The Work-Habits Intervention Model: A 12-month Study to Change Work-Email Habits

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Introduction

The fact that 'old habits die hard' is the mainstay of many maladaptive behaviors. Entrenched habitual propensities to maintaining existing behaviors are often blamed for failure to give up smoking, to change one's diet, or to undertake more physical exercise (Conroy, Maher, Elavsky, Hyde & Doersken, 2013; Danner, Aarts & DeVries, 2007). Accordingly, intervention programs focus on teaching people how to extinguish old 'bad' habits and develop new 'good' habits (Gardner, 2015; Webb, Sheeran & Luszcynska, 2009).

Habits are cue-generated sequences of actions, originally directed towards the achievement of domain-relevant goals, which have become automated through repetition and association with positive consequences (Oullette & Wood, 1998; Polites & Karahanna, 2013; Verplanken & Aarts, 1999). Habits have traditionally been researched within fields of behavioral and social psychology and are of particular interest to a range of disciplines and applications (e.g., health psychology, Gardner, 2015; marketing, Verplanken, Herabadi, Perry & Silvera, 2005; Verplanken & Wood, 2006; and, information systems, Polites & Karahanna, 2013). However, to-date, research in occupational and organizational psychology has largely ignored the role of habits in work-activity[1].

Work-habits differ from other habits in several ways. First, they are related to work-relevant goals and triggered by work-relevant cues (Polites & Karahanna, 2013). A work-habit could include a nurse checking a patient's notes as soon as they enter a hospital cubicle. Second, they are often embedded within an interrelated system of group and organizational actions (Frese & Zapf, 1994; Polites & Karahanna, 2013) that may impact the extent to which an action becomes habitual. So, a nurse can only check a patient's notes if these have been left in the cubicle by the last nurse who worked the shift. Third, a work-habit is usually only considered to be 'good' or 'bad' in terms of how it impacts relevant outcomes. When a nurse

[1] A notable exception is within the realms of action regulation theory (ART), which outlines how well-practiced and goal-directed work behaviors become habituated when the lowest levels of conscious regulation are required to enact them, and situational parameters do not change (Frese & Zapf, 1994).

checks a patient's notes habitually, this is good if it means that important data can be immediately obtained, but bad if the nurse relies on the notes more than their own assessment of the patient's condition and misses a new development.

It is clear then that work-habits may manifest differently, and require a different approach to being 'changed', than habits conceptualized by, for example, the health literature. So, whilst smoking would universally be considered a 'bad' habit that can be developed and maintained on an individual basis outside of a social system, work-habits exist in an organizational system, and context will determine the extent to which they are 'good' or 'bad' and need changing, as per the above example. Understanding how, when and why work-habits need to change therefore requires an understanding of whether the work-habit is 'effective' or not. If a work-habit is associated with ineffective outcomes it will need changing, and a clear rationale will need to be presented to workers to indicate how and why changing the existing habit will be beneficial.

The aim of this study is to explain how to improve work-habits over time, through proposing the Work-habits Intervention Model (WhiM). In developing our model, we take a two-part approach (Dubin, 1978) that involves (i) examining and proposing theory in relation to the phenomenon of work-habits and work-habit change; (ii) testing the applicability of such theory in respect of a specific, applied example of the phenomenon. Thus, to satisfy part 1, we present the WhIM in four-stages, indicating what variables are likely to be important in understanding how to change work-habits, and how these variables relate to each other. To satisfy part 2, after each stage of model development, we generate hypotheses to verify the applicability of the WhIM in relation to the specific example of work-email habits. Work-email has multiple functional operations and is used frequently throughout a working day (Whittaker & Sidner, 1996). Actions that make full use of the functionality of a system, and are repeated frequently, are more likely to become automated (Limayem, Hirt & Cheung, 2007; Oullette & Wood, 1998), so there is a very high propensity for people's work-email actions to become habitual (Mazmanian et al., 2005; Middleton & Cukier, 2006; Turel et al., 2011). We apply the WhIM in a work-email context via a 12-month study, using an active and wait-list control group (see Method). We then consider the extent to which the WhIM may need to be amended or adapted in light of our empirical application (Dubin, 1978), and suggest how future research can improve understanding and practice in relation to promoting effective work-habits (see Discussion).

In proposing the WhIM, we make three key contributions. First, we suggest that changing entrenched behaviors at work is driven by a two-stage process whereby workers (i) are exposed to clear and rationalized action plans (Fleig, Pomp, Parschau, Barz, Lange et al., 2013) that explain how and why changing a habit will enable them to be more effective *and* (ii) workers state their intention to use these plans (Gardner, Phillips & Judah, 2016). Drawing on Gardner et al.'s (2016) health-based instigation-execution model, we agree that intentions to act are important to promoting behavior change in regard to any habit, but we further develop this conjecture by attesting that intentions to act will not result in behavior change *at work* if a suitable action plan has not been developed to rationalize and guide this.

Second, we propose that in a work context, habit change in and of itself is not sufficient for determining whether an intervention has been effective. The work-habit change must be associated with a consequential improvement in relevant work-goal attainment *and* well-being (the most salient outcomes for conceptualizing effectiveness in work domains: Quick, Macik-Frey & Cooper, 2007) to indicate that the intervention has been effective. This point is especially important to elucidate in a work context where work-habits are not always obviously 'good' or 'bad'. Separating the change in action (habit) from the change in outcomes (good or bad) enables us to identify that work-habit change is effective if it helps people to achieve their work-goals and improve their well-being, but not effective if it stifles goal achievement or negates well-being.

Our third contribution is to illustrate how long-term and field-based approaches to intervention applications are necessary when examining work-habit change. This is because work-habits are often embedded in organizational and group systems. Applying an intervention over the longer term and within the environment in which the habit-change needs to be enacted is therefore important. We also draw on best practice in intervention designs that show how within-person change and between-person differences interact to explain the dynamics of habit-change.

In relation to these contributions, we develop evidence-based guidance on how the negative effects of work-habits might be ameliorated through application of the WhIM. Such guidance provides an important practical contribution to the field, and also indicates a potential benefit to the development of a new model or approach to understanding an applied phenomenon (Dubin, 1978; Gregor, 2006).

We choose to examine work-email habits as an applied 'test-bed' for the WhIM, because work-email habits are a strong example of a work-habit, as illustrated earlier. For example, as per other work-habits, work-email habits (i) are triggered by work-relevant cues (e.g., an email notification) and goals (e.g., the need to communicate with colleagues), (ii) are dependent on system embeddedness (a worker cannot automatically respond to a notification if no-one has sent an email), and (iii) require an evaluation of outcomes to understand their 'goodness' or 'badness' (does automatic responding have a beneficial impact on work goals and/or well-being?). The lack of constitutional goodness or badness of a work-email habit is clear, and has repercussions for the likely success of any intervention. For example, an intervention to stop people checking email notifications immediately is likely to have diverse effects because the habit has a differentially good or bad impact on work-relevant goals and well-being, depending on the context and the other people or systems at work that will be affected by this. To illustrate, automatically responding to email notification cues can provide timely and helpful replies to customers and coworkers (Mazmanian, Orlikowski & Yates, 2005). Equally however, such habits can lead to addictive behaviors that reduce work efficiency (Turel, Serenko & Bontis, 2011). To change work-email habits, a model that takes this into account is needed.

As discussed then, in the sections below then we set out our development of the WhIM across four stages in relation to work-habits. For each stage, we then present hypotheses in relation to the applied context of work-email, used to provide an initial test of our theorizing (Dubin, 1978).

Model Building Stage 1: Understanding how Habits Change

Gardner et al. (2016) presented an instigation-execution model to inform interventions targeted at health-habits. In this model, a habitual response involves (i) a cognitive mechanism, or automated intention to act (Gardner, 2015), as separate to (ii) the automated execution of actions (Gardner, Rebar & Lally, 2019). Health-habits are formed by learning associations between cues and actions, often as a result of repeated application (Conroy et al., 2013; Danner et al., 2007; Gardner et al., 2015). When cues are stable, control over one's action becomes more reliant on the environmental stimulus and less reliant on cognitive or motivational processes (Aarts, Verplanken & van Knippenberg, 1998; Wood & Neal, 2007). In changing habits, because actions can be inhibited or forgotten (Fleig et al., 2013), it is changing the habitual impulse to act (the intention or instigation) that makes the greatest impact (Gardner, 2015). This means that interventions to break an entrenched habit first require people to develop new intentions in relation to their environmental cues (Conroy et al., 2013). Developing new intentions is a stronger predictor of behavioral change than developing frequent executions of a new action (Gardner et al., 2016; 2019).

