analysis were gathered by means of a structured questionnaire, an instrument frequently used in the social sciences. The sampling procedure was carried out using the convenience sampling method and was aimed at organizations that used remote working to perform tasks during the COVID-19 pandemic. To gain access to employees with remote working status, we contacted executive managers and HR managers initially. After receiving contact information, all potential respondents were first convinced of the academic purpose of the research. All potential research respondents are assured anonymity and that no third party, including the employer, will have access to the data, according to the ethical approval process. To provide additional security for the remote working status of the respondents, Klassen and Jacobs' (2001) method for electronic surveys was applied. Respondents were employees who had an active remote working status at the time of the research. With a response rate of 74.4%, a total of 227 valid questionnaires were collected. The participants in the study were employed by organizations from various industries, such as logistics, marketing, and education, and were engaged in a variety of jobs, including marketing, logistics, administration, and the like. In addition to items related to the observed monitoring and self-discipline variables, the questionnaire also contained demographic data that were used in the analysis as categorical variables.

To achieve a satisfactory predictability of the study, statements and constructs that were tested in previous research were used, in accordance with the recommendations stated by Amankwaa et al. (2019). The participants rated all items on a five-point Likert scale in the format settled on, from "strongly disagree" (indicated by 1) to "strongly agree" (indicated by 5). Two measurement scales were used in the study.

Monitoring. The acceptance of monitoring in remote working was observed through three statements: "Providing daily reports.", "Clocking in/out via business communication APPs.", and "Keeping cameras switched on during working time". The mentioned items were used in the study conducted by Wang et al. (2020).

Self-Discipline. This variable was measured using the following statements: "I am good at resisting temptation.", "I have trouble concentrating.", and "People would say that I have iron self-discipline". The statements were previously used in research conducted by Lindner et al. (2015) and Wang et al. (2020).

Categorical variables used in the study include the following demographic characteristics: gender (coded as male or female), age (recoded, up to 40, more than 40 years), education (secondary, tertiary), marital status (single, living with a spouse or partner), and children (no, yes). Some specific life and work circumstances were used as additional categorical variables, such as: IntpDay – Average amount of time spent on internet per day (up to 10 hours per day, more than 10 hours per day), ExpeRW – Previous experience with remote working (yes, no), DurWT – Duration of working time during remote working (standard, longer), AdapWT – Adaptability of working time during remote working (standard, adapted to company, adapted to employees), and RiskPer – Risk perception during the COVID-19 pandemic (low risk, moderate risk, and high risk). The aforementioned categorical variables were included in the analysis based on the assumption that they may have an impact on remote working.

For the achievement of the specified research objectives, a multi-phased complex methodological framework was employed. The initial step of the analysis includes identifying Self-discipline and Monitoring as dependent (continuous) variables and ten categorical characteristics of respondents, as a group of independent variables (i.e. classifiers).

In order to determine the classification-predictive potential of individual classifiers from the perspective of the observed dependent variables, within the first step, the procedure for testing hypotheses about the statistical significance of differences between (appropriate) mean values of variables Self-discipline and Monitoring, at the level of defined categories of each of the ten independent variables, was conducted. The selection and application of a specific statistical (parametric / non-parametric) test (for two or more subsamples) is conditioned by the results of checking the appropriate assumptions on which their valid application is based. In fact, the possibility of applying the independent samples *t*-test or the Mann-Whitney *U* test, that is, the ANOVA *F* test or the Kruskal-Wallis test, was considered, depending on whether the observed classifiers contain two, or more than two categories, respectively. In addition, the examination of the dependency present between all pairs of independent (categorical) variables, based on the application of the χ^2 test, is an analytical activity that completes the previous step of the used methodological framework.

According to the specified types of dependent and independent variables, for the purpose of identifying individual classifiers that, under the conditions of their simultaneous analysis and consideration, contribute to the greatest extent in predicting the values of dependent variables at the level of the observed respondents, the Classification and Regression Tree algorithm (CART) is applied. In accordance with the opinion of Otoiu & Titan (2020) and Podhorska et al. (2020), the CART algorithm is chosen due to the fact that it represents one of the most efficient and widely used statistical approaches in solving research problems of classification and regression, but also the fact that it yields results that are quite clear and easy to interpret. Its popularity is conditioned by the methodological advantages that it provides over alternative methods, which are primarily related to the fact that the CART algorithm is a non-parametric approach that can equally well be applied for quantitative, qualitative, and combinations of data (Strzelecka & Zawadzka, 2021; Romeo et al., 2021). More precisely, within this (second) step, for both dependent variables individually, CART trees were created for the complete sample of respondents (n=227). The construction of CART models was performed using the ten-fold cross-validation method, with maximum tree depth set at 5 levels (by default), while the minimum number of cases in parent and child nodes is fixed at 40 and 10 cases, respectively. This specification of key parameters of the models is primarily determined by the used sample size.

