THE EFFECT OF WORK MOTIVATION AND WORK LIFE BALANCE ON EMPLOYEE PRODUCTIVITY IN STARTUPS IN WEST JAVA

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ABSTRACT

Startups in West Java operate in high velocity environments characterized by tight deadlines, rapid change, and flexible working arrangements, which may shape employee productivity. This study examines the effects of work motivation and work life balance on employee productivity among startup employees in West Java, Indonesia. Using a quantitative cross-sectional design, data were collected through a structured questionnaire from 42 startup employees and analyzed using PLS-SEM. The measurement model demonstrated adequate convergent validity with AVE values exceeding 0.50 for all constructs (Employee Productivity is 0.744; Work Life Balance is 0.681; Work Motivation is 0.712, and discriminant validity was supported by HTMT values below 0.85. The structural model explained 17.2% of the variance in employee productivity ($R^2 = 0.172$), with acceptable model fit 0.086. The results show that work life balance significantly influences employee productivity ($\beta = -0.421$, $p = 0.002$), while work motivation does not have a significant effect ($\beta = 0.016$, $p = 0.950$). The novelty of this study lies in providing empirical evidence from Indonesian startups showing that productivity is more strongly associated with work life conditions than with general motivation levels in the observed sample. Practically, the findings suggest that startups should implement structured flexibility, strengthen boundary management, and provide supportive leadership to sustain productivity.

Keywords: Work Motivation; Work Life Balance; Employee Productivity; Startups; Human Resources Management

1. Introduction

Startups operate in dynamic environments that demand speed, innovation, and continuous adaptation. In such contexts, employees often face intense workloads, rapid changes in roles, and flexible work arrangements that can be both enabling and challenging. Recent research on startup contexts highlights that employee well-being often including work life balance becomes a critical factor for sustaining performance in innovative startups (Ammirato et al., 2024). At the same time, flexible working practices may provide autonomy and efficiency, yet they can also create unintended downsides such as work intensification and blurred boundaries between work and personal life (Soga et al., 2022). These conditions make employee productivity in startups particularly dependent on both psychological resources (e.g., motivation) and contextual resources (e.g., work life balance).

Work motivation is widely recognized as a fundamental driver of performance. Self-determination theory (SDT) explains that employees can be motivated by autonomous reasons (intrinsic enjoyment, personal meaning) and controlled reasons (external rewards, pressures), and these motivational qualities relate differently to work outcomes (Ryan & Deci, 2000). A recent meta-analysis further supports that different forms of motivation show distinct relationships with employee attitudes, well-being, and performance (Van den Broeck et al., 2021). For startups, where goal achievement and agility are critical, motivation can become a key engine of productivity.

Besides motivation, work life balance has become increasingly central in contemporary work settings. Work life balance refers to employees' perceived equilibrium between work demands and non-work life domains, which can influence well-being and job outcomes (Brough et al., 2014; Gragnano et al., 2020). In startup environments, flexibility can support balance, yet without boundaries it can also intensify work life conflict and negatively affect sustainable performance (Soga et al., 2022). Therefore, understanding how work motivation and work life balance jointly relate to productivity is important for startup HR management, particularly in emerging economy regions such as West Java.

1.2 Problem statement

Although prior studies frequently link work motivation to performance and work life balance to job outcomes, empirical evidence focusing on startup employees in West Java remains limited. Startups differ from traditional organizations due to rapid scaling, high uncertainty, and often informal HR systems. This creates a need to examine whether work motivation and work life balance significantly explain employee productivity in this specific context.

1.3 Research questions

This study addresses the following questions:

1. Does work motivation significantly affect employee productivity in startups in West Java?
2. Does work life balance significantly affect employee productivity in startups in West Java?
3. Which factor shows a stronger association with employee productivity in this context?

1.4 Research objectives and contribution

This study aims to test the effects of work motivation and work life balance on employee productivity among startup employees in West Java. The study contributes by integrating two key antecedents of productivity in a high velocity startup context and providing managerial implications for designing HR interventions that sustain performance and employee well-being.

