Sectoral Disparities in the Digital Workplace: A Comparative Statistical Analysis of Remote Work Patterns and Productivity Scores in the Evolving Digital Society

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ABSTRACT

The global transition to remote work has highlighted significant variations in efficacy across different industries. While the digital workplace is now standard, a data-driven understanding of the factors that determine productivity in this new paradigm is essential for optimizing performance and supporting workers. This study aims to move beyond anecdotal evidence by quantitatively analyzing the disparities in remote work patterns and their impact on productivity scores. A cross-sectional, comparative statistical analysis was conducted on a dataset of 300 remote workers across five key sectors: Healthcare, IT, Finance, Retail, and Education. The methodology involved using Analysis of Variance (ANOVA) to test for significant differences in mean productivity scores between sectors. A Multiple Linear Regression model was then developed to identify the most significant predictors of worker productivity from a range of variables related to demographics, work patterns, and digital tool usage. The ANOVA test confirmed a statistically significant difference in mean productivity scores across sectors (F-statistic: 3.6368, p-value: 0.0065), with the Retail sector exhibiting the highest mean productivity and Healthcare the lowest. The Multiple Linear Regression model was highly significant and explained 59.3% of the variance in productivity scores (R-squared = 0.593). Four key predictors were identified as statistically significant: task completion rate (positive), late task ratio (negative), calendar scheduled usage (positive), and tool usage frequency (positive). A planned machine learning classification phase was aborted due to a lack of variance in the categorical productivity label, as all participants were categorized as 'Low'. The study concludes that significant sectoral disparities in remote work productivity are prevalent and that effective work management behaviors are more predictive of performance than hours worked or demographic characteristics. The findings underscore the need for organizations to focus on optimizing task management systems and provide sector-specific support. Future research should employ mixed-methods and longitudinal designs to further explore these dynamics.

Keywords Digital Workplace, Productivity, Remote Work, Sectoral Disparities, Task Management

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Introduction

The global shift towards remote work has transformed the traditional operational models of businesses, particularly in the wake of the COVID-19 pandemic [1]. This trend reflects a growing acceptance of digital collaboration tools that enhance business continuity and collaborative practices across various sectors. The increased use of digital platforms has become essential in enabling remote work, facilitating communication, and maintaining productivity during disruptions [2].

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Remote working has rapidly evolved from a niche arrangement to a standard operational model, fundamentally altering work processes and organizational structures. While many employees had some prior, often unofficial, experience with remote work, the pandemic acted as a major catalyst, forcing widespread adoption and acceptance [3]. This paradigm shift is significant, with research indicating that billions of people globally now use digital technologies to work from locations outside of a traditional office. Central to this transformation is the pivotal role of digital tools in maintaining business continuity. The digitization of services has been shown to enhance operational efficiency and align with sustainable practices, while a proliferation of collaboration platforms has enabled effective project management and communication for geographically dispersed teams, boosting worker autonomy and productivity [4].

Despite these advantages, the transition presents notable challenges. The increased reliance on digital platforms has been linked to stress and technostress for many individuals, revealing a complex relationship between technology and employee well-being [5]. While these tools enhance connectivity, they can also introduce new obstacles that organizations must navigate. At the same time, the advanced capabilities of these platforms have enabled significant innovation. Studies suggest that integrating both explicit and tacit knowledge sharing through digital channels can foster creativity among remote workers. In this digitally-driven landscape, effective communication tools are vital for facilitating the knowledge exchange and innovation processes critical for navigating the contemporary economy [6].

The most critical observation from this widespread shift has been the emergence of significant disparities in productivity and efficacy across different industry sectors. Emerging evidence clearly shows that while some sectors report enhanced productivity, others have seen diminished effectiveness, highlighting a complex landscape that requires a data-driven investigation. Organizational factors, particularly leadership styles and culture, play a crucial role in these outcomes [7]. Research demonstrates that organizations led by individuals who cultivate a collaborative and connected culture fare better during remote transitions. Transformational leaders adept at using digital communication can effectively bridge the gap of physical distance, fostering employee engagement and productivity [8].

Ultimately, the effectiveness of remote work is influenced by a combination of industry-specific challenges, the nature of the work itself, and an organization's internal practices. Some industries have struggled to adapt the necessary technologies, contributing to lagging productivity [9]. The degree of digital business intensity and the pre-existing collaborative practices within an organization are also strong determinants of success. Furthermore, tasks that demand high levels of spontaneous creativity may be less suited to remote conditions compared to more structured work. This body of evidence strongly suggests that a one-size-fits-all approach to remote work is misleading; rather, success depends on a nuanced understanding of these interacting factors [10].

