Jurnal Organisasi dan Manajemen
Journal Homepage : http://jurnal.ut.ac.id/index.php/JOM

Does Work from Home Enhance Individual Productivity? A Predictive Analytics Using Machine Learning Towards Well-Being, Work -Life Balance, Technological and Organizational Support

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Article Info

Keywords:
Working from home;
Well-being;
Productivity;
Work life balance;
Technological support

JEL Classification:
C45, I31, J24, M54

DOI:
10.33830/jom.v21i2.9833.2025

Article History
Received: August 11, 2024
Accepted: October 21, 2025
Publish: December 22, 2025

Abstract

Purpose – This study aims to identify the main predictors of employee productivity among individuals who work from home. The research explores how well-being, work-life balance, focus, and organizational as well as technological support influence employees' ability to perform effectively in a remote work setting.

Methodology – Data were collected from 461 employees across various organizations. The study applied predictive analytics through several machine learning methods, including random forest and K-nearest neighbor algorithms, to test models related to individual productivity, well-being, work-life balance, organizational, and technological support.

Findings – The results show that employee well-being, satisfaction, and work-life balance are the strongest predictors of productivity during work from home. The second strongest predictor is the ability to stay focused, followed by the ability to complete tasks on time and satisfaction with work-life balance. Technological support was found to be a necessary precondition to enhance productivity.

Originality – This study contributes to the growing literature on remote work by integrating individual, organizational, and technological factors into a comprehensive predictive model that explains employee productivity in work-from-home settings.

1. Introduction

The shift towards work-from-home (WFH) has been extensively documented in recent years, particularly following the COVID-19 pandemic. Various studies have also explored the impact of personal, organizational, and technological factors on employee productivity while WFH. However, inconsistencies and gaps in the literature persist, highlighting the need for further investigation into the predictors of employee productivity in remote work settings, especially in Indonesia.

The EY Work Reimagined Survey reported that 40% of companies in Indonesia supported temporary remote work arrangements, particularly within digital banking, startup, and IT sectors

(EY, 2023).While remote and hybrid work models are increasingly adopted across industries, these arrangements also present several challenges. Telework environments tend to reduce spontaneous social interactions and increase feelings of isolation, while employees often struggle with time management due to digital overload and overlapping personal demands. Moreover, remote work can blur the boundaries between professional and personal life, complicating individuals' efforts to maintain a healthy work–life balance (Figueiredo & Margaça, 2025). Conversely, a significant portion of employees (57%) preferred a hybrid work model, citing benefits such as cost savings, reduced stress, improved work–life balance, and increased efficiency. In addition, Putri et al. (2021) found that work-from-home arrangements significantly improve employees' work–life balance in Indonesia, particularly among female workers. These findings suggest that flexible work arrangements, including hybrid and remote models, can enhance both productivity and employee well-being by allowing better management of work and personal life responsibilities.

Suhariadi et al. (2023) conducted research at a top-ranking public university in Indonesia, assessed how well individuals adapted to WFH using a productivity measurement framework. With 556 respondents, some data were analyzed using AMOS to explore factors such as job crafting, work stress, organizational support, boredom, work engagement, productivity, and mental health. The structural equation modeling (SEM) confirmed that the productive behavior of teaching staff was essential for the success of WFH, validating the indicators used to measure productivity and highlighting the ecological implications of this new work paradigm, based on this research, work stress, job crafting and work engagement as part of individual and organizational factor predicted productive behavior.

Another individual factor which predicted productivity was work life balance. Prior research had presented conflict evidence regarding the relationship between work-life balance (WLB) and productivity in work from home setting. Another individual factor which predicted productivity was work life balance. Prior research had presented conflict evidence regarding the relationship between work-life balance (WLB) and productivity in work from home setting. Some studies suggested that WFH enhanced WLB by reducing commuting time and providing flexible work arrangements, which in turned, it improved productivity (Grant et al., 2019).

Moderates telework increases job satisfaction, while excessive telework without proper boundaries intensifies work family conflict (Shin, 2025). Additionally, value congruence and meaningful telework experiences significantly strengthen employee well-being and job satisfaction within sustainable HR systems (Kautish et al., 2025). On the other hand, WFH can disrupt work–life balance due to blurred boundaries between professional and personal life, increasing stress and potentially reducing productivity. Structured boundary management strategies, supported by technology, are essential to help employees maintain WLB and sustain productivity in remote work settings (Shirmohammadi et al., 2022).

This discrepancy indicated the need for a more comprehensive analysis of WLB in WFH setting. Ongoing evaluation of the impact of WFH on productivity and employee well-being is crucial for organizations aiming to optimize their work strategies in the long term, suggesting that WFH is not merely a temporary solution but is likely to become an integral part of the future work landscape globally and in Indonesia (George et al., 2022). Concerning organizational factors, previous studies have highlighted that organizational support including managerial guidance, team coordination, and leadership is linked to higher productivity in a WFH environment. Specifically, Aboelmaged et al. (2012), as cited in Rimadias (2020) empirically confirmed that management support, trust, leadership style, and organizational commitment significantly enhance teleworkers' perceived productivity, indicating that organizational factors play a crucial role in supporting employee performance during remote work.

However, inconsistent findings remain regarding its role in mitigating WFH challenges. While some studies highlight the positive impact of strong leadership and clear communication on employee motivation and efficiency, others suggest that WFH limits effective supervision and collaboration, leading to decreased engagement and productivity (Dick et al., 2020). This inconsistency calls for further empirical research on how different dimensions of organizational support influence productivity during WFH. Furthermore, interpersonal relationships among coworkers play a critical role in enhancing remote workers' well-being, work–life balance, and job satisfaction (Buonomo et al., 2024). These findings suggest that organizational support should not only focus on managerial guidance but also foster positive coworker interactions to sustain productivity and overall well-being in remote work settings.

Other predictors of productivity come from technological factors, including technological infrastructure, which is often cited as a crucial determinant of WFH productivity. Several studies suggest that access to advanced technology, integrated communication tools, and strong IT support increases productivity (Dick et al., 2020). However, recent research shows that technology can also become a source of technostress. For instance, technology overload and constant ICT demands during teleworking can increase anxiety, disrupt workflow, and reduce employee performance (Fernandez-Fernandez et al., 2025). Similarly, a systematic review concluded that remote workers frequently experience technostress due to digital interruptions, excessive connectivity, and continuous notifications, all of which hinder concentration and productivity (Bahamondes-Rosado et al., 2023).