2. Literature Review

2.1 Work Motivation

Work motivation refers to the internal and external forces that initiate, direct, and sustain work related behavior, distinguishes autonomous motivation (e.g., intrinsic interest, identified regulation) from controlled motivation (e.g., external regulation, introjection) and emphasizes that motivation quality matters for performance and well-being (Ryan & Deci, 2000; Gagné & Deci, 2005). Empirically, multidimensional motivation measures such as the Multidimensional Work Motivation Scale (MWMS) have been validated across multiple countries and languages, supporting robust measurement of motivational regulations (Gagné et al., 2015). Moreover, meta-analytic evidence suggests that intrinsic motivation is strongly related to well-being and attitudes, while identified regulation can be especially relevant for performance-related outcomes (Van den Broeck et al., 2021). In startups, motivational drivers may be shaped by meaningful projects, rapid learning opportunities, recognition, and perceived autonomy.

2.2 Work Life Balance

Work life balance is commonly conceptualized as a subjective assessment of balance between work responsibilities and other life domains. A widely used approach measures balance as perceived equilibrium rather than objective time allocation, acknowledging that different employees may experience balance differently under similar workloads (Brough et al., 2014). Work–life balance is also linked to broader well-being frameworks; for example, employees may balance not only work and family, but also health and other non-work domains, which can affect satisfaction and functioning (Gragnano et al., 2020). In startup contexts, flexible working arrangements may improve balance by enabling autonomy; however, research also shows the "hidden costs" of flexibility, including boundary blurring, intensification, and socio-technical risks that can harm well-being and performance if unmanaged (Soga et al., 2022). Therefore, work–life balance may act as a supportive condition for sustainable productivity.

2.3 Employee Productivity

Employee productivity in this study refers to individual work output and effectiveness in completing tasks within expected standards. In organizational research, individual performance is often measured using multidimensional frameworks such as task performance, contextual performance, and counterproductive work behavior. The Individual Work Performance Questionnaire (IWPQ) is one established instrument capturing these dimensions (Koopmans et al., 2014). Recent work also supports cross-cultural adaptation and validation, including evidence from Indonesia (Widyastuti et al., 2024). For startup employees, productivity is reflected in timely completion of tasks, quality of deliverables, efficiency, and ability to meet targets within a fast-paced environment.

2.4 Hypotheses Development

2.4.1 Work Motivation and Employee Productivity

Motivated employees tend to invest greater energy and persistence in work tasks, which improves task performance and productivity. SDT suggests that autonomous motivation promotes deeper engagement and more adaptive functioning, which can be particularly valuable in demanding work settings (Ryan & Deci, 2000; Van den Broeck et al., 2021).
H1: Work motivation positively affects employee productivity in startups in West Java.

2.4.2 Work Life Balance and Employee Productivity

When employees perceive better work–life balance, they may experience lower strain and better recovery, enabling sustained concentration and performance. In startups, balance can buffer the negative consequences of work intensification and support sustainable productivity (Ammirato et al., 2024; Soga et al., 2022).
H2: Work life balance positively affects employee productivity in startups in West Java.

2.4.3 Conceptual Model

The conceptual model proposes two direct predictors work motivation and work life balance on employee productivity.

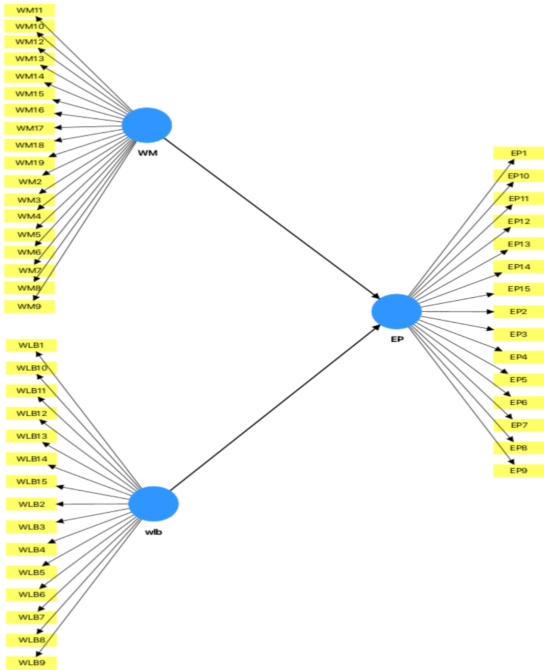

Figure 1. Conceptual Model

3. Research Method

3.1 Research Design

This study uses a quantitative explanatory approach with a cross-sectional survey design to test hypothesized relationships among constructs.

3.2 Population and Sample

The population consists of employees working in startups located in West Java, Indonesia. Respondents were recruited using non-probability sampling (purposive/convenience) based on the criteria: (1) currently employed in a startup, (2) minimum tenure of [e.g., 6 months], and (3) willing to participate voluntarily. The final sample size was n = 42**.**

3.3 Measurement and Instrument

All constructs were measured using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree).

