ZOOM FATIGUE, SOCIAL PRESENCE, AND PERFORMANCE: HOW DO REMOTE WORKERS FEEL?

by

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Dedicado a mi madre, a mi abuela, a toda mi familia

y a todo aquel desahuciado que tiene

que marchar a vivir una cultura diferente.

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Abstract

The prevalence of remote work due to COVID-19 has imposed different challenges to workers around the world, including distracting or inadequate home-office environments, the adoption of a myriad of collaborative tools, as well as the lack of social interaction and peer presence. This study (N = 197) aims to understand how social presence, the sense being with another online, relates to workers' perceived performance. We also explore three antecedent factors that influenced the social presence observed: the portion of a workweek devoted to online meetings, experienced fatigue, and facilitating conditions of their organization. Participants were recruited on Prolific and asked to fill out a 22-question survey about these measurements to obtain the degree of social presence they experienced – understood as an individual construct that consist of elements from two different measures: social presence of the collaboration tool and social presence of coworkers. A blended theoretical framework emerged from the results, illustrating the social presence as determinant element of perceived performance at work. This research offers practical contributions for both future scholars and practitioners to understand how social presence should be integrated in discussions about the adoption of new technologies for remote work, and how collaborative tools' sense of human warmth and contact might affect the workers' self-perceived performance.

List of Abbreviations Used

AIC – Akaike Information Criterion

BIC – Bayesian Information Criterion

CB-SEM – Composite Based Structural Equation Modeling

CFA – Confirmatory Factor Analysis

CFI – Comparative Fit Index

GBP – Pound Sterling

KMT - Krejcie and Morgan Table

ML – Maximum Likelihood

MTurk – Amazon Mechanical Turk

ONS – Office of National Statistics (United Kingdom)

REB – Research Ethics Board

RMSEA – Root Mean Square Error of Approximation

SEM – Structural Equation Modelling

SRMR – Standardized Root Mean Square Residual

TLI – Tucker-Lewis Index

UTAUT – Unified Theory of Acceptance and Ease of Technology

UK – United Kingdom

VPN – Virtual Private Network

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Chapter 1 – Introduction

1.1 Context

The ubiquity of the Internet and its innumerable applications has changed the way that we interact. According to The World Bank, more than 68% of the world population has access to Internet, and the figure reaches more than 90% in average when it comes to privileged, OECD countries (The World Bank, 2022). Due to this proliferation, when the COVID-19 pandemic became endemic in April 2020, 87% of worldwide workers were able to hold their work activities from home, relying on different software to accomplish their daily tasks. The COVID-19 pandemic caused many governments to impose confinement measurements that "increased Internet traffic demand of residential users, in particular, for remote working, entertainment, commerce, and education, which, as a result, caused traffic shifts in the Internet core" (Feldmann et al., 2020) which we are still experiencing today.

The importance and frequency of remote work thus increased during the pandemic (Mouratidis & Papagiannakis, 2021) and companies are planning to increase the share of remote workers in the future, confirming an upward trend of telework (Ozimek, 2020). However, the adoption of remote work technologies is still understudied (L. Yang et al., 2022). With the memory of the pandemic still fresh in the minds of most workers, we are thus presented with an excellent opportunity to advance the understanding the long-term impacts of remote work and how it shapes human behaviour and perception. The present research explores the

effects of videoconferencing technologies among full-time workers when it comes to their self-perceived performance. Specifically, we observe the impacts of social presence has on perceived performance, as well as sociotechnical factors that can influence the degree of social presence experienced by remote workers.

The social presence theory conceives this measure as “the ability of a communication medium to transmit social cues” (Short, 1976), as well as “the salience of the other in a mediated communication and the consequent salience of their interpersonal interactions” (Short, 1976). From these definitions, one can understand that social presence is inherent to all communication mediums, and it can be measured as the perceived warmth, conveying a feeling of human contact, sociability, and sensitivity embodied in it (Rice & Case, 1983).

Recent authors indicated that this single approach to social presence might be problematic for virtual communities, as their members interact with both computer-mediated mediums and fellow members of the online group. Thus, they have defended a multi-dimensional approach that asks for both the medium warmth and the sensitivity emanated from other users (Lu et al., 2016). Thereby, this study subscribes to the multi-dimensional approach of the social presence theory and considered two factors when building the items for the instrument research: social presence of the communication tool as well as social presence of colleagues.

The research described in this dissertation is part of a wider project that explores cognitive factors in remote work. In a forthcoming study prepared by Conrad et al. (forthcoming), researchers explored the relationship between work

environments, social presence, and productivity among remote workers. The research described in this dissertation extends the work completed by Conrad et al. (forthcoming) in three ways. First, it replicates their findings of a relationship between social presence and perceived productivity, though with a different population of British remote workers. Second, it replicates their findings related to social presence by replicating their results and refining the instrument observed. Third, it offers insights into additional specific factors that can influence the observed social presence. Ultimately, this research offers insight into the ways that organizations can leverage remote work technologies by improving the experience of social presence in an organization.

1.2 Research questions and hypotheses

The study focused on the relationship between social presence and perceived productivity, with specific attention to the factors that can contribute to the experience of social presence. The research questions that guided this study were as follows:

RQ1. Is there a relationship between remote workers' experience of social presence and work productivity?

RQ2. What factors contribute to the social presence experienced by remote workers?

In the prior survey study described by Conrad et al. (forthcoming), social presence was found to positively influence perceived productivity. In addition, they explored factors that influenced social presence and found that users perceived self-efficacy

of collaborative tools influenced social presence. However, the study had some limitations which motivated our research questions. First, the study relied on a conception of self-efficacy that has since been improved upon by researchers and may be captured by more modern constructs, such as that articulated by the Unified Theory of Acceptance and Ease of Technology (UTAUT; Venkatesh et al, 2003). Second, the authors did not incorporate experienced collaboration tool fatigue in their model, which has been documented as a predictor of effective remote work (Riedl, 2022). Third, the online meeting hours measurement used in the prior study reflected an absolute value and should have incorporated percentages or a Likert-scale option to be impartial. These insights informed the hypotheses by helping us to understand the influence of some measurements over the others, build a research instrument that include the proper items and design research questions that informs the model in an impartial manner.

We thus developed a second survey to expand their findings and explore three factors that could influence social presence: an organization's facilitating conditions, the proportion of a worker's workweek spend in meetings, and the degree of fatigue experienced by the worker that they attribute to their remote working tool. All these elements were measured by using a 5-point Likert scale to keep uniformity with the previous study. This survey approach is commonly employed by information systems and organizational behaviour researchers to answer questions about individual experience, using a covariance-based structural equation model (Dash & Paul, 2021). The hypotheses that we chose to test were expressed as follows, and are summarized by the image below:

H1. Reported social presence positively influences perceived performance.

H2. Facilitating conditions will positively influence experienced social presence

H3. The proportion of a worker's work week spent in meetings will positively influence experienced social presence.

H4. Experienced collaboration tool fatigue will have a negative impact on experienced social presence.

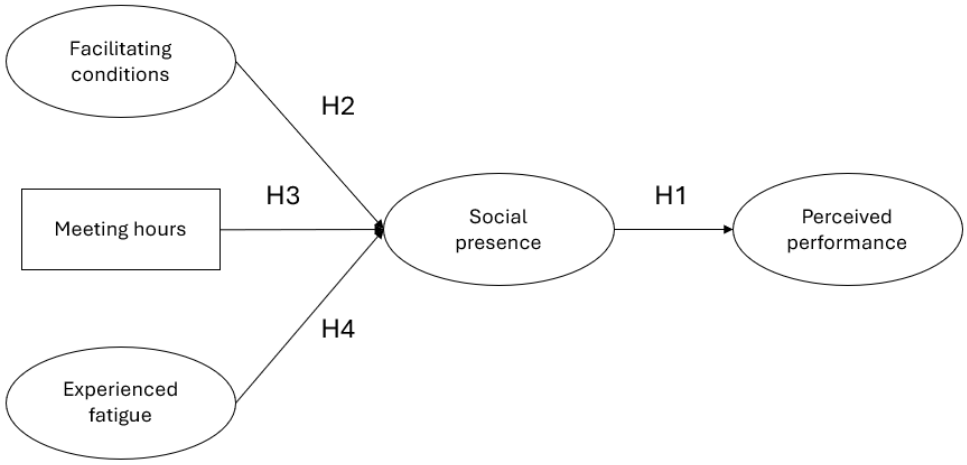

Figure 1 — Research model and hypotheses.