Recent empirical evidence showed that well-being does not always exert a direct influence on job performance; instead, its effect may occur indirectly through work engagement. However, some studies had quantitatively assessed the relative importance of well-being in comparison to technological and organizational factors. Furthermore, the ability to maintain focus and complete tasks on time also had been identified as a major challenge in remote work (Diab-Bahman & Al-Enzi, 2020; Dick et al., 2020). The interplay between well-being, ability to maintain focus and complete tasks on time, work-life balance, and job performance remained an underexplored area that this study sought to address.

Despite various studies examining the relationships among personal, organizational, and technological factors associated with productivity, there remains a notable lack of comprehensive predictive models. Most prior research has relied on qualitative or descriptive approaches to assess remote work productivity (Dick et al., 2020; Soroui, 2021), limiting the ability to identify key determinants in a systematic and data-driven manner. In addition, earlier studies generally conceptualized work-from-home (WFH) as a planned and voluntary work arrangement implemented prior to the COVID-19 pandemic, rather than the large-scale and often mandatory shift observed during the pandemic (Kellerman, 2025).

However, the COVID-19 pandemic introduced a fundamentally different paradigm in which employees were compelled to work from home without prior preparation, creating new challenges related to work design, technological support, and productivity (Wang et al., 2021). Furthermore, many organizations have continued remote or hybrid work arrangements post-COVID without fully assessing the factors that influence employee productivity under this new context (Burdett et al., 2024). Therefore, this study seeks to address these gaps by analyzing the determinants of productivity in post-COVID WFH arrangements.

The mixed evidence on work–life balance (WLB) and technological support factors highlights the need for more detailed, data-driven investigations using machine learning approaches to identify key determinants of work-from-home (WFH) productivity. Building on recent advances in human resource analytics, this study extends previous research by implementing machine learning algorithms Random Forest, K-Nearest Neighbors, and boosting to predict employee productivity based on well-being, the ability to maintain focus and complete tasks on time, work–life balance, technological support, and organizational support. Consistent with the findings of Wu and Fukui (2025), machine learning approaches are particularly well suited for capturing complex, non-linear relationships and interactions among multiple employee-related predictors, thereby providing a more robust and evidence-based understanding of productivity determinants than traditional qualitative or descriptive methods.

The findings of this study aim to bridge existing gaps by offering empirical insights into the determinants of WFH productivity. By applying predictive analytics, this research provides a novel perspective on how personal, organizational, and technological factors interact to shape employee performance in a remote work setting. The study's contribution lies in its ability to go beyond descriptive analysis by offering a predictive model that can guide organizations in optimizing WFH policies to increase productivity.

1.1. Remote Work Productivity

Based on previous studies, the conceptual framework of this study was established on the foundation provided by Aboelmaged et al. (2012), as cited in Rimadias (2020). Using this framework, the study examined perceived productivity among remote employees, particularly teleworkers in Egypt. Rimadias (2020) empirically confirmed that demographic factors (such as age, gender, education, and family support), individual factors (including attitude toward work-life balance, self-regulation, and personality traits), organizational factors (such as management support, leadership style, and trust), and technological factors (including access to ICT and collaborative tools) significantly contributed to teleworkers' perceived productivity during the COVID-19 pandemic. These findings indicate that employee productivity is shaped by a combination of personal, organizational, and technological determinants, providing a robust foundation for examining productivity in remote work environments.

1.2. Demographic Factors on Productivity

Demographic factors referred to the characteristics of employee, including age, gender, educational background, job type, marital status, and family support systems such as dual-income households and caregiver assistance. Wardani et al. (2020) explained that demographic factors refer to the characteristics of employees, including age, gender, educational background, job type, marital status, and family support systems, such as dual-income households and caregiver assistance. Individual factors, as described by Diener et al. (1999), as cited in Kassim et al. (2025) represent internal attributes of employees, including work-life balance attitude, self-regulation, self-discipline, and personality traits, all which influence productivity. Diener et al. (1999), as cited in Yunxiao & Ping (2025) highlighted the significance of well-being, emphasizing that employees' subjective perception of their life satisfaction and affective experiences is a key determinant of their overall performance. Integrating these findings suggests that both demographic and individual factors, mediated by employees' subjective well-being and work-life balance, play a crucial role in shaping perceived productivity (Kassim et al., 2025; Wardani et al., 2020; Yunxiao & Ping, 2025).

1.3. Technology's Role in Boosting Productivity

The role of ICT infrastructure, remote communication tools, and digital support systems was crucial in facilitating productivity. Some studies supported the notion that access to proper technology enhances remote work productivity (Soroui, 2021), while others reported that intensive ICT use in work-from-home arrangements can generate technostress and techno-invasion, leading to blurred work–life boundaries and reduced employee well-being (Anakpo et al., 2023; Molino et al., 2020).

Leadership, communication, job design, workload management, and overall management support also playe a crucial role in employee productivity (Ghosh & Huang, 2020). Effective leadership and supportive management could enhance employee engagement and productivity in a remote working setting.

1.4. Individual Factors: Well-Being, Work-Life Balance, and Self-Discipline

Well-being is defined as an evaluation of life experiences consisting of cognitive and affective dimensions (Diener et al., 1999, as cited in Yunxiao & Ping, 2025). Individuals experience higher subjective well-being when they feel pleasant emotions, happiness, and life satisfaction (Wardani et al., 2020). Moreover, remote working has been shown to influence multiple dimensions of workplace well-being, including affective, cognitive, social, and psychosomatic aspects, which collectively affect productivity (Charalampous et al., 2025). Psychosocial and ergonomic factors further play a critical role in sustaining well-being and performance among remote workers (Oakman et al., 2020).

Work-life balance (WLB) is defined as a condition in which individuals experience satisfaction in both work and family roles with minimal conflict and is considered to involve equal time, satisfaction, and involvement between work and non-work domains indicating high feasibility (Fisher et al., 2009, as cited in Kassim et al., 2025). However, the benefits of flexibility are not automatic. Intensive reliance on digital technologies in remote work may also generate technostress and blur work–life boundaries, potentially undermining employees' well-being and work–life balance if not properly managed (Molino et al., 2020). In this regard, individual self-regulation and organizational support play a crucial role in determining whether work-from-home arrangements improve or impair work–life balance and productivity outcomes.