Although Gardner's instigation-execution model promotes the importance of changing intentions for changing health behaviors, it does not specify how new intentions come to be consolidated. We suggest that providing a rationalized action plan is a key mechanism for consolidating new intentions at work. As the automatic instigation of a habit process means that the original purpose of an old action has been lost, a different response might be elicited if a new behavior can be rationalized (Aarts et al., 1998) and a clear execution plan put in place (Fleig et al., 2013). A rationalized action plan explains why a change in action is required, and how such a change would improve attainment of work-goals and well-being. For example, in dealing with work-email in the dial-up era, a worker probably logged in only a handful of times per day, so it made sense to deal with work-email at the point it was received (Whittaker & Sidner, 1996). But in today's environment, immediate response habits could now be considered maladaptive (Mazmanian et al., 2005), creating reactive, addictive, and high-stress emailing cultures (Turel et al., 2011). Therefore, providing a new, rationalized plan for responding to a work-email cue (e.g., turn off email notifications, or only check email at pre-defined times during the day) may allow individuals to recognize a new purpose to their activity (e.g., improving well-being, achieving task goals more effectively) and provide the cognitive switch that provokes an intention to change behavior and achieve one's goals (Fleig et al., 2013; Gollwitzer & Sheeran, 2006; Holland, Aarts & Langdendam, 2006). Action plans do not need to be set by the worker (Webb et al., 2009); however, it appears that an action plan must be rationalized in terms of attaining personal work and well-being goals for it to be translated into a new intention and change effected (Quinn, Pascoe, Wood & Neal, 2010; Wood & Neal, 2007). Therefore, we suggest that within the WhIM, changes in work-habits will emerge if both rationalized action plans have been accepted by the worker, and they have stated an intention to use these. This suggests a two-stage process is an important precursor to any changes in behavior observed.

Testing Stage 1 of the WhIM, with a work-email application

To test the notion that work-habit change involves exposure to rationalized action plans, and a stated intention to use these plans, our intervention for improving work-email use involved two-stages. First, we provided regular rationalized action plans, relating to improving work-email use. Second, we asked members of the intervention group about their stated 'intention to use' each action plan (as per Fleig et al., 2013; Gollwitzer & Sheeran, 2006; Holland et al., 2006). We therefore hypothesized that changes in work-email actions would be mediated by stated intentions to use the action plans (expressed over the 12-month period) in response to each plan.

H1: 'Intention to use' a rationalized action plan for improving the use of work-email mediates the change in actions for dealing with work-email amongst the intervention group.

Model Building Stage 2: Individual Differences in Changing Habits - Self-regulation

To understand the dynamics of habit-change, both within-person influences (changes in actions and/or outcomes across the intervention period) and between-person influences (individual differences in propensity to change) should be examined. A key set of between-person differences relevant to change are self-regulation resources (Gardner, 2015; Webb et al., 2009). Self-regulation resources assist people in exercising control over themselves to achieve desirable standards (Vohs & Baumeister, 2004). Self-regulation resources can be features of (i) the person (e.g., trait self-control, self-efficacy), and (ii) the context (e.g., job control, job support) (Gardner, 2015; Neal, Wood & Drolet, 2013; Ohly, Goritz & Schmitt, 2017).

When self-regulation resources are low, people are likely to succumb to existing habits, supplanting intentions to behave differently (Neal et al., 2013). This is because active self-regulation, (i.e., consciously inhibiting habits) is effortful and resource-depleting in the long term (Danner et al., 2007; Muraven & Baumeister, 2000; Ohly et al., 2017; Quinn et al., 2010). Those with more stable personal resources for self-regulation, such as higher trait self-control (Elfhag & Morey, 2008; Tangney, Baumeister & Boone, 2004), higher self-efficacy (Lloyd, Bond & Flaxman, 2017; Wang, Wu, Parker & Griffin, 2018), or more autonomous and supportive job environments (Ohly et al., 2017; Park & Kim, 2019), are likely to override old, unwanted habits, by stating, acknowledging, and sticking to clear intentions and action plans (Carver & Scheier, 2008; Muraven & Baumeister, 2000). In other words, people with higher levels of self-regulation resources are more likely to believe that they can change their actions, and have the willpower, support, and control over their work to do this (Baumeister & Alghamdi, 2015; Verplanken & Wood, 2006).

Within the WhIM, we operationalize self-regulation resources in terms of both person (self-control, self-efficacy) and job context (job control, job support). These self-regulation resources have been examined in previous research related to how people attempt to exert control over their work behaviors, as we outline below. In terms of person-based self-regulation resources, trait self-control involves having the foresight to plan ahead and keep action on track in pursuing goals (Carden & Wood, 2018). People with higher levels of self-control are less likely to develop strong, unhealthy habits, to be tempted or distracted by goal-averse activity and are better able to reorganize their situation to reduce exposure to cues that prompt habitual, goal-averse responses (Carden & Wood). Self-efficacy is another person-based regulatory resource important for changing behaviors (Blume, Ford, Baldwin & Huang, 2010). Those with higher levels of self-efficacy believe in their ability to exert control over their tasks and are optimistic about the outcomes of their goal-oriented activity (Bandura, 1997; Di Maio, Keller, Hohl, Schwarzer & Knoll, 2021). Self-efficacy moderates the relationship between intentions and action change, as those with higher self-efficacy are better able to overcome obstacles and keep motivated (Luszczynska, Schwarzer, Lippke, & Mazurkiewicz, 2011; Verplanken & Wood, 2006). This is also the case when attempting to develop healthier habits (Di Maio et al., 2021).

In relation to contextual self-regulatory resources, both job control and job support have been found to be important as workers attempt to change their behaviors and habits (Blume et al., 2010). In terms of job control, action regulation theory (Frese & Zapf, 1994) posits that when individuals have autonomy over their work (i.e., job control) they are able to engage in regulatory activity to achieve their goals in the most efficient way. When activity needs to change, because parameters change or goals are no longer effectively being achieved, those with control over their work can switch from automated modes to engage more conscious levels of regulation. This allows workers with job control to enact new action sequences and monitor whether they are leading to more desirable outcomes.

Job support involves feeling supported by managers and co-workers. It is a staple of intervention research that a supportive training environment, and being given the opportunity to practice new behaviors in a safe and supportive way, results in greater training transfer (Colquitt, LePine & Noe, 2000). It is therefore likely that when people have higher levels of job support in their work environments, they will feel able to try out new work behaviors in relation to the intervention.

Within the WhIM, we suggest that individual differences in self-regulation resources are likely to impact the extent to which the two-stage process (outlined above) will result in actual habit change.

Testing Stage 2 of the WhIM, with a work-email application

Both personal and contextual self-regulatory resources are likely to be important in testing the WhIM, with a work-email intervention. Self-control has been found to help resist habitual responding in relation to digital activity (Duckworth, White, Matteucci, Shearer & Gross, 2016). Relating to work-email habits in particular, those with higher levels of trait self-control are better able to resist or ignore new email notifications (Russell, Woods &

Banks, 2017) and achieve task goals in relation to work-email demands (Rosen, Simon, Gajendran, Johnson, Lee, & Lin 2019). For work-email habits specifically, Huang, Lin and Lin (2011) and Huang and Lin (2014) also found that those with higher levels of self-efficacy felt more in control and made sustained changes to improving work-email use, following an intervention.

As such, we hypothesized:

H2: The extent to which workers' 'intention to use' rationalized action plans positively predicts changes in work-email actions, is strengthened when person-based regulation resources are higher, in terms of (a) trait self-control and (b) self-efficacy.

Although job control and support have not been explored in work-email intervention contexts (to our knowledge), a seminal meta-analysis of training transfer in organizations, suggests their importance for behavior change following an intervention (Blume et al., 2010).

As such, we hypothesize that:

H3: The extent to which workers' 'intention to use' rationalized action plans positively predicts changes in work-email actions is strengthened when contextual regulation resources are higher, in terms of (a) perceived job control and (b) perceived job support.

Model Building Stage 3: Action Change and Impact on Goals and Well-being

In relation to work-habits, it is important to measure both action change and changes in effectiveness of outcomes, related to goal attainment and well-being. As discussed, a work-habit that is beneficial for one person and one goal, can be detrimental to another person with another goal (Middleton & Cukier, 2006; Russell & Woods, 2020). When habit-change is associated with an improvement in goal attainment, we anticipate a corresponding and contemporaneous improvement in well-being outcomes. This directional relationship between goal attainment and well-being has been well-supported across many models and theories of goals (e.g., Barrick, Mount & Li, 2013; Carver & Scheier, 1990; DeShon & Gillespie, 2005; Emmons, 1996; Locke & Latham, 2006; Ryan & Deci, 2000). This directional relationship is likely to be coupled closely in time as attaining goals is an affective event that creates a proximal positive emotional reaction (Frijda, 1993; Weiss & Cropanzano, 1996). At work, well-being is often measured in terms of affective well-being, comprising a hedonic tone and arousal element, and job satisfaction (Warr, 1978). Affective well-being is commonly measured in terms of negative activated affect (NA) and positive activated affect (PA) (Tellegen, Watson & Clarke, 1999).

