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Technocognitive Structuration: Modeling the Role of Cognitive Structures in Technology Adaptation

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Abstract

The way we use technology both shapes and is shaped by our environment. These same technologies also shape and are shaped by our cognitive structures. While several existing theories explain individuals' adaptations of technology, these theories typically focus on social and behavioral dynamics, with little attention on how technology adaptation changes individuals' internal representations and associations. This is an important oversight to address, given that contemporary technologies such as social media, big data, artificial intelligence, and wearable devices are known to impact how we process information and conceptualize problems. In this study, we extend the adaptive theory of structuration for individuals (ASTI) to create a theory of technocognitive structuration. Technocognitive structuration proposes that exploitative and exploratory cognitive adaptations mediate how technology adaptations impact task adaptations. We tested this mediating effect using an online experiment, supported by a series of pilot studies and illustrations. The results support the proposed mediating role of cognitive adaptation. These findings challenge existing research on technology adaptation and suggest that not only is cognitive adaptation an important phenomenon to study in its own right but it may also be an important element to consider when making causal claims about other outcomes linked with technology adaptation.

Keywords: Adaptive Structuration Theory for Individuals, Cognitive Structures, Structuration, Experiment

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1 Introduction

Existing studies have demonstrated that the ongoing use of digital technology can change how individuals understand concepts (Introna, 2016) and how they analyze problems (Cavanaugh et al., 2016). These types of cognitive changes can impact how individuals perform their jobs (Orlikowski & Gash, 1994), how they view others (Knight & Tsoukas, 2019), and even how they view themselves (Saiphoo & Vahedi, 2019). Yet we lack a theory to explain how and when specific cognitive changes occur in relation to the features of digital technologies and the way those features are used.

Part of the challenge when modeling cognitive changes related to the ongoing use of technology is that the features of digital technologies vary widely, and individuals often use similar technological features for different tasks and in different ways (DeSanctis & Poole, 1994; Majchrzak et al., 2000; Jones & Karsten, 2008). Digital technologies therefore possess a malleability, which opens up new possibilities, many of which may not have been predicted or intentionally designed (Benbya et al., 2020). This malleability allows individuals to discover new ways to align specific features and tasks with the social and technical demands of their environment (Carlo et al., 2012; Sarker et al., 2019).

Despite these complexities, recent work by Schmitz et al. (2016) identified some common processes to explain how individuals adapt digital technologies, and those authors formalized these processes into an adaptive structuration theory for individuals (ASTI). ASTI argues that technology adaptations trigger task adaptations, and these adaptations combine to form new structures that may become persistent in the presence of positive performance feedback. As part of the explanation of ASTI, Schmitz et al. (2016, p. 668) imply that cognitive changes mediate the relationship between technology adaptations and task adaptations, explaining that "In the process of appropriating a new technology, individuals interact with these embedded biases and respond by adapting processes and task structures. Technology adaptation imposes different structures back into the technology, embedding new biases and assumptions of how the changed technology should operate." This makes sense, as individuals must create some internalized representation of their environment if they are to intentionally pursue new possibilities and outcomes (Giddens, 1984, Feldman, 2004; cf. Vygotsky, 1978; Simon, 1988).

While ASTI acknowledges the mediating role of biases and assumptions, it does not explicitly model cognitive structures as part of technology adaptation. This omission of cognitive structures means that ASTI models how individuals modify the features of a technology and their existing task practices, without modeling why individuals make those modifications. We argue that this is an important oversight for three reasons. First, the logic of ASTI implies that adaptations in cognitive structures mediate the process by which technology adaptations lead to task adaptations. If this logic is not actually formalized and tested, then the theory is at risk of affording unreliable causal inferences. Second, in light of growing concerns that the use of technology may be changing how individuals think in undesirable ways (Knight & Tsoukas, 2019; Moravec et al., 2019; Saiphoo & Vahedi, 2019), we argue that it is important to study cognitive adaptation and to study how and when these adaptations occur. Third, a large body of literature exists on the development of cognitive structures in non-technology-specific contexts. Connecting ASTI with that existing literature presents an opportunity to bridge insights across literatures, and to make theoretical contributions to both ASTI and the literature on cognitive structures.