1.5. Productivity in the Work-From-Home (WFH)

Diab-Bahman and Al-Enzi (2020) examined the employees' perceptions in Kuwait by comparing old working conditions (OWC) to the current working conditions (CWC) during working- from- home arrangements. The results indicated that employees perceived greater flexibility and reported completing approximately 80% of their workload under CWC. The findings of the present study also identified changes in employees' expectations regarding work arrangements.

These result may contrast with findings from prior studies sugesting that physical activity associated with commuting can have positive implications for employees' functioning at work. For example, recent evidence from Finnish employed adults shows that both active commuting, such as walking or cycling, and leisure-time physical activity are positively associated with perceived cognitive functioning and work ability (Jussila et al., 2025). Although employees working from home no longer engage in daily walking or cycling as part of their commute, the core insight from this study highlights the continued importance of maintaining regular physical activity. Therefore, similar health-promoting routines can be intentionally integrated into WFH contexts to support cognitive performance and overall productivity.

DeFilippis et al. (2020) analyzed employee work patterns before and during mandatory work-from-home (WFH) arrangements implemented during the COVID-19 pandemic. Using large-scale digital trace data from more than three million workers across 21,000 firms worldwide, the study found that total working hours increased substantially during WFH, accompanied by significant rises in meeting hours and digital communication activities. Despite these longer working hours, overall work effectiveness declined, as employees faced higher coordination and communication costs. These findings suggest that although employees spent more time working while at home, their productivity did not increase proportionally, highlighting the challenges organizations face when designing effective WFH policies.

In addition to individual factors, organizational factors are also significantly related to employee productivity. Organizational factors are defined as variables associated with an organization's structure and systems, including leadership, coordination, policies, workload, job design, and workplace communication. This study examines how perceived productivity among Egyptian teleworkers is related to individual, organizational, and technological factors. Specifically, it investigates the roles of demographic characteristics, job satisfaction, work attitudes, IT training, IT infrastructure, management support, job security, organizational commitment, and work flexibility. The results highlight the crucial role of individual and organizational factors in shaping perceived productivity among Egyptian teleworkers. However, perceived productivity was not significantly influenced by technological factors, work attitudes, or demographic characteristics.

According to Aboelmaged et al. (2012), as cited in Rimadias (2020) several forms of management support including good leadership, effective communication, and information sharing, as well as active support from managers through providing resources, motivating employees, and defining related policies are important in promoting employee productivity. Rimadias (2020) confirmed this finding empirically in the context of teleworkers during the COVID-19 pandemic in Indonesia, showing that management support, IT infrastructure, positive attitude toward teleworking, and organizational commitment significantly increased perceived productivity. Trust and management style were also identified as key organizational factors affecting worker effectiveness, whereas overworking and a lack of time for family and non-work-related activities (personal factors) were found to weaken e-workers' productivity.

1.6. Integration of Individual, Technological, and Organizational Dimensions

Technological support is another important variable related to employee productivity. According to Aboelmaged et al. (2012), as cited in Rimadias (2020) technological support is defined as greater access to the internet and electronic communication, along with more training in the use of ICT. Several studies highlight the role of technological support in enhancing employee productivity. Rimadias (2020) empirically confirmed that access to technological resources, collaborative tools, and organizational support significantly increased perceived productivity among teleworkers during the COVID-19 pandemic. Furthermore, remote reporting and the effective use of ICT were found to leverage technological advantages, thereby further improving productivity.

Similarly, the availability of communication tools and IT support improves WFH performance (Dick et al., 2020), while appropriate technological infrastructure can moderate job stress and work–family conflict, thereby supporting employee effectiveness (Fedorowicz et al., 2022). At the same time, excessive digital demands may lead to technostress, disrupting workflow and reducing productivity (Bahamondes-Rosado et al., 2023). Collectively, these studies underscore that a combination of well-designed technological infrastructure, collaborative tools, and organizational support is essential for achieving productive and engaged remote work.

Technological support is a crucial determinant of employee productivity in remote and hybrid work settings. Recent research highlights that the mere presence of technology is not sufficient; rather, its effectiveness depends on the existence of mechanisms that reduce technostress. Hang et al. (2022) found that technostress inhibitors—such as technical support, user involvement, and adequate training—moderate the negative effects of techno-stressors on employees' well-being, thereby sustaining performance in highly digitalized work environments. In addition, the implementation of comprehensive electronic human resource management (e-HRM) systems, encompassing e-recruitment, e-training, e-performance appraisal, and digital communication tools, has been shown to enhance employee productivity when supported by appropriate organizational policies and infrastructure (Muchsinati et al., 2024). Taken together, these findings suggest that a combination of accessible technological resources and organizational support mechanisms is essential for maximizing productivity in work-from-home arrangements.

Moreover, Soroui (2021) found that work–life balance and remote working outcomes were significantly enhanced by organizational technological support. The greater the availability of IT infrastructure to support work-from-home arrangements, the higher the level of employee productivity.

Kitagawa et al. (2021) analyzed how work-from-home (WFH) arrangements affected worker productivity during the COVID-19 pandemic. Using survey data from four manufacturing companies in Japan, the study found that average WFH productivity improved by more than 10% compared to the early stages of the pandemic. However, WFH productivity remained approximately 20% lower than in traditional office settings. The study also identified key factors influencing WFH effectiveness, including the home work environment, task characteristics, and technological support, with higher levels of technological support associated with higher productivity.

Martin et al. (2022) examined the relationship between the use of digital collaboration and communication tools—such as groupware, workflow systems, instant messaging, and web conferencing—and changes in remote workers' subjective well-being (job satisfaction and job stress) and productivity before and during the first COVID-19 lockdown in spring 2020. The results demonstrated that the use of these digital tools significantly influenced workers' job satisfaction, job stress, and productivity during the lockdown. Furthermore, employees who regularly used all four tools prior to the lockdown were better protected from most negative effects, except for increased job stress. These findings have important theoretical and managerial implications for the future of digitally transformed remote work.

Fedorowicz et al. (2022) found that the adoption of innovative information and communication technologies (ICTs), such as collaboration software and digital communication tools, significantly improved employee productivity during work-from-home (WFH) arrangements. The study also indicated that the availability and effective use of technology helped reduce work stress and work–family conflict, particularly among managerial employees. These findings underscore the importance of investing in technological infrastructure to support employee performance in remote work environments.