This study is guided by two primary research objectives. The first objective is to quantitatively analyze the relationship between specific remote work patterns and productivity scores across five key sectors: Healthcare, IT, Finance, Retail, and Education. The central hypothesis is that statistically significant disparities in productivity exist between these sectors, driven by the unique operational demands and digital maturity of each industry. This analysis seeks to move beyond anecdotal observations and provide empirical evidence to confirm whether the challenges and successes of remote work are sector-dependent.

The second objective is to identify and model the most significant predictors of worker productivity in the digital workplace. This involves examining a range of variables—from work behaviors like task completion rates and tool usage to demographic factors like age and experience—to determine which have the most substantial impact on performance. The aim is to develop a statistical model that not only explains the variance in productivity but also highlights the specific, actionable behaviors that correlate most strongly with success in a remote environment, thereby providing a basis for targeted organizational strategies.

Literature Review

Theoretical Foundations of Remote Work Productivity

The theoretical foundations of remote work productivity can be examined through established frameworks such as the Technology Acceptance Model (TAM) and Self-Determination Theory (SDT). These frameworks elucidate how digital tools facilitate telecommuting and the psychological factors influencing employee motivation and performance in remote settings.

The Technology Acceptance Model (TAM) posits that perceived ease of use and perceived usefulness significantly impact user acceptance of technology. This model is instrumental when analyzing the modern digital tools employed in remote work. For instance, Grant et al have developed the E-Work Life Scale, which measures various dimensions of remote working and emphasizes the usability of these digital platforms, thereby linking TAM with remote work performance [3]. Furthermore, evidence supports that workers' self-efficacy affects their performance, highlighting the need to select appropriate tools that enhance user experience and productivity [4].

Self-Determination Theory (SDT) further contributes to understanding remote work by emphasizing the role of autonomy and intrinsic motivation. Research indicates that when employees feel competent and autonomous in remote work environments, their motivation to engage increases, thereby enhancing productivity [5]. Slemp et al illustrate that leader support for autonomy fosters intrinsic motivation, which is critical in remote settings with reduced supervision [5]. Additionally, Qi et al explore the impact of self-control on remote workers' self-efficacy, providing insights on how intrinsic attributes influence efficacy and effectiveness in non-traditional work environments [6].

Moreover, the application of self-leadership strategies has been shown to promote remote workers' independence and encourage effective work habits, which can mitigate the challenges posed by physical distance [7]. This aligns with findings from Nwoko and Yazdani, who discuss the importance of training and resources to develop self-leadership skills among remote workers, ultimately contributing to improved engagement and productivity [7]. The context of enforced remote work during the pandemic also highlighted the necessity of adapting leadership styles to support worker autonomy, which is essential for sustaining motivation and enhancing performance [8]. Troll et al provide insights into the influence of self-control as a psychological antecedent impacting job performance during remote work, indicating that individuals equipped with better self-control strategies are more likely to thrive in telecommuting arrangements

[9].

Empirical Studies on Digital Work Patterns

Empirical studies on digital work patterns reveal that various factors such as work hours, task management, and the adoption of digital tools interactively influence employee performance and organizational efficiency. Considering recent technological advancements, the integration of artificial intelligence (AI) and automation into workflows is becoming a critical component in shaping the efficacy of remote work environments.

Podolsky et al explored how task interdependence affects performance among telecommuters, revealing that as the proportion of telecommuters in a group increases, the negative effects of task interdependence are mitigated. Their research indicates that effective management practices and supportive norms can enhance telecommuter integration, positively influencing overall group productivity and creativity when leveraging digital tools [10]. This underscores the importance of designing task management frameworks that accommodate remote communication and collaboration, which are critical in maintaining workflow efficiency.

The impact of AI on workflow efficiency has been a focal area of research, promising significant enhancements to productivity across various fields. Nair et al documented the potential of AI in radiology to improve productivity through automated processes that streamline workflow, particularly in analyzing images where AI can perform tasks rapidly compared to human counterparts [1]. Their review suggests that integrating AI technologies can lead to substantial improvements in operational efficiency, particularly in clinical settings where time is critical.