This study therefore extends ASTI to address our need to relate technology use and cognitive adaptation. We explore two primary research questions:

RQ1: Which type of cognitive adaptations can individuals experience when they are adapting tasks and technologies?

RQ2: What is the role of these cognitive adaptations in different structuration episodes?

The next section presents the theoretical background. First, we discuss cognitive structures and their role in helping individuals adapt to their environment. Next, we propose two types of cognitive adaptation and hypothesize how each type mediates the impact of different technology adaptations on different task adaptations. We then present our empirical approach, which is centered upon an online experiment supported by a series of pilot studies and illustrations. The results support our hypotheses and highlight the importance of considering cognitive structures. These findings make a valuable contribution to IS literature by bringing together existing insights around cognitive adaptation, technology adaptation, and task adaptation.

2 Theoretical Background

2.1 Cognitive Structures and Adaptation

The concept of cognitive structures dates back to Piaget (1955, 1970). Piaget used the concept of a "structure" to describe how individuals internalize the world they experience. He differentiated between perceptual structures, which only change in their level of precision, and cognitive structures, which change in both substance and architecture. Piaget (1955) described how cognitive structures are formed as individuals come to understand their environment in terms of constituent elements, some of which operate, at least partly, independently of one's own actions. Subsequent research has shown that the formation of cognitive structures is also influenced by individuals' interactions with others in their social surroundings, as shared cognitive structures emerge to enable communication, by encouraging individuals to internalize the world in socially compatible ways (DiMaggio, 1997). Consumer research has also demonstrated that cognitive structures enable individuals to relate different tools and transfer knowledge across them (Zinkhan & Braunsberger, 2004). For this reason, cognitive structures often demonstrate a close relationship with the symbolism, language, and tools used by individuals (Evermann, 2005; Karimi & Ferreira, 2016; Lee et al., 2020).

According to Piaget (1955, 1970), the adaptability of cognitive structures is a fundamental characteristic of those structures. Where a cognitive structure performs well—meaning the environment assimilates an individual's cognitive structures and conforms to their expectations—the elements of the structure and the relationships among those elements tend to stabilize (see also Hayes-Roth, 1977; Karimi & Ferreira, 2016). Where the structure performs less well—meaning the individual is forced to accommodate the environment and bend to its successive constraints—the elements of the structure are decomposed, and new elements and relationships emerge. This may result in one new structure or multiple nested structures that are better suited to specific conditions and contexts (Dixon et al., 2012; Uddén et al., 2020; cf. Gernigon et al., 2023).

As a formal definition, Brainerd (1973, p. 176) suggests that cognitive structures should be considered "internalized wholes whose laws of composition are mental operations and whose self-regulatory rule is the principle of equilibration," before elaborating that "the function of a cognitive structure is to interpret (assimilate) reality so that the cognizer can behave intelligently." This view of cognitive structures places them at the center of intentionality, an essential mechanism to allow an individual to move from the perception of what exists in the environment to the ability to make intelligent actions (see Botvinick, 2008; Coopmans et al., 2023).

We can illustrate this with a hypothetical scenario. Imagine two sports trainers, Jane and Mark, who both store data for each of their clients on a spreadsheet. This data includes all of the training regimes they prescribe for each client, as well as regular measurements of changes in their clients' physical condition, such as increases or decreases in weight or resting heart rate. Both trainers receive feedback from clients that they are not satisfied with their progress. Jane, who often reads medical articles and attends physiology seminars, begins to examine the available technology features and is impressed that the tool allows her to view data in different ways. This prompts Jane to reconsider how different training regimes might suit different people, so she starts using the technology to critique the outcomes of each regime for different types of clients. Mark, who often reads psychology articles and attends coaching seminars, also examines the technology features. This prompts Mark to reconsider how he communicates training regimes to clients. Mark decides that the data is missing too many tacit details for him to draw conclusions about the effectiveness of specific regimes. Mark adapts his use of technology to reassure clients, rather than change which regimes they are prescribing, e.g., he adapts his use of the technology so that he can use it to show his clients that they are making good progress. In this example, Jane and Mark experience similar technology adaptations. However, they make different cognitive adaptations, resulting in different task adaptations.