This study follows a similar approach by examining how these factors influence the productivity of remote employees. In addition, theories of well-being (Diener et al., 1999, as cited in Yunxiao & Ping, 2025; Wardani et al., 2020), work–life balance (Fisher et al., 2009), and technological support (Soroui, 2021) provide significant theoretical foundations. These concepts emphasize that individual well-being, work-life balance, and adequate technological infrastructure play crucial roles in enhancing remote employee productivity. Furthermore, organizational support theories (Ghosh & Huang, 2020) highlight the importance of leadership, management support, and communication in fostering engagement and productivity among remote workers.

In contrast, excessive or unstructured use of technology can blur the boundaries between work and personal life, potentially undermining employees' work–life balance and overall well-being (Shirmohammadi et al., 2022). Their study identifies three main strategies that remote and mobile workers use to manage these boundaries: physical boundaries, temporal boundaries, and psychological boundaries. Moreover, Shirmohammadi et al. (2022) highlight how technology, when integrated effectively with work practices, can support employees by leveraging five key affordances: mobility, connectedness, interoperability, identifiability, and personalization. These findings suggest that while technology has the potential to enhance productivity and flexibility, it must be accompanied by deliberate strategies to maintain healthy work–life boundaries.

Ghosh & Huang (2020) provided evidence showing that more capable managers are associated with higher employee productivity. On the other hand, excessive digital demands and technostress can disrupt workflow and reduce productivity (Bahamondes-Rosado et al., 2023). Together, these findings highlight that while organizational and technological resources are critical for sustaining engagement and performance, they must be managed carefully to prevent negative effects on remote workers' productivity.

In summary, previous study address the important of individual factors namely well-being, work life balance, self -discipline as the important factors that related to perceived productivity of remote employees. Further technological support is very important factor during working from home, although technostress issues arise, with proper care and ensuring employee well-being through technological support led to promising result in enhancing productivity of employee who work remotely. Last, organizational factors including leadership, management support, good communication and coordination were among prominent variables that related to perceived productivity.

The hypotheses in this research were built based on a combination of expert opinions and prior empirical studies, emphasizing individual well-being, ability to focus and completing job, work-life balance, technological support, and organizational factors as key determinants of employee productivity during hybrid and work from home.

H_1: Individual Factors as Predictors of Employee Productivity
The first hypothesis examined individual factors, namely employee well-being, ability to focus, task completion ability, and work–life balance, positively predict employee productivity during WFH.

H_2: Organizational Factors as Predictors of Employee Productivity
The second hypothesis proposes that organizational factors influence employee productivity. Specifically, coordination with coworkers, collaboration and communication, and perceptions of leadership and managerial support are expected to positively predict employee productivity during WFH.

H_3: Technological Factors as Predictors of Employee Productivity
The third hypothesis focused on technological factors that predict employee productivity. Specifically, system reliability, ease of use, and access to technical support are expected to positively predict employee productivity during WFH.

2. Research Methods

In the present study, non-probability sampling was employed as the data collection technique, specifically convenience sampling, whereby members of the target population were selected based on their accessibility, availability, and willingness to participate. Convenience sampling is a commonly used non-probability method in quantitative research because it enables researchers to efficiently collect data from participants who are easy to reach within practical constraints of time and resources (Memon et al., 2025). Although convenience sampling limits the generalizability of findings due to potential sampling bias, it is frequently applied in survey-based research when probabilistic sampling methods are impractical (Rahman, 2023).

The population in this study consisted of employees who worked from home (WFH) in Jakarta. According to Hasibuan (2020), approximately 679,215 employees were working from home in Jakarta. Given the large population size, convenience sampling was considered appropriate for this study, and the sample size was determined using Slovin's formula based on practical research considerations (Adeoye, 2023).

Slovin Formula:

$$n = \frac{N}{1+N} e2$$

$$n = \frac{679.215}{1+679.215\ (0.05)2}$$

$$n = 251$$

Description:
n = sample size
N = population
e = margin of error

It represented the required sample size, N was the population size, and e was the acceptable margin of error. Based on the calculation using the Slovin formula, the required sample size for this study was determined to be 251. A total of 461 samples of respondents participated in this survey.

The study measured several key variables related to employee experiences during WFH. Employee productivity was assessed through self-perceived productivity. Individual predictors included employee well-being, representing overall life satisfaction and happiness; the ability to focus while working outside a corporate environment; the ability to complete tasks on time; and perceptions of work–life balance in terms of satisfaction, involvement, and allocation of time between work and non-work activities. Organizational factors captured employees' views on coworker coordination and leadership or management support during WFH. Meanwhile, technological factors reflected employees' perceptions of the effectiveness of technology, infrastructure, and tools in supporting productivity.

Based on the sample size this study which were involved 461 respondents comprising 43.8% male and 56.2% female employees, with the majority earning between 5-10 million IDR (48.7%). Most participants were married (61.8%), and 52.1% held a bachelor's degree. A predictive analysis approach was used in this research with machine learning algorithms, including Boosting Regression, K-Nearest Neighbors Regression, and Random Forest Regression with Random Forest as the primary reference. Some data were split into training (258), testing (138), and validation (65) sets. They were analyzed using JASP software. Seven predictors of perceived productivity were examined: four individual variables (e.g., employee well-being and work-life balance), two organizational factors (e.g., coordination and management support during WFH), and one technological support variable. Measurement scales were adapted from previous research (Aboelmaged et al., 2012; Diener et al., 1999; Fisher et al., 2009).

This research used predictive analysis with machine learning to examine the relationship between employee productivity and various predictors during remote working. Three supervised learning algorithms were selected: Random Forest, K-Nearest Neighbors (K-NN), and boosting. The rationale for choosing these algorithms was based on their strengths in handling structured data, their ability to capture complex interactions between variables, and their suitability for predictive analytics in social science research.

This study employed several machine learning algorithms to classify and predict employee productivity. Random Forest was selected as the primary method because of its robustness in handling non-linearity, its ability to model interactions between predictors, and its ensemble mechanism that reduces overfitting while providing clear measures of variable importance. K-Nearest Neighbors (K-NN) was used for comparison due to its simplicity and effectiveness in situations where the data distribution is unknown, allowing classification based on the similarity of respondents. Boosting methods were also included to evaluate the performance of a strong sequential ensemble model, as boosting improves predictions by correcting previous errors and is effective in reducing both bias and variance.