1.3 Expected research contributions

The biggest impact that this research pursues is bringing the social presence construct, which prevails in educational research, to the labour and human resources field. In this way, by establishing the conceptual and practical relationship between the measurement and remote work environments, this thesis shed light on how employers and workers could improve perceived performance. As well, this document expects to support previous investigators' (Caspi & Blau, 2008; Lu et al., 2016; Ning Shen & Khalifa, 2008) findings about the

multidimensionality of the social presence theory in online settings and how it should include, at least, elements from mediating software along with elements for the other users' interactions.

1.4 Thesis overview

This thesis is divided in five chapters. Chapter 2 will explore existing literature in the measurements utilized in the research instrument to properly define the scope and theorical bases of the construct. Chapter 3 discusses the methodology utilized, especially the reasoning behind the selection of CB-SEM, lavaan, and Prolific to conduct the instrument. Chapter 4 talks about the results obtained, how to interpret the different figures and indices obtained with the software. Chapter 5 puts these numbers in context and test the hypotheses. Chapter 6 concludes this work and indicates what would be the next actions researchers could take when analysing this phenomenon.

Chapter 2 – Literature Review

This section will provide an overview of the literature concerning the central topics, measurements, and research questions that guided this thesis. In section 2.1, a general panorama of the state of the art is presented while section 2.2. focuses on the measurements and items used.

2.1. State of art

The COVID-19 pandemic deeply impacted the way that we interact with others. The substantial regulatory changes and lockdowns propelled the adoption of communication software tools as main method of telework. As mentioned in the preceding paper by Conrad et al. (forthcoming), the number of remote workers in developed countries rose from 8% to 35%-50% in the first months of the pandemic (Morikawa, 2020.). In parallel, studies in OECD countries had found that "managers and workers had an overall positive assessment from teleworking for both firm performance and individual well-being" (Criscuolo et al., 2021), which could result in an increased share of remote workers even after the restrictions related to the sanitary emergency are lifted.

As more workers and employees adopt new technologies, the information systems and communication channels will gain importance as determinant factors for productivity, comfort, and quality of work; it is natural for researchers in the information systems field to raise questions about those socio-technical elements that influence such factors (Conrad et al., forthcoming). Recent experiments had raised concerns about workers' productivity while working at home (Galanti et al.,

2021; L. Yang et al., 2022), with elements such as living with a minor children, social isolation, or family-work tensions being moderators for stress and productivity levels. These papers shed light on the relationship between personal and environmental aspects over labour-related measurements and help us predict that there are still other moderating factors that need to be understood and addressed to obtain a full picture of the work-from-home reality.

Fauville et al. (2021) sustain that research and articles focusing on those moderating effects, especially the ones including fatigue, are yet rare. Thus, this thesis topic is extremely relevant in nowadays academic discussions, not only because this is an innovative phenomenon, but also and especially because this kind of research could provide stakeholders enough information to take decisions to improve the workers' satisfaction and improve the quality of work.

The antecedent established by Conrad et al. (forthcoming) indicated that workplace ergonomics and social presence are significant factors for perceived performance, as the latter heavily depends on the collaborative platform efficacy. Subsequently, it is necessary to delve in the social presence construct and its mediators to obtain a broader picture of the perceived performance dimension due to its importance and prominence in the model proposed.

2.1. Measurements and items construction

This investigation relies on the following items and measurements that have been tested by different authors. We will review prior work related to these instruments in turn.

2.1.1 Perceived performance

Perceived performance is understood as the degree to which workers believe that the use of a particular technology enhances their performance (Tahssain & Zgheib, 2009). This means that the perceived performance is a self-reported measurement rooted in the workers' beliefs and requires, at least, a degree of interaction with a communication tool so they can form an opinion about it. It is therefore a subjective measure of productivity that incorporates an assessment of a worker's objective behaviour.

This type of instrument has the advantage that it can be applied to workers in very different contexts. As mentioned in the previous section, workers are influenced by the socio-technical elements that surround their work-from-home environments; therefore, it makes sense that perceived performance is included as a dependent variable in the construct. The items used in the research instrument were obtained from Williams & Anderson (1991), as they measured the organizational commitment and responsibilities' fulfillment from workers and has been widely implemented in similar experiments since its creation.

2.1.2 Social presence

Social presence is described as the ability to perceive other humans in an online environment. It has been heavily discussed in e-learning (Conrad et al., forthcoming; Garrison et al., 1999; Richardson et al., 2017), but due to the ubiquity of the Internet and the growing number of activities that can be held online, the social presence theory is gaining relevance and could be incorporated to any virtual

activity that involves more than one party or mediating tool. As mentioned by Conrad et al. (forthcoming), “social presence is related to but distinct from online community engagement and social immersion”, in a way that it also evaluates the trustworthiness and social connections that can be developed in occasion of the usage of communication tools using. At the same time, the consensus in the information system research field is that social presence is composed of a social and a technical factor, meaning that users can experience social presence from their interactions with other members of society, but also from the software that serves as channel of those interactions (Lu et al., 2016).

Some researchers have identified a distinct measure of social presence of colleagues which may be applicable to remote work contexts (Lu et al., 2016). Social presence of colleagues responds to the social part of the wider theory. It is based in the idea that trust relationships can be developed in online environments, but considers the limitations related to the lack of a physical presence (Lu et al., 2016). It has been demonstrated that the social presence of colleagues might have an important mediating relationship with performance due to its inclusion of involvement and engagement as an important part of the measurement, and at the end, of the capacity of workers to measure their performance by interacting with others (Richardson et al., 2017). It is important to clarify that the difference between existing employees and new hires during COVID was not observed in this study, but it might be interesting to elaborate on this issue in ulterior research, as the existing employees might have a different standard of social presence.

The five items used for this endeavour were taken from Lu et al. (2016) and ask workers about their capacity to perceive the coworkers' attitude, look, warmth, and human touch while working from home. These items were combined with the ones presented in the following section, and they comprise the measurement as a whole.

By contrast, other researchers have identified a social presence of collaborative tools, which was indicated as the capacity of technological facilitators to enable communication (Di Martino & Wirth, 1990). This type of social presence corresponds to an intrinsic characteristic of the software and was used to evaluate characteristics of a communication technology. The items used by these past researchers were related to the communication tool's ability to demonstrate that there is person behind the screen (Di Martino & Wirth, 1990).

The social presence of collaborative tools is especially relevant to design social environments and interfaces, and also understand the effect of those communication systems on workers and their tasks. The items selected for the research instrument are taken from Gefen & Straub (2003) and Bergefurt et al. (2021) and they try to capture the sense of personalness, sociability, human warmth, and sensitivity in the online meeting tools. We thus created a social presence construct that incorporated elements of both social presence of colleagues and social presence of collaborative tools, as described by the past literature.

2.1.3 Facilitating conditions

Collaboration tool efficacy has been found to be an important factor in experienced social presence (Conrad et al., forthcoming) as well as in remote work satisfaction broadly (Staples et al., 1999). However, this measure does not account for additional factors related to a work environment that can determine success, such as technical support and system compatibility. Information systems scholars have since developed a deeper understanding of the facilitating conditions of a technology, which determines its acceptance and satisfaction. According to Venkatesh et al. (2003) facilitating conditions measures “the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system”. This construct is sensitive to the preparedness and provision of training, continuous support, and investment in digital infrastructure to benefit employees.

Facilitating conditions are intimately related to technological anxiety, as previous research has declared, the individuals’ ability to access support resources increases the positive perceptions of a certain technology that is being used, improving the ease of use (K. Yang & Forney, 2013). This measurement has also been broadly discussed in pedagogical settings, with recent findings suggesting a significant moderator effect between facilitating conditions and perceptions of interactivity of collaboration tools in remote learning environments (Camilleri & Camilleri, 2022). The items used in the research instrument for this section were selected from Venkatesh et al. (2003) and asked the users for the resources’

availability, knowledge, compatibility, and support when working with the online meeting tools.

Venkatesh et al. (2003) has been highly cited and used as benchmark in studies related to user experience and adoption of new technologies, but it has also been proved that its measurements had underperformed in new iterations (Dwivedi et al., 2011). This thesis plans to test them again in a new model and observe if its performance varies in this specific, work-from-home frame.

2.1.4 Experienced fatigue

The literature review of experienced fatigue has been described as scarce when it comes to analysis of communication tools and their effect in peoples' fatigue. Much of the literature is now only emerging, and it has been identified as an area of interest by senior information systems scholars (Riedl, 2022). Nadler (2020) indicated that this fatigue is caused by multiple factors including looking at a screen for a prolonged period of time, the social relationships and dynamics that are developed in videoconferences, as well as the reminiscence of previous times where videocalls were an exemption, not the rule.