The analysis of the collected data and all necessary statistical calculations were carried out using the statistical software package IBM SPSS Statistics (version 20.0) and Microsoft Office Excel.

3. Results

The results of conducted data analysis and application of CART algorithm, in the context of defined research objectives, are presented and statistically interpreted. Starting from the point that the observed independent variables are characterized by a different number of categories, testing the statistical significance of the differences in the mean values of the Self-discipline variable was carried out using the Mann-Whitney test (for eight categorical variables with two modalities), that is, the Kruskal-Wallis test (in the case of two independent variables with three categories). The selection of the mentioned non-parametric tests is conditioned by the results of checking the fulfillment of the assumption regarding the normality of distribution of Self-discipline, at the level of individual modalities of ten independent variables. More precisely, the results of the Shapiro-Wilk test suggest, with a risk of type I error α = 0.05, that the assumption regarding the normality of distribution of variable Self-discipline is not rejected only for the category "adapted to employees" of variable Adaptability of working time during remote working (*SW* test statistic = 0.953, *p*-value = 0.188 > α) and "high risk" category within variable Risk perception during the COVID-19 pandemic (*SW* test statistic = 0.944, *p*-value = 0.149 > α). In the case of other two categories of these two variables, as well as all the categories of the remaining eight independent variables, the normality of the distribution of Self-discipline was not confirmed, since, for the 20 resulting SW test statistics, the obtained *p*-values are less than α. Mann-Whitney *U* test statistics and corresponding p-values, calculated for two-category independent variables (Table 1), suggest that there is a statistically significant difference between the mean values (i.e. medians) of the Self-discipline at the level of corresponding categories of the following variables: Gender (male/female), Children (no/yes), and Duration of working time during remote working (standard/longer). In the case of the remaining 5 independent variables, no statistically significant differences were observed, since the resulting *p*-values are higher than the test significance level, α = 0.05.

Table 1. Mann-Whitney *U* test results for variable Self-discipline (Authors)

Dependent variable	Independent (2-group) variables	Mann-Whitney *U* test statistic	*Z* approximation value	*p*-value	Decision
Self-discipline	Gender	4600.0	-3.506	0.000	H_1
	Age	5771.0	-0.771	0.441	H_0
	Education	3238.0	-0.344	0.731	H_0
	Marital status	3511.5	-0.417	0.677	H_0
	Children	5176.0	-2.057	0.040	H_1
	IntpDay	5657.0	-0.735	0.462	H_0
	ExpeRW	4765.0	-1.327	0.184	H_0
	DurWT	5457.5	-1.999	0.046	H_1

On the other hand, in the case of independent variables with three categories (i.e. Adaptability of working time during remote working and Risk perception during COVID-19 pandemic) the obtained values of the Kruskal-Wallis test statistic and resulting p-values (Table 2) suggest that there is not enough empirical evidence to accept the alternative hypothesis about the existence of statistically significant differences between the mean values (i.e. medians) of variable Self-discipline at the level of at least two modalities in their composition.

Table 2. Results of Kruskal-Wallis test for variable Self-discipline (Authors)

Dependent variable	Independent (3-group) variables	Chi-square approximation	Degrees of freedom	*p*-value	Decision
Self-discipline	AdapWT	1.379	2	0.502	H_0
	RiskPer	0.097	2	0.953	H_0

Viewed from the perspective of the construction of CART decision tree, which divides data into homogeneous subsets using binary recursive partitions, and in accordance with the previously elaborated test results, it is expected that independent variables for which the alternative hypothesis is accepted are in the strongest relationship with the dependent variable and that they will, consequently, be positioned at the top of the hierarchical tree. In other words, as a consequence of the verified statistical significance of the observed differences in the mean values of Self-discipline, determined at the level of individual categories of the variables Gender, Children and Duration of working time during remote working, it can be stated that they have the highest classification-predictive potential.

In accordance with previously emphasized notes, regarding the number of modalities of categorical variables, testing the statistical significance of differences between mean values of variable Monitoring was also conducted using the Mann-Whitney *U* and Kruskal-Wallis test. As in the case of Self-discipline variable, the selection of non-parametric tests was carried out according to the suggestions obtained by the procedure of testing hypotheses about the normality of particular dependent variable's distribution at the level of individual categories of the set of independent variables. In this sense, the results of Shapiro-Wilk test indicate, with the type I error rate $\alpha = 0.05$, that there is no evidence for rejecting the assumption of normality of Monitoring distribution only for the "high risk" category within Risk perception during COVID-19 pandemic variable (*SW* test statistic = 0.942, *p*-value = 0.133 > α). In all remaining cases, the normality of distribution of the Monitoring variable was not confirmed, since the obtained *p*-values, for 21 resulting *SW* test statistics, are significantly less than α.