This idea that cognitive structures sit between the perceptual features of an environment and an individual's ability to act upon it resonates closely with the description of "embedded biases" in the original ASTI. However, the concept of biases implies that this mediating cognitive layer is inherently difficult to change and that the cognitive layer may inhibit the scrutinization of behaviors, even if those behaviors do not lead to desirable outcomes (Kahneman & Tversky, 1996; Haselton et al., 2006). In other words, embedded biases are useful for explaining why adaptation does not occur at an individual level but less useful for explaining why adaptation sometimes does occur. In contrast to cognitive biases, cognitive structures rely on some ongoing congruency between intentional acts and perceived outcomes, meaning that discrepancies among structures and outcomes often lead to adaptation (Feather, 1971). As a practical example of this, Johansson et al. (2021) showed that investors may create more complex cognitive structures when evaluating female entrepreneurs and that these complex structures may enable them to overcome prejudicial gender biases. Thus, while cognitive structures may become embedded over time alongside different biases—becoming more stable and less fleeting as they do so—these cognitive structures also provide the sensitizing device that allows individuals to intentionally adapt.

2.2 Technology and Task Structures and Adaptation

Schmitz et al. (2016) made two key distinctions when they proposed ASTI to explain individual-level structuration episodes. The first distinction is between technology adaptations and task adaptations. According to ASTI, technology adaptations occur when individuals perceive new features that present additional capabilities. These technology adaptations precede task adaptations, but they have no consequences in isolation. Task adaptations, on the other hand, occur when individuals change their practices because of the new features they have perceived.

The second distinction is between exploratory adaptations and exploitative adaptations. This distinction has been widely applied to study organizational learning (March, 1991), innovation (Jansen et al., 2006), process management (Benner & Tushman, 2003), and system use (e.g., Sun et al., 2019). Exploitative adaptations are incremental changes used to better align usage episodes with intended performance outcomes. These adaptations serve to extend existing structures, often by partitioning components and/or fine-tuning associations. Exploratory adaptations can be more dramatic, often emerging in response to new and unexpected desired outcomes. Such adaptations often remove or introduce components, which can change the configuration of the structure in more fundamental ways.

These two distinctions afford four different types of adaptation. *Exploitative technology adaptations* occur when an individual attempts to modify technology features consistent with what that individual perceives is intended or standard for the technology. This often means expanding feature use. Returning to the example of our trainers, Jane and Mark, imagine Mark notices that many of his clients are wearing smartwatches to track how many steps they take, both during their weekly training session and during the rest of the week. This reveals a new technological capability to Mark. Exploitative task adaptations occur when an individual attempts to modify existing task processes while adhering to the current structure and target objective of those work processes. Mark thus begins setting goals for the number of steps his clients should take during the week and starts recording their steps between training sessions to keep track of their progress.

Exploratory technology adaptations occur when an individual attempts to modify the technology features in a way they perceive as unusual or in a way that departs from what is standard for the technology. For example, imagine that Jane also realizes that her clients are wearing smartwatches. She notes that these smartwatches keep track of heart rate, and she knows that resting heart rate is also an indicator of stress, even if she believes this is not the intended purpose of this feature in this context. Exploratory task adaptations occur when an individual attempts to modify current task processes while generating new target objectives for the work processes. Jane thus decides that she will start asking her clients to record their resting heart rate throughout the week, so they can schedule their training sessions together for the times when the client is in a suitable physiological state for rigorous exercise.