There may also be evidence that users are affected by prolonged direct eye contact, positioning of the camera – as subjects' faces might appear larger or closer in online calls and this might trigger anxiety responses, and having their own images on screen for prolonged times, affecting users' experienced fatigue (Karl et al., 2022).

Nadler (2020) also indicated that, while participating in videocalls “participants are not engaged as human actors but ‘flattened’ into a totality of third skin comprising person, background, and technology”, and this could signify an extra effort of users to maintain concentration and performance levels (Fauville et al., 2021). The items used in this section are part of the General Online Call Experienced Fatigue measurement, which is related to the Zoom Exhaustion and Fatigue Scale explored by Fauville et al. (2021) and Lu et al. (2016) and they capture the users’ tiredness after participating in online meetings.

Chapter 3 - Methodology

This chapter describes the discussions and factors considered when implementing the research instrument. Section 3.1. discusses the research instrument characteristics and how it is related to the theorical framework mentioned beforehand, followed by section 3.2. which is about the Research Ethics Board approval process that was vital to conduct this research. Section 3.3. scrutinizes the nature of crowdsourced platforms in social sciences experiments, its prevalence among other study methods, and the decision of the researcher to use Prolific. This section is followed by 3.4., which briefly mentions the compensation that participants received, as well as section 3.5., which introduces the population demographics. Finally, section 3.6. talks about the analysis of the data and the reasons behind the selection of CB-SEM for this paper.

3.1 Research instrument characteristics

In response to a previously described survey (Conrad et al., forthcoming) and a review of the literature, a questionnaire was built in order to explore the facilitating conditions (Venkatesh et al., 2003), general online call experienced fatigue (Fauville et al., 2021; Lu et al., 2016), social presence (Bergefurt et al., 2021; Gefen & Straub, 2003; Lu et al., 2016), and perceived work performance (Williams & Anderson, 1991). The questionnaire also added two extra measurements: most used online call tool which was included as a control variable, and percentage of time spent in online meetings per week. The former was included to investigate what was the preferred software among employers; the

latter was included according to a recommendation made by a reviewer of the preceding paper by Conrad et al. (forthcoming) as a possible mediating condition for social presence. The questionnaire instrument is provided as Appendix D to this document.

3.2 Research Ethics Board approval

The research described in this study was part of a series of experiments exploring the relation between mind wandering, productivity, and social presence, circumscribed to remote work settings named “Working or wandering? A survey of factors that lead to productive remote work environments” (Conrad et al., forthcoming). As part of this long-term project, the research instrument was presented as an addendum to the existing project to the Dalhousie University Social Sciences and Humanities Ethics Board. This committee approved the new instrument on October 13th, 2022, under the REB no. 2021-5858.

Participants provided informed consent following the REB approved protocol. They were informed about the Board approval, and its contact information was provided in case they had any ethical concerns about their participation. As well, they were informed that there would not be a way for their responses to be identifiable, as the data collected would not be connected by any means to their demographic information, as they will remain anonymous. Participants were also informed that the results of this study would be made available by accessing Dr.

Conrad's website[1] upon completion of its defence, because no contact information was collected.

3.3 Crowdsourced platforms

Due to the digital nature of the investigation and following the common practices in psychological and social sciences research (Gosling & Mason, 2015), crowdsourcing platforms were the only channels considered for conducting this study. According to Steelman et al. (2014), "online crowdsourcing markets entail web-based environments in which employers post outsourced tasks to an undefined, anonymous network of laborers who are compensated for their distribution", allowing researchers to easily access heterogeneous populations in a shorter time.

When selecting a crowdsourcing platform, MTurk would seem an obvious choice due to its prominence. MTurk has gained significant terrain amongst its competitors, and according to Bohannon (2016) its presence in published papers reporting social sciences experiments rose more than 1900% in its first five years of existence. Nevertheless, a decision was made not to use Amazon's platform due to the following: firstly, its users are predominantly American – accounting for at least 92% of active respondents on October 14th, 2022[2] (Difallah et al., 2018), reducing the possibility of obtaining a representative sample– especially when the targeted population corresponds to British users due to the UK connectivity rates

[1] The website can be found at https://colinconrad.com/study-results

[2] Date in which the experiment was conducted in Prolific.

and work-from-home preparedness, as it will be discussed in section 3.5.1. Secondly, researchers have found “compelling evidence of a decrease in MTurk data quality, which can have a substantial negative impact on study results and conclusions” due to users using VPNs to overpass the geographical filters, as well as poor pre-screening practices (Chmielewski & Kucker, 2019). Finally, there have been strong claims insinuating that 96% of Amazon’s MTurk workers receive “a median hourly wage of 2 [USD]” (Hara et al., 2018) while “requesters are paying 11.58 [USD] per hour on average” (Hara et al., 2018) suggesting that Amazon might keep a disproportionally high portion of participants’ earnings, as well as the fact that MTurk’s particular design enlarges the sources of unpaid work such as “task search, task rejection, [and] task return” (Hara et al., 2018).

In contrast, Prolific – a UK based company – has demonstrated that, even when the data collected is “not significantly different than MTurk’s […,] participants seem to be more naïve to common experimental research tasks, and offer a more diverse population in terms of geographical location, ethnicity, etc.” (Palan & Schitter, 2018). Also, “one of the key advantages of Prolific over other platforms is that researchers can pre-screen participants based on pre-screening questions used in earlier studies” (Palan & Schitter, 2018), reducing the sources of unpaid work by decreasing the task rejection and return rates. Thus, the researcher selected Prolific to recruit and conduct the survey.

3.4 Compensation to participants

In an effort to implement a model for a fairer sharing economy in academic experiments as discussed by (Graham & Anwar, 2018), as well as to help workers "overcome some of the risks of predatory capitalism" (Graham & Anwar, 2018) related to the little bargaining power when circumscribed to a crowdsourced platform (Graham & Anwar, 2018), participants were paid 0.75 GBP to complete a 4-minute task.

Considering this minutes-to-GBP relation, it is possible to calculate a 11.25 GBP hourly pay rate for the experiment, which is greater than the current minimum wage in the UK (*Low Pay Commission Consultation 2022*, n.d.). This guarantees that the research not only complies with current labour legislation, but also recognizes workers' efforts and time when interacting with the research instrument.

It is worth clarifying that every person was entitled to payment as soon as they gave their informed consent to participate in this study, meaning that even if they did not complete the survey, they received the same compensation as their counterparts who successfully completed the questionnaire and clicked the "Finish" button in the last page.

3.5 Population demographics

A total of 203 full-time workers located in the UK were recruited on October 14th, 2022, for this endeavour. Of those 203 responses, 197 were utilized in this research. The selection and data cleaning process are detailed in the following table:

Detail	n	% of total collected
Complete responses	187*	92.12
Trial responses, complete	10*	4.92
Trial responses, incomplete	0	0
Incomplete responses	3	1.48
Participant deleted by Prolific due to unusually short response time	3	1.48
Total responses utilized	N = 197	97.4
Total responses recorded	203	100

Table 1 — Composition of the responses and N value composed by the sum of elements with an asterisk.

3.5.1 Why UK workers?

According to The Future of Remote Work: An Analysis of 2,000 Tasks, 800 Jobs, and 9 Countries | (McKinsey, n.d.) the UK is the country with best potential to implement remote work without productivity losses when compared to China, France, Germany, India, Japan, Mexico, Spain, and the United States, as illustrated in Figure 2. One of the causes stated by the Institute for the elevated UK potential is its strong financial sector, which tends to be the most suitable for remote work (*The Future of Remote Work: An Analysis of 2,000 Tasks, 800 Jobs, and 9 Countries | McKinsey*, n.d.), as well as its high connectivity to the Internet, as Table 2 depicts.