3. Results and Discussions

Individual well-being and work-life balance play a crucial role in influencing productivity. Diener et al. (1999) subjective well-being theory, as cited in Yunxiao & Ping (2025) individuals with higher levels of life satisfaction and positive affect tend to demonstrate enhanced productivity. Similarly, Guest (2002) work–life balance and spillover perspective, as cited in Vhutali (2025) overflow theory suggests that work-life balance enhances productivity through positive spillover between work and non-work domains. Together, these studies reinforce that well-being and work-life balance are key predictors of productivity, while context and population characteristics may influence the observed effects.

Furthermore, this study also confirms the relevance of Herzberg's two-factor theory, which suggests that technological and organizational support play an important role in enhancing employee productivity. However, the findings indicate that individual factors have a stronger influence than technological and organizational factors in predicting productivity during WFH. This provides a new perspective for future research to further examine the role of individual factors in productivity prediction models.

Table 1 indicates that well-being, the ability to focus while working from home, the ability to complete assigned work, work–life balance, technological support, and organizational support significantly predict productivity during remote work. All three prediction algorithms using machine learning demonstrate high validation accuracy and test accuracy, with values greater than 0.7.

Table 1. The Comparison of Random Forest, K-Nearest Neighbors and Boosting Algorism

Algorism	Validation Accuracy	Accuracy Test
Random Forest	0.815	0.761
K-Nearest Neighbors	0.846	0.717
Boosting	0.785	0.768

Source: processed data

From a methodological perspective, the use of three machine learning algorithms (Random Forest, K-Nearest Neighbors (K-NN), and boosting) in this study provided insight into predictive validity of productivity factors. The finding showed that Random Forest with 20 trees provided the highest validation accuracy (81.5%), it suggested that the decision of tree-based approach could be a reliable tool in predicting employee productivity based on individual, technological, and organizational factors.

Table 2. Random Forest Classification

	Predictor per				Validation	Test	OOB
Tress	**Split**	**n(Train)**	**n(Validation)**	**n(Test)**	**Accuracy**	**Accuracy**	**Accuracy**
20	2	258	65	138	0.815	0.716	0.807

Source: processed data

Further, the table also explained the results which were based on the importance of variables. It focused on technological support as predictors of employee productivity, followed by the organizational support and good coordination within team member as another organizational variable in predicting employee productivity during working from home. The results of this research also highlighted that individual factors were the first before the other factors namely, chronological and organizational factors in predicting employee productivity during working from home.

Table 3. The Importance Variables (random forest)

		Total increase in node purity
Well-being	0.069	0.052
Focus	0.018	0.045
Ontime	0.071	0.027
Sat	0.019	0.014
Tech	0.006	0.003
Organ	0.004	-0.004
Coord	0.007	-0.005

Table 4. the results of K-Nearest Neighbors using nine neighbors showed 84.6 % the accuracy of validation. In which well-being, being able to focus on work during WFH, ability to complete the work based on the deadline, work-life balance, technological support as well as organizational support significantly predicted productivity during remote working.

Tabel 4. K-Nearest Neighbors, Confusion Matrix and Boosting Classification Results

K- Nearest Neighbors Classification							
Nearest neighbors	**Weights**	**Distance**	**n(Train)**	**n (Validation)**	**n(Test)**	**Validation Accuracy**	**Test Accuracy**
9	rectangular	Eucliden	258	65	138	0.846	0.717
Confusion Matrix							
						Predict	
						0	1
Observed					0	32	29
Boosting Classification							
					1	10	67
				65	138	0.785	0.768

Source: processed data

The confusion matrix results indicate that the model effectively classified most employees into productive and non-productive categories while working from home. A total of 69.7% of respondents were identified as productive, while 30.3% fell into the non-productive group. The model correctly classified 67 productive employees, although 10 were misclassified as non-productive. For the non-productive category, 32 employees were accurately predicted, whereas 29 were incorrectly labeled as productive. These results suggest that the model performs reasonably well, but there is still room for improvement, particularly in reducing false positives.

The Boosting Classification model produced strong predictive performance, with a validation accuracy of 76.8% based on 65 validation samples and a comparable test accuracy from 138 test samples. These results indicate that the model generalizes well and can classify employee productivity with a relatively high level of accuracy. The analysis also highlights those key factors such as the ability to complete work within deadlines, overall well-being, work-life balance, ability to focus during WFH, organizational support, and technological support play a significant role in predicting productivity during remote work. This reinforces the importance of both individual and contextual elements in shaping employee outcomes while working from home.

Table 5. explained the results which based on relative influence of boasting predictive analysis. It showed similar findings with random forest analysis in term of the prominent individual factors which predicted employee productivity during WFH. Both algorisms highlighted the important role of employee well-being in predicting productivity. However, the result was slightly different in term of technological support and organizational support in predicting employee productivity, in which the result of random forest analysis indicated that technological support came before the organizational support in predicting employee productivity during WFH.

Tabel 5. Relative Influence

	Relative Influence
Ontime	31.684
Well-being	31.306
Sat	22.522
Focus	8.573
Organ	3.985
Coord	1.930
Tech	0.000

Source: processed data

3.1. Individual Factors as Predictors of Employee Productivity

Based on the results of the analysis, **Hypothesis 1 was supported.** Individual factors significantly predict employee productivity. This finding is evident in the results generated by the Random Forest, K-Nearest Neighbors, and Boosting algorithms, which showed that individual support significantly predicted productivity during remote work. Predictive analysis using machine learning indicated high validation and testing accuracy, both greater than 0.70.

One individual predictor of employee productivity during WFH was work–life balance (WLB). The results confirmed that WLB significantly predicted productivity. The more individuals experienced equal satisfaction, equal time, and equal involvement in work and non-work domains, the more productive they tended to be. Employees perceived working from home as an opportunity to spend more time with their families and enjoy flexible work arrangements. Many employees reported having a happy family life, and some respondents noted having support systems to assist with caregiving duties. However, the findings also indicated no significant difference in WLB and productivity between employees who had caregivers and those who did not. This suggests that maintaining balance between work and personal life is essential to promoting productivity during WFH.