Similarly, Tromp et al highlighted the advantages of automated interpretation systems within healthcare routines, illustrating how AI can validate processes and provide consistent measurements with less variability than human evaluations [11]. Their multicenter study confirms that automated systems enhance diagnostic accuracy and reduce the workload on healthcare professionals, aligning with findings from Gaube et al regarding challenges associated with clinical decision aids and clinicians' susceptibility to automation bias [12]. This illustrates the need for careful integration of AI tools to maximize workflow efficiency while mitigating potential drawbacks.

The implementation of AI also transcends healthcare. Sabatini et al described a complete digital workflow for dental applications that significantly reduced manual input time through AI-enhanced design software [13]. This innovation illustrates how automation can streamline traditionally intensive labor processes, aligning closely with findings by Vandewinckele et al, who emphasized that AI in radiotherapy workflows can optimize treatment quality, positively affecting patient outcomes [14].

Moreover, the scope of automation in banking, as captured by Venigandla and Vemuri, illustrates how AI-driven predictive analytics can enhance operational efficiency by automating data analysis and fraud detection [15]. The incorporation of AI technologies in banking improves transaction monitoring and enables faster response times to potential fraudulent activities.

Work hours, task management, and digital tool adoption significantly intersect with the impact of AI in the workplace, shaping an overall landscape of enhanced productivity and performance. Research suggests that organizations should be purposeful in adopting digital tools and integrating AI in ways that complement human capabilities without overwhelming employees with technology's complexities. The interplay of these factors ultimately informs how effectively organizations can adapt to the evolving digital work environment, balancing efficiency with human-centered practices.

The Identified Gap in Current Research

The current research landscape on remote work reveals a notable gap in large-scale, cross-sectoral comparative analyses using standardized productivity metrics. This gap is compounded by a lack of studies that incorporate robust statistical modeling and machine learning approaches to understand and predict remote work performance effectively. While existing works assess various aspects of remote working, they often do not leverage comprehensive methodologies that could yield actionable insights applicable across diverse sectors.

One of the central challenges addressed in the literature is the measurement of productivity in remote work settings. Tramontano et al developed the e-Work Self-Efficacy Scale aimed at assessing digital competencies essential for remote working [16]. Their work underscores the importance of capturing productivity metrics while understanding the contextual factors affecting productivity and well-being in remote environments. However, this raises implications regarding the uniformity of measurement tools across diverse sectors, complicating the ability to draw generalized conclusions when different studies utilize distinct metrics.

Additionally, Takalo et al emphasized the need for frameworks focusing on cross-sectoral collaboration within organizations [17]. Their findings suggest that standardized instruments for measuring collaboration effectiveness could enhance understanding of how different sectors respond to remote work arrangements. Despite the proliferation of remote work, comprehensive evaluations that incorporate various sector-specific variables and consistent metrics remain underrepresented in the literature.

Moreover, Chang et al explored the psychological factors influencing productivity in remote settings, finding a connection between proactive coping and perceived work productivity [18]. While these psychological dimensions are crucial, translating these findings into a more extensive framework that encompasses various industry contexts is essential for enhancing predictive analytics in remote work performance.

As organizations increasingly adopt technology-driven solutions for remote work, the interplay of AI and workflow efficiency is a significant area of inquiry. Studies like that of Prasad et al validate the relationship between remote work and occupational stress among IT employees [19]. There remains an opportunity to apply machine learning techniques to predict how these stress factors influence productivity across various sectors. Addressing these aspects is paramount to building a nuanced understanding of remote work dynamics.

To bridge this identified gap, future research should employ large-scale comparative analyses that utilize consistent productivity metrics across various sectors, combined with robust statistical and machine learning models. Such approaches would enhance the understanding of remote work performance and facilitate the formulation of evidence-based policies and practices tailored for diverse industrial contexts, ultimately leading to improved workplace strategies that better accommodate the shift to remote and hybrid work environments.

Method

This study employed a cross-sectional, comparative quantitative research design to analyze sectoral disparities in remote work performance. This approach was chosen for its suitability in capturing a snapshot of work patterns and productivity across different industries at a single point in time, allowing for efficient comparison. The entire methodology was implemented programmatically using Python, leveraging a suite of core data science libraries. Specifically, the Pandas library was utilized for all data loading and manipulation tasks, statsmodels provided the framework for rigorous statistical modeling, and scikit-learn was the chosen library for implementing the machine learning pipeline.