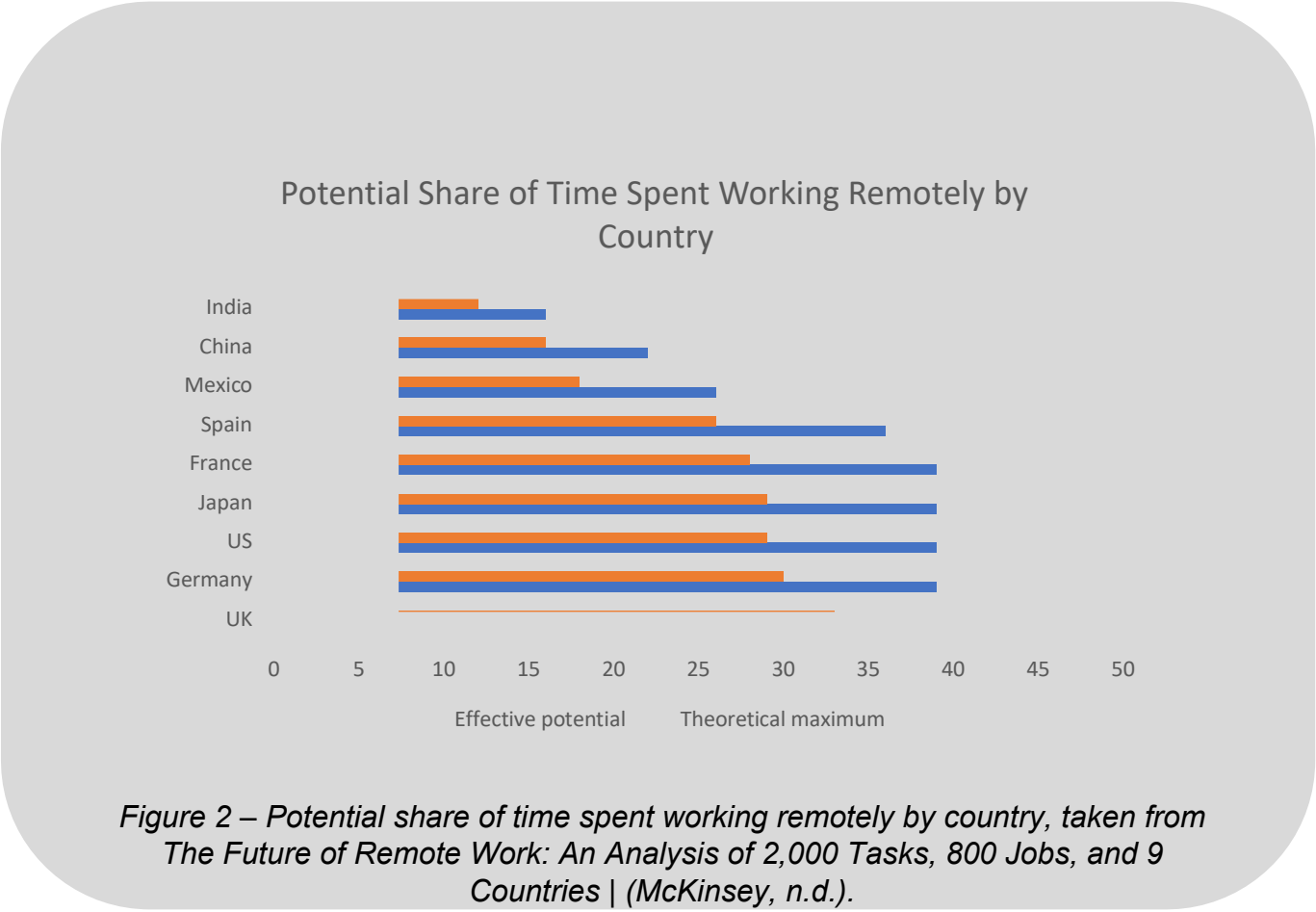

Figure 2 – Potential share of time spent working remotely by country, taken from The Future of Remote Work: An Analysis of 2,000 Tasks, 800 Jobs, and 9 Countries | (McKinsey, n.d.).

Country	% of population using the Internet
United Kingdom	94.82
Spain	93.21
United States	90.9
Japan	90.22
France	84.8
Mexico	71.97
China	70.4
India	43

Table 2 – Internet penetration per country (The World Bank, 2022)

3.5.2 Participant characteristics

Participants were pre-screened by Prolific to guarantee that: i) they were proficient in English – the language of the instrument and research, ii) that they

were full-time workers, iii) that they were located in the UK and most of their activities take place in that jurisdiction, and iv) that the sample is representative when compared to the UK population[3]. According to the Labour Market Overview, UK (Office for National Statistics, 2022) the average age of UK workers is 40.3. Meanwhile, the mean age of the study sample is 37.165 years old. The following table expands on the age brackets as percentage of the population sample.

Bracket (working ages)	As % of N = 197
Aged 20 to 24 years	6.09137056
Aged 25 to 29 years	21.319797
Aged 30 to 34 years	20.3045685
Aged 35 to 39 years	19.7969543
Aged 40 to 44 years	10.1522843
Aged 45 to 49 years	9.64467005
Aged 50 to 54 years	4.06091371
Aged 55 and more years	8.62944162

Table 3 – Age brackets of the study sample.

The latitude and longitude measurements were collected in order to guarantee that participants were located in the UK. Figure 3 specifies the location of the respondents. All participants had 30 minutes to complete the task, and a reminder appeared 5 minutes before that limit. The average completion time of the

[3] As previously stated, Prolific uses responses from previous experiments to establish the eligibility of participants. Also, Prolific offers an option to obtain a representative sample "that reflects the demographic distribution of a given (often national) population, with the aim of making [the] research findings more generalisable." (Prolific, 2022). This function was used for the present study.

instrument was 2.82 minutes, with a minimum of 0.68 minutes and a maximum of 21.4 minutes. The coefficient of variation of the completion time is 82.3%, demonstrating a smaller dispersion in the distribution than the mean.

Figure 3 – Location of the respondents.

3.6 Structural equation model analysis

SEM is a set of methods used in social sciences in order to "[develop] and use […] quantitative methods for analyzing causation in non-experimental data" (Bollen et al., 2022). A recent review conducted by Bollen et al. (2022) that looked into papers published in the last decade demonstrated that SEM was mainly used

to “measure abstract concepts, to explore measurement invariance, to validate new measures, […] to predict membership in latent classes [… as well as] mediation” (Bollen et al., 2022). Given that the main objective of this research is to confirm the existence of abstract concepts minted by the different previously mentioned authors, SEM happens to be a comprehensive method that allows the researchers to evaluate each of the items – or latent variables – and their influence in a whole model.

One of the most prominent advantages of SEM “is that the path diagram and the equations make model specification explicit” (Bollen et al., 2022), allowing researchers to evaluate the reliability and plausibility of the constructs at a glance. Also, the fact that SEM evaluates “how well [the] indicators measure the latent variable and obtain estimates of their reliability and validity” (Bollen et al., 2022) means that researchers have the opportunity to test and eliminate the indicators that might not be significant for the construct, as did occur in this particular case.

In contrast, authors have also pointed out different weaknesses that SEM possesses. For one, the measures of fit “are sometimes influenced by model size, sample size, variable distributions, and other characteristics unrelated to the validity of the structure of the model” (Bollen et al., 2022), which is especially challenging for a relatively small experiment with N = 197.

3.6.1 Minimum sample size

Previous researchers had described the sample size issue in the following way: “in fitting latent-variable […] inferences are made from observed data to the

model believed to be generating the observations. These inferences are dependent in large part on the degree to which the information available in a sample mirrors the information in the complete population" (Tanaka, 1987). In essence, larger sample sizes generate more information, which can mean a better chance to observe the phenomena, but can also lead to ineffective or misleading statistical inferences (Lin et al., 2013).

To solve this challenge and constitute a common ground, several guidelines have been proposed to determine sample sizes. The most popular guidelines and how they could be applied to the model are described in Table 4. Due to the relative simplicity of the model, the researcher decided to err on the side of caution and take the most conservative estimation by collecting 203 data points that resulted in N = 197 after the data cleaning process.

Method	**Explanation**	**Minimum N for this study**
Sample-to-item ratio *(Gorsuch, 1990)*	Based on items on a study. The ratio should not be less than 5 people per item.	$\mathrm{N} = 5 \times \mathrm{n\ items}$ $\mathrm{N} = 5 \times 22$ $\mathrm{N} = 110$
Sample-to-variable ratio (Hair et al., 2018)	Based on independent variables. The ratio should not be less than 20 per independent variable.	$\mathrm{N} = 20 \times \mathrm{n\ ind.var.}$ $\mathrm{N} = 20 \times 4$ $\mathrm{N} = 80$
KMT (Krejcie & Morgan, 1970)	Sample of 384 is sufficient for a population of 1,000,000 or more.	$\mathrm{N} = 384$

Method	Explanation	Minimum N for this study
Sample size guidelines for SEM *((Kline, 2016))*	A sample between 100 and 200 is medium-sized and might be ideal for a simple model.	$100 < \mathrm{N} < 200$
Minimum R^2 *(Kock & Hadaya, 2018)*	The value would depend on the maximum number of arrows pointing at a construct – 5 for this experiment – and the minimum R^2 for the model – 0.10.	$\mathrm{N} = 147$

Table 4 – Methods to determine the minimum sample size.

3.6.2 Covariance-based SEM

When it comes to SEM, researchers have two options: covariance-based and factor-based calculations. The first "includes generalized structured component analysis" (Hwang et al., 2019) while the latter is "represented by covariance structure analysis" (Hwang et al., 2019). This research subscribes to the covariance-based SEM due to its flexibility and growing popularity ((Hwang et al., 2019; Sarstedt & Hwang, 2020).

