

Work-related Mobile Instant Messaging Use After Work Hours During Covid-19 Pandemic

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Abstract. The Covid-19 pandemic has a far-reaching impact on workplace practices with billions of employees worldwide have to alter work patterns. Most employees fully embraced digital technologies, including mobile instant messaging (MIM) apps, to fulfil their work obligations under new normal. However, the work-related MIM use does not translate into good practice. Its use has extended beyond the contracted schedule, worsening work-life balance, job satisfaction and job performance among employees. Despite the gradual easing of lockdown measures, work-related MIM use after work hours will likely continue to an undetermined period as herd immunity is yet to achieve. Therefore, this captures the urgency to understand the mechanism on how work-related MIM use after work hours can be beneficial to employees during the pandemic, which is under-represented. The study elicited data through an online survey from 368 full-time employees in Malaysia. The evidence suggested employees who obtained information sharing gratification, mobile convenience gratification and self-presentation gratification enjoyed better WLB, subsequently formed higher job satisfaction and ultimately enhance their job performance, based on the postulation of the Uses and Gratification theory and Job Demands-Resources theory. Thus, work-related MIM use after work hours should not be interpreted negatively. Both researchers and practitioners should work jointly on how to implement practices concerning healthy yet sustainable MIM use after work hours to be more resilient for future pandemics.

1 Introduction

The Covid-19 pandemic is perhaps the first significant crisis in the digital age. It has a far-reaching impact on workplace practices with billions of employees worldwide have to alter work patterns due to the implementation of movement control by governments (Richter, 2020). To ensure the business continuity, digital work is no longer an option. Most employees fully embraced digital technologies to fulfil their work obligations remotely under new normal. As one of the digital technologies, MIM serves as the basic tool for connectivity and collaboration. It has gained popularity among employees for professional purposes before the pandemic (Safieddine & Nakhoul, 2021), but work-from-home as the

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result of lockdown has accelerated its adoption. In a study to investigate key smartphone-based activities, the usage of MIM increased by 64 percent during the Covid-19 pandemic (Ohme, et al. 2020). Given the significant spike in usage, MIM serves as an ideal resource as its flexibility permits various work practices without complicated customization. However, the work-related use of MIM by itself does not translate into good practice. Its use has extended beyond the contracted 8-hours schedule during the pandemic, pushing the work-related MIM use after work hours to a new limit. Therefore, it has been viewed as a double-edged sword, which could be a blessing to specific groups of employees and a curse to others. The constant connectivity afforded by MIM blurred the boundaries between the work and non-work sphere even more, making work-life balance (WLB) a far-reaching dream. Furthermore, employees struggled to look for new ways to demonstrate their commitment by working longer hours (Hafermalz, 2020). However, working for long hours, generally without additional remuneration, does not only impact negatively on employee's job satisfaction but also risk their job performance (Perrigino & Raveendhran, 2020). Supporting the detrimental effects, the survey by Deloitte revealed that 46% of employees expect a drop in job performance due to the Covid-19 pandemic (Boichenko & Tymchenko, 2020). Unquestionably, the pandemic is not short-term and the struggle among employees is real. Despite the gradual easing of lockdown measures, work-related MIM use after work hours will likely continue to an undetermined period as herd immunity is yet to achieve. Therefore, this perfectly captures the urgency to understand the underlying mechanism on how work-related MIM use after work hours can be beneficial to employees during the pandemic, which is under-represented. Relying on the Uses and Gratification (U&G) theory and Job Demands-Resources (JD-R) theory, the study aims to examine the underlying mechanisms which relate the gratifications obtained from work-related MIM use after work hours to job performance through the sequential mediators of WLB and job satisfaction. It is hoped that the finding will provide crucial insight on how to implement practices concerning healthy yet sustainable MIM use after the paid work hours during the pandemic or for future pandemic-related crisis.