Research Design and Dataset

The analysis was conducted on a secondary dataset comprising 300 remote workers, evenly distributed across five distinct industry sectors: Healthcare, IT, Finance, Retail, and Education. The dataset contained a rich array of variables designed to capture a holistic view of the remote work experience. These included demographic data such as age; digital work patterns, quantified by metrics like average_daily_work_hours, task_completion_rate, late_task_ratio, and tool_usage_frequency; and two key performance metrics. The first, productivity_score, is a continuous variable representing a granular measure of output, while the second, productivity_label, is a categorical variable intended for classification. As a critical initial data preparation step, the non-predictive worker_id column was programmatically removed to prevent it from erroneously influencing the statistical models. Furthermore, a systematic check for missing values was conducted to ensure the dataset's integrity and completeness, a prerequisite for reliable analytical outcomes.

Statistical Analysis Protocol

The first phase of the analysis involved a robust statistical investigation to identify and explain performance differences between sectors. An Analysis of Variance (ANOVA) was performed using the f_oneway function from the scipy.stats library. This test was critical for formally assessing the null hypothesis that the mean productivity_score is equal across all five industry sectors. A statistically significant result ($p < 0.05$) would provide strong evidence to reject this hypothesis, indicating that sectoral affiliation has a measurable impact on productivity.

Subsequently, to identify the specific drivers of performance, a Multiple Linear Regression model was developed using the Ordinary Least Squares (OLS) function from the statsmodels.api library. This model was designed to predict the continuous productivity_score based on all other relevant variables. To prepare the data for regression, categorical features like industry_sector were transformed into a numerical format using the pd.get_dummies function. The drop_first=True parameter was explicitly set during this process to create k-1 dummy variables, a standard practice to prevent the issue of perfect multicollinearity (the "dummy variable trap"). The model's comprehensive summary provided key diagnostics, including the R-squared value, which quantifies the proportion of variance in productivity explained by the predictors, and the p-values for individual coefficients, used to determine the statistical significance of each predictor's impact.

Machine Learning Modeling Approach

The second phase was designed to explore predictive modeling by classifying the categorical productivity_label. The planned approach was to build and evaluate a set of robust classification models. This began with partitioning the data into an 80% training set and a 20% testing set using scikit-learn's train_test_split function, with a random_state of 42 set to ensure the split was deterministic and reproducible. A sophisticated preprocessing pipeline was constructed using the ColumnTransformer object. This pipeline was configured to apply StandardScaler to all numerical features—a crucial step to normalize their scales and ensure that algorithms sensitive to feature magnitude (like Logistic Regression) would perform optimally. Simultaneously, it applied OneHotEncoder (with the handle_unknown='ignore' parameter to gracefully manage any new categories in the test set) to all categorical features.

This preprocessed data was intended for training and evaluating three distinct supervised classification algorithms: LogisticRegression (configured with max_iter=1000 to ensure convergence) as a strong baseline model, alongside two powerful ensemble methods, RandomForestClassifier and GradientBoostingClassifier, chosen for their ability to model complex, non-linear relationships. Model performance was to be assessed using accuracy_score and a detailed classification_report, which provides precision, recall, and F1-score for each class. However, a preliminary class distribution check revealed that the target variable, productivity_label, contained only one unique class ('Low') for all 300 participants. This lack of variance made a classification task infeasible, as a machine learning model cannot learn to distinguish between categories when only one is present. Consequently, this entire machine learning phase of the methodology could not be executed.

Result and Discussion

This section presents the findings from the statistical analysis and discusses their implications in the context of the research objectives. The analysis successfully identified significant disparities in remote work productivity across different industry sectors and pinpointed key behavioral patterns that predict worker performance. The discussion synthesizes these quantitative results, interprets their meaning for the evolving digital workplace, and acknowledges the inherent limitations of the study.

Significant Sectoral Differences in Productivity

The initial descriptive statistics revealed notable variations in mean productivity scores across the five sectors, with Retail showing the highest average score (39.35) and Healthcare the lowest (34.41). To determine if these observed differences were merely due to chance or represented a true underlying pattern, an Analysis of Variance (ANOVA) was conducted. The ANOVA test yielded a compelling and statistically significant result (F-statistic = 3.6368, p-value = 0.0065). With a p-value well below the conventional 0.05 alpha level, the null hypothesis—that there is no difference in mean productivity scores among the sectors—was decisively rejected. This confirms that the industry sector to which a worker belongs is a significant factor in their remote work productivity.