In the WhIM therefore, in line with previous intervention studies (Oliver & MacLeod, 2018), we suggest that sustained behavior change (i.e., change in action frequency over time) is likely to be associated with an improvement in perceived goal attainment (in relation to the specific work-context or phenomenon), which is contemporaneously associated with improvements in well-being. If both goal attainment and well-being are associated with a change in work-habits, it means there is a close coupling of desired outcomes with behavior change, and therefore behavior change is more likely to endure (Aarts & Dijksterhuis, 2000; Limayem et al., 2007). Habit strength alone is not enough to sustain a new habit; it must be associated with outcomes that are preferential to outcomes associated with old habits (Gardner, Corbridge & McGowan, 2015), as well as being closely linked in time (Mesner, Foster & French, 2016).

Further, a significant, practical assertion modelled in the WhIM is that only when both goal attainment and well-being are improved, as a result of an intervention to change work-habits, can it be claimed that the intervention has been effective. A work-habit itself cannot be referred to as ‘effective’ without knowing how it impacts valued outcomes over a prolonged period.

Testing Stage 3 of the WhIM, with a work-email application

Given the above discussion, we therefore anticipate that change in work-email actions over a longer-term intervention program will predict improvements in well-being outcomes (NA and PA, and job satisfaction) via the mediating effect of perceived goal attainment. Studies into the impact of work-email on both work and well-being goals are apparent within the research literature (Russell & Woods, 2020) and indicate that unless both outcomes are achieved, 'paradoxes' in the effectiveness of people's behaviors are apparent (Dawley & Anthony, 2003; Middleton & Cukier, 2006; Mazmanian et al., 2005/2013).

H4: Over the 12-month intervention period, changes in work-email actions will positively predict changes in perceived goal attainment, which will mediate a proximal change in well-being in terms of (a) higher levels of perceived job satisfaction (b) lower levels of NA and (c) higher levels of PA.

Building the Model Stage 4: The Final Stage towards a Proposed WhIM

Considering all of the preceding relationships, we propose, using Figure 1 to illustrate, a Work-habits Intervention Model (WhIM) which brings together the individual components from the preceding stages. As seen in Figure 1, the WhIM provides a unique approach to understanding and predicting work-habit change by focusing on: (i) a two-stage process involving exposure to rationalized action plans and a stated intention to act on these; (ii) changes in actions *and* changes in associated outcomes; (iii) 'effectiveness' of change being appraised in terms of how both goal attainment and well-being are impacted; (iv) long-term exposure to an intervention in a field setting to encourage embeddedness; and, (v) both within person (change in actions and outcomes) and between person (self-regulatory resources as moderators) dynamics.

Testing Stage 4 of the WhIM, with a work-email application

To test the full WhIM in an applied setting, we use a path analytical approach, using 12 months of data on work-email habit change, to examine whether and how our predictions are verifiable with this initial test-bed study (Dubin, 1978). Figure 1 provides a pictorial overview of the WhIM and summarizes the first four hypotheses. Because we wish to examine the relationship between all of the WhIM variables in one analysis that allows for the directionality of relationships to be established, and as summarized in Figure 1, we hypothesize that:

H5: A greater intention to use rationalized action plans predicts changes in work-email actions, which in turn predicts higher levels of (a) perceived job satisfaction (b) lower levels of NA and (c) higher levels of PA via perceived goal attainment as a proximal mediator to well-being. The extent to which intentions to act result in changes to work-email actions, is moderated by self-regulation resources relating to (d) trait self-control, (e) self-efficacy, (f) perceived job control and (g) perceived job support.

[INSERT FIGURE 1 ABOUT HERE]

Method

To test the WhIM in relation to an applied work-email context, a 12-month field intervention program was designed with two-stages to the intervention: (i) regular exposure to rationalized action plans, and (ii) stated intentions to act (or not) on each plan. Plans were provided to participants on a regular basis over two four-month periods, and participants stated their intention to use each plan (see details below). Change in work-email actions, and outcomes relating to any change were measured around 4-6 weeks after the end of the intervention period. When examining changes to habits it is recommended that outcome variables be measured close enough in time to the habit-change intervention for the relationship to be established, but not so close to the intervention that evidence for sustained change cannot be shown (Lally & Gardner, 2013; Ployhart & Vandenberg, 2010).

Participants and Procedure

Some 320 employees of an international charity were emailed information about the study, including full ethical details, and invited to take part. Information was also posted on the organization's intranet pages. Employees were invited to complete a 'benchmarking' survey, in the latter half of January 2017, by the organization's Human Resources Director. Participants were given a link and a two-week window within which to complete the survey. One week later, the same Director emailed all employees again and asked them to complete another survey about their email use. Only participants who had completed both surveys were included in the study (*N*=127). Participants were then randomly allocated to either the active intervention group (*N*=64), or to a 'wait-list' control group (*N*=63) (see Briner & Walshe, 2015). Over the course of the 12-month study period, 16 participants left the organization, and two further participants dropped out before starting the intervention, leaving *N*=58 in the control group and *N*=61 in the intervention group. Not all participants participated at each time point (see Analysis). There were three time points, referred hereafter as 'T1': Time 1, 'T2': Time 2, and 'T3': Time 3. T1 refers to the time prior to the intervention period; T2 refers to the time during which the intervention is delivered; T3 refers to the time at the end of the 12-month study period. Demographic data were collected relating to age, gender, location, department, and job-level, and is reported for the participants who completed surveys at T1 and T3 (only those who completed T1, T2 and T3 measures). This data is summarized, per group, in Table 1. Attrition analysis is presented in the Analysis section.

[ENTER TABLE 1 ABOUT HERE]

Over the intervention period (T2, commencing on March 8th, 2017), the intervention group was provided with 23 evidence-based 'email tips', sent every two-weeks via email from the research team up to December 2017 (with a short break during the summer). These tips were generated from academic research and represented rationalized action plans across four categories for improving work-email use: (i) ‘Sending’ email, (ii) ‘Receiving/Checking’ email, (iii) ‘Managing’ email systems, and (iv) ‘Choosing Communication’ modes appropriately. Example tips can be made available by contacting the authors.

Due to the two-stage nature of this intervention design, immediately after receiving each tip, intervention group participants were asked about ‘intention to use’ the tip, and were given the instruction: *“Using the voting links above, in response to this tip, do you intend to adopt this approach in your use of email, moving forwards? If you already use this approach, please choose ‘yes’. If you have any comments about this tip, please reply to this email and let us know what you think.”* Participants could then click on a button to indicate “Yes, I intend to use this tip” or “No, I do not plan to use this tip.” A manipulation check was undertaken to examine attention to the two-stage intervention (Hauser, Ellsworth & Gonzalez, 2018). Of those in the intervention group who were exposed to regular, rationalized action plans (stage 1), only 8% never expressed an intention to use (or not) the action plan (stage 2), across the intervention period. We also calculated the mean value of ‘intention to act’ for the intervention group (0.532) compared to the control group (necessarily 0). There was a significant difference ($p<.001$, 95% credibility interval 0.431 to 0.630), with values at 20th and 80th percentiles of 0.428 and 0.693, respectively. These checks indicate that the majority of participants in the intervention group engaged with the intervention.

A follow-up ‘email-use’ survey was completed in January 2018 (T3) by participants in both the control and intervention groups.

Measures

Table 2 summarizes the schedule of data collection. For all multi-item scales, scale scores were calculated by reverse coding items where appropriate, summing all items, and dividing by the number of items in the scale.

[ENTER TABLE 2 ABOUT HERE]

Control Data

T1 data for well-being outcomes and perceived goal attainment (see below) were used as lagged control variables in all models where T3 well-being and goal attainment outcomes were included.

Predictor Variable

In our model, the predictor variable was whether the participants were in the intervention group and receiving rationalized action plans (coded '1') or the control group (coded '0'). Receiving rationalized action plans is stage 1 of the two-stage intervention process.

Mediator Variables

Intention to use action plans. Participants in the intervention group were asked about their intention to use each rationalized action plan or 'tip' as stage 2 in the two-stage intervention process. Participants were coded '1' if the participant had received the action plan and had indicated they intended to use it (i.e., could only be in the intervention group). A code of '0' indicated that the participant had: voted that 'no' they did not intend to use the tip (i.e., could only be in the intervention group); participants in the control group were also coded '0'. We then calculated the proportion of '1' responses (out of the total '1' and '0' responses) in the intervention group and created an average. Data were coded as missing if we received no responses.