2 Literature review

Previous studies with similar contexts were mainly dominated by email (Becker, et al. 2019; Belkin, Becker, & Conroy, 2020) and smartphone (Ohme, et al. 2020; Park, Kim, & Lee, 2020), with a limited representation of MIM as research context. However, different technologies embedded with different functionalities, which could yield significantly different work outcomes. This introduces challenges in comparing research findings and elucidating the controversy in findings. Though lacking MIM-specific study, its consequences remain a controversy due to its flexibility 'paradox.' As expected, consequences have been predominantly negative, including increased work-family conflict (Gadeyne, et al. 2018), job burnout (Park, et al. 2020) and higher turnover intentions (Belkin, et al. 2020). Nevertheless, few studies found positive outcomes. For example, the study by Bauwens, et al. (2020), in which communication technology has enhanced job performance and better balanced the work and life domains. Clearly, there is far less research on the potential benefits of work-related MIM use after work hours. Therefore, there is a need to identify the conditions under which work-related MIM use after work hours is beneficial. However, this involves a complex mechanism that is harder to disentangle, given the current predominantly habitual use of MIM. Furthermore, studies with similar contexts have treated the role of technology deterministically, which proposes that the technological features can produce the desired social outcomes. However, past review has suggested media use is a rational personal choice that is highly driven by individual motives and gratifications (Schlachter, et al. 2018). As such, for the present

study, there are five gratifications concerning work-related MIM use after hours during pandemic, including (a) social interaction gratification (SIG); (b) information sharing gratification (ISG); (c) mobile convenience gratification (MCG); (d) professional advancement gratification (PAG), and (e) self-presentation gratification (SPG).

3 Research Model and Hypothesis Development

The study integrates U&G theory (Katz, Haas, & Gurevitch 1973) and JD-R theory (Demerouti, et al. 2001) to examine the underlying mechanisms on how work-related MIM use after work hours can enhance job performance through sequential mediators of WLB and job satisfaction. U&G theory is a useful foundation to examine why employees are gratified toward work-related MIM use after work hours. It postulates that users are rational and consciously aware of their needs in the media selection process (Katz et al. 1973). Specifically, MIM offers social interaction platform for employees to gain social support from work contacts during the pandemic (Ohme, et al. 2020). These supports strengthen the SIG. Besides, work-related information sharing through MIM after work hours grants employees the efficiency in completing the work tasks, achieving ISG. Meanwhile, the flexibility of MIM offers employees the autonomy to control the spatio-temporal context of work, which enhances the MCG (Garfin, 2020). Also, using MIM to access work resources during non-work time, employees strive to build up their professional standing and advance their career ladder, thereby obtaining PAG (Padmavathy, et al. 2018). Furthermore, constant virtual presence through MIM after work hours helps in projecting the image as “ideal” employees and contributing to SPG (Munch, 2020). These gratifications serve as valued job resources to employees during the pandemic. Based on the JD-R theory, job resources have motivational impacts and are generally used to predict beneficial employee outcomes, such as work engagement and job performance (Demerouti, et al. 2001). As such, it is anticipated that these resources aids in juggling various competing demands from both work and non-work realms and thus achieving better WLB. The better WLB would then predict greater job satisfaction. Ultimately, employees' positive attitudes towards their job will result in these employees taking reasoned action by putting extra effort to enhance their overall job performance. This prediction is based on the study by Haar and Brougham (2020), in which WLB and job satisfaction sequentially mediated the relationship between the job autonomy (job resource) and turnover intentions among New Zealand employees. Thus, the proposed relationships are hypothesized as:

H1: WLB and job satisfaction sequentially and positively mediate the relationship between SIG and job performance.

H2: WLB and job satisfaction sequentially and positively mediate the relationship between ISG and job performance.

H3: WLB and job satisfaction sequentially and positively mediate the relationship between MCG and job performance.

H4: WLB and job satisfaction sequentially and positively mediate the relationship between PAG and job performance.

H5: WLB and job satisfaction sequentially and positively mediate the relationship between SPG and job performance.