Table 3. Mann-Whitney *U* test results for variable Monitoring (Authors)

Dependent variable	Independent (2-group) variables	Mann-Whitney *U* test statistic	*Z* approximation value	*p*-value	Decision
Monitoring	Gender	5939.5	-0.757	0.449	H_0
	Age	4538.5	-3.362	0.001	H_1
	Education	2771.5	-1.669	0.095	H_0
	Marital status	3154.0	-1.390	0.164	H_0
	Children	5021.5	-2.394	0.017	H_1
	IntpDay	5995.5	-0.022	0.982	H_0
	ExpeRW	5146.5	-0.479	0.632	H_0
	DurWT	5111.0	-2.723	0.006	H_1

Consequently, the values of the Mann-Whitney *U* test statistic and the corresponding *p*-values, calculated for two-category variables (Table 3), confirm the presence of statistically significant differences between the mean values (i.e. medians) of the Monitoring variable at the level of the defined categories for the following independent variables: Age (up to 40/more than 40 years), Children (no/yes) and Duration of working time during remote working (standard/longer). It is interesting to note that only difference, compared to the results obtained for Self-discipline, represents variable Age, which replaced Gender variable in the list of extracted categorical variables. In the case of the remaining 5 two-category independent variables, no statistically significant differences were observed.

Table 4. Results of Kruskal-Wallis test for variable Monitoring (Authors)

Dependent variable	Independent (3-group) variables	Chi-square approximation	Degrees of freedom	*p*-value	Decision
Monitoring	AdapWT	7.033	2	0.030	H_1
	RiskPer	16.757	2	0.000	H_1

When it comes to the Adaptability of working time during remote working and Risk perception during COVID-19 pandemic, as three-category variables, the results of the Kruskal-Wallis test, in contrast to the conclusions drawn for Self-Discipline, indicates completely different regularities. More precisely, in the case of both independent variables, the obtained values of Kruskal-Wallis test statistic and the resulting *p*-values (Table 4) indicate the presence of statistically significant differences between the mean values (i.e. mean ranks) of Monitoring variable at the level of at least two categories. Since the alternative hypothesis was accepted, a post-hoc analysis, based on the application of Mann-Whitney *U* test, was conducted (Table 5). In the case of variable Adaptability of working time during remote working, statistically significant differences were confirmed between the following pairs of categories: "standard vs. adapted to company" and "adapted to company vs. adapted to employees". For the variable Risk perception during the COVID-19 pandemic, the pairs of categories for which the alternative hypothesis was accepted are: "low risk vs. moderate risk" and "low risk vs. high risk".

Table 5. Post-hoc analysis results for variable Monitoring (Authors)

Independent variables	Pairs of categories	Mann-Whitney *U* test statistic	*Z* approximation value	*p*-value	Decision
RiskPer	LR vs. MR	2712.0	-3.644	0.000	H_1
	MR vs. HR	1676.5	-1.146	0.252	H_0
	LR vs. HR	418.0	-3.364	0.001	H_1
AdapWT	Standard/AtC	3992.0	-2.048	0.041	H_1
	AtC/AtE	1153.5	-2.304	0.021	H_1
	Standard/AtE	1332.5	-0.724	0.469	H_0

According to the previously interpreted test results, the strongest connection with the dependent variable Monitoring is present in the case of the following independent variables: Age, Children, Duration of working time during remote working, Adaptability of working time during remote working, and Risk perception during COVID-19 pandemic. Consequently, these five categorical variables are characterized by the highest classification-predictive power, viewed from the perspective of the construction of CART tree.

3.1. Results of interdependency analysis of categorical variables

After the statistical interpretation of the obtained results of dependency analysis for Self-discipline and Monitoring, as target (continuous) variables, and a set of independent (categorical) variables, in accordance with the methodological guidelines presented in the Data analysis section, an examination of the interdependence present between all pairs of categorical variables was conducted, based on on the application of Chi-square tests. The conducted interdependency analysis included a total of 45 different pairs of available 10 categorical variables, and depending on their number of modalities but also the elements of the resulting contingency tables, the statistics of the following Chi-square tests were used to draw conclusions regarding their interdependence: Pearson Chi-square test (χ^2) or Yates' Continuity Correction (YCC).

The obtained results of the analysis of interdependence suggest the rejection of the null and the acceptance of the alternative hypothesis, which claims that observed two categorical variables are dependent, in the case of the following pairs: Gender & Age (YCC = 6.860; p_{value} = 0.009), Gender & IntpDay (YCC = 4.222; p_{value} = 0.040), Gender & ExpeRW (YCC = 5.359; p_{value} = 0.021), Gender & DurWT (YCC = 12.853; p_{value} = 0.000), Age & Children (YCC = 30.240; p_{value} = 0.000), Age & DurWT (YCC = 11.717; p_{value} = 0.001), Age & AdapWT (χ^2 = 6.063; p_{value} = 0.048), Children & Marital status (YCC = 42.096; p_{value} = 0.000), Children & IntpDay (YCC = 4.810; p_{value} = 0.028), Marital status & IntpDay (χ^2 = 3.918; p_{value} = 0.048), Marital status & ExpeRW (χ^2 = 4.484; p_{value} = 0.034), DurWT & AdapWT (χ^2 = 33.606; p_{value} = 0.000), DurWT & RiskPer (χ^2 = 8.904; p_{value} = 0.012) and AdapWT & RiskPer (χ^2 = 23.580; p_{value} = 0.000). In the case of all remaining pairs of categorical variables, the presence of statistically significant dependency between them was not confirmed.