Change in work-email actions. Frequency of use of actions can be used as a proxy for 'habit' (Ouellette & Wood, 1998), with execution/instigation frequency a better predictor of behavior change than measures that focus on automaticity (Labrecque & Wood, 2015). We examined reported changes in frequency with which 22 commonplace work-email actions (Russell & Woods, 2020) had been executed in the past month, using a 5-point scale (where -

1 = never to 5 = always), from T1 to T3. Change in frequency of use was calculated by subtracting the value of each action at T1 from the values of each action at T3, and squaring the difference, to obtain a change score that did not imply change in actions in one direction to be ‘better’ than change in actions in another direction (because different work-email actions cannot universally be related to the satisfaction of people’s goals: Russell & Woods, 2020)[2]. We then took the square root of the change to convert the change score back into its original metric and to ensure extreme changes in action were not given undue weight in the analyses. Changes in action over the 22 items were summed and divided by 22 for each person[3].

Perceived goal attainment. We asked participants to rate on a five-point scale (where 1= never, 2= seldom, 3= sometimes, 4=often and 5=always) the extent to which, “Over the past month the strategies that I used to deal with my work-email helped me to…: achieve goals relating to ‘work’, ‘feel a sense of well-being’, ‘feel in control’, and ‘show consideration towards others’”. These goals are considered to be especially salient to people’s work-email activity, with different goals being differently relevant to different people (Russell & Woods, 2020*)*. As such, this variable represents an index of participants’

[2] Any action is simply a behaviour until it is executed frequently and automatically in response to a cue, as per the definition of a habit. This is why, for each of the 22 work-email actions examined, we asked our participants to indicate the frequency with which they were used, in response to the cue of ‘sending, receiving or managing’ work-email. If application of any action changed from high to low frequency or low to high frequency, the bigger the ‘change’ score will be, and hence an indication that a habit (rather than simply an action) has developed or been extinguished.

[3] Please note that the use of simple change scores has attracted some criticism. We opted to use simple change scores for four reasons. First, the explanation is intuitive to understand and the resulting score meaningful, as values are based on equivalent ratings over time periods with the same participants. Second, there is precedent for using simple change scores in (i) time series analyses, (ii) multi-level modelling (via centering processes), and (iii) latent change score analyses. Third, an alternative to using change scores would be to directly ask participants if they have changed their actions over the preceding months, which would be problematic because participants in the intervention condition were not blinded to the provision of tips. Asking for retrospective reports of action change would introduce a demand characteristic. Fourth, we investigated the convergence of our difference score with an indicator of action change derived from regression analysis by regressing each work-email action score at T1 onto its corresponding score at T3, and saved the unstandardized residual. The residual reflects the amount of change in action. To remove the direction of change, as above, we squared the residual and then took the square root. We then summed the resulting values for each of the 22 actions and divided by 22. The correlation between our original difference scores and the scores derived from regression residuals was 0.86, indicating a very high level of convergence between both approaches. In light of all four reasons, we therefore decided to use simple change scores in the analyses.

perceptions of different goal attainment in relation to work-email, rather than a cohesive scale. Scores for each goal were summed and divided by 4 to give a composite *perceived goal attainment* score at T1 (control) and T3.

Moderator Variables

Four self-regulation variables were collected at T1. *Trait self-control* was measured on the Conscientiousness scale of the 50-item Big Five Factor Marker (Goldberg, Johnson, Eber, Hogan, Ashton & Cloninger, 2006). Participants were asked to respond to 10 statements (e.g. "I am always prepared") on a 5-point scale (1='Very inaccurate' to 5='Very accurate', α=0.82). *Self-efficacy* was measured on an 8-item scale (Chen, Gully & Eden, 2001), with items such as "I am confident that I can perform effectively on many different tasks" on a 5-point scale (1=strongly disagree, 5=strongly agree, α=0.74). *Perceived job control* was measured on a 6-item scale (Breaugh, 1985, e.g., "Can you control the sequencing of your work activities?" α=0.86). *Perceived job support* was measured on a 4-item scale (Daniels, 2000, e.g., "Can you seek advice from other people about work problems?", α=0.86). Answers for *perceived job control* and *perceived job support* were coded on a 5-point scale (1=never, 5=very often).

Outcome Variables

Well-being. Two measures were used at T3 (with T1 controls). Affective well-being was assessed on a short-form scale (Russell & Daniels, 2018) via measures of *NA,* using items: Angry; Calm, reversed; Anxious; At Ease, reversed (α = 0.78 T1, α=0.84 T3) and *PA,* using items: Tired, reversed; Active; Bored, reversed; Motivated; (α = 0.73 T1, α=0.84 T3). Ratings were on a six-point scale reporting the extent to which 'In dealing with my work email, over the past month, I have generally felt…" for each item (1='not at all' and 6='very much so'). As with goal attainment, affective well-being was assessed in the context of work-email use, to ensure optimum conceptual concordance with the intervention's purpose as recommended by Briner and Walsh (2015). *Job satisfaction* (Bowling & Hammond, 2008) was measured using a 3-item scale (e.g., "All in all, I am satisfied with my job"). Participants rated their response in reference to the past month on a 7-point scale (1=strongly disagree, 7=strongly agree, $\alpha = 0.84$ T1, $\alpha=0.78$ T3).

Testing for Factorial Invariance

We conducted factorial invariance analysis on scales of two or more items that were designed to capture one underlying latent construct (Widaman, Ferrer & Conger, 2010), allowing us to establish if the measure was stable over repeated data collection points. We had two data collection waves (T1 and T3) and three of our measures satisfied Widaman et al.'s (2010) criteria (as above). We tested three types of invariance using Bayesian factor analysis (because of our small sample sizes). For PA and NA tests, we factored in differential responding to positively and negatively valenced items (Russell & Daniels, 2018) by allowing residuals of negatively valenced items to correlate, and residuals of positively valenced items to correlate. Results are presented in Table 3. The results support factorial invariance for the measures.

[ENTER TABLE 3 ABOUT HERE]

Analysis

Missing Data Analysis

Little's (1988) Missing Completely at Random (MCAR) Test was significant when including ($\chi2=208.51$, df= 135, $p < .01$) or excluding ($\chi2=187.95$, df= 135, $p < .01$) those who left the organization during the course of the study. Therefore, given the number of missing variables, we opted not to use multiple imputation or other missing data techniques in the analyses. Instead, we only used data from participants who supplied data at all three time intervals, given data were collected at each interval ($N = 46$; 25 in the intervention group). In this group, Little's MCAR Test was not significant ($\chi2=34.67$, df= 36, $p > .10$).

Attrition Analysis

We undertook attrition analysis, using Goodman and Blum's (1996) four step approach with the T1 variables of NA, PA, job satisfaction, goal attainment and each self-regulatory resource (trait self-control; self-efficacy, job control and job support). Initially we excluded those who had left the organization by T3, and then performed the analyses again with leavers included. We found no evidence that attrition biased subsequent data analysis. In step 1, multiple logistic regression analyses indicated no non-random sampling, as no individual variable predicted drop-out from the study (p >.10) and the overall regression equations were not-significant (p > .10). Goodman and Blum (p. 635) indicate steps 2-4 only need to be performed if there are significant results at step 1.

Hypothesis Testing

The hypotheses were tested in a path analytic framework. We used Bayesian estimation with manifest variables in MPlus (Muthén & Muthén, 2017), which is an appropriate approach given the relatively small sample size and significant departures in non-normality for some variables (notably positive intentions to use action plans which was assigned '0' to all in the control group) (see Zyphur & Oswald, 2013 for a discussion)[4]. To further protect against the impact of reduced samples sizes by T3, we used a four staged forward-stepped approach to building our model.[5] Snijders and Bosker (2004) indicate that a stepped approach is appropriate to retain model power and reduce the risk of convergence failure, or tendency to over-fit data, when N is low and the number of predictor variables are high.

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[4] Bayesian path analysis is suitable for small samples, complex models and non-normal data. Whereas classical approaches, such as maximum-likelihood (ML), rely on frequentist probability (probabilities of observed data patterns being true over time, to substantiate rejection of the null hypothesis), Bayesian analysis looks at probabilities of parameters of interest having an effect within the time period of interest (Zyphur & Oswald, 2013). Running a ML path analysis with moderated and mediated effects would require much greater sample sizes than we would have been able to obtain from our population, because of how ML treats missing data and non-normal distributions (Weston & Gore, 2006).

[5] For each model, the number of iterations was set to a minimum of 5000, with thinning applied every 20 iterations.

Hypothesis 1 was tested in a Stage 1 model. Hypotheses 2 and 3 were tested in a Stage 2 model, whereby each moderator was assessed separately, in separate models first. Only moderator terms that were significant in both the individual and combined Stage 2 model testing were retained. Hypothesis 4 was tested in a Stage 3 model. The final, full Stage 4 model (Hypothesis 5) was then tested, including any moderator terms significant at earlier stages. Residuals between the well-being indicators at T3 were allowed to correlate. T1 control variables were entered at earlier stages as relevant. Following MacKinnon, Lockwood and Williams (2004), indirect effects were deemed significant only if constituent paths attained significance, and the coefficient of the indirect effect was also significant.