4 Methodology

Given the present research context, the target population was employees in Malaysia. The sample was selected using purposive sampling to ensure that only respondents meeting the

criteria were included (Sekaran & Bougie, 2016). These criteria spelled out that a respondent (1) must be a full-time employee and (2) must use MIM for work-related purposes after work hours. Surveys were completed online with 368 usable responses, exceeding the minimum sample size of 98 required by the power analysis with a medium effect size of 0.15 and a standard minimum power of 0.80 (Faul, et al. 2009). Respondents were primarily male (57.3%), 26–40 years old (44.6%), married (52.4%), obtained Bachelor’s degree (32.9%), with organization tenure of 1 to 5 years (47.6%) and served as middle management (47.3%), as reported in Table 1.

Table 1. Demographic of respondents.

| Demographic Variables | Frequency | Percentage (%) |
|------------------------------------|------------------|-----------------------|
| Gender | | |
| Male | 211 | 57.3 |
| Female | 157 | 42.7 |
| Age | | |
| 25 and below (Gen Z) | 72 | 19.6 |
| 26 to 40 (Gen Y) | 164 | 44.6 |
| 41 to 55 (Gen X) | 100 | 27.2 |
| 56 and above (Baby Boomer) | 32 | 8.7 |
| Marital Status | | |
| Single | 171 | 46.5 |
| Married | 193 | 52.4 |
| Divorced / Widowed | 4 | 1.1 |
| Educational Level | | |
| Certificate | 37 | 10.1 |
| Diploma | 98 | 26.6 |
| Bachelor’s Degree | 121 | 32.9 |
| Professional Degree | 57 | 15.5 |
| Master’s Degree | 49 | 13.3 |
| Ph.D. Degree | 6 | 1.6 |
| Organization Tenure (years) | | |
| < 1 | 37 | 10.1 |
| 1 – 5 | 175 | 47.6 |
| 6 – 10 | 100 | 27.2 |
| >= 11 | 56 | 15.2 |
| Job Level | | |
| Entry-level | 130 | 35.3 |
| Middle management | 174 | 47.3 |
| Upper management | 64 | 17.4 |

4.1 Instrument and measurement

The predictor constructs and criterion construct were assessed using the 5-point Likert scale and 7-point, respectively, by means of reflective multiples items. Both Likert scales were used to measure to what extent respondents agreed or disagreed with the provided statements, ranging from “strongly disagree” to “strongly agree.” Work-related MIM after work hours was measured based on the gratifications obtained among the employees. To measure SIG, six items were adapted from the scale of Lee, Lee, and Choi (2012). The ISG was measured using seven items adapted from the studies by Mouakket (2019) and Baek, et al. (2011). Both MCG and SPG were measured using the scale developed by Ha, et al. (2015) with five-item and six-item, respectively. PAG was assessed using the scale of Smock, et al. (2011). Both mediators, WLB and job satisfaction, were measured using a five-item scale developed by Talukder, et al. (2018) and a six-item scale developed by

Rehman and Waheed (2011), respectively. Finally, the criterion construct, job performance was measured using the six-items scale originated from Huang and Liu (2017). To ensure content validity, these scales were pre-tested with five potential respondents. Based on the feedback, slight modifications were made to the wordings of some items for better comprehension. After revision, the survey was further piloted with another 100 respondents. All indicators and constructs demonstrated adequate reliability and validity based on the data collected from pilot testing.

4.2 Common Method Variance (CMV)

As the questionnaire was self-reported from a single source in a cross-sectional survey-based study; thus, the study utilized both procedural and statistical remedies to reduce the effects of CMV. Several procedural remedies, such as protecting the anonymity of respondents, different scale formats for predictor and criterion constructs, were applied (Podsakoff, et al. 2003). As for the statistical procedure, a marker variable with three items extracted from the study of Lin, Huang, and Hsu (2015), was adopted to assess the potential threat of CMV (Lindell & Whitney, 2001). The slight changes in the R² value confirmed that the CMV was not a potential threat.

5 Data analysis

As the study aimed to predict employee’s job performance by testing several mediating effects simultaneously in one complex sequential mediation model, PLS-SEM was the most rigorous and appropriate option. Furthermore, PLS-SEM was the most preferred alternative if the study delved into a prediction for assessing the statistical model (Sarstedt, et al. 2016). The data were analyzed in SmartPLS 3.3.2 software (Ringle, Wende, & Becker, 2015) and interpreted based on a two-stage approach: (1) measurement model assessment and (2) structural model assessment.