A summary analysis of the presented results reveals that the variables Gender, Age, and Duration of working time during remote working are characterized by the largest number (i.e. four) of statistically verified interdependencies, from the point of view of the available set of categorical variables. In addition to these, variable Children stands out, for which dependence was confirmed with three (out of ten), remaining independent variables. In this context, it is interesting to note that these are precisely the variables that, through the procedure of testing the hypotheses about the equality of mean values of dependent variables, were found to have the greatest discriminating power. At the same time, unlike the variable Duration of working time during remote working, it is important to emphasize that Gender, Age, and Children refer to the key demographic characteristics of the respondents.

3.2. CART decision trees for Self-discipline

Based on previously stated observations, and in accordance with the set parameters for the algorithm application, a CART tree was created for Self-discipline variable at the level of complete sample of respondents, using 10 independent categorical variables (Figure 1).

The results of applying the CART algorithm indicate that the created model contains, within 4 levels of tree depth, a total of 14 nodes, out of which 8 are terminal. At the same time, the statistical significance of the classification-predictive potential was confirmed in the case of 5 variables, while the rest were eliminated from the final model. More precisely, at the first level of tree branching, variable Gender is singled out, for which, therefore, can be stated to have the greatest (statistically significant) importance (i.e. power) in the segmentation of respondents and predicting the value of variable Self-discipline. The second level of tree branching reveals the next two statistically significant categorical variables, i.e., Children and Average amount of time spent on internet per day (IntpDay), which contribute to the further partition of subsamples composed of male and female respondents, respectively. Similarly, in terms of the number of extracted variables, at the third level of depth of displayed CART tree, the variables Duration of working time during remote working (DurWT) and Risk perception during COVID-19 pandemic (RiskPer) were extracted, with the latter reappearing in the last branch of the model, forming the final four terminal nodes (i.e. nodes 11, 12, 13 and 14).

It is interesting to note that categorical variables whose statistical significance was confirmed during the construction of this CART tree also represent the variables with the highest discriminant potential from the perspective of dependent variable Self-discipline (i.e. Gender, Children, DurWT), that is, for which the largest number of statistically significant relationships (i.e. dependencies) with the remaining independent variables were verified (Gender & DurWT–4 confirmed relations, Children & IntpDay–3 relations, and variable RiskPer–2 relations).

Terminal node with the lowest predicted value of Self-discipline is node 5, with a mean 2.905, which is more than 0.6 points lower than the mean value recorded for the initial node (3.529). More precisely, 28 respondents distributed within this node are characterized by a lower average value of Self-discipline compared to the average of this dependent variable determined for the total sample of 227 respondents. For members of this group (12.3% of the sample size), based on the generated classification rule, it is characteristic that they are female persons who use the Internet up to 10 hours per day, on average. Viewed from the opposite angle, Self-discipline mean value recorded in node 3 (3.858) represents the highest predicted value and is approximately 0.33 points higher than the overall mean for entire sample (i.e. initial node).