Results

Table 4 shows the alphas, means, standard deviations, and correlations for all study variables.

[INSERT TABLE 4 ABOUT HERE]

In Bayesian analysis, model convergence is indicated by the Potential Scale Reduction (PSR) value being less than 1.01 (Muthén, 2010). All models (Stages 1, 2, 3, 4) demonstrated good model convergence. In each model, a PSR of less than 1.01 was reached by the 600th iteration or sooner and remaining below 1.01 until the 5000th iteration. Good model fit is indicated a Posterior Predictive Checking (PPC) value that includes zero in its 95% confidence interval (CI) (Muthén, 2010), as well as values of the Confirmatory Fit Index (CFI) greater than 0.90 (preferably > 0.95) and a Root Mean Square Error of Approximation (RMSEA) less than 0.10 (e.g., Iacobucci, 2010). In all models, the 95% CI of the PPC included zero. Four models had CFIs in excess of 0.95 and RMSEA's of 0.05 or lower (Stage 1, Stage 2 models testing conscientiousness and self-efficacy interactions, Stage 4) and one other model had a CFI of 0.90 and RMSEA of 0.10 (Stage 3). Despite good fit indicated by the PPC, two models had problematic CFIs and/or RMSEAs (Stage 2 models testing job control and job support interactions, CFI = 0.91 and 0.87 respectively, RMSEA = 0.19 and 0.25 respectively). However, neither job control nor job support featured in the final model (see below).

In the first stage model that tested Hypothesis 1, we tested whether exposure to rationalized action plans alone would lead to a direct change in work-email actions (B = 1.59, *ns*). Exposure to rationalized action plans was related to positive intentions to use action plans (B = 0.53, p < .01), supporting the first part of Hypothesis 1. However, positive intentions to use action plans were not related to changes in work-email actions (B = 0.12, *ns*). Therefore, Hypothesis 1 was not supported overall.

In the Stage 2 models, examining the moderator Hypotheses 2 and 3, we found no support for trait self-control, job control, or job support in models testing each interaction term separately. We found support only for interactions between self-efficacy and positive intentions to use action plans on change in work-email actions (B = 3.07, p < .01). We therefore retained the interaction between positive intentions to use action plans and self-efficacy on change in work-email actions. Therefore, there is no support for Hypothesis 3 and support for Hypothesis 2 in relation to self-efficacy only. The form of the interaction is explained in the Stage 4 model (Hypothesis 5).

The Stage 3 model included perceived goal attainment (Hypothesis 4). After controlling for T1 levels of criterion variables, T3 perceived goal attainment was associated with change in work-email actions (B = 0.06, p < .01). In turn, T3 goal attainment was related to T3 NA (B = -0.18, p < .01) and PA (B = 0.20, p = .05), but not T3 job satisfaction (B = 0.17, *ns*). The indirect effects of change in work-email actions through goal attainment reached significance for NA (-0.01, p = .05), but only at p < .10 for PA (0.01, p = .06). Therefore, there is only marginal support for Hypothesis 4 in relation to affective well-being but not job satisfaction.

Figure 2 summarizes the results of the final model (Hypothesis 5) incorporating all elements and Table 5 summarizes the indirect effects. The final model demonstrates a significant relationship between the intervention (exposure to rationalized action plans) and positive intentions to use action plans ($B = 0.53$, $p < .01$) and the relationship between intention to use action plans and change in email work-actions was moderated by self-efficacy ($B = 22.42$, $p < .01$). An analysis of the simple slopes (illustrated in Figure 3) revealed a significant positive relationship between change in work-email actions and positive intentions to use action plans, only for those higher in self-efficacy (+1 standard deviation, $B = 9.04$, $p < .01$). There was no relationship for those at mean levels of self-efficacy ($B = 1.00$, *ns*) and at one standard deviation below the mean ($B = -7.16$, *ns*).

[INSERT TABLE 5, AND FIGURES 2 & 3 ABOUT HERE]

In relation to the effects of the intervention on perceived goal attainment and well-being (Hypothesis 5), there was evidence that the intervention had indirect effects through positive intentions to use rationalized action plans and then through change in work-email actions moderated by self-efficacy, on perceived goal attainment (Table 5, indirect effects 11.87, $p < .05$) and through perceived goal attainment on NA (-0.10, $p = .05$). An analysis of the simple slopes revealed the moderated mediated effects of the intervention on perceived goal attainment was positive for those with high self-efficacy (+ 1 SD, perceived goal attainment 0.45, $p < .05$). For those with high self-efficacy there were indirect effects of the intervention on NA (-0.08, $p < .05$). There was little or no evidence that the intervention had beneficial effects for those with mean or lower levels of self-efficacy (mean levels, perceived goal attainment 0.04, *ns*; negative affect -0.01, *ns*; -1 SD, perceived goal attainment -0.34, *ns*; negative affect 0.05). There was no evidence of relationships between perceived goal attainment and either PA or job satisfaction in this final model or any other evidence of any (moderated) mediated effects of the intervention on these aspects of well-being (Table 5).

Therefore, in summary, Hypothesis 5 is supported in relation to NA only as an outcome, and self-efficacy only as a regulatory resource that facilitates intention to use action plans into changes in work-email actions.

Discussion

In this paper, the WhIM was constructed, tested and evaluated via the application of a work-email habit change intervention, delivered in a field setting, over 12-months. A two-stage process of exposure to a rationalized action plan, and a stated intention to use this, predicted behavior change for those with higher levels of self-efficacy, in turn predicting a reduction in negative affect via heightened goal achievement.

Theoretical Implications

Gardner and colleagues' instigation-execution model (2016) suggests that habit change is more likely to be enacted (execution) when people commit to a cognitive intention to change (instigation). We extended this theorizing from the health domain in the WhIM by arguing that the inclusion of a rationalized action plan (Fleig et al., 2013) would be important for driving instigation-execution as the rationalized plan provides workers with a clear purpose and process to justify making a change. This was supported in our empirical work but a proviso is added: only when an individual also has higher levels of self-efficacy (i.e., they believe that they can effect change) did work-email habits change as a result of a rationalized action plan being translated into an intention.

Further, we stipulated in the WhIM that a change in work-habits could only be considered to be effective if the change predicted improvements in goal attainment and well-being. In our study, when workers changed their work-email actions this was more likely to reduce their negative well-being, as a result of them perceiving that they were attaining their goals. This indicates that the change was 'effective'. We argue that it is important to include effectiveness criteria when examining changes in work-habits, as it is not always clear in work domains as to whether a habit aids or desists from effectiveness. Because the WhIM separates actions from outcomes, values are not attributed to habits until criteria (and evaluations) for effectiveness are established.

Modifications to the WhIM

Although our work-email study did not find that all variables hypothesized in the WhIM related to changing work-email habits, this could be due to the specific context presented by work-email. We therefore suggest that – at this stage – it would be premature to suggest that these variables are removed from the model, as they could be relevant in other work-habit domains. For example, in the work-email study, we found that improving work-email habits might mitigate negative affect but does not actively make people happier (PA) and more satisfied. We suggest that this is likely to be a function of context: if work-email is perceived as a stressor (Barley, Meyerson & Grodal, 2011), then changing responses to the stressor can reduce anger and anxiety (NA) but not necessarily create an actively positive reaction. It is important to include effectiveness measures in the WhIM that are relevant to the intervention, and so we retain PA and job satisfaction as well-being outcomes worth testing in relation to other work-habits (Briner & Walshe, 2015; Oliver & MacLeod, 2018).

Further, in relation to self-regulatory resources, whilst self-efficacy was the only regulatory resource found to have a moderating effect, it is possible that this is again a function of work-email as a tool. Most people already have control over how they use their work-email (Russell, Jackson & Banks, 2019), which may have negated the extent to which regulatory resources (such as self-control or job control) were cued as relevant – hence the null effects. Indeed, other regulatory resources could be investigated in future and added to the model. For example, self-determination resources (encompassing autonomy, competence and relatedness) could be helpful to consider the motivational drivers of work-habit change (Deci & Ryan, 2000).

Effect sizes in this model were relatively modest. Whilst effect-sizes can differ in field-based intervention studies (Blume et al., 2010), the generally low effect sizes could be attributed to the use of a wait-list control group in the intervention design. In work-contexts, interventions have the greatest effects on behavior change when the whole organization is involved (Baumeister & Alghamdi, 2015; Polites & Karahanna, 2013). This reflects the importance of understanding that work behaviors are embedded in a whole organizational/group system; we suggest in our Introduction that this is a differentiator of work-habits, compared to many other 'types' of habit. Due to only a small proportion of the organization being involved in the intervention, attempts to apply changes could have been hindered by other users of the work-email system (on whom each worker depends) still utilizing old and potentially problematic habits themselves. Although use of control groups is considered to be best practice in health and clinical intervention study designs (Eccles, Grimshaw, Campbell & Ramsay, 2003), in future applications of work-habit change interventions, it may be inappropriate to utilize such designs, if these prevent habit-change across the whole organizational system from being addressed concurrently. Researchers may need to pay heed to guidance provided by Eccles et al (2003) on how to establish causation if control groups are not used (e.g. via repeated time-series analysis).