Lavaan is a package provided in the R programming language, a language often used for statistical calculations, and was selected as software to conduct the covariance-based SEM calculations. The reasons behind this selection are: i) lavaan's open source nature, which aligns with the open science philosophy that is a common aim in this long-term research project, ii) its inclusion of "all of the main features of commercial SEM software" (Gana & Broc, 2019) and iii) the fact

that it is not necessary to master R to make a good usage of lavaan (Gana & Broc, 2019) as the Master of Digital Innovation is a non-technical program.

Chapter 4 – Results

This chapter was written according to the recommendations made by Ockey & Choi (2015) and Deng (2022). First, section 4.1. will present the model proposal and the hypothesized regressions. Section 4.2. identifies the model by its degrees of freedom, omitted items, covariance matrix, and parameter estimator. Later on, section 4.3. present the absolute and relative model fit indices, meanwhile section 4.4. introduces a brief model interpretation, the relationship between latent variables, and the factor loadings.

4.1 Model proposal

The hypothesized relationships between measurements were established in figure 4, where each latent variable is enclosed in an ellipse, observed variables are in rectangles Bollen et al, (2022) and the arrows indicate an expected directional relationship between two variables. The arrows that have numbers indicate that these relationships were fixed at 1, meanwhile the others are free parameters (Ockey & Choi, 2015).

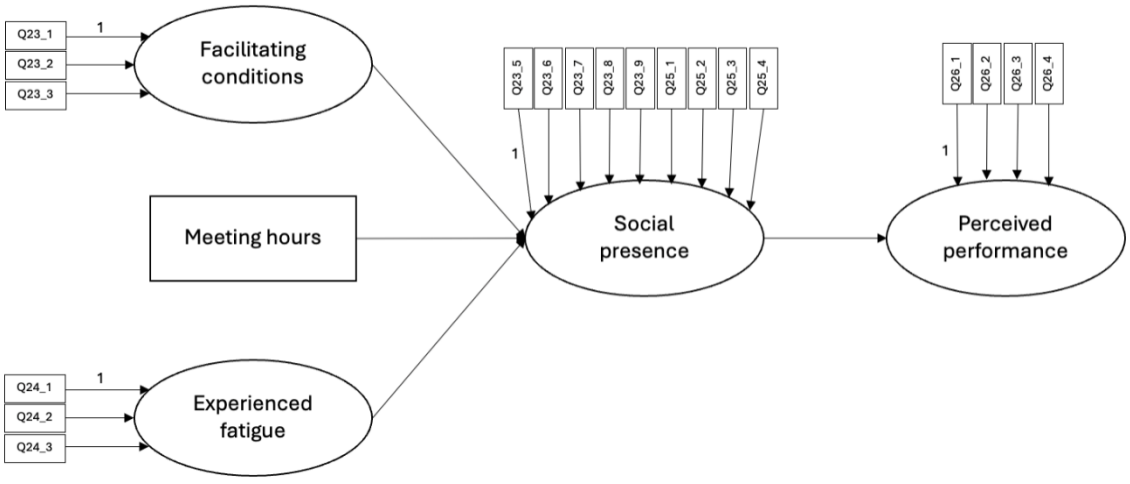

Figure 4 – Proposed model and items.

The model construct suggests that perceived performance, measured by four items in the questionnaire, is affected by the social presence perceived by workers, which was measured by nine items. In turn, social presence is affected by facilitating conditions (measured with three items) experienced fatigue (measured by three items) and meeting hours (which was a single item in the questionnaire). All these items were taken from the authors mentioned in the literature review and had been validated in several opportunities, except of the meeting hours item created by Conrad et al. (forthcoming) and was revised in this document according to reviewers' comments.

CFA was used in this study to keep homogeneity with the previous study by Conrad et al. (forthcoming) and to allow comparison between both experiments.

4.2 Model identification

First of all, it is important to mention that normal theory-based maximum likelihood (ML) was used for the parameter estimation, obtaining 39 model parameters. Furthermore, factor Q23_4[4] had to be omitted due to a low loading of 0.41, confirming the facilitating conditions' underperformance in recent studies when compared by the original, as stated by Dwivedi et al. (2011).

According to Ockey & Choi (2015), a covariance matrix has to be presented to facilitate future model replications. Therefore, it was added as follows:

[4] Q23_4 was a measure of facilitating conditions and corresponded to the question "I can get help from others when I have difficulties using the online meeting tool." (Venkatesh et al, 2003).

	Estimate	Standard error	z-value	P (>|z|)
Facilitating Conditions covariance with Experienced Fatigue	-0.058	0.034	-1.710	0.087

Table 5 – Covariance matrix.

As stated by Ockey & Choi (2015), researchers are encouraged to report skewness, which is the degree of asymmetry in the data set, as well as kurtosis values, which is the existence of extreme outliers (Mangiafico, 2016). Attending their recommendations and guidelines, the following data was prepared using R's psych package.

Items	Skewness	Kurtosis
Q23_1	-0.7	0.46
Q23_2	-1.63	3.37
Q23_3	-0.68	-0.61
Q24_1	0.43	-0.55
Q24_2	0.65	-0.38
Q24_3	0.42	-0.66
Q23_5	-0.44	-0.39
Q23_6	-0.28	-0.62
Q23_7	-0.6	-0.25
Q23_8	-0.18	-0.79
Q23_9	-0.03	-0.64
Q25_3	-0.09	-0.91
Q25_4	-0.23	-0.74

Items	Skewness	Kurtosis
Q26_1	-0.96	1.62
Q26_2	-1.39	4.06
Q26_3	-1.35	3.61
Q26_4	-0.96	1.4

Table 6 – Skewness and Kurtosis calculations per item.

4.3 Model fit

The indices presented in tables 7 and 8 “provide an indication of the extent to which the observed data matrix and the hypothesized model data matrix are the same” (Ockey & Choi, 2015).

Absolute Fit Indices	Value
Chi-square (P-value)	0.000
Standardized Root Mean Square Residual (SRMR) (Bentler, 1995)	0.069
Root Mean Square Error of Approximation (RMSEA) (Steiger & Lind, 1980)	0.072

Table 7 – Absolute Fit Indices.

Relative Fit Indices	Value
Comparative Fit Index (CFI) (Bentler, 1990)	0.942
Tucker-Lewis Index (TLI)	0.932

Table 8 – Relative Fit Indices.

As this model is not nested, the following values are reported as well:

Relative Fit Indices	Value
AIC (Akaike, 1987)	6157.123
BIC (Raftery, 1995; Schwarz, 1978).	6285.168

Table 9 – Relative Fit Indices for a non-nested model.

4.4 Model interpretation

After obtaining the CB-SEM calculations, the following graph was drawn, demonstrating that there is a regression between all the latent variables created.

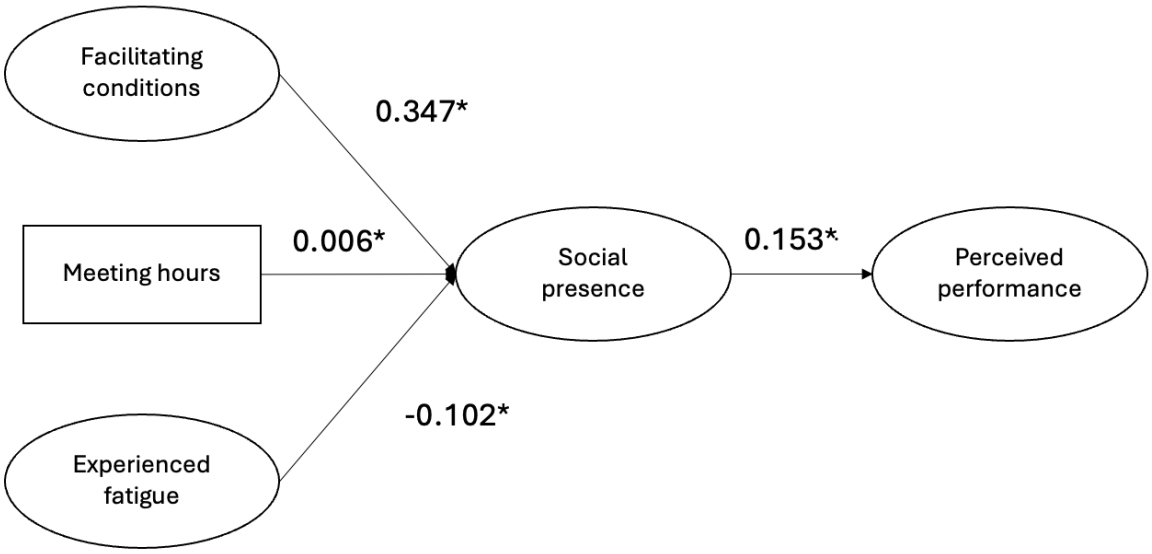

Figure 5 – Model results.