According to spillover theory, work and personal life are not separate entities; individuals must create positive spillovers between work and non-work domains. Positive spillover occurs when flexibility enables individuals to engage effectively in both work and family responsibilities, whereas negative spillover arises when work–family boundaries are rigidly structured in space and time (Guest, 2002, as cited in Vhutali, 2025). Recent empirical evidence supports this notion, showing that effective work-life balance and mental well-being significantly enhance employees' performance, particularly among women in the workplace (Fedorowicz et al., 2022). These findings indicate that work-life balance, mediated by positive spillover between personal and professional domains, plays a crucial role in improving productivity and overall job performance.

To enhance employee productivity, organizations should implement interventions that facilitate positive spillover. Recent empirical evidence demonstrates that work–life balance significantly contributes to employee productivity, particularly when flexible work arrangements are implemented. Flexible schedules, remote work options, and family-friendly policies help employees manage work and non-work roles effectively, which in turn sustains productivity in work-from-home and hybrid work environments (Firdausi & Indiyati, 2024).

3.2. Organizational Factors as Predictors of Employee Productivity

Based on the results of the analysis, **Hypothesis 2 was supported**. Organizational support was identified as a significant predictor of employee productivity, with a mean decrease in accuracy of 0.004. The findings indicate that the availability of organizational support—such as leaders demonstrating concern for employees' issues, facilitating open communication, and ensuring smooth collaboration among team members—predicts higher employee productivity.

These findings are consistent with previous research suggesting that organizational support enhances employee productivity (Ghosh & Huang, 2020). Recent studies in remote and hybrid work environments also emphasize the importance of team cohesion and collaborative behaviors such as open communication, mutual support, shared goals, and trust in contributing to team effectiveness and productivity. For example, comparative research on virtual and in-person project teams shows that structured communication and team-building activities increase trust, collaboration, and overall team productivity (Amewuda et al., 2024). In addition, research on remote team dynamics highlights the challenges of fostering cohesion and collaboration without physical presence, underscoring the need for strong managerial support and deliberate team coordination strategies to sustain productivity in virtual settings (Chinyuku & Qutieshat, 2025). A strong and supportive team environment, in which employees collaborate effectively and managers provide clear expectations and support, is essential for improving coordination and overall productivity in remote work contexts.

3.3. Technological Factors as Predictors of Employee Productivity

Based on the results of the analysis, **Hyphotesis 3 is supported**. Technological support significantly predicted employee productivity during remote work. The validation accuracy and accuracy test both exceed 0.7, indicating a strong predictive relationship. Specifically, the K-Nearest Neighbors (KNN) algorithm, using nine neighbors, achieved an 84.6% validation accuracy, further reinforcing the role of technological support in productivity outcomes. The availability of technology and infrastructure during work-from-home (WFH) arrangements was essential to maintain employee productivity. This study also showed that access to technological support, such as laptops, digital workspaces, and collaboration platforms, enhanced productivity during WFH. These findings align with recent research suggesting that technological support can play a crucial role in maintaining employee well-being and work performance in highly digitalized work environments. Hang et al. (2022) found that technostress inhibitors such as adequate technical support, user involvement in ICT implementation, and training help mitigate the negative effects of technology-related stressors on employees' well-being, which in turn supports sustained performance in remote work settings.

Some respondents in this study reported that technological support, including digital collaboration platforms, significantly improved their ability to work remotely. However, certain tasks remained difficult to execute remotely due to challenges in sharing data and transfering knowledge. Therefore, organizations should consider redesigning jobs, incorporating technological assistance, and implementing accessible data systems to facilitate the efficiency of work processes. Some conflicts demanded employees, and they had to be faced while working from home, technological support could enhance collaboration and promote a more flexible work style, ultimately leading to greater productivity.

These findings also related with Herzberg's Two-Factor Theory, which suggested that lack of technological support could be a source of dissatisfaction. Employees who did not have access to adequate technological tools and infrastructure might experience frustration, disrupting their productivity. Furthermore, technology would not only support work execution but also helped employees feeling connected, reducing feeling of isolation.

The type of technological support required varies across employees. Employees in private and small companies sought basic technological support, such as device availability and internet access, to effectively work from home. Conversely, employees in larger companies generally did not face such issues regarding device availability or internet costs. Instead, they sought advanced technological support, such as new applications and the digitalization of work processes. Notably, digital literacy training proved to be the most in demand form of technological support for this group of employees.

In conclusion, different approaches to technological support were necessary to improve productivity among employee who were from various backgrounds. These findings reinforced Herzberg's Motivation theory, emphasizing that organizations must provide well developed IT system and technological support to ensure employee motivation and optimal performance remote working environment.

3.4. Managerial Implication and Future Direction

The ability to maintain focused is one of the key challenges in work-from-home (WFH) arrangements, as employees often face competing demands and role conflicts while performing tasks remotely. One strategy to maintain focus is through cognitive flexibility, defined as an individual's capacity to adapt thinking, generate alternative solutions, and apply multiple approaches effectively in changing work situations. Recent research demonstrates that the cognitive demands inherent in flexible work arrangements can enhance cognitive flexibility, which in turn improves employees' work engagement and ability to concentrate on tasks (Uhlig et al., 2023). Employees with higher cognitive flexibility are better able to manage interruptions, switch between tasks efficiently, and maintain sustained attention, which supports overall task performance. These findings suggest that fostering cognitive flexibility is critical for sustaining focus and productivity in remote and hybrid work settings.

Therefore, productive WFH requires employees to adjust their expectations regarding the work environment and manage limitations associated with remote work. Mental transitions from office environments to home-based work must be managed effectively to support task completion, even when proper equipment is unavailable. Supporting this argument, well-being during remote work increases when employees experience fewer challenges and positive work characteristics, with self-discipline and workload influencing this relationship (Winkler-Titus et al., 2021). Thus, productive WFH requires both cognitive flexibility and strategic approaches to managing challenges while leveraging the positive aspects of the remote work environment.

One effective approach to achieving work–life balance (WLB) while working from home is through boundary management strategies. Shirmohammadi et al. (2022) highlight that employees can manage work–life boundaries by regulating physical, temporal, and psychological aspects of their work. Their findings indicate that technology plays a critical role in supporting these strategies, enabling individuals to maintain clear separations between work and personal domains. For example, structured digital workspaces, company email accounts, and platform-specific access help employees focus on work-related tasks while minimizing intrusion from personal matters. By integrating technological tools with deliberate boundary management practices, organizations can enhance employees' WLB and overall well-being in remote work settings.