We now suggest that the WhIM be applied and validated, utilizing 5 key principles for implementation (see Figure 4), across other work-habit domains, elucidated from the findings of this initial study. We anticipate that when variables and relationships are tested across other work contexts, the WhIM can continue to be modified and amended according to the weight of evidence. As such, we present the WhIM as a propositional 'work in progress', albeit grounded in evidence-based and theoretically sound conjecture, to which we hope colleagues will be able to contribute over time.

[INSERT FIGURE 4 ABOUT HERE]

Limitations

In relation to the measurement of habit-change, our participants reported changes in frequencies of work-email actions over time. We did not look at automaticity in measuring ‘habit change’ or use established scales of ‘habits’ as these scales were too generic and difficult to apply to email-specific behaviors. We justify this because specificity is considered to be important in measuring habit change (Sniehotta & Pressau, 2012) and frequency is considered to be a bigger predictor of sustained change than automaticity (Labreque & Wood, 2015). As such, although our measures were sufficient in this context, other researchers may prefer to use alternatives. We also did not test if people were reducing the frequency of old actions or increasing the frequency of new actions; we only measured the extent to which frequency changed. This is because we did not wish to imply that any action was good or bad. If researchers wish to separate increases or decreases in work habit-use then the WhIM allows for this; however, it should still be accompanied by measures of subsequent goal attainment and well-being over time to ascertain if the habit change has been effective.

Although longer-term intervention programs are desirable for allowing new behaviors to be embedded, the downside is that attrition rates can be high (Goodman & Blum, 1996). We retained 39% of our participants from T1 to T3 (a 12-month period). Although this is unfortunate, it is roughly in line with attrition rates recorded in similarly long-term or field-based programs (Etter, 2005; Salanova, Bakker & Llorens, 2006). By using a Bayesian approach to analyzing our data, we could accommodate small sample sizes, and took care to check the non-random attrition of participants.

Finally, we note that mediation is best tested when variables can be temporally separated to establish causation. In testing the WhIM, we took ratings of goal attainment and well-being at the same time point (T3) yet examined goal attainment as a causal mediator of well-being. We justify this approach for theoretical and practical reasons. Theoretically, goal attainment is presented as a precursor to well-being, according to major theories (Barrick, Mount & Li, 2013; Carver & Scheier, 1990; DeShon & Gillespie, 2005; Emmons, 1996; Locke & Latham, 2006; Ryan & Deci, 2000). As the variables are considered to be temporally proximal in their occurrence, it is a meaningful supposition to observe the relationship as a mediation. Practically, because of the close coupling of well-being and goal attainment in time, if we did separate our data collection on each measure, we would have needed to gather goal attainment data at T3, and then capture well-being very soon afterwards (at a T4 data collection period). To avoid further attrition from the study, and to reduce demands on participants, we chose not to do this. We therefore appreciate that whilst our mediation path is theoretically robust and practically sound, future research may need to address the methodological constraints of supporting this relationship.

Future Research Pathways

Although the WhIM has been designed to examine the effectiveness of habit change interventions in a work context, it is possible that it could also assist in predicting the sustainability of interventions in other settings. For example, interventions still fail in the health-habits domain and research continues to investigate why. The WhIM could provide some insight here as it does not ascribe a value to a habit until effectiveness criteria has been satisfied. Most health-habits are labelled as ‘good’ or ‘bad’ simply on the basis of their constitution, but, to the individual, is this necessarily perceived so clearly? For example, reducing the frequency with which people smoke improves their fitness and long-term health prognosis, clearly showing attainment of relevant goals (a good outcome). However, in the short-term, well-being goals could be impeded as people experience withdrawal symptoms and have to change their social patterns (potentially construed as bad outcomes). If short-term well-being or goal attainment are perceived to be impoverished as a result of habit change, this could explain why some interventions will fail. Including a focus on short- and long-term effectiveness criteria, beyond the obvious health goals, could be illuminating.

Further, in testing the WhIM we found that providing regular action plans will not change actions in and of themselves, but they can provoke an intention to change, which then changes actions (for those with higher self-efficacy). This shows the importance of including regular explanations of purpose and process in attempting to change work-habits. One-off interventions may not be enough to provoke a habit switch, even when accompanied by action plans. It will be interesting to examine in future research how often rationalized action plans need to be provided and converted to intentions for sustainable change to occur.

Implications for Practice

A key aim of this research was to provide recommendations for researchers and practitioners to optimize the implementation of habit change interventions in work. We suggest three key recommendations. First, by training participants in self-efficacy, the WhIM indicates that action plans and intentions are much more likely to be translated into behavior change. Self-efficacy is a regulation resource that Park and Kim (2019) consider to be trainable. It has previously been associated with successful interventions to change work (Wang et al., 2018) and work-email (Hair, Renaud & Ramsey, 2007; Huang et al., 2011) behaviors. Second, we suggest that rationalized action plans be regularly presented to participants across the duration of the intervention program, to continue to remind participants of what they need to do, how they need to do it, and why. By keeping the purpose of the intervention in conscious awareness, it is more likely that change will be enacted (Gardner, 2015). Third, we suggest that specific, goal-focused feedback on effectiveness be regularly provided to participants. We found that goal attainment and well-being could both be predicted by changes in work-email habits, and the WhIM emphasizes how important it is for goal attainment and well-being to improve, for change to be sustained over time. Therefore, when an intervention produces incremental improvements in relevant goals and well-being, providing specific feedback to participants about this is likely to maintain motivation to continue with the change program (Locke & Latham, 2006).

Conclusions

The Work-habits Intervention Model (WhiM) extends theory from the health-habits domain to explain and predict how the two-stage process of (i) providing regular rationalized action plans and (ii) stating intentions to use these is more likely to result in sustained behavior change, for those with higher levels of self-efficacy. Change in work-habits then leads to enhanced well-being, via the perception that goal attainment has improved. The key aim of this paper was to explain how to improve work-habits over time. Using the WhIM, this was achieved by: (i) including *both* rationalized action plans and intentions as drivers of change, (ii) separating actions from outcomes to ensure goal attainment and well-being improved over time (stipulating these as key criteria of effectiveness) and (iii) explicating self-regulation resources as moderators of plan-intention-action relationships. We found evidence to support the WhIM in a long-term, field-based design that examined both within and between person dynamics in a work-email context. We now suggest that the WhIM be further investigated, modified and refined as it is applied to a range of other real-world contexts.

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Tables

Table 1

Demographic Data by Group

Demographic Data	T1 Control Group (N=58)	T1 Intervention Group (N=61)	T3 Control Group (N=21)	T3 Intervention Group (N= 25)
Gender				
Male	21 (36%)	18 (30%)	6 (29%)	5 (20%)
Female	37 (64%)	43 (70%)	15 (71%)	20 (80%)
Age				
16-20	0	0	0	0
21-30	6 (10%)	12 (20%)	2 (10%)	5 (20%)
31-40	20 (34%)	23 (38%)	9 (43%)	8 (32%)
41-50	21 (36%)	15 (25%)	7 (33%)	8 (32%)
51-60	10 (17%)	11 (18%)	3 (14%)	4 (16%)
61+	1 (2%)	0	0	0
Location				
Head Office	48 (83%)	56 (92%)	16 (76%)	23 (92%)
Regional Office	9 (16%)	4 (7%)	5 (24%)	1 (4%)
Home/Other	1 (2%)	1 (2%)	0	1 (4%)
Department				
Comms and Fundraising	27 (47%)	28 (46%)	11 (52%)	12 (48%)
Global Programs	20 (34%)	22 (36%)	7 (33%)	10 (40%)
Operations	11 (19%)	11 (18%)	3 (14%)	2 (8%)
Job Level				
Administrative	9 (16%)	6 (10%)	3 (14%)	2 (8%)
Admin-Management	13 (22%)	24 (39%)	6 (29%)	8 (32%)
Project/Middle Management	32 (55%)	29 (48%)	11 (52%)	15 (60%)
Director	4 (7%)	2 (3%)	1 (5%)	0

Table 2

Variables Captured at Different Time Points

	Survey/Study Stage	Date of Administration	Completion rates (control group)	Completion rates (intervention group)	Variables
TIME 1	'Benchmarking' Survey (pre-training)	January 2017	N=58	N=61	• Demographic data • Self-regulation resources
	'Email-use' Survey 1	January 2017	N=58	N=61	• Control data • Frequency of use of work-email actions (23 actions) • Email-related well-being data • Goal attainment data
TIME 2	Allocation of training tips	Between March 13th and 24th July, 2017. 12 tips administered.	N/A	Intentions received from N=53	• Stated intention to use or not use the tip
		Between 7th August and 18th December, 2017. 11 tips administered.[6]		Intentions received from N=39	
TIME 3	'Email-use' Survey 3	January 2018	N=27 (N=21 who also completed all T1 and T2 measures)	N=31 (N = 25 who also completed all T1 and T2 measures)	• Frequency of use of work-email actions (23 actions) • Email-related well-being • Goal attainment data