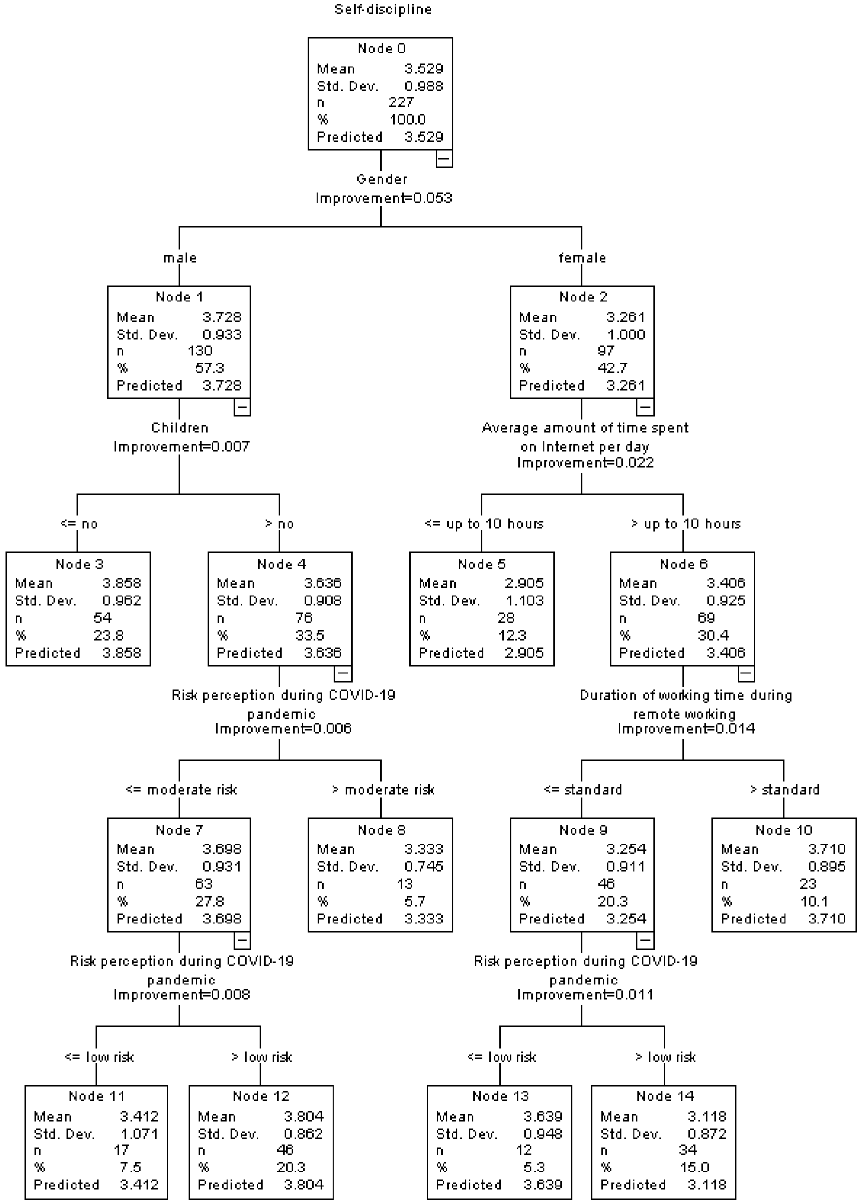

Figure 1. CART tree model for Self-discipline

Respondents allocated in this (sub)sample can be described as male persons, without children. Also, since this particular node is characterized by the largest participation of respondents (i.e. 23.8% of the sample size), in relation to the remaining 7 terminal nodes, it can be stated that node 3 also represents a modal one, i.e. the most probable terminal node. The derived classification rules for the remaining terminal nodes, ranked according to the realization probability, can be formulated as follows:

- Node 12: If the person is male, with children, and moderate risk perception during the COVID-19 pandemic, then the expected value of the Self-discipline variable will be 3.804, with a probability of 0.203;
- Node 14: If the person is female, with the habit of using the Internet more than 10 hours a day on average, with standard duration of working time during remote working, and moderate risk perception during the COVID pandemic, then the expected value of Self-discipline will be 3.118, with a probability of 0.150;
- Node 10: If the person is female, with the habit of using the Internet more than 10 hours a day on average and longer duration of working time during remote working, then the expected value of Self-discipline will be 3.710, with a probability of 0.101;
- Node 11: If the person is male, with children and low risk perception during the pandemic, then the expected value of Self-discipline will be 3.412, with a probability of 0.075;
- Node 8: If the person is male, with children and high risk perception during the COVID-19 pandemic, then the expected value of Self-discipline will be 3.333, with a probability of 0.057;
- Node 13: If the person is female, with the habit of using Internet for more than 10 hours a day, with standard duration of working time during remote working, and usual risk perception during the pandemic, then the expected value of Self-discipline will be 3,639, with probability 0.053.

3.3. CART decision trees for Monitoring

Similar to the previously described procedure, the CART tree for variable Monitoring, developed for the complete sample of 227 respondents, using the 10 independent variables, is shown in Figure 2. The created CART model contains a maximum of 5 levels of tree depth and a total of 10 nodes, six of which are terminal. The statistical significance of the classification-predictive potential was confirmed in the case of 5 variables, while the rest were eliminated from the final model. More precisely, at the first level of the tree branching, the variable Risk perception during COVID-19 pandemic (RiskPer) is singled out, for which, accordingly, can be stated to have the greatest (statistically significant) importance (i.e. power), in the segmentation of respondents and prediction of Monitoring values. At each of the four remaining tree branching levels, one new statistically significant categorical variable is singled out, i.e., Age, Marital status, Adaptability of working time during remote working (AdapWT) and Duration of working time during remote working (DurWT), respectively.

Based on the comparison with the results presented in the first step of the analysis, it is interesting to note that most of the isolated categorical variables whose statistical significance was confirmed during the construction of the CART tree are actually the variables with the highest discriminating power, viewed from the perspective of the dependent variable Monitoring (i.e., Age, DurWT, AdapWT, and RiskPer), that is, for which the highest or high number of statistically significant dependencies with the remaining independent variables was verified (Age & DurWT – 4 confirmed relations, Marital status & AdapWT – 3 relations, and RiskPer – 2 relations).