2.3 A Model of Technocognitive Structuration

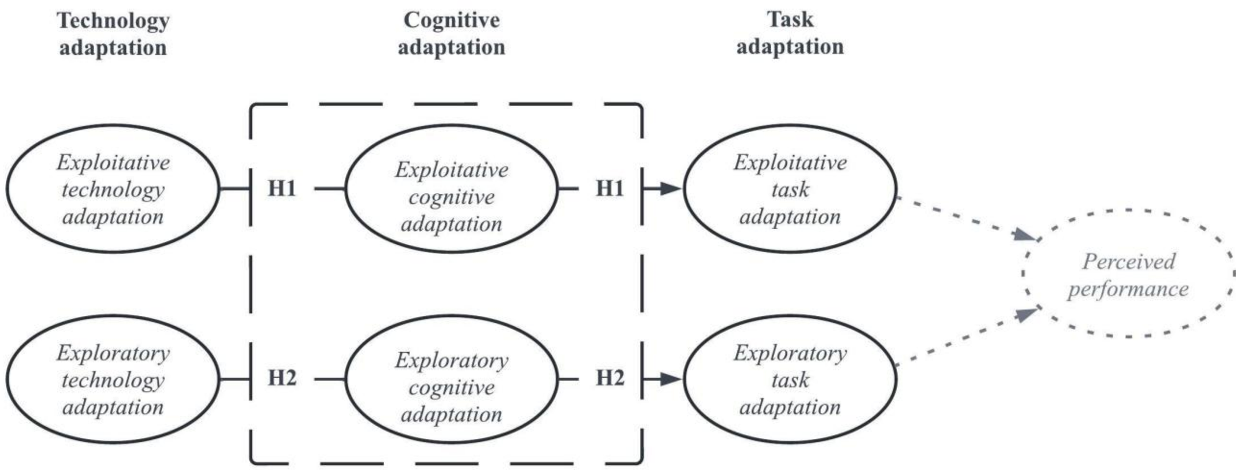
Building on the discussion of cognitive structures, and Schmitz et al.'s (2016) distinction between exploitative and exploratory adaptations, we propose two new constructs to model cognitive adaptations related to the use of technology. We propose that these cognitive adaptations mediate the relationship between technology adaptation and task adaptation, i.e., that cognitive adaptation provides the link from an individual's perception of technology features to their intentional adaptation of tasks, as part of structuration episodes. Figure 1 illustrates these mediating relationships in the form of a research model.

The first construct is *exploitative cognitive adaptation*, which is defined as *the process when an individual modifies existing cognitive structures to integrate new features, without changing the associations among familiar features.* Piaget (1955, 1970) explained that cognitive structures build on a layer of perceptual structures. Several other scholars have attempted to deconstruct this perceptual layer. For example, Ulrich (1995) described that the perception of the features of a technology exists at multiple levels of abstraction. As an individual learns more about the features of the technology and the task to be performed, this requires a more detailed deconstruction of each feature. This learning might be firsthand, where the individual was dissatisfied by their performance and began exploring new features, it might be gleaned from watching others, where observing another actor's performance demonstrated the existence and value of a feature, or it might be mandated by authority figures, where the individual was instructed to expand their use of specific features (Jasperson et al., 2005). In each case, the individual intentionally expands their perceptions to accommodate the discovery of new nuances among the features of a technology that constrain their actions or the discovery of new consequences of their actions (cf. Poole et al., 1996). This amounts to a "scaling" of technology on different dimensions, as individuals consider new features and subfeatures over time (DeSanctis & Poole, 1994). The cumulative effect of this process is that an individual becomes aware of new features without necessarily having to change their understanding of other familiar features.

Returning to the earlier example, upon learning about his clients' use of smartwatches, Mark was exposed to a new technology feature—the step counter. Upon learning about this new feature, Mark was prompted to consider how this might be relevant in his interactions with his clients. Mark already believed that he trained clients because they wanted to lead healthier lives and that his training was based on observing them and providing feedback. However, he had not considered that he could observe them outside of their training sessions. Upon realizing that this is possible, his cognitive structure became more detailed, and the observation feature of his cognitive structure was decomposed into observation-during-training sessions and observation-between-training sessions. Mark was already concerned about how he could balance his role as a motivator with the need for his clients to maintain personal responsibility while taking into account the need to maintain privacy and boundaries. These concerns were also elaborated as part of this cognitive adaptation, as Mark started to anticipate how clients might react if he were to request access to different measures from their smartwatches.

This discussion illustrates how exploitative technology adaptation relies on exploitative cognitive adaptation if it is to result in exploitative task adaptation. Thus, we hypothesize:

H1: Exploitative cognitive adaptation mediates the relationship between exploitative technology adaptation and exploitative task adaptation.