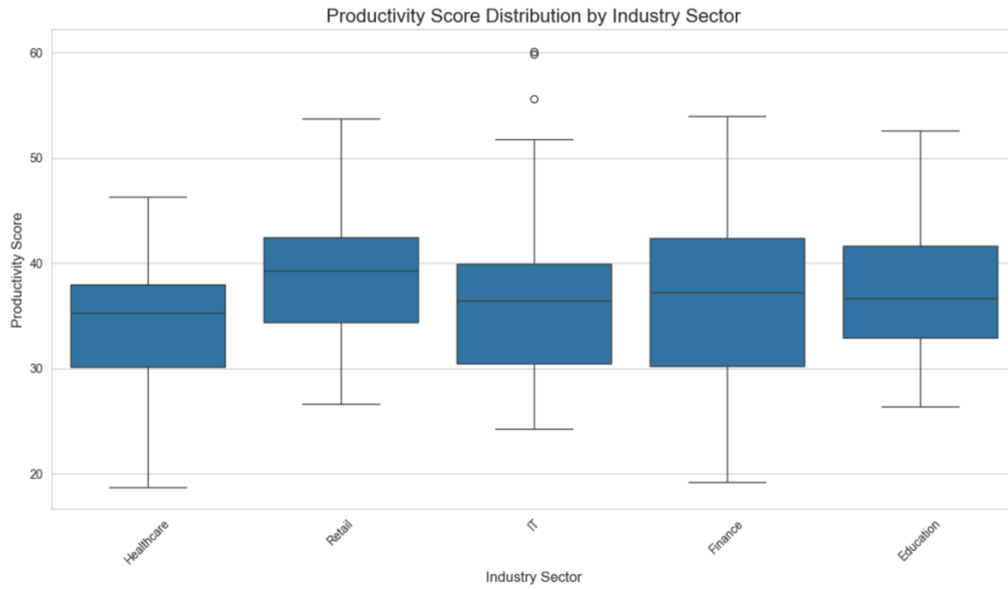

Figure 1 **Productivity Score Distribution by Industry Sector**

Figure 1 illustrates the distribution of productivity scores across five different industry sectors, revealing key differences in both performance levels and consistency. The horizontal line within each box, representing the median score, is highest for the Retail and Finance sectors, suggesting they have the highest typical productivity. In contrast, the Healthcare sector shows the lowest median score. The height of the boxes indicates variability; for instance, the taller boxes for Retail and IT signify a wider range of productivity outcomes among their workers, whereas the shorter box for Healthcare suggests more uniform performance. Notably, the IT sector displays two outliers, representing individuals with exceptionally high productivity scores that fall well outside the typical range for that group.

This core finding suggests that the nature of an industry's work, its digital maturity, and its cultural adaptation to remote models play crucial roles in determining efficacy. The superior performance in the Retail sector may be attributable to roles that are highly task-oriented, transactional, and easily quantifiable through digital platforms (e.g., sales figures, customer service tickets processed). Conversely, the lower scores in Healthcare likely reflect the profound challenges in translating complex, collaborative, and often hands-on work into a remote setting. This could be compounded by significant operational friction, such as navigating patient confidentiality regulations (e.g., HIPAA) in a distributed environment, the inherent difficulties in providing empathetic care through digital mediums, and the need for specialized, reliable telehealth infrastructure that may not be universally available or adopted. The IT and Finance sectors, while not at the top, likely benefit from a higher baseline of digital literacy, whereas Education may face unique hurdles related to student engagement and the practical limitations of virtual instruction.