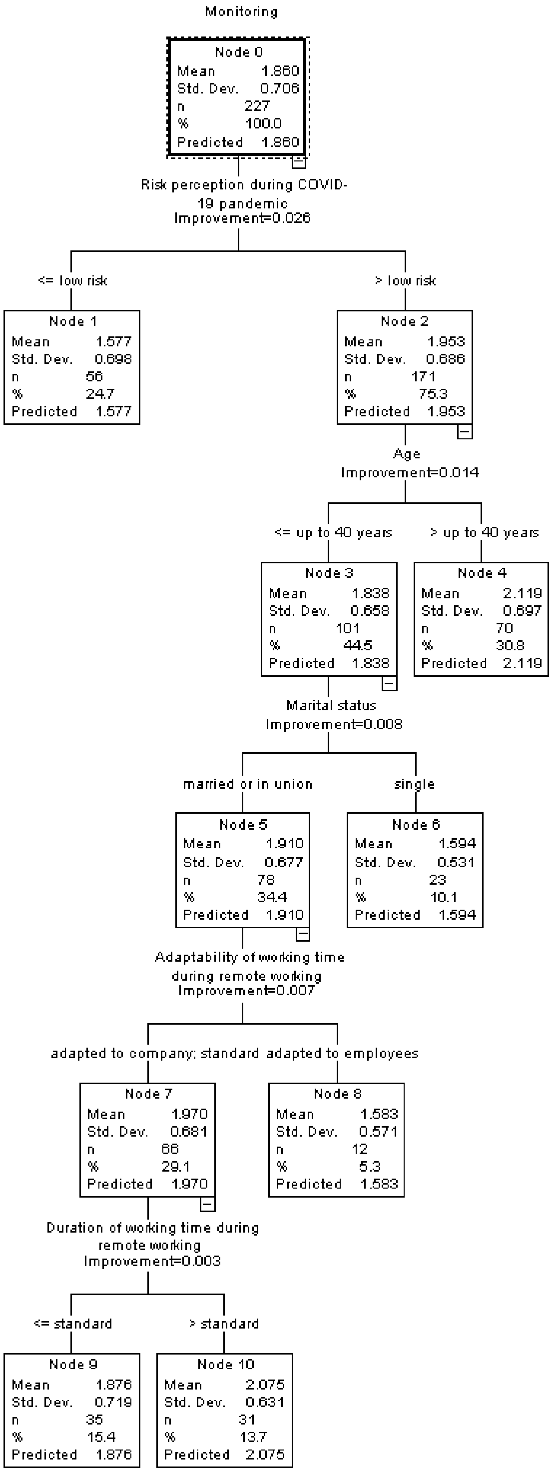

Figure 2. CART tree model for Monitoring

Terminal node with the lowest predicted value of Monitoring is node 1, with an average value 1.577, which is approximately 0.3 points lower than the mean value recorded for the initial node (1.860). More precisely, 56 respondents distributed in this node are characterized by a lower average value of Monitoring compared to the average of this dependent variable determined at the level of complete sample (*n*=227). For the members of this group (24.7% of the sample size), based on the generated classification rule, it is characteristic that they are male or female persons with low risk perception during the COVID-19 pandemic. Compared to this node, two other terminal nodes, node 8 and node 6, are characterized by very close average values of the Monitoring variable, i.e., 1.583 and 1.594, respectively. Derived classifications rules for these two terminal nodes can be formulated in the following manner:

- Node 6: If it is a person with moderate or high risk perception during the COVID-19 pandemic, age up to 40 years, with marital status defined as single, then the expected value of Monitoring will be 1.594, with a probability of realization of 0.101;
- Node 8: If it is a person with moderate or high risk perception during the COVID-19 pandemic, age up to 40 years, married or in union, with working time during remote working adapted to employees then the expected value of Monitoring will be 1,583, with probability of realization 0.053.

Viewed from the opposite angle, the Monitoring average value recorded in node 4 (2.119) represents the highest predicted value, and is 0.26 points higher than the overall mean determined for the entire sample (i.e. initial node). Respondents allocated within this subsample can be described as persons (regardless of gender) older than 40 years, with moderate or high risk perception during the COVID-19 pandemic. Also, since this particular node is characterized by the largest participation of respondents (i.e., 30.8% of the sample size), in relation to the remaining 5 final nodes, it can be stated that node 4 also represents a modal, i.e. the most probable terminal node.

The classification rules for the remaining two final terminal nodes, ranked according to the probability of realization, can be formulated as follows:

- Node 9: If it is a person with moderate or high risk perception during the COVID-19 pandemic, age up to 40 years, which is married or in union, with standard working time during remote working or adapted to company, and standard duration of working time during remote working, then the expected value of Monitoring will be 1.876, with a probability of realization 0.154;
- Node 10: If it is a person with moderate or high risk perception during the COVID-19 pandemic, age up to 40 years, married or in union, with standard working time during remote working or adapted to company, and longer duration of working time during remote working, then the expected value of Monitoring will be 2.075, with a probability of realization 0.137.