Note: The dotted lines represent relationships already established in the ASTI model

Figure 1. Research Model: A Technocognitive Structuration Theory

The second construct is *exploratory cognitive adaptation*, which is defined as *the process when an individual modifies a cognitive structure to include new features, and this modification changes the associations among familiar features.* Piaget made the distinction between "assimilation" and "accommodation," noting that "assimilation is conservative and tends to subordinate the environment to the organism as it is, whereas accommodation is the source of changes and bends the organism to the successive constraints of the environment." (1955, p. 352) Thus, while exploitative cognitive adaptation emphasizes assimilation, exploratory cognitive adaptation emphasizes accommodation. This different emphasis assumes that in exploratory cognitive adaptation, some features have been perceived that have triggered cascading changes in existing cognitive structures.

The manner in which individuals experience these cascading changes is not clear. However, given that individuals often find it difficult or uncomfortable to deconstruct existing structures and begin searching for unfamiliar possibilities (cf. Shultz & Lepper, 1996), we can assume that the discovery of new features is likely to present some form of uncertainty or excitement. Faced with the need to consider new possibilities, individuals may be able to make progress by "forgetting" some of their existing associations, thereby overcoming existing fixations that may stand in the way of new formulations (Storm & Patel, 2014). Individuals may also make progress by "reliving the memory traces" of how they constructed their existing structures and critically reflecting on their past assumptions in light of new information (Rerup & Feldman, 2011). The discovery of new features may also trigger the "recombinant search" described by Fleming (2001), in which new features

> *prompt us to look backward in time to consider the components and untried combinations that were available at the time of invention; they prompt us to look forward to predict which inventions are more likely to motivate further recombination. Prediction of further recombination depends on the fundamental tension between exploration of untried possibilities and exploitation of previous successes* (Fleming, 2001, p. 119, drawing on March, 1991).

Returning to the earlier example, when Jane learned about the heart rate measures in her clients' smartwatches, and this reminded her that heart rate is a possible indicator of stress, she was prompted to consider how the timing of her training sessions might impact her clients' lives. She wondered if training sessions should be scheduled at times when clients are more stressed and when training might let them blow off steam. Alternatively, she wondered if there is some health risk associated with scheduling training at times when clients are already under physiological duress. While Jane suspected that the discovery of this technological capability should trigger some significant task adaptations, it was not obvious without more reflection which of those opposing task adaptations (if either) would be more likely to improve her performance as a trainer. This also triggered Jane to reflect on how she should evaluate her performance as a trainer. She "relived" her previous assumptions that she should focus on the physiological and medical aspects of training clients and asked herself whether she should consider additional goals related to mental health and well-being, or whether client safety should be her priority.

This discussion illustrates how exploratory technology adaptation relies on exploratory cognitive adaptation if it is to result in exploratory task adaptation. Thus, we hypothesize:

H2: *Exploratory cognitive adaptation mediates the relationship between exploratory technology adaptation and exploratory task adaptation* .

3 Method

We tested our two hypotheses with an online experiment (Fink, 2022). The experiment was designed to induce different adaptation types (exploitative vs. exploratory technology adaptations) in different test groups. This type of intervention was important to examine causal links among constructs in a rigorous manner. We supported the experiment with an illustrative qualitative follow-up in a naturalistic setting. The qualitative study was designed to produce stories of real-world adaptations, or "vignettes," that could enrich findings by demonstrating how adaptation can occur over longer time periods in complex and rapidly evolving technology use contexts.

The experiment adopted a between-subjects design that separated participants into two test groups. For Group A, we elicited an exploitative technology adaptation. For Group B, we elicited an exploratory technology adaptation. This allowed us to examine the causal effects of these alternative adaptation types. We expected that Group A would experience higher levels of exploitative technology adaptation, exploitative cognitive adaptation, and exploitative task adaptation, and Group B would experience higher levels of exploratory technology adaptation, exploratory cognitive adaptation, and exploratory task adaptation. We further expected that exploitative cognitive adaptation would mediate the relationship between exploitative technology adaptation and exploitative cognitive adaptation, and that exploratory cognitive adaptation would mediate the relationship between exploratory technology adaptation and exploratory cognitive adaptation (see Figure 1).