5.1 Measurement model assessment

The reflective measurement model was assessed through the examination of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity (Hair, et al. 2019). As shown in Table 2, although not all loadings were greater than 0.708, the deletion was unnecessary as average variance extracted (AVE) and composite reliability (CR) for those indicators had achieved beyond the threshold value of 0.50 and 0.70, respectively (Hair, et al. 2019). Thus, all constructs met the reliability and convergent validity requirements. The discriminant validity was confirmed using the Heterotrait-Monotrait (HTMT) ratio of correlation criterion (Henseler, Ringle, & Sarstedt, 2015). All constructs demonstrated a sufficient level of discriminant validity with all the values lower than the stringent criterion of 0.85 (Kline, 2011) (see Table 3).

Table 2. Measurement model assessment.

| Constructs | Items | Factor Loading | Composite Reliability | Average Variance Extracted |
|------------|-------|----------------|-----------------------|----------------------------|
| SIG | SIG1 | 0.738 | 0.864 | 0.514 |
| | SIG2 | 0.759 | | |
| | SIG3 | 0.680 | | |
| | SIG4 | 0.752 | | |
| | SIG5 | 0.686 | | |

| | | | | |
|-----|------|-------|-------|-------|
| | SIG6 | 0.681 | | |
| ISG | ISG1 | 0.751 | 0.898 | 0.594 |
| | ISG2 | 0.816 | | |
| | ISG3 | 0.739 | | |
| | ISG4 | 0.784 | | |
| | ISG5 | 0.767 | | |
| | ISG6 | 0.765 | | |
| MCG | MCG1 | 0.821 | 0.891 | 0.622 |
| | MCG2 | 0.787 | | |
| | MCG3 | 0.799 | | |
| | MCG4 | 0.791 | | |
| | MCG5 | 0.744 | | |
| PAG | PAG1 | 0.766 | 0.833 | 0.561 |
| | PAG2 | 0.724 | | |
| | PAG3 | 0.898 | | |
| | PAG4 | 0.573 | | |
| SPG | SPG1 | 0.842 | 0.872 | 0.578 |
| | SPG2 | 0.742 | | |
| | SPG3 | 0.670 | | |
| | SPG4 | 0.763 | | |
| | SPG5 | 0.775 | | |
| WLB | WLB1 | 0.789 | 0.866 | 0.564 |
| | WLB2 | 0.775 | | |
| | WLB3 | 0.725 | | |
| | WLB4 | 0.732 | | |
| | WLB5 | 0.731 | | |
| JS | JS1 | 0.830 | 0.885 | 0.564 |
| | JS2 | 0.824 | | |
| | JS3 | 0.699 | | |
| | JS4 | 0.661 | | |
| | JS5 | 0.799 | | |
| | JS6 | 0.675 | | |
| JP | JP1 | 0.783 | 0.889 | 0.573 |
| | JP2 | 0.786 | | |
| | JP3 | 0.714 | | |
| | JP4 | 0.766 | | |
| | JP5 | 0.741 | | |
| | JP6 | 0.750 | | |

Table 3. Heterotrait–monotrait (HTMT) ratio.

| | ISG | JP | JS | MCG | PAG | SPG | SIG | WLB |
|-----|-------|-------|-------|-------|-------|-----|-----|-----|
| ISG | | | | | | | | |
| JP | 0.765 | | | | | | | |
| JS | 0.717 | 0.763 | | | | | | |
| MCG | 0.763 | 0.698 | 0.721 | | | | | |
| PAG | 0.110 | 0.080 | 0.078 | 0.068 | | | | |
| SPG | 0.250 | 0.284 | 0.289 | 0.231 | 0.082 | | | |

| | | | | | | | | |
|-----|-------|-------|-------|-------|-------|-------|-------|--|
| SIG | 0.845 | 0.782 | 0.806 | 0.828 | 0.082 | 0.365 | | |
| WLB | 0.624 | 0.538 | 0.611 | 0.612 | 0.126 | 0.333 | 0.630 | |