4. Conclusions

In conclusion, this study concludes that employee well-being, work-life balance, focus, and timely task completion are the main predictors of productivity during work from home, with technological support serving as an enabling condition. The research objective is achieved by identifying these key predictors, with individual factors exerting a stronger influence than organizational and technological factors. The findings imply that remote work productivity can be enhanced by prioritizing employee well-being, maintaining work-life balance, and providing adequate organizational and technological support. Accordingly, organizations are encouraged to implement integrated work-from-home policies that emphasize well-being, flexibility, and the effective use of technology. This study is limited by its focus on selected sectors and the exclusive use of machine learning methods; future research should adopt mixed-method approaches, focus on specific sectors, and consider demographic factors to provide more comprehensive insights.

References

Aboelmaged, M. G., Mohamed, S., & Subbaugh, E. (2012). Factors influencing perceived productivity of Egyptian teleworkers: An empirical study. *International Journal of Productivity and Performance Management*, *61*(2), 3–22. https://doi.org/10.1108/13683041211230285

Adeoye, M. A. (2023). Review of sampling techniques for education. *ASEAN Journal for Science Education*, *2*(2), 87–94.

Amewuda, R., Ocansey, T. F., Bag, P. M., & Street, G. (2024). Comparative analysis of communication, team cohesion, flexibility, and productivity in virtual and in-person project management: Evidence from Germany. *Journal of Project Management Practice*, *4*(2), 77–96.

Anakpo, G., Nqwayibana, Z., & Mishi, S. (2023). The impact of work-from-home on employee performance and productivity: A systematic review. *Sustainability*, *15*, Article 4529. https://doi.org/10.3390/su15054529

Bahamondes-Rosado, M. E., Cerdá-Suárez, L. M., Félix, G., Ortiz, D., & Espinosa-Cristia, J. F.

(2023). Technostress at work during the COVID-19 lockdown phase (2020–2021): A systematic review of the literature. *Frontiers in Psychology*, *14*, Article 1173425. https://doi.org/10.3389/fpsyg.2023.1173425

Buonomo, I., Clara, D. V., Martinai, P., Francesco, D., & Paula, B. (2024). Feeling supported as a remote worker: The role of support from leaders and colleagues and job satisfaction in promoting employees' work–life balance. *International Journal of Environmental Research and Public Health*, *21*, Article 770. https://doi.org/10.3390/ijerph21060770

Burdett, A., Etheridge, B., Tang, L., & Wang, Y. (2024). Worker productivity during COVID-19 and adaptation to working from home. *European Economic Review*, *167*, Article 104788. https://doi.org/10.1016/j.euroecorev.2024.104788

Charalampous, M., Grant, C. A., & Tramontano, C. (2025). Getting the measure of remote e-working: A revision and further validation of the e-work life scale. *Employee Relations*, *45*(1), 45–68. https://doi.org/10.1108/ER-11-2021-0483

Chinyuku, C., & Qutieshat, A. (2025). The impact of remote work on building effective teams: Exploring the challenges of fostering team cohesion in remote work environments. *International Journal of Advanced Business Studies*, *4*(2), 133–148. https://doi.org/10.59857/VRXH4886

DeFilippis, E., Imping, S. M., Singell, M., Polzer, J. T., & Sadun, R. (2022). The impact of COVID-19 on digital communication patterns. *Humanities and Social Sciences Communications*, *9*, 1–11. https://doi.org/10.1057/s41599-022-01190-9

Diab-Bahman, R., & Al-Enzi, A. (2020). The impact of the COVID-19 pandemic on conventional work settings. *International Journal of Sociology and Social Policy*. https://doi.org/10.1108/IJSSP-07-2020-0262

Dick, E. A., Raithatha, A., Musker, L., Redhead, J., Mehta, A., & Amiras, D. (2020). Remote reporting in the COVID-19 era: From pilot study to practice. *Clinical Radiology*, *75*(9), 710.e5–710.e8. https://doi.org/10.1016/j.crad.2020.06.016

Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being: Three decades of progress. *Psychological Bulletin*, *125*(2), 276–302.

EY. (2023). *Wellbeing, pay and career advancement opportunities prolong workplace tensions for Southeast Asian employees, including Indonesia*. https://www.ey.com/en_id/newsroom/2023/12/wellbeing-pay-and-career-advancement-opportunities

Fedorowicz, J., Ajjan, H., & Owens, D. (2022). Work-from-home performance during the pandemic: How technology availability moderates job role stress and family–work conflict. *National Bureau of Economic Research*. https://doi.org/10.3386/w26947

Fernandez-Fernandez, M., Martinez-Navalon, J.-G., Gelashvili, V., & Prado Roman, C. (2025). Retraction notice to "The impact of teleworking technostress on satisfaction, anxiety and performance". *Heliyon*, *11*, Article e44187. https://doi.org/10.1016/j.heliyon.2025.e44187

Figueiredo, E., & Margaça, C. (2025). Loneliness and isolation in the era of telework: A comprehensive review of challenges for organizational success. *Healthcare*, *13*, Article 1943. https://doi.org/10.3390/healthcare13161943

Firdausi, W., & Indiyati, D. (2024). The impact of flexible working arrangements on employee productivity: The mediating role of work–life balance. *International Journal of Science, Technology & Management*, *5*(4), 801–807.

Fisher, G. G., Bulger, C. A., & Smith, C. S. (2009). Beyond work and family: A measure of work/nonwork interference and enhancement. *Journal of Occupational Health Psychology*, *14*(4), 441–456. https://doi.org/10.1037/a0016737

George, T. J., Atwater, L. E., Maneethai, D., & Madera, J. M. (2022). Supporting the productivity and wellbeing of remote workers: Lessons from COVID-19. *Organizational Dynamics*, *51*(2), Article 100869. https://doi.org/10.1016/j.orgdyn.2021.100869

Ghosh, D., & Huang, X. (2020). Managerial ability and employee productivity. *Studies in*

Economics and Finance, *32*, 151–180. https://doi.org/10.1108/S1474-787120200000032006

Grant, C. A., Wallace, L. M., Spurgeon, P. C., Tramontano, C., & Charalampous, M. (2019). Construction and initial validation of the e-work life scale to measure remote e-working. *Employee Relations*, *41*(1), 16–33. https://doi.org/10.1108/ER-09-2017-0229