3.4. Summary of CART results

The results obtained by applying the CART decision tree provide a specific insight into the importance of the simultaneous influence of individual demographic characteristics of the observed employees, as well as categorical variables concerning the level of their digital literacy and work-life circumstances they were faced with during the COVID-19 pandemic on the level of Self-discipline, on one hand, and the acceptance for Monitoring during remote work, on the other hand. Observed at the level of a sample of 227 respondents, the variable Gender was identified as the most responsible for the classification of employees according to the demonstrated level of Self-discipline during remote work. Generally, a higher level of Self-discipline when working from home is characteristic of male employees. In this context, male employees who do not have children are characterized by the highest degree of Self-discipline in remote work, while the group of female employees who use the Internet up to 10 hours a day, on average is characterized by the lowest degree of Self-discipline. It is interesting to note that female employees who use the Internet more than 10 hours a day, on average, with longer duration of working time during remote working exhibit a fairly high level of Self-discipline. Consequently, it can be stated that for the segmentation of female employees, in terms of the demonstrated level of Self-discipline, the variable Average amount of time spent on the internet per day is the most responsible. On the other hand, the variable Children is considered the most significant in the segmentation of male employees, in the mentioned context. This is supported by the observation that, compared to male employees with no children, a lower level of Self-discipline was recorded among male employees who have children. When it comes to this specific group, a lower level of Self-discipline is manifested by male employees with children, who exhibited high risk perception during the COVID-19 pandemic. Additionally, the level of Self-discipline recorded among the group of male employees with children characterized by moderate risk perception is slightly lower compared to the (highest) level of Self-discipline in remote work recorded among the group of male employees without children.

On the other hand, as a variable that can be considered the most significant for the classification of employees according to the acceptance of Monitoring during remote work, Risk perception during the COVID-19 pandemic was singled out. In general, there is a greater need for supervision when working from home among employees characterized by moderate or high risk perception during the COVID-19 pandemic. In this context, employees with low risk perception during the COVID-19 pandemic are characterized by the least acceptance for Monitoring when working remotely, while the group of employees, over 40 years old (regardless of their gender), with moderate or high risk perception during COVID- 19 pandemic is characterized, in general, by the greatest need for supervision. It is interesting to note that the group of employees with moderate or high risk perception during the COVID-19 pandemic, aged up to 40, who are single, on one hand, that is, who are married or in union, but with working hours during remote work that are adapted to employees, on the other hand, are characterized by a rather low acceptance for Monitoring, which is at an almost identical level identified for the group of employees with the least acceptance of Monitoring. However, in the case of employees with moderate or high risk perception, aged up to 40, who are married or in union, in a situation where working hours during remote work are adapted to the company or standard, there is a noticeable increase in the acceptance for Monitoring. At the same time, the need for supervision becomes particularly pronounced if employees with previous characteristics are faced with a longer duration of working time during remote working. The acceptance of Monitoring of this group of employees is approximately at the same, although lower, level established for the group of employees with the greatest acceptance of Monitoring.

4. Results

Summarizing the results of the study, it is possible to generally conclude that employees with remote working status are less ready to accept monitoring of their work at remote workplaces, but at the same time they are aware that their self-discipline is lower. When demographic characteristics and daily life circumstances are included in the analysis, such as gender, age, education, marital status, children, average amount of time spent on internet per day, previous experience with remote working, duration of working time during remote working, adaptability of working time during remote working, and risk perception, it can be concluded that there is a discrete percentage of employees with remote working status who accept direct monitoring and who can achieve self-discipline at the remote working place. On the other hand, monitoring and self-efficacy are inversely related. Jensen et al. (2020) state that increasing the visibility of monitoring has a positive impact on employee performance and emphasize the importance of conspicuous monitoring for effective remote working. Jeske (2021) states that the negative consequence of direct monitoring using cameras is that part of the private life of remote workers is revealed which they may not be ready to share with others. Direct monitoring can create a sense of distrust among employees and cause a decrease in self-efficacy and performance. The confirmation of the double effect, positive and negative, on the performance and self-efficacy of remote workers indicates the need to review the current practice of immediate and direct monitoring and the application of more sophisticated systems based on remote sensing.