And they are specified in the following table:

	Estimate	Standard Error	z-value	P (>|z|)
		Social presence		
Meeting hours	0.006	0.003	2.097	0.036
Facilitating conditions	0.347	0.142	2.452	0.014

	Estimate	Standard Error	z-value	P (>|z|)
Experienced Fatigue	-0.102	0.050	-2.030	0.042
Perceived performance				
Social presence	0.153	0.060	2.537	0.011

Table 10 — Model regression estimates, standard error, z-value, and P.

In addition, the following chart presents the items' factor loadings and their standard error, demonstrating the high feasibility of the items to explain each one of the constructs set.

Items	Estimate	Standard Error	z-value	P (>|z|)
Facilitating Conditions				
Q23_1	1			
Q23_2	1.206	0.145	8.291	0.000
Q23_3	1.251	0.15	8.344	0.000
Experienced fatigue				
Q24_1	1			
Q24_2	1.083	0.044	24.692	0.000
Q24_3	1.028	0.052	19.949	0.000
Social presence				
Q23_5	1			
Q23_6	1.047	0.100	10.442	0.000
Q23_7	0.995	0.098	10.175	0.000

Items	Estimate	Standard Error	z-value	P (>|z|)
Q23_8	1.262	0.096	13.104	0.000
Q23_9	1.175	0.098	11.973	0.000
Q25_3	1.063	0.104	10.232	0.000
Q25_4	1.126	0.99	11.354	0.000
Perceived Performance				
Q26_1	1			
Q26_2	1.058	0.066	15.916	0.000
Q26_3	1.076	0.068	15.837	0.000
Q26_4	1.041	0.063	16.474	0.000

Table 11 – Factor loadings, standard error, z-value, and P per item.

Chapter 5 – Discussion

This chapter discusses the findings of the experiment. Section 5.1. delves into the SEM and descriptive statistics results and what they mean according to the model proposal and hypotheses. Section 5.2. discloses the theoretical implications and section 5.3. expands on the practical implications of the findings.

5.1 Results interpretation

We assessed our model based on the common models of fit (SRMR = 0.069; RMSEA = 0.072; CFI = 0.941; TLI = 0.932) as described by Kline (2016) as well as the regression coefficients of the positive influence of social presence on productivity (β = 0.153; p = 0.011), as well as the positive influence of meeting hours (β = 0.006; p = 0.036) and negative influence of facilitating conditions (β = 0.347; p = 0.014) on social presence (β = -0.102; p = 0.042).

Kline (2016) describes the SRMR as a measure of the goodness of fit of the structural equation model and asserts that SRMR values under 0.05 represent excellent fit, while values under 0.08 represent acceptable fit. The RMSEA fit statistic, by contrast, was developed by Steiger in 1980 and its cut-off point has been reduced considerably in the last fifteen years (Hooper et al., 2008). The most recent consensus among authorities indicates that the value should not exceed 0.070 to be considered as excellent (Steiger, 2016). The value obtained in this experiment is 0.072, indicating that the model has an acceptable, almost excellent fit.

When created the CFI and TLI acceptable values were above 0.900. However, the most recent consensus established a cut-off value of 0.95 or above (Kline, 2016). The present experiment obtained values of 0.942 for CFI and 0.932 for TLI, indicating an acceptable relative fit. It is worth mentioning that CFI is “one of measures least effected by sample size” (Fan et al., 1999). Meanwhile, the SRMR value of 0.072 deems goodness of fit as it is lower than 0.08 (Hu & Bentler, 1999). Taken together, These figures suggest that the model overall is acceptable, but could be optimized by adding items and obtaining their Phi values, which is akin to their covariance for the case of CFI, as well as enlarging the sample size for the case of RMSEA and SMRM (Hooper et al., 2008).

As observed in Figure 4, some parameter values were fixed at 1, as it is required in SEM methodologies. In Table 11 it is evident that, except of Q23_7, all free parameters obtained greater values than 1, demonstrating the significance of them for the model and its latent variables. Furthermore, according to Table 6, no skewness absolute value exceeded 3.000 and no kurtosis absolute value is greater than 10.000, fulfilling the (Kline (2016) guidelines. In fact, the distribution of most items (Q24_1, Q24_3, Q23_5, Q23_6, Q23_8, Q23_9, Q25_3, and Q25_4) are approximately symmetric and similar to a normal distribution; there are only three highly skewed distributions (Q23_2, Q26_2, and Q26_3). Both values demonstrate the high quality of the information collected with the instrument as it falls into normal ranges. Taken all together, the model is interpreted to be a valid measure of our hypotheses.

In order to prevent misspecification, the global chi-square values were not the only indices of fit observed. This document followed the recommendations by Hertzog (2019) to address the robustness of the model, and according to this author, the fact that our model has i) a large p-value, ii) a large R square value, and iii) medium but significant path coefficients, its evidence enough to inform the model fitness and discard misspecification or potential heteroscedasticity in the values. Nevertheless, attending to recommendations of the evaluating panel of this thesis, further heteroscedasticity analysis would be done by using a robust measure in lavaan, such as a maximum likelihood estimation with robust standard errors and mean-and-variance adjusted statistics.

Our initial hypotheses were thus all supported by the findings; therefore, the null was rejected. Table 12 compares the hypotheses and the regressions found in the model to support or reject them. The first hypothesis was supported, indicating that social presence is a predictor of perceived performance. Furthermore, it is clear that the facilitating conditions of the employee's company is associated with social presence, being the factor that alters the latter the most, as well as the strongest relationship in the whole construct. The fourth result of -0.102 explains a negative association between experienced fatigue and social presence, meaning that the greater the fatigue, the lower the presence.

The third hypothesis has weaker evidence, though is largely supported by the observation. Meeting hours was observed to be a significant predictor of social presence though the low value regression coefficient of 0.006 suggests that the impact is likely very small. Nonetheless, the evidence supports the hypothesis,

through would warrant future investigation as a potentially small influencer of the construct.

According to the thesis committee, other measurements such as percentage of allotted tasks done in a week could be considered in replacement of meeting hours in further research, as that one might be more precise.

Research Question	Regression	Result
H1. Reported social presence positively influences perceived performance	0.153*	Supported
H2. Facilitating conditions will positively influence experienced social presence	0.347*	Supported
H3. The proportion of a worker's work week spent in meetings will positively influence experienced social presence	0.006*	Supported
H4. Experienced collaboration tool fatigue will have a negative impact on experienced social presence.	-0.102*	Supported

Table 12 — Research questions and regressions' relation.

5.1.1. Components of the social presence measurement

One of the key findings from this study is a valid relationship between social presence and perceived performance. As evident in the introduction and literature review chapters, the social presence measurement is composed by two elements described by Gefen & Straub (2004), Bergefurt et al. (2021) and Lu et al. (2016), which are social presence of colleagues and social presence of collaborative tools. Both concepts are intimately related, as they are based on the following precepts: i) the Internet is usually conceived as an ethereal space that lacks physical social presence (Gefen & Straub, 2003), ii) the generalized lack of presence hinders the

development of trust relationships and affects online behaviour (Lu et al., 2016), iii) trust is an important element in all human relationships as it helps to predict behaviours (Bergefurt et al., 2021), and iv) “the greater the social presence, the more trust than can be developed” (Gefen & Straub, 2003). Aside from this common ground, both kinds of social presence are understood as an inherent quality of the communication medium (Lu et al., 2016)to express intimacy and psychological closeness with others (Short, 1976).

As mentioned by Lu et al, (2016)the social presence measurement cannot be understood from a unidimensional perspective, as users do not only interact with software; they use those mediums to communicate with peers.

Since telework is understood as the combination of collaborative activities and technological facilitators to enable communication (Di Martino & Wirth, 1990), it is necessary to understand social presence as a multi-dimensional measurement, which is the reasoning behind the selection of nine items encompassing both technological and social aspects in a single latent variable.

5.1.2. Social presence in professional mediums

After the defence of this document, it became clear that social presence can also be determined by the expected outcome of the interaction between participants and the nature of their relationship. Weidlich et al. (2022) had suggested that users might change their attitudes towards other members in the online community based on the purpose and task that they are developing online. The authors exemplify this by indicating that workers in a professional training

session might prefer “relative psychological distance (…) to facilitate question-asking and to allow for mistakes and misunderstandings” (Weidlich et al., 2022), and this might be also the case for short courses and seminars with a more professional, career oriented focus – where anonymity might be preferred and sharing rich interpersonal experiences might be considered a distraction for the purposes and timing of the activity.