Guest, D. E. (2002). Human resource management, corporate performance and employee wellbeing: Building the worker into HRM. *Social Science Information*, *41*(2), 335–358. https://doi.org/10.1177/0539018402041002005

Hang, Y., Hussain, G., Amin, A., & Abdullah, M. I. (2022). The moderating effects of technostress inhibitors on techno-stressors and employee outcomes. *Frontiers in Psychology*, *12*, Article 821446. https://doi.org/10.3389/fpsyg.2021.821446

Hasibuan, L. (2020). Update: 679 ribu pegawai di Jakarta kini work from home. *CNBC Indonesia*. https://www.cnbcindonesia.com/lifestyle/20200326171524-33-147759

Jussila, J. J., Pulakka, A., Appelqvist-Schmidlechner, K., Ervasti, J., Halonen, J. I., Lahti, J., Mikkonen, S., Salo, P., & Lanki, T. (2025). Associations of active commuting and leisure-time physical activity with perceived cognitive function and work ability among Finnish employed adults. *BMC Public Health*, *25*, Article 1423. https://doi.org/10.1186/s12889-025-22634-2

Kassim, S. N. F., Kasim, N. M., Thangadurai, T. a/p, & Masran, M. H. (2025). The relationship between work–life balance and job satisfaction among medical doctors in Johor Bahru. *International Journal of Research and Innovation in Social Science*, *9*, 3885–3903. https://doi.org/10.47772/IJRISS

Kautish, P., Marc, W., & Lavuri, R. (2025). Values, wellbeing, and job satisfaction in telework: Evidence from IT-enabled service firms. *Technology in Society*, *80*, Article 102762. https://doi.org/10.1016/j.techsoc.2024.102762

Kellerman, A. (2025). Global trends in work location before, during, and after COVID-19. *Journal of Urban Affairs*. https://doi.org/10.1080/21650020.2025.2570279

Kitagawa, R., Okudaira, H., & Ohta, S. K. (2021). Working from home and productivity under the COVID-19 pandemic. *PLOS ONE*, *16*(12), Article e0261761. https://doi.org/10.1371/journal.pone.0261761

Martin, L., Hauret, L., & Fuhrer, C. (2022). Digitally transformed home office impacts on job satisfaction, job stress, and job productivity. *PLOS ONE*, *17*(3), Article e0265131. https://doi.org/10.1371/journal.pone.0265131

Memon, M. A., Thurasamy, R., Ting, H., & Cheah, J.-H. (2025). Purposive sampling: A review and guidelines for quantitative research. *Journal of Applied Structural Equation Modeling*, *9*(1), 1–23. https://doi.org/10.47263/JASEM.9(1)01

Molino, M., Ingusci, E., Signore, F., Manuti, A., Giancaspro, M. L., Russo, V., Zito, M., & Cortese, C. G. (2020). Wellbeing costs of technology use during COVID-19 remote working. *Sustainability*, *12*, Article 5911.

Muchsinati, E. S., Oktalia, A., & Priscilla, Y. G. (2024). How e-human resource management can increase employee productivity in F&B in Batam. *Journal of Human Resource Studies*, *5*(4), 443–458.

Oakman, J., Kinsman, N., Stuckey, R., Graham, M., & Weale, V. (2020). A rapid review of mental and physical health effects of working at home. *BMC Public Health*, *20*, Article 1825. https://doi.org/10.1186/s12889-020-09875-z

Putri, A., Amran, A., & Putri, A. (2021). Employees' work–life balance reviewed from work from home aspect during COVID-19 pandemic. *International Journal of Management Science and Information Technology*, *1*(1), 1–5. https://doi.org/10.35870/ijmsit.v1i1.231

Rahman, M. (2023). Sample size determination for survey research and non-probability sampling techniques. *Journal of Entrepreneurship, Business and Economics*, *11*(1), 42–62.

Rimadias, S. (2020). Factors affecting perceived productivity on teleworkers during the COVID-19 pandemic in Indonesia. *Jurnal Ilmu Manajemen dan Ekonomika*, *4*(3), 43–53.

Shin, J. (2025). Impact of telework on job satisfaction and work–family conflict. *SAGE Open*, *15*, 1–14. https://doi.org/10.1177/21582440251342349

Shirmohammadi, M., Au, W. C., & Beigi, M. (2022). Remote work and work–life balance. *Human Resource Development International*, *25*(2), 163–181. https://doi.org/10.1080/13678868.2022.2047380

Soroui, S. T. (2021). Understanding the drivers and implications of remote work. *Technology in Society*, *64*, Article 101328. https://doi.org/10.1016/j.techsoc.2020.101328

Suhariadi, F., Sugiarti, R., Hardaningtyas, D., & Mulyati, R. (2023). Work from home: A behavioral model of Indonesian education workers' productivity. *Heliyon*, *9*(3), Article e14082. https://doi.org/10.1016/j.heliyon.2023.e14082

Uhlig, L., Korunka, C., & Kubicek, B. (2023). A two-wave study on the effects of cognitive demands of flexible work. *Applied Psychology*, *72*(3), 625–646. https://doi.org/10.1111/apps.12392

Vhutali, M. (2025). The impact of work–life balance and mental health well-being on women's performance in the workplace. *International Journal of Applied Research in Business and Management*, *6*, Article HRMIC. https://doi.org/10.51137/wrp.ijarbm.416

Wang, B., Liu, Y., & Parker, S. K. (2021). Achieving effective remote working during the COVID-19 pandemic. *Applied Psychology*, *70*, 16–59. https://doi.org/10.1111/apps.12290

Wardani, L. M. I., Wulandari, S., Triasti, P., & Sombuling, A. (2020). The effect of psychological capital on work engagement. *TEST Engineering & Management*, *83*, 17220–17229.

Winkler-Titus, N., Gerber, C., & Ngalo, V. (2021). Well-being of remote workers. *SA Journal of Human Resource Management*, *19*, Article a2876. https://doi.org/10.4102/sajhrm.v19i0.2876

Wu, W., & Fukui, S. (2025). Using human resources data to predict turnover of community mental health employees. *International Journal of Mental Health Nursing*, *33*(6), 2180–2192. https://doi.org/10.1111/inm.13387

Yunxiao, B., & Ping, W. S. (2025). The influence of meaning in life on subjective well-being among vocational college students. *International Journal of Academic Research in Business and Social Sciences*, *15*(2), 1556–1564. https://doi.org/10.6007/IJARBSS/v15-i2/24866