Additional argumentation for the application of remote sensing for remote working monitoring is provided by the conclusions about the effects of electronic monitoring stated by Jeske (2022) and which emphasizes several insights: firstly, monitoring has a negative impact on well-being, secondly, the data obtained through monitoring can be of benefits for improving the practice of remote working, and thirdly, the appropriate monitoring approach of remote working can be well integrated into the system for taking care of the health of employees. As very important strategic directives for remote sensing in urban areas Zhu et al. (2019) state the use of remote sensing data for monitoring economic activity and behaviors and lifestyles. The connection between remote sensing data and algorithms in the domain of daily health habits, such as sleep duration and quality, healthcare procedure and physical activity, is particularly noteworthy. Cheng et al. (2020) state that flexible force-sensitive sensors can be successfully used to monitor human health status. By applying different sensing mechanisms based on mechanical stimulations, it is possible to obtain data on human physiological activities such as tension, pressure, torque, and stress. Systematizing previous research and rapid changes in sensing technologies, the same authors state that all sensors in health monitoring systems can be classified into two large groups: wearable and implantable sensors. Wearable sensors are typically positioned on the skin of the human body and are used to observe physical movements and vital signs, such as blood pressure, pulse, breathing, etc. Implantable sensors are not visible they are found in the body and are used in the field of physiological parameter monitoring and adjuvant therapy. Suzuki and Matsui (2012) state that a remote sensing method based on heart rate variability using compact microwave radar and detecting changes in the autonomic nervous system enables accurate identification of stress levels at any remote location. The combination of remote sensing and mobile phones enables obtaining valuable data for healthcare monitoring in a simple way through the use of integrated fingerprint sensors (Das et al., 2022). In this way, mobile phones become part of remote sensing systems capable of collecting basic data about the health of employees in remote locations. Mobile phones provide additional support for the application of remote sensing in monitoring the health of employees in a cost-effective manner (Vashist et al., 2014). By connecting remote sensing, cloud computing and wireless technologies it is possible to monitor the key health parameters of employees who perform tasks through remote working.

Additional support in monitoring the health of remote workers can be affective sensing systems that were created with the aim of enabling support for the diagnosis and monitoring of depression. Alghowinem et al. (2013) using distance between the eyelids and duration of blinks as eye movement features determined their significant predictability in identifying depressed subjects. Considering the possibility of applying the eye-tracking system in organizational research, Meißner and Oll (2017) suggest the following areas as very relevant: attention patterns, mental states, cognitive load, emotional arousal, and level of processing, which can be used to assess the difficulty of a work task. This was confirmed in their research by Shojaeizadeh et al. (2019) providing evidence that an eye tracking system based on machine learning can be very successful in automatic task demand detection. The eye tracking system through the collection of remote sensing data and their processing can act preventively in preventing injuries or mistakes by detecting fatigue (Peißl et al., 2018). Also, this kind of system can be successfully applied to detect a drop in performance. The above indicates a significant potential for application in the practice of remote working in the field of monitoring the performance of employees, their fatigue and general health status.

Employees who work from remote workplaces have tacitly accepted "voluntary visibilizing practices" in remote working in order to prove to their superiors their commitment to job tasks or doing overtime (Delfino & van der Kolk, 2021). Monitoring of employees should be ethical and essentially related to work, while surveillance for the purpose of curiosity or to intimidate is perceived as absolutely unacceptable (Laker, 2020). Therefore, the consent agreement for monitoring should be an integral part of the system for monitoring the activities of remote workers (Sipior, 2021) Special attention should be paid to the method of data collection, data storage policy, authorized persons for data access and length of storage of the collected data. Monitoring based on remote sensing enables a discreet approach to monitoring employees at remote workplaces and at the same time can enable the collection of data on the health of employees in order to prevent negative effects such as stress, workload, or depression. Additionally, discrete remote sensing based monitoring retains the feature of "presence" which can have a positive effect on preventing the appearance of the loneliness effect among employees who have remote working status.

5. Conclusions

The results of the study revealed a low willingness of remote employees to accept direct and immediate monitoring of their work, but at the same time only a discrete percentage of them can achieve self-discipline. A review of literature and relevant research confirmed that conspicuous monitoring can have a positive impact on performance, but at the same time it has a negative impact on self-efficacy, well-being and health of employees. This erodes the positive effects of remote working and creates a poor practice. The previous notes points to a significant theoretical and practical gap and the need to apply a more sophisticated approach. Remote sensing provides solutions that enable discrete monitoring while simultaneously tracking the health of employees who work remotely. Most of the recent research in the field of remote working has been related to the social aspects and the identification of appropriate practical guidelines for managers to effectively manage remote workers. There is a lack of research that will include other aspects of remote working, as well as research that integrates the achievements of different disciplines, especially remote sensing and social science. In this context, our study intends to encourage an integrated approach to remote working research. Future research should integrate remote sensing and remote working through a multidisciplinary approach oriented towards recognizing the best practices of both disciplines in order to successfully create the potential for improving and remote working development.

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Marko Slavković
Faculty of Economics,
University of Kragujevac,
Kragujevac,
Serbia
mslavkovic@kg.ac.rs
ORCID 0000-0002-2604-1228

Milan Stamenković
Faculty of Economics,
University of Kragujevac,
Kragujevac,
Serbia
m.stamenkovic@kg.ac.rs
ORCID 0000-0003-0689-0369

Marina Milanović
Faculty of Economics,
University of Kragujevac,
Kragujevac,
Serbia
milanovicm@kg.ac.rs
ORCID 0000-0002-6245-5313

Stefan Sretenović
Independent Researcher,
Kragujevac,
Serbia
st.sretenovic@gmail.com
ORCID 0009-0002-3515-9532