Even when those scenarios might differ totally from having a job interview or interacting in social media – where the salience of the members and its feelings might be more important – all these scenarios are relevant to the social presence construct and might modify the way that it can be measured.

Further research in this direction might move from the generalizing social presence construct to one that accounts for contextual factors (Mykota, 2018; Weidlich et al., 2022).

5.2 Theoretical implications

According to the experiment, social presence is a predictor of the workers’ perceived performance. A greater feel of social presence – both of the software tools and the coworkers – will lead to an augmented performance. This finding corroborates the results described by Conrad et al. (forthcoming) which found a relationship between reported social presence and perceived productivity, and contradicts previous research, which indicated that affective and social connections during work might divert cognitive resources away from performance in a way that they can be allocated to affect regulation and social interaction

(Daniels et al., 2014). The findings lend general support to past research from the learning literature which found that social presence is an early predictor of success and performance, as Joksimovic et al., (2015) described in an educational settings' analog case. The present study demonstrates that the theory is also true for professional and work environments, and not just academia.

These finding also add new insight into the varieties of social presence that can influence productive remote work. While Conrad et al. (forthcoming) drew from an understanding of social presence that is rooted in the e-learning literature, this study extends these results by drawing from past research into the social presence experienced from tools (Bergefurt et al., 2021; Gefen & Straub, 2003) as well as social presence experienced by colleagues (Lu et al., 2016). The construct observed in this study draws from elements of both of these prior constructs to establish the foundations of a valid social presence measure based on both social and technical factors related to remote work.

As studied in the literature review chapter of this document, facilitating conditions are defined as the extent to which a person feels that there is a technical and organizational frame to support them when interacting with an information system (Venkatesh et al., 2003). The association shown in this study establishes that having a well-defined infrastructure that surrounds the worker could augment the social presence experienced by the worker, meaning that they feel accompanied and surrounded by support systems and communication channels, providing them a sense of humanity and personalness. This personalness is vital for remote working environments, which are highly isolating already (Ballarotto et

al., 2021). If employers ask themselves how they can improve the workers' feel of social presence, this study could give some light and recommend implementing infrastructure and communication channels that employees can rely on if they face problems.

Finally, our observation about the influence of meetings and zoom fatigue corroborates emerging theories about the negative impacts of fatigue and cyberstress on remote work (Riedl, 2022). While the proportion of a workweek spent in online meetings had a positive influence on social presence, similar to the past finding by Conrad et al. (forthcoming), their impact was very small. However, the observed influence of fatigue on social presence suggests that the quality of the meeting matters; long and sustained exposure to the online meeting tools resulted in a decreased social presence because of the allocation of cognitive resources decreased along time spent in those meetings, as the covariance drawn between both variables in figure 5 might suggest. This is consistent with previous research that signaled the decreased quality of work when spending too much time in online meetings – hence, Zoom Fatigue (Nesher Shoshan & Wehrt, 2022).

5.3 Practical implications

While writing the second chapter of this document, it was evident that the social presence construct was created when considering educational settings. A previous literature review by Dikkers (2016) indicated that the social presence research started in 2006 by analysing contents of online classes and implementing emotion identification skills in K-12 educators in graduate programs. Since then,

most of the papers implementing this methodology and theory subscribed to pedagogical settings, making impressive findings when understanding that continuing online interactions resulted in better connection rates, increased emotion, self-disclosure, and at the end, better results in grades and students' overall satisfaction.

This study demonstrated that the postulates from educational research are relevant for human resources and labour research. Workers feel that they are more productive when they feel a greater deal of social presence, and that the experience of a lived social experience is an important predictor of online work success. Practitioners would benefit by considering prior findings from the e-learning literature and best practices. For example, by providing interactive and media rich feedback to remote workers (Thomas et al., 2017), business leaders may contribute to improved remote work experience and productivity. Hopefully, these findings are enough motivation for other researchers to continue analysing this measurement in labour relations and telework.

The findings also provide insight into the types of tactics that remote work employers can employ to improve productivity. As the literature review and questionnaire indicated, facilitating conditions are understood as all the elements and infrastructure that are designed to accompany the workers in their daily tasks and support them in case they need assistance. Facilitating conditions account for the capacity of the workers to understand and interact with the software and tools upon provided. It follows that employers may benefit by implementing better training programs and support systems to make employees feel supported through

their activities. They may benefit by providing time for organic learning, perhaps together with their teams. If workers are better prepared to use remote work tools and are supported by effective infrastructure (e.g., fast internet, professional licenses to remote work software), then they are more likely to be productive.

This research did not include other factors that might alter the social presence, such as trust levels or good relationship between coworkers. As social presence is defined by factors like friendliness, contact, warmth, and ease of communication, it might be important to build a measurement that includes more of these factors and see if the association between items is greater or lower. Taken together, practitioners and employers would benefit by identifying possible social factors that could positively impact their employee's experience of social presence and test the implementation of these techniques.

5.4 Limitations

This study was limited by factors related to the data collection process and the instrument design. First, the survey could be designed with a subjective dependent variable, as perceived productivity, as this would reduce the potential biases linked to self-reported instruments that might cast doubts on the validity of our construct. Recent studies had indicated that self-reported objective variables "adds predictive power in the explanation of performance data and other questionnaire data" (Tempelaar et al., 2020), advocating for the implementation of other subjective measurements to corroborate the postulates described in the hypotheses section.

As mentioned in Section 3.6.1., the sample size for this study was small, leading to lower SMRM, RMSEA and p values for the model. To overcome this problem, a second iteration of the research instrument could be developed to recruit 20% to 30% of participants of the original sample and observe the model fit sensitivity to such changes.

Also, as mentioned in section 5.1.2., the social presence construct could use contextual explanatory items as suggested by Mykota (2018) and Weidlich et al. (2022) to understand how different tasks and expectations modulate the measurement itself and the model as a whole.

Finally, it would be worth including mediating effects in this structural equation modelling – such as industry, meeting size, impact of other platforms in countries with a lower Internet penetration rate, and others, in order to obtain a broader picture of the phenomena and see how the model variates according to those conditions. Future work that includes a larger sample size can investigate such effects to further improve the model.

Chapter 6 - Conclusion

This thesis presents compelling evidence – via structural equation modelling – to declare that social presence is, in fact, an important element to consider when discussing ways to increase the perceived performance of remote workers in a highly-connected country, such as the UK. These findings support previous research that indicated that more, sustained social interactions could, in fact, increase levels of satisfaction and positive attitudes towards online activities such as video calling.

The adoption of facilitating conditions as a mediator of social presence, and at the end, as a relevant factor to determine the perceived performance of workers, demonstrated that companies might want to introduce support programs and training for their collaborators, as well as modify the organizational culture to make the support systems more prominent and clearer across the company: in this way, workers might not only benefit from having a support network, but might also feel that their work is more productive as they feel accompanied through their daily tasks; especially when it comes to specialized software that they are using to develop the majority of their activities.

The fact that collaboration tool was not a significant factor in the determination of any of the measurements in the model – that lead the researcher to include it as a control variable, indicates that workers might not perceive a greater difference between the different online meeting software that are common in the UK. This might change according to the resources' availability and popularity of other tools in different countries. Future research could try to compare the results

of a similar question about preferred or most used collaboration tool in different nations to see if the scarcity of resources – such as the availability of mobile data or reliable connections – or the differences in work culture and market penetration of those regions might trigger different results where collaboration tool could be, in fact, a mediating factor.

At the same time, the social presence construct could be informed by different influencers such as commitment, trust, affective investment, level of participation or any other item that might be relevant for the discussion. Also, other measurements of productivity – such as kind of task developed, percentage of work completed during a work week, or even percentage of goals achieved during a set timeframe – could be included to obtain a broader picture of the situation, as many researchers have questioned the ideality of self-reported measurements in equation modelling. Further studies could explore the possibility of implementing behavioural experiments while interacting with different pieces of software instead of using a questionnaire to obtain more data that might contribute to this field.

Lastly, this research has demonstrated that there are more research opportunities to analyze how workers opinion and deal of performance might be affected after the COVID-19 pandemic, and how the adoption of new technologies has to be accompanied by social networks and presence to make it a human, enjoyable experience.

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Appendices

Appendix A – Recruitment posting

The recruitment will be posted on Prolific's platform.The text will read:

"We are conducting an academic survey to study what factors influence your productivity when working remotely. Specifically, we are investigating whether there is a relationship between how you use workplace technology, your focus on your work, your collaborations and, in turn, productivity. To understand the relationship between these factors, we have created the survey linked below. At the end of the survey, you will receive a link to receive credit for taking our survey.