5.2 Structural model assessment

Prior to assessing the structural model, the collinearity issue was first investigated. All inner VIF values were below the most conservative cut-off value of 3.3 (Diamantopoulos & Siguaw, 2006), suggesting that collinearity was not a threat. Next, a 5,000 re-samples bootstrapping procedure (95 percent, bias-corrected and accelerated, one-tailed) was run to assess the mediating effects (Preacher & Hayes, 2008), as summarized in Table 4. If the 95% bootstrap confidence interval (BCI) did not straddle a zero, then the conclusion of significant mediation could be made (Hayes, 2009). Hence, only ISG ($\beta = 0.017$, $t = 1.908$, $p < 0.05$, LL: 0.006, UL: 0.035), MCG ($\beta = 0.014$, $t = 2.081$, $p < 0.05$, LL: 0.006, UL: 0.032) and SPG ($\beta = 0.009$, $t = 1.831$, $p < 0.05$, LL: 0.003, UL: 0.021) significantly affected on job performance through WLB and job satisfaction. Thus, H2, H3 and H5 were supported, while H1 and H4 were not supported.

Table 4. Mediating effect.

| Hypothesis | β | Standard Error | t-values | p-values | BCI LL | BCI UL | Decision |
|----------------------------|---------|----------------|----------|----------|--------|--------|---------------|
| H1: SIG -> WLB -> JS -> JP | 0.011 | 0.007 | 1.518 | 0.065 | 0.002 | 0.027 | Not supported |
| H2: ISG -> WLB -> JS -> JP | 0.017 | 0.009 | 1.908 | 0.028 | 0.006 | 0.035 | Supported |
| H3: MCG -> WLB -> JS -> JP | 0.014 | 0.007 | 2.081 | 0.019 | 0.006 | 0.032 | Supported |
| H4: PAG -> WLB -> JS -> JP | -0.003 | 0.004 | 0.657 | 0.255 | -0.009 | 0.004 | Not supported |
| H5: SPG -> WLB -> JS -> JP | 0.009 | 0.005 | 1.831 | 0.034 | 0.003 | 0.021 | Supported |

5.3 In-sample and out-of-sample predictive relevance

The in-sample predictive power was measured using the coefficient of determination, R^2 . The R^2 (0.503) revealed that the model explained 50.3% of the variance in job performance, which implied a substantial predictive power (Cohen, 1988), comparable to studies with similar context (Huang & Liu, 2017; Sheer & Rice, 2017). Finally, the PLSPredict with a 10-fold procedure was run to assess the out-of-sample predictive power of the key endogenous construct, job performance (Shmueli, et al. 2019). The model showed a satisfactory predictive power ($Q^2_{predict} = 0.494$) and a medium predictive relevance as most errors of the PLS model was relatively lower than the LM model (see Table 5).

Table 5. PLSPredict assessment.

| | PLS | LM | PLS - LM |
|-----------|-------|-------|----------|
| Indicator | RMSE | RMSE | RMSE |
| JP4 | 1.112 | 1.168 | -0.056 |
| JP6 | 1.069 | 1.062 | 0.007 |

| | | | |
|-----|-------|-------|--------|
| JP3 | 1.225 | 1.234 | -0.009 |
| JP1 | 1.113 | 1.119 | -0.006 |
| JP2 | 1.110 | 1.151 | -0.041 |
| JP5 | 1.114 | 1.120 | -0.006 |