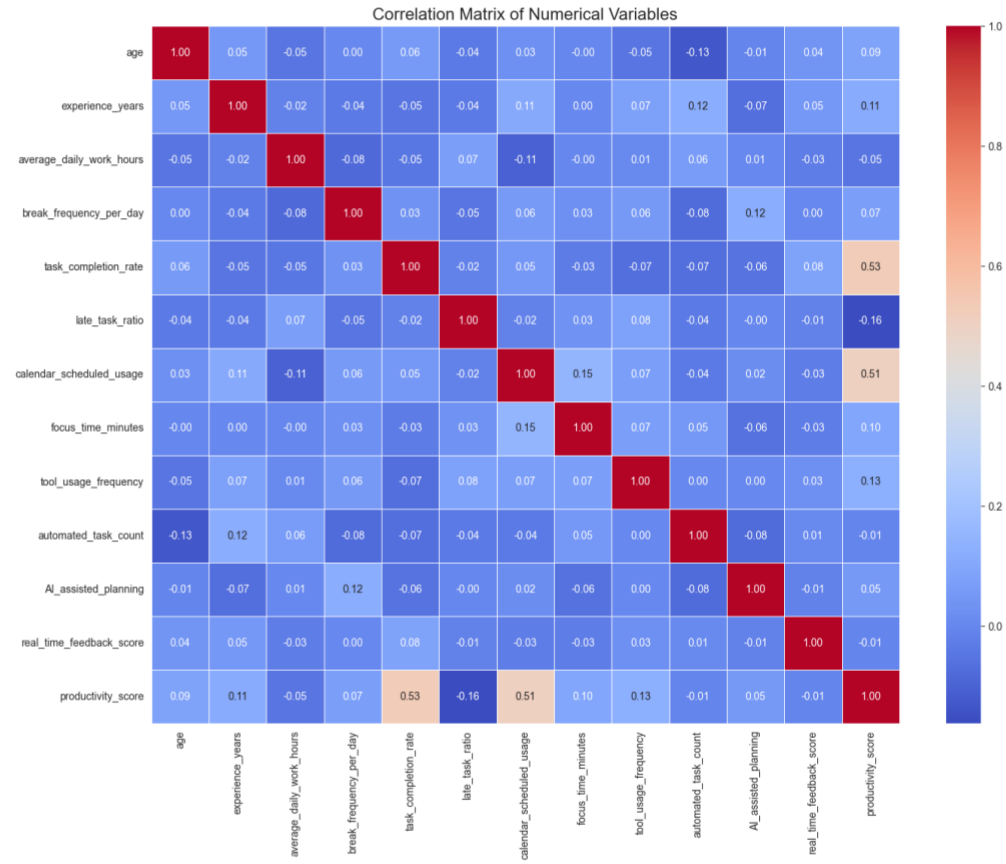

Figure 2 Correlation Matrix of Numerical Variables

Figure 2 displays the correlation matrix for the numerical variables in the study, visually representing the strength and direction of their linear relationships. The color scale indicates that red tones signify a positive correlation, blue tones a negative correlation, and lighter colors a relationship close to zero. When examining the productivity_score (the last row/column), the most notable findings are the moderate positive correlations with task_completion_rate (0.53) and calendar_scheduled_usage (0.51). This suggests that higher rates of task completion and more frequent use of a digital calendar are associated with higher productivity. In contrast, late_task_ratio has a weak negative correlation (-0.16), while variables like age, experience_years, and average_daily_work_ hours show very weak correlations, reinforcing the regression model's conclusion that work management behaviors are more influential than demographics or time spent working. The matrix also clearly visualizes the strong positive correlation between age and experience_years (0.85), which is the source of the multicollinearity warning mentioned in the regression analysis.

Identification of Key Productivity Predictors

To delve deeper into the specific factors driving individual performance, a Multiple Linear Regression model was developed. The model proved to be highly significant overall (Prob (F-statistic): 1.14e-44) and successfully explained 59.3% of the variance in the productivity_score (Adjusted R-squared = 0.567). This indicates that the selected variables account for a substantial portion of what makes a remote worker productive. The analysis of individual coefficients pinpointed four statistically significant predictors of productivity (p <

0.001), all of which relate to work management rather than demographic characteristics.

The most influential predictor was the task_completion_rate (coefficient = 0.3199), indicating a strong, positive relationship where higher completion rates directly correlate with higher productivity. This aligns with theories of motivation that link a sense of accomplishment to performance. Conversely, the late_task_ratio had a powerful negative impact (coefficient = -9.7483), highlighting that even a small increase in the proportion of overdue tasks is a significant drag on overall performance. Furthermore, calendar_scheduled_usage (coefficient = 0.1586) and tool_usage_frequency (coefficient = 0.1793) were also significant positive predictors. Equally important is the lack of statistical significance for variables like age, experience_years, and average_daily_work_hours. This challenges the common managerial assumptions that productivity is a simple function of time spent working or years of experience. Instead, these results collectively paint a clear picture: productivity in a remote setting is primarily a function of effective self-management—diligently completing tasks, avoiding delays, proactively structuring the workday, and adeptly leveraging available digital tools.