- **Work motivation**: measured using intrinsic and extrinsic motivation items adapted from SDT-based measures (Gagné et al., 2015)
- **Work life balance**: measured using perceived balance items adapted from validated work life balance measures (Brough et al., 2014) and relevant balance dimensions (Gragnano et al., 2020).
- **Employee productivity**: measured using task performance-oriented items adapted from the IWPQ approach (Koopmans et al., 2014), aligned with productivity indicators such as effectiveness, efficiency, quality, and timeliness.

3.4 Data Collection Procedure

Data were collected through an online questionnaire distributed to startup employees across sectors. Participation was voluntary and anonymous. Respondents were informed about the research purpose and confidentiality.

3.5 Data Analysis Technique

Data were analyzed using PLS-SEM to evaluate both measurement and structural models. The measurement model was assessed using indicator reliability, internal consistency reliability (Cronbach's alpha, composite reliability), convergent validity (AVE), and discriminant validity (HTMT). The structural model was assessed using path coefficients, significance via bootstrapping, coefficient of determination (R^2), and effect sizes. This approach is appropriate for predictive models with latent constructs (Hair et al., 2021).

3.6 Ethical Considerations

Respondents provided informed consent. No personally identifying information was collected, and results are reported in aggregate.

4. Results and Discussion

4.1 Measurement Model Assessment (Indicator Reliability, Internal Consistency, and Convergent Validity)

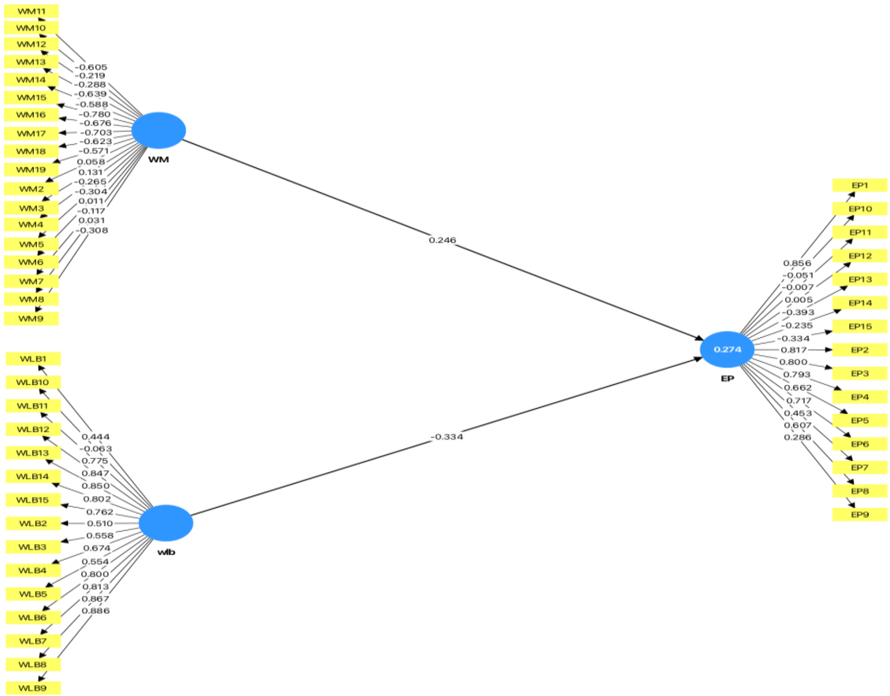

Figure 2. Outer Loading Factor

The reflective measurement model was evaluated by examining outer loadings, internal consistency reliability, and convergent validity, following widely used PLS-SEM guidelines (Hair et al., 2019, 2022). For indicator reliability, a commonly applied rule of thumb suggests that outer loadings should be ≥ 0.70, indicating that the construct explains at least ~50% of an indicator's variance ($0.70^2 \approx 0.49$). Indicators with loadings between 0.40 and 0.70 may be retained depending on theoretical relevance and whether removing them improves composite reliability (CR) and average variance extracted (AVE), while indicators < 0.40 are typically considered for removal due to weak reliability (Hair et al., 2019, 2022). In this study, several indicators showed loadings below 0.70, suggesting that not all items contributed strongly to their constructs; therefore, indicator level refinement should be considered in subsequent model iterations.