[6] Only 2 tips for managing email

Table 3

Factorial Invariance Statistics for Scales from T1 to T3

Type of invariance Measures	Configural (same factor structure)	Metric (same factor loadings)	Strong (same item intercepts)
Job satisfaction	CFI = 1.00 RMSEA = 0.00 PPC = .52	CFI = 1.00 RMSEA = 0.00 PPC = .57	CFI = 1.00 RMSEA = 0.00 PPC= .40
NA	CFI = 1.00 RMSEA = 0.00 PPC = .29	CFI = 1.00 RMSEA = 0.00 PPC = .38	CFI = 1.00 RMSEA = 0.00 PPC = .13
PA	CFI = 1.00 RMSEA = 0.00 PPC = .37	CFI = 1.00 RMSEA = 0.00 PPC = .41	CFI = 1.00 RMSEA = 0.00 PPC = .22

CFI = Confirmatory fit index; RMSEA = Root Mean Square Error of Approximation; PPC = posterior predictive checking. Good fit is indicated by CFI $\geq$ .95, RMSEA $\leq$ .10, PPC $\geq$ .05. Invariance is indicated by ΔCFI between models of < .01 (Cheung & Rensvold, 2002).

Table 4

Descriptive Statistics, Reliabilities (Cronbach's alpha), and Correlations for Study Variables

	Variable	Mean	*SD*	α	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
1.	Intervention (1,0)	0.54	0.50	-	--													
2.	Trait self-control (T1)	3.82	0.57	.82	.09	--												
3.	Self-efficacy (T1)	3.86	0.36	.74	-.16	.46**	--											
4.	Job control (T1)	3.82	0.62	.86	.02	-.01	.15	--										
5.	Job support (T1)	3.65	0.75	.86	.10	-.12	.23	.44**	--									
6.	Perceived goal attainment (T1)	3.23	0.48	.58	-.07	.35*	.39**	.20	.24	--								
7.	PA (T1)	2.68	0.51	.73	.16	-.02	-.03	.06	.15	.14	--							
8.	NA (T1)	4.33	0.41	.78	.10	.03	-.08	-.25	-.21	-.37*	-.56**	--						
90.	Job satisfaction (T1)	5.88	0.92	.84	-.04	.18	.36*	.21	.38*	.16	.17	-.19	--					
10.	Change in work-email actions (T1-T3)	14.79	4.84		.17	-.19	.03	.00	.28	.13	.24	-.01	.40*	--				
11.	Intentions to use action plans (T2)	0.29	0.68		.85**	.14	.00	.21	-.03	.06	.24	-.10	.15	.14	--			
12.	Perceived goal attainment (T3)	3.22	0.69	.86	.15	.14	.20	.16	.16	.53**	.30*	-.34*	.34*	.42**	.28	--		
13.	PA (T3)	2.84	0.48	.84	.11	-.01	-.02	.24	.12	.21	.50**	-.58**	.19	-.03	.25	.34*	--	
14.	NA (T3)	4.09	0.42	.84	-.04	.11	-.14	-.22	-.20	-.27	-.40**	.48**	-.34*	-.08	-.24	-.42**	-.55**	--
15.	Job satisfaction (T3)	5.49	1.16	.78	.10	.06	.15	.25	.26	.12	.04	-.18	.45**	.18	.11	.29	.23	.23

Note. N = 46 on all variables, except change in work-email use T1-T3, N = 39.

* $p < .05$, ** $p < .01$.

Table 5

Indirect Effects in Final Model

Indirect effect	No control
Change in work-email actions → Perceived goal attainment → PA	0.01
Change in work-email actions → Perceived goal attainment → NA	-0.01*
Change in work-email actions → Perceived goal attainment → Job satisfaction	0.01
Intervention → Intentions to use action plans → change in email use	0.53
Intervention → Intentions to use action plans moderated by self-efficacy → change in work-email actions	11.87**
Intervention → Intentions to use action plans → change in work-email actions→ Perceived goal attainment	0.02
Intervention → Intentions to use action plans moderated by self-efficacy → change in work-email actions→ Perceived goal attainment	0.59*
Intervention → Intentions to use action plans → change in work-email actions→ Perceived goal attainment → PA	0.00
Intervention → Intentions to use action plans moderated by self-efficacy → change in work-email actions→ Perceived goal attainment → PA	0.07
Intervention → Intentions to use action plans → change in work-email actions→ Perceived goal attainment → NA	0.00
Intervention → Intentions to use action plans moderated by self-efficacy → change in work-email actions→ Perceived goal attainment → NA	-0.10†
Intervention → Intentions to use action plans → change in work-email actions→ Perceived goal attainment → Job satisfaction	0.00
Intervention → Intentions to use action plans moderated by self-efficacy → change in work-email actions→ Perceived goal attainment → Job satisfaction	0.11

Note. † < .10, * $p < .05$, ** $p < .01$.

Figures

Figure 1

Testing the WhIM (Hypothesis 5) in a 12-month field intervention to improve work-email use.

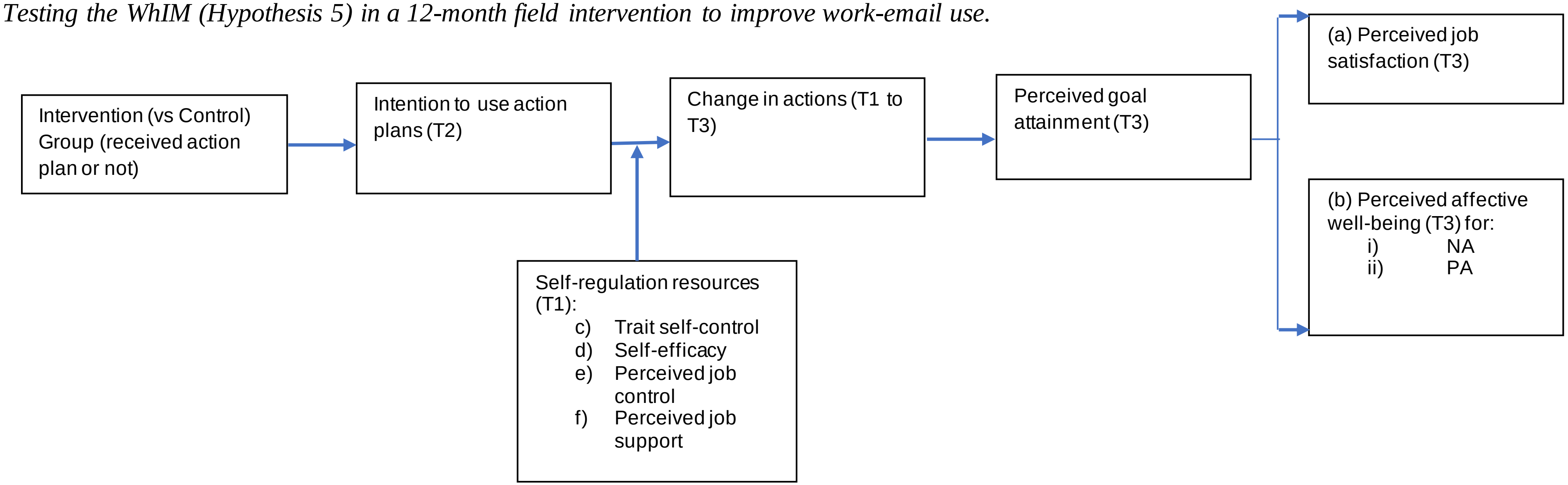
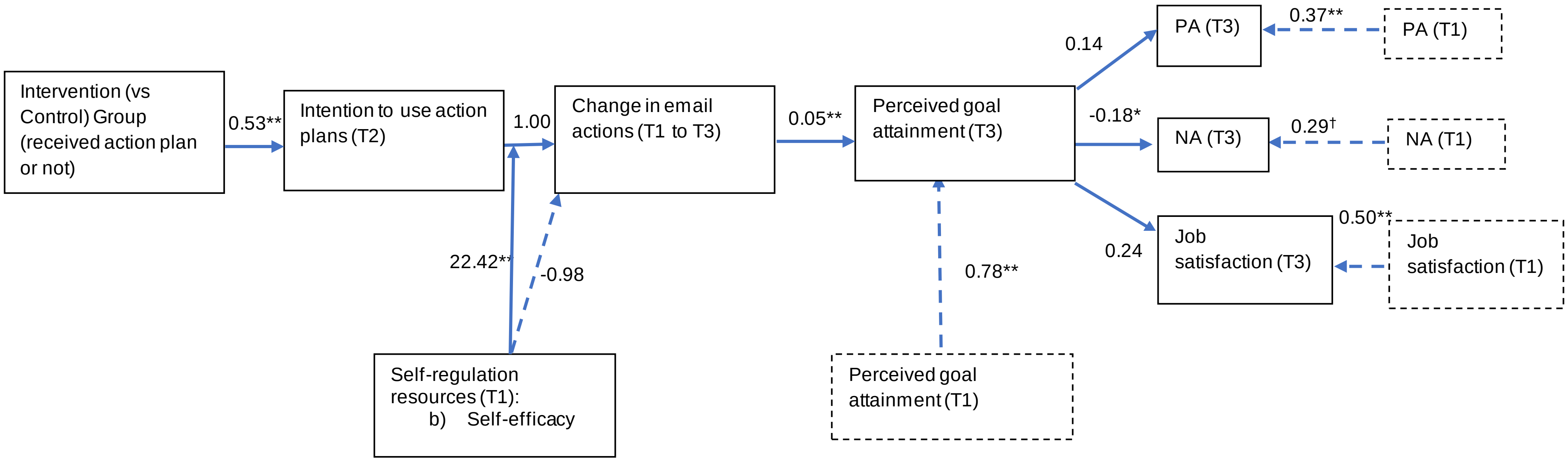