Comparison with Previous Research

The findings of this study both support and extend existing literature on remote work. The identification of task management behaviors (task_completion_rate, late_task_ratio) as primary drivers of productivity aligns with tenets of self-determination theory, which posits that autonomy and a sense of competence are key motivators. Our results provide empirical evidence that workers who exhibit behaviors associated with high autonomy and competence are indeed more productive. Furthermore, the significance of tool_usage_frequency and calendar_scheduled_usage supports the TAM, suggesting that the perceived usefulness and actual use of digital tools are critical for performance. Where this study makes a novel contribution is in its cross-sectoral analysis. While much of the prior research has focused on single industries (often IT), our finding of statistically significant performance disparities between sectors like Healthcare and Retail addresses an identified gap, demonstrating that a "one-size-fits-all" approach to remote work is inadequate.

Limitations of the Study

While this study provides valuable insights, its limitations must be acknowledged. The primary limitation was the lack of variance in the productivity_label variable, where all 300 participants were categorized as 'Low'. This prevented the planned machine learning classification analysis and suggests that the dataset, while useful for regression, may not be representative of a wider performance spectrum. This uniformity could stem from the data collection instrument's criteria or reflect a genuine, widespread adaptation challenge among the sampled population. The regression model's summary included a warning about a large condition number (2.58e+03), suggesting a potential for multicollinearity among predictor variables. While this does not invalidate the model's overall explanatory power, it advises a cautious interpretation of the precise magnitude and significance of individual coefficients. The study's cross-sectional nature provides a snapshot in time but cannot establish causality. For instance, while high tool usage is correlated with high productivity, we cannot determine if tool usage drives productivity or if more productive workers simply use more tools.

Directions for Future Research

Based on the findings and limitations of this study, several avenues for future research are recommended. To understand the nuanced, human factors behind the observed sectoral differences, future research should incorporate qualitative methods. In-depth interviews or focus groups with workers in low-performing sectors like Healthcare could uncover specific pain points, workflow challenges, and cultural barriers that quantitative data alone cannot reveal. Future studies should employ a longitudinal design to track remote worker productivity over time. This would help establish causal relationships between work patterns and performance and analyze how productivity evolves as workers and organizations adapt to remote models.

There is a clear need for research using more diverse and balanced datasets that include a full range of performance outcomes (Low, Medium, and High). Such datasets would enable the use of sophisticated machine learning models to build robust predictive tools for identifying at-risk workers and forecasting performance. Future research could design and test interventions based on this study's findings. For example, a study could implement a training program focused on improving task and schedule management for a cohort of remote workers and measure the subsequent impact on their productivity scores.

Conclusion

This study successfully demonstrated that significant, statistically measurable disparities in remote work productivity exist across different industry sectors. The findings confirmed that industries such as Retail, which may have more easily quantifiable and task-oriented workflows, adapt more productively to remote settings than sectors like Healthcare, which face inherent complexities in digital translation. More importantly, the research identified that the primary drivers of individual productivity are not demographic factors like age or experience, nor the sheer volume of hours worked, but rather the adoption of effective work management behaviors. High task completion rates, low instances of tardiness, and consistent use of digital scheduling and work tools are the most reliable predictors of a productive remote worker. Consequently, the practical implications for organizations are clear: efforts to enhance remote work efficacy should pivot from monitoring time to enabling better task and workflow management. This involves investing in intuitive digital tools, providing training on effective scheduling and self-management techniques, and developing sector-specific support strategies that address unique industry challenges. The limitations of this study, particularly the lack of variance in the performance data, also highlight a critical direction for future research. There is a pressing need for more nuanced, mixed-methods studies that combine quantitative analysis with qualitative insights to explore the human factors behind these sectoral differences, as well as longitudinal studies to track the evolution of remote work productivity over time.

Declarations

Author Contributions

Conceptualization: M.S.H.; Methodology: R.R.N.F.; Software: M.S.H.; Validation: R.R.N.F.; Formal Analysis: M.S.H.; Investigation: R.R.N.F.;

Resources: R.R.N.F.; Data Curation: M.S.H.; Writing Original Draft Preparation: R.R.N.F.; Writing Review and Editing: M.S.H.; Visualization: M.S.H.; All authors have read and agreed to the published version of the manuscript.

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The data presented in this study are available on request from the corresponding author.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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