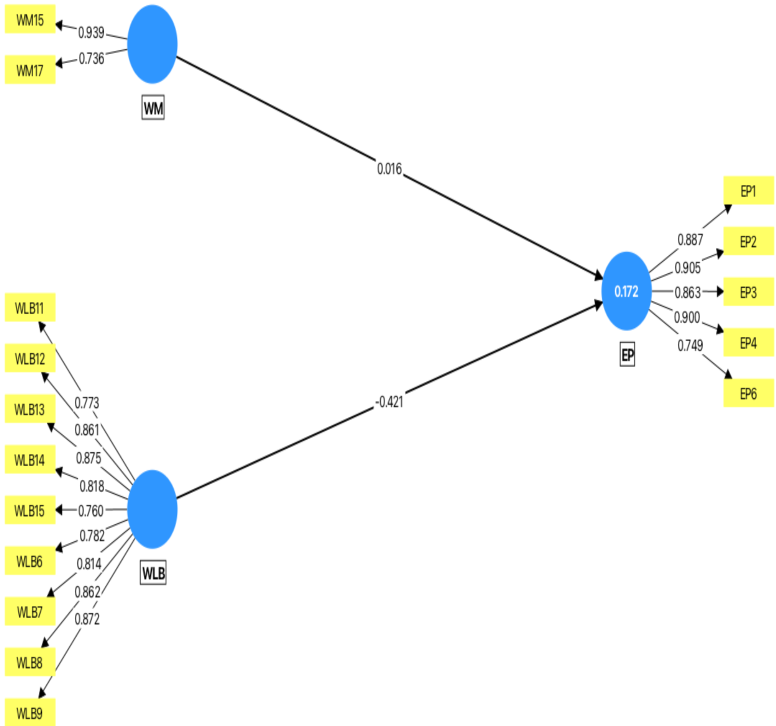

Figure 3. Final PLS-SEM output

During the initial estimation, several indicators exhibited outer loading values below 0.70, suggesting weak contributions to their respective constructs. Therefore, these low-performing indicators were removed (dropped) from the model. The estimation was then re-run iteratively after item deletion to improve the quality of the measurement model and ensure that only indicators meeting the recommended threshold were retained. Figure 3 presents the final PLS-SEM output after removing all indicators with outer loadings below 0.70. Accordingly, the indicators shown in the figure represent the re-estimated model, where the retained items satisfy the minimum loading criterion (≥ 0.70), thereby supporting the adequacy of the convergent validity in the final measurement model.

Table 1. Average Variant Extracted (AVE)

	Average Variance Extracted (AVE)	Decision
EP	0,744	VALID
WLB	0,681	VALID
WM	0,712	VALID

Convergent validity was assessed using AVE, where AVE ≥ 0.50 indicates that a construct explains more than half of the variance in its indicators on average (Fornell & Larcker, 1981; Hair et al., 2022). The AVE values met this criterion for all constructs:

Employee Productivity (AVE = 0.744), Work–Life Balance (AVE = 0.681), and Work Motivation (AVE = 0.712).

Table 2. Construct Reliability

	Cronbach's alpha	Decision
EP	0,913	Reliable
WLB	0,942	Reliable
WM	0,628	Reliable

Table 3. Composite Reliability

	Cronbach's alpha	Decision
EP	0,916	Reliable
WLB	0,961	Reliable
WM	0,827	Reliable

Internal consistency reliability was evaluated using Cronbach's alpha and composite reliability (CR/rho A). A general rule is CR ≥ 0.70 for acceptable reliability (Hair et al., 2019, 2022). The results indicate strong reliability for Employee Productivity (α = 0.913; CR = 0.916) and Work–Life Balance (α = 0.942; CR = 0.961). Work Motivation shows lower alpha (α = 0.628) but acceptable composite reliability (CR = 0.827), which may suggest heterogeneous indicators (e.g., combining intrinsic and extrinsic motivation without separating dimensions) or the presence of weaker items conditions that can reduce alpha even when CR remains acceptable (Hair et al., 2022; Ryan & Deci, 2000).

4.2 Discriminant Validity (HTMT and Fornell–Larcker)

Discriminant validity was assessed using the HTMT criterion, where values below 0.85 (more conservative) indicate satisfactory discriminant validity (Henseler et al., 2015). The HTMT values met this standard: WLB–EP = 0.418, WM–EP = 0.236, and WM–WLB = 0.626, supporting discriminant validity. The Fornell–Larcker criterion also indicated that the square roots of AVE exceeded the inter-construct correlations (Fornell & Larcker, 1981). Together, these results suggest that the constructs capture distinct concepts.