Appendix B – Questionnaire recruitment document

DALHOUSIE UNIVERSITY

Working or wandering? A survey of factors that lead to productive remote work environments. Pt 2.

Introduction

You are invited to take part in a research study being conducted by Dr. Colin Conrad, assistant professor at the School of Information Management at Dalhousie University.

Purpose and Outline of the Research Study

The purpose of this study is to investigate factors that influence productivity when working remotely. The rapid shift to remote-work associated with COVID-19 imposed new and unique challenges, including isolation and a lack of peer presence, distracting home-office environments and the adoption of unfamiliar remote collaboration platforms. Understanding these challenges, and the sociotechnical factors that can potentially mediate the impact of these challenges on effective remote work productivity, is necessary if the shift to remote work post-COVID is to become permanent.

To better understand how these factors impact remote-work productivity, we aim to survey approximately 200 people who meet the following criteria:

- Over 18 years of age
- Proficient in English
- Are residents of the United Kingdom

- Work full-time
- Conduct at least some of their work activities remotely

What you will be asked to do

If you choose to participate in this research, you will be asked to answer 22 questions in an anonymous online survey. Questions concern aspects related to your experience during the period you work remotely: your proficiency with work-from-home technologes; your sense of social presence while working remotely; fatigue which you might have experienced; your productivity.

The survey should take less than 5 minutes to complete, but you are given up to 30 minutes if needed.

How your information will be protected

Your participation in this study is entirely voluntary. You do not have to answer questions that you do not want to, and you are welcome to stop the survey at any time if you no longer want to participate. All you need to do is close your browser tab or window. We will not include any incomplete surveys in our analyses. If you do complete your survey and you change your mind later, we will not be able to remove the information you provided as we will not know which response is yours.

Your responses to the survey will be anonymous. This means that there are no questions in the survey that ask for identifying details such as your name or email address. All anonymous responses will be saved by Dr. Conrad on a secure server at Dalhousie University. The data will be analyzed by members of the research team led by Dr. Conrad, and results from this survey may be shared with students at Dalhousie University for teaching purposes. We will describe and share the general findings on scientific conferences or journals.

We have taken care to limit the amount of sensitive and intimate data collected from this survey. The risks associated with this study are no greater than those you encounter in your everyday life.

Benefits, Possible Risks and Discomforts

There will be no direct benefit to you in participating in this research beyond the compensation of £0.75. The research, however, might contribute to new knowledge related to ways of structuring the work environment of people working remotely in order to maximize productivity and satisfaction with the job. If you would like to see a summary of the results, please visit Dr. Conrad's website after November 2022: https://colinconrad.com/study-results/

You should discuss any questions you have about this study with Dr. Colin Conrad. Please ask as many questions as you like at any time. Our contact information is provided below:

Dr. Colin Conrad: colin.conrad@dal.ca

If you have any ethical concerns about your participation in this research, you may contact Research Ethics, Dalhousie University at (902) 494-3423, or email ethics@dal.ca (and reference REB file # 2021-5858)."

If you agree to complete the survey, please follow the link here/click continue.

Appendix C – Debriefing form

Note: Following the survey, the text below will be presented.

Study Title:	Working or wandering? A survey of factors that lead to productive remote work environments
Principal Investigator:	Dr. Colin Conrad
Collaborator:	Dr. Frederike Marie Oschinsky Dr. Michael Klesel
Research Assistants:	Kydra Mayhew Kiera O'Neil Francesco Usai Juan Chaves Baquero
Contact information:	Colin.Conrad@dal.ca

Thank you for taking part in our study. Your participation helps inform our understanding of which factors influence remote-work productivity. The rapid shift to remote-work associated with COVID-19 imposed new and unique challenges, including isolation and a lack of peer presence, distracting home-office environments and the adoption of unfamiliar remote collaboration platforms. Understanding these challenges, and the sociotechnical factors that can potentially mediate the impact of these challenges on effective remote work

productivity, is necessary if the shift to remote work post-COVID is to become permanent. This questionnaire helps us understand the role that these factors may play, and we hope that our results will help people and companies that are significantly engaged with remote-work to make informed decisions when structuring their remote-work environment.

We thank you for your participation!

Appendix D – Questionnaire instrument

This questionnaire instrument uses a 5-point Likert scale as its preceding one by Conrad et al. (forthcoming).

MEASUREMENT	ITEM
BLOCK 1 - THE FOLLOWING QUESTIONS CONCERN THE TOOL THAT YOU USED MOST OFTEN TO CONDUCT ONLINE MEETINGS IN THE PAST 6 MONTHS. PLEASE ANSWER THE FOLLOWING QUESTIONS WHILE IMAGINING THAT TOOL.	
COLLABORATION TOOL	Q22_1. Which tool do you use most often for online meetings? Response option: Single choice (Zoom; MS Teams; Google Meet; Cisco WebEx; Skype; Other).
MEETING HOURS	Q5. In an average work week, what percentage of time do you spend in online meetings?[5] Response option: Percentage slider.
FACILITATING CONDITIONS (VENKATESH ET AL, 2003)	Q23_1. I have the resources necessary to use the online meeting tool.
	Q23_2. I have the knowledge necessary to use the online meeting tool.
	Q23_3. The video conference tool is compatible with the online meeting tool.
	Q23_4. I can get help from others when I have difficulties using the online meeting tool.
SOCIAL PRESENCE – MEETING TOOLS SECTION	Q23_5. There is a sense of human contact in the online meeting tool.
	Q23_6. There is a sense of personalness in the online meeting tool.

[5] Conrad et al. (forthcoming) implemented the following item to determine a meetings measurement: “How many digital meetings do you have on an average day?”. A fellow reviewer suggested implementing a Likert-scale to measure the frequency instead of an absolute number of meetings, due to the different backgrounds of the respondents and how their interpretation of meeting could differ (i.e., disparities in duration between one SCRUM meeting versus one seminar).

(GEFEN & STRAUB, 2004; BERGEFURT ET AL., 2021)	Q23_7. There is a sense of sociability in the online meeting tool.
	Q23_8. There is a sense of human warmth in the online meeting tool.
	Q23_9. There is a sense of human sensitivity in the online meeting tool.
	Response option for questions Q23_1 to Q23_9: 5-point Likert scale matrix (Strongly agree; agree; neither agree nor disagree; disagree; strongly disagree).
BLOCK 2 - FOR THE FOLLOWING QUESTIONS CONSIDER THE TIMES YOU PARTICIPATED ONLINE MEETINGS. PLEASE ANSWER THE FOLLOWING QUESTIONS WHILE IMAGINING A TYPICAL ONLINE MEETING AT YOUR WORKPLACE IN THE PAST 6 MONTHS.	
GENERAL ONLINE CALL EXPERIENCED FATIGUE (FAUVILLE ET AL., 2021; LU ET AL., 2016)	Q24_1. How tired do you feel after video conferencing?
	Q24_2. How exhausted do you feel after video conferencing?
	Q24_3. How mentally drained do you feel after video conferencing?
	Response option for questions Q24_1 to Q23_3: 5-point Likert scale matrix (A great deal; a lot; a moderate; a little; not at all).
SOCIAL PRESENCE – COLLEAGUES' SECTION (LU ET AL., 2016)	Q25_1. I can make sense of the attitude of my coworkers by interacting with them when video conferencing.
	Q25_2. I can imagine how my coworkers look by interacting with them when video conferencing.
	Q25_3. There is a sense of human touch to communicate with coworkers when video conferencing.
	Q24_4. Communicating when video conferencing is warm.
	Response option for questions Q25_1 to Q24_4: 5-point Likert scale matrix (Strongly agree; agree; neither agree nor disagree; disagree; strongly disagree).
BLOCK 3 - THE FOLLOWING QUESTIONS CONCERN YOUR OVERALL PERFORMANCE AT YOUR JOB. PLEASE ANSWER THE FOLLOWING	

QUESTIONS CONCERNING YOUR JOB PERFORMANCE OVER THE PAST 6 MONTHS	
PERCEIVED WORK PERFORMANCE (WILLIAMS, ANDERSON, 1991)	Q26_1. I adequately completed my assigned duties.
	Q26_2. I fulfilled responsibilities specific in my job description.
	Q26_3. I performed tasks that are expected of me.
	Q26_4. I met formal performance requirements of my job.
	Response option for questions Q26_1 to Q26_4: 5-point Likert scale matrix (Strongly agree; agree; neither agree nor disagree; disagree; strongly disagree).