For the research setting in our experiment, we chose to focus on individuals' adaptation of word processor software, e.g., Microsoft Word or Apple Pages. This had two advantages. First, these tools are widely used across a range of contexts, thereby reducing the chance that some participants will have limited experience with the technology. Second, the main purpose of using these word processors, namely creating and editing text documents, is relatively consistent across individuals, which lessens the threat that participants will misunderstand experiment-related tasks. The overall study is composed of three phases: (1) pilot studies (2) online experiment (3) illustrative qualitative study.

3.1 Pilot Studies

We ran multiple pilot studies to validate both the measurements and the experimental protocol. For the measurements, we used three rounds of surveys to develop the complete survey, which initially included a set of five exploitative cognitive adaptation and five exploratory cognitive adaptation items. We used a variety of contexts for these pilot studies, as we wanted to create generalizable measures that could be adjusted for multiple technology domains. First, we sent 12 postgraduate students a survey that included all of the intended measures, adapted to ask about their use of smartphones to access news stories. We used this context because news consumption and online media are commonly cited when discussing the link between technology use and cognitive adaptation (Moravec et al., 2019; Greene et al., 2021). Qualitative feedback highlighted multiple areas where wording in the survey was unclear or questions were repetitive, so we revised the survey, resulting in four items for exploitative cognitive adaptation and four for exploratory cognitive adaptation. We adapted the survey to ask about the use of agile tools and sent it to a small-to-medium software firm (approximately 80 developers), where 40 people responded. We chose this context because it represented a specialized and collaborative domain, in contrast to the more individualized and casual context of news consumption. The results showed descriptive support that items were clustering and that participants were not suffering from fatigue, so we proceeded to a larger survey of 544 participants recruited from Prolific.com, which focused on wearables and fitness apps. We performed a confirmatory factor analysis (CFA) on the measurement model for the six factor model plus the additional factor for *perceived performance*, which was included in the original ASTI (Schmitz et al., 2016). The results showed a good model fit with $\chi^2/df = 2.132$, SRMR = 0.041, GFI = 0.933, NFI = 0.933, CFI = 0.963, AGFI = 0.901, and RMSEA = 0.046. We returned to the literature on cognitive structures to refine our measures once more and then progressed to test our experimental protocol.

For the next pilot study, we investigated possible manipulations for exploitative and exploratory technology adaptation. This was challenging, as many adaptations occur in (and create) highly specialized and idiosyncratic contexts. Hence, we needed to implement manipulations that (1) could be easily understood by subjects, (2) were sufficiently complex to challenge subjects to initiate nontrivial adaptation, and (3) limited the confounding factors that could make it difficult to compare results across experimental groups. To help us identify possible manipulations, we created an online questionnaire that included three sections. The first section explained that participants would be asked to use a word processor, e.g., Microsoft Word or Apple Pages, to create a one-page CV. The second section asked participants to write down at least two specific features of a word processor that they thought could be useful when creating this one-page CV. Participants were instructed that at least one of these features should represent a "designed" capability, i.e., "if the designers of the word processor saw how you used this feature to make the CV, they would probably not be surprised." We anticipated that these suggestions would represent exploitative technology adaptations. Participants were also instructed that at least one of these features should be a "non-designed capability," i.e., "a non-designed capability, i.e., some feature that, if the designers of the word processor saw how you used this feature to make the CV, they would probably be surprised." We anticipated that these suggestions would represent exploratory technology adaptations.

We distributed the survey to research students from the IS groups in two European public universities. The submission window lasted for one week. In the end, after screening out the uncompleted responses, there were 11 valid responses containing in-depth insights. We read participants suggestions independently and then exchanged individual views. After several iterations, we identified one suitable feature that represented exploitative technology adaptation and one that represented exploratory technology adaptations.

For exploitative technology adaptations, several participants mentioned the use of unfamiliar fonts. This adaptation fits our definition of exploitative technology adaptation, as it requires that individuals modify a feature (the fonts they can select) in a way that represents expanded use while also ensuring that those individuals should have established perceptions of what is intended or standard for that feature. While using a new font may seem like a minor adaptation, changing a font can have significant implications for the aesthetics of a document (Lupton, 2024), the suitability for different audiences (Wallace et al., 2022), or even the perceived ideology and values of the creator (Haenschen & Tamul, 2020). For exploratory technology adaptations, the most suitable suggestion was the use of the "eye dropper"; a feature that allows individuals to match the colors of