Table 4. Heterotrait-Monotrait Ratio (HTMT) – List

	Heterotrait-Monotrait Ratio (HTMT)
WLB <-> EP	0,418
WM <-> EP	0,236
WM <-> WLB	0,626

4.3 Model Fit (SRMR)

Model fit was evaluated using SRMR, where values below 0.10 are generally considered acceptable for approximate model fit, and values below 0.08 indicate good fit in many SEM contexts (Hair et al., 2022; Hu & Bentler, 1999). The model produced SRMR = 0.086, indicating acceptable overall fit for the proposed PLS-SEM model.

Table 5. Model Fit

	Rule of thumb	Estimated model	Decision
SRMR	Less than 0,10	0,086	Fit
d ULS	>0.05	1,001	Fit
d G	>0.05	0,858	Fit
Chi-square	X^2 statistic > X^2 table	172,778	Fit

NFI	Closer to 1	0,712	Fit

4.4 Structural Model Assessment (Explained Variance)

The model's explanatory power was assessed using R^2 for Employee Productivity. The results show $R^2 = 0.172$ (adjusted $R^2 = 0.129$), indicating that Work Motivation and Work Life Balance explain 17.2% of the variance in Employee Productivity. In behavioral research, such values often indicate small-to-moderate explanatory power and suggest that other factors (e.g., job demands/resources, leadership, role clarity, work design) may also be important for productivity in startups (Cohen, 1988; Hair et al., 2022).

Table 6. R-square

	R-square	R-square adjusted
EP	0,172	0,129

4.5 Hypothesis Testing (Bootstrapping Results)

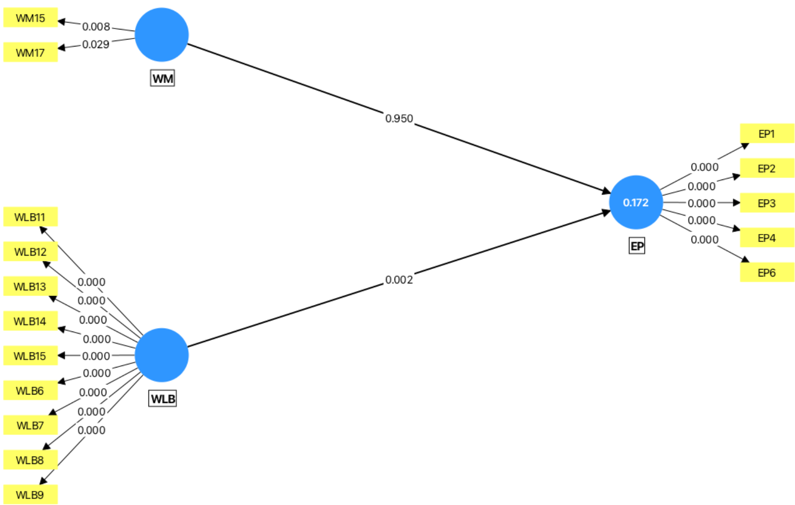

Table 7. Bootstrapping

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
WLB -> EP	-0,421	-0,429	0,134	3,156	0,002	Significant
WM -> EP	0,016	-0,033	0,248	0,063	0,950	Not significant

The results indicate that Work–Life Balance has a significant negative effect on Employee Productivity ($\beta = -0.421$, $p = 0.002$), while Work Motivation does not significantly affect Employee Productivity ($\beta = 0.016$, $p = 0.950$).

4.6 Discussion

4.6.1 The Effect of Work Life Balance on Employee Productivity

The significant negative relationship between work life balance and productivity is noteworthy. Prior research typically links better work life balance to more favorable work outcomes because balance supports recovery and reduces strain, which can enable sustained performance (Brough et al., 2014; Gragnano et al., 2020). However, the startup context can complicate this relationship. Startups often operate under tight deadlines and high velocity, where productivity is frequently associated with rapid responsiveness, extended availability, and accelerated delivery cycles. Under such conditions, employees who maintain stronger boundaries to protect balance may report lower immediate output, even if their well-being is better protected in the long run. This interpretation aligns with evidence suggesting that flexible work practices can have "two sides": they may empower employees, but also create trade-offs and unintended effects, such as boundary blurring and work intensification, depending on how flexibility is structured and managed (Soga et al., 2022).