Figure 2

Final Path Model with Direct and Indirect Effects and Controls



Note. dashed boxes or arrows represent non-hypothesized effects, including effects from control variables. Model fit: 95% CI of Bayesian Posterior Predictive Checking using Chi-Square -36.05 – 28.57; Confirmatory Fit Index = 0.96; Root Mean Square Error of Approximation, 0.05.
† < .10, * p < .05, ** p < .01.

Figure 3

Relationship between Intentions to use Rationalized Action Plans and Change in Work-email Actions T1-T3, Moderated by Self-efficacy

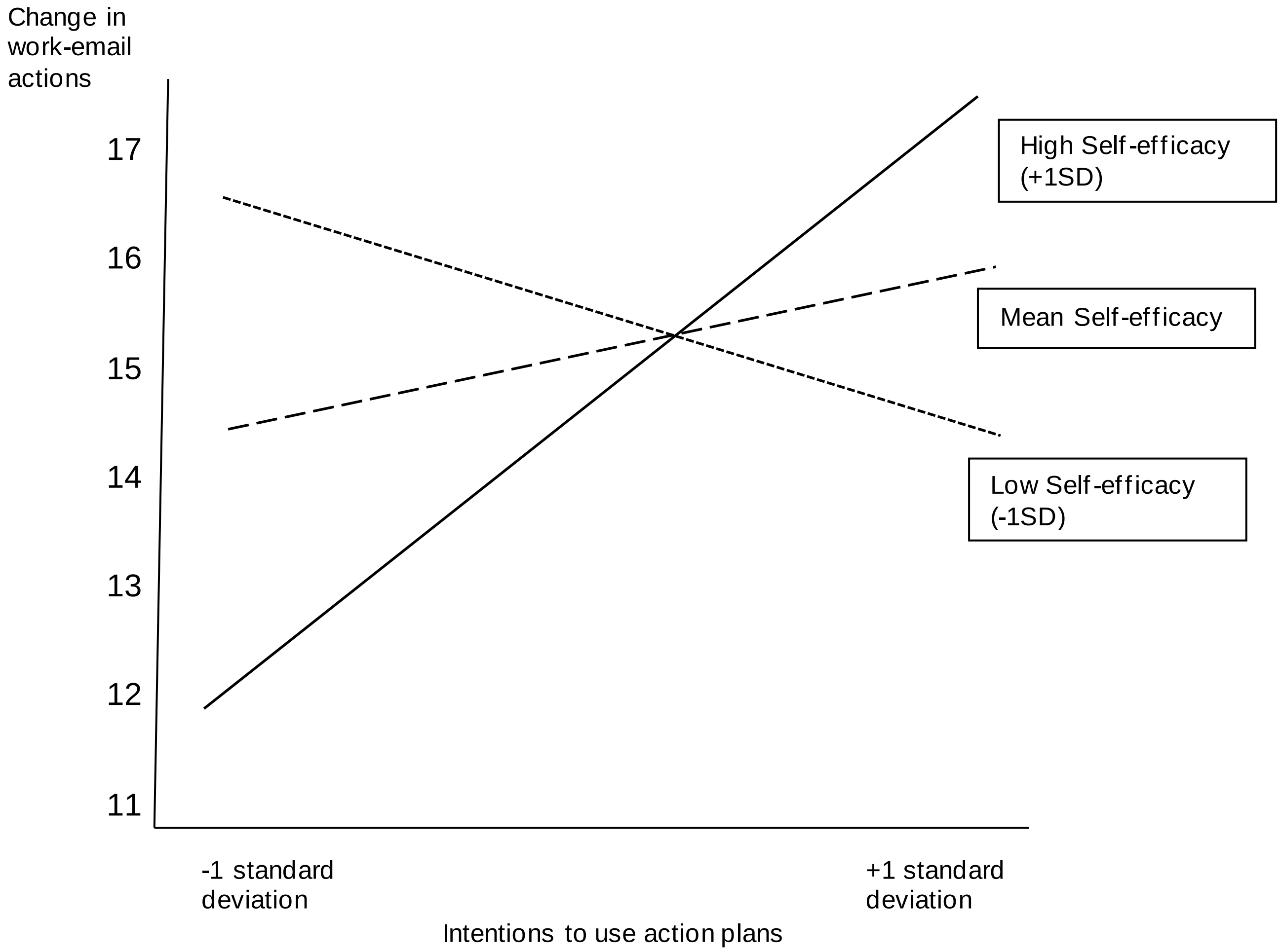
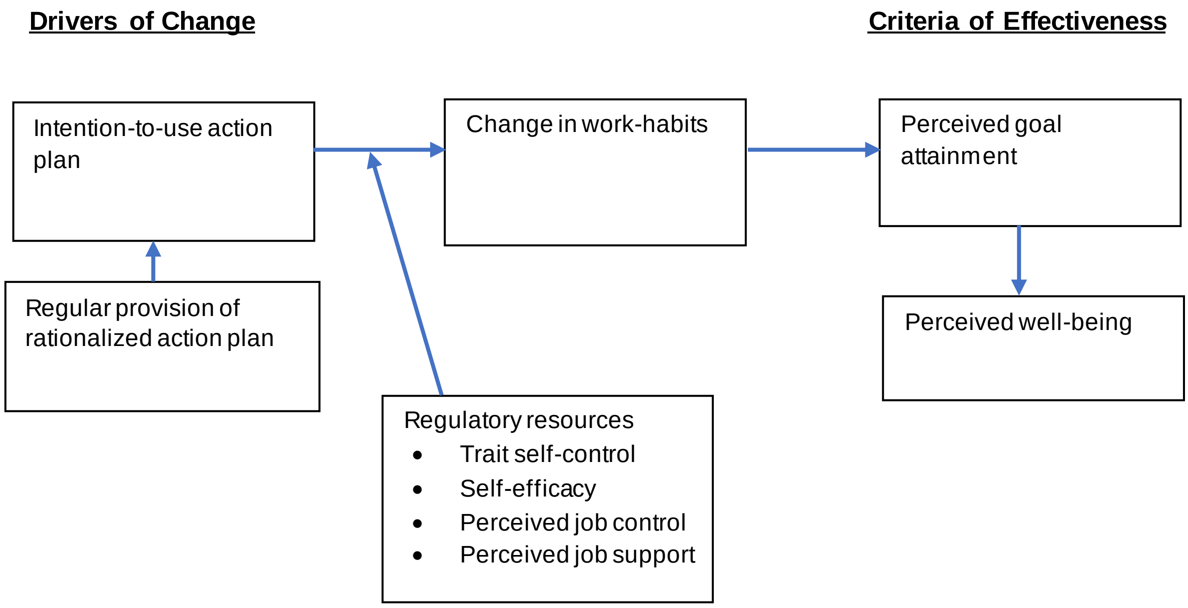


Figure 4

The Work-habit Intervention Model



Principles

1. *Provide regular rationalised action plans and obtain intentions-to-act on these to encourage change in a two-stage process*
2. *Provide/develop personal and contextual regulatory resources to maximise the likelihood of intentions translating to habit-change*
3. *Because work-habits are not intrinsically 'good or bad', the effectiveness of work-habit intervention change should be rated according to whether habit change is associated with improvements in work-relevant goal attainment and well-being*
4. *Action change and outcome effectiveness should be captured and measured over the long-term, attending to dynamic and causal relationships within and between people*
5. *Work-habits are embedded within group and organisational systems, so work-habit interventions need to involve whole-system designs to optimise the sustainability of effective work-habit change*