6 Discussions, implications and limitations

The evidence suggested employees who obtained ISG, MCG and SPG enjoyed better WLB, in turn, developed favorable attitudes towards their jobs and ultimately contributed more effort for better job performance. This finding confirmed the beliefs of U&G theory and JD-R theory, in addition to some previous empirical evidence (Haar & Brougham, 2020). Unexpectedly, WLB and job satisfaction failed to sequentially transmit the effect of SIG and PAG on job performance. This could be attributed that the proposed relationship was not linear. Indeed, a reasonable level of work-related MIM use after work hours can be viewed as job resources, but up to a specific limit. Beyond that, it may rather act as a job demand. For example, excessive use of MIM for work-related purposes after work hours for social interaction during the pandemic, especially these interactions involve supervisors, might result in unfavorable outcomes, e.g., social exhaustion and stress (Dhir, et al. 2018). Besides, the proposed relationships might be contingent on other variables, such as individual preferences. Since most respondents are Gen Y with constant attempts to seek new opportunities in career advancement, they might be reluctant to reveal their ambitious goal among co-workers (Jha, Sareen, & Potnuru, 2019). Nevertheless, these non-significant relationships might require further studies to identify their exact cause.

Though statistically significant conclusions were not made for all the proposed relationships; nevertheless, these results forward various implications. Theoretically, the findings confirmed that the complexity involved in unveiling the mechanism under which work-related MIM use after work hours was beneficial during the pandemic. In view of this, the study highlighted the 1) critical role of job resources as the trigger for the motivational path, supporting the assertions of JD-R theory and 2) the humanistic view of U&G theory, in which employees are actively and rationally in selecting MIM to obtain different gratifications for beneficial performance outcomes. Practically, employers should 1) increase job resources, 2) foster WLB and 3) nurture job satisfaction to enhance job performance. During pandemic, when job demands are likely to rise further, employers should continue to use MIM as its use contributes towards better job performance. However, employers can empower employees to decide the extent to practice work-related MIM after work hours based on individual's needs and preferences, as employees were gratified differently. Besides, employers should provide necessary training to ensure employees can make healthy use of MIM without causing detrimental effects on work and non-work-related demands. Furthermore, supervisors should lead by example as it is critical that the values and expectations are reflected through their actual doing. This is crucial during the pandemic as employees are physically isolated from other co-workers and might closely mirror their supervisor's actions (Perrigino & Raveendhran 2020).

Despite the implications discussed above, several limitations were acknowledged. First, as the study adopted a cross-sectional design, future research can be replicated by using longitudinal field surveys or experimental research design to investigate the mediating effects that unfold through time (Leatherdale, 2019). Second, the data used was single source self-reported. Though marker variable approach was used to rule out the threat of CMV, future research can be designed as multilevel by gathering performance data from

multiple sources, either objective measures, such as yearly performance appraisals, or subjective measures, such as reviews from managers, colleagues, or customers (Wong, 2016). The third limitation is related to the heterogeneity issue among the sample population. Future research may use multi-group analysis to identify heterogeneity issues and compare the results based on observable factors, such as employee-specific characteristics (e.g., generational cohorts, personal traits) and organizational factors (e.g., leadership style, co-workers' pressure) to enhance the possibilities of developing organizational policies that meet the needs of each category during the pandemic.

7 Conclusion

During Covid-19 pandemic, MIM is intensively used as a professional tool. Therefore, the study adds to the existing literature on work-related MIM after work hours by challenged the predominant propositions that it is an undesirable practice. Despite not all the proposed relationships were found to be significant, it highlighted the complexity of the mechanism involved. To be beneficial, work-related MIM use after work hours served as job resources to attend to work and non-work responsibilities which contribute to WLB, in turn help in forming favorable job attitudes and ultimately enhance the job performance. Thus, work-related MIM use after work hours should not be interpreted negatively but rather viewed as a practice for enhancing job performance. However, employers should exercise caution on developing one-size-fits-all solutions, as not everyone is gratified in the same way. There were multiple layers as to why employees practice work-related MIM after work hours during the pandemic, which, at the present stage of research, could not be easily investigated; nevertheless, it is necessary to be considered critically to unveil the underlying 'black box.' Both researchers and practitioners should work jointly to gain better insights on how to proactively manage tech-driven transformation processes driven by the pandemic. The goal should be that of facilitating those employees equipped with MIM to enhance their performance without compromising WLB and job satisfaction. Undoubtedly, putting the genie back into the bottle will not solve the problem; thus, a healthy and sustainable approach is needed on how to work the best with it.

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