A second explanation is measurement direction. In many instruments, items can reflect work–life conflict rather than balance (e.g., "work interferes with personal life"), and if such items are not reverse-coded, a construct labeled "work–life balance" may actually behave like "work life conflict." In that case, the negative coefficient would be theoretically consistent higher conflict would be associated with lower productivity while a properly coded "balance" construct would be expected to show a positive relationship with productivity (Brough et al., 2014; Gragnano et al., 2020). Therefore, the present finding should be interpreted alongside a careful inspection of item wording and coding direction.

Regardless of which interpretation applies, the results underscore that work life issues are salient predictors of productivity in startups. This is consistent with recent literature emphasizing employee well-being as an important sustainability factor for performance in innovative startup settings (Ammirato et al., 2024). Practically, startups should not assume that flexibility automatically produces balance; instead, they need structured flexibility clear boundary norms, realistic workload planning, and supportive leadership to sustain both productivity and well-being (Soga et al., 2022).

4.6.2 The Effect of Work Motivation on Employee Productivity

Contrary to many theoretical expectations, work motivation did not significantly affect productivity in this study. Self-determination theory suggests that higher quality motivation (autonomous motivation) is linked to more adaptive functioning and performance-related outcomes (Ryan & Deci, 2000). Moreover, meta-analytic evidence indicates that work motivation—especially more self-determined forms tend to show positive associations with beneficial work outcomes (Van den Broeck et al., 2021). Therefore, the non-significant result may reflect contextual and methodological factors rather than a genuine absence of motivational influence.

First, the measurement reliability for Work Motivation indicates potential heterogeneity ($\alpha = 0.628$). When intrinsic and extrinsic aspects are combined into a single construct without modeling their dimensionality explicitly, the composite may become less coherent, weakening predictive relationships (Hair et al., 2022; Van den Broeck et al., 2021). Second, in startups, productivity may be constrained by structural and operational factors such as role ambiguity, resource limitations, coordination problems, or shifting priorities so that motivation alone does not translate into measurable output. In such settings, motivated employees may still struggle to perform if the system does not provide adequate job resources or clear goals. Third, the sample size ($n = 42$) may limit statistical power to detect smaller effects; thus, future studies with larger samples and more refined motivation measurement (e.g., separating intrinsic vs. extrinsic) are recommended. Overall, the findings suggest that in the observed startup context, productivity may be more strongly linked to work life domain factors than to generalized motivation scores, at least within the current measurement structure.

4.7 Practical Implications

Given the significant association between work life balance and productivity, startup HR practices should prioritize interventions that support boundary management and sustainable work patterns. These include setting clear expectations regarding after-hours communication, ensuring fair workload distribution, and strengthening supportive leadership practices. At the same time, motivation focused initiatives should be aligned with system enablers such as clear goals, feedback mechanisms, and resources that allow motivated employees to convert effort into output. Future HR programs may also benefit from differentiating intrinsic and extrinsic motivation strategies consistent with SDT (Ryan & Deci, 2000).

4.8 Limitations and Future Research

This study is limited by a cross-sectional design and self-reported measures, which may introduce common method bias. The R^2 indicates that additional determinants of productivity should be incorporated in future research, such as job demands/resources, role clarity, leadership support, and burnout/engagement. Future studies should also validate the work–life balance scale direction and consider modeling motivation as multidimensional to improve measurement quality and explanatory power (Hair et al., 2022; Van den Broeck et al., 2021).

5. Conclusion

This study examined the effects of work motivation and work life balance on employee productivity among startup employees in West Java, Indonesia, using PLS-SEM. The results indicate that work life balance is a significant predictor of productivity, showing a negative and significant relationship with employee productivity ($\beta = -0.421$; $p = 0.002$), while work motivation does not show a significant effect on productivity ($\beta = 0.016$; $p = 0.950$). The structural model explains 17.2% of the variance in employee productivity ($R^2 = 0.172$), suggesting that productivity in startups is influenced not only by individual level motivation but also by broader work context factors. Overall, the findings highlight the importance of managing work life conditions in startups through structured flexibility, clear boundary norms, supportive leadership, and workload management to sustain productivity. Future studies are recommended to use larger samples, apply refined measurement (e.g., separating intrinsic and extrinsic motivation), and include additional predictors such as job demands/resources, role clarity, and burnout/engagement to improve explanatory power and strengthen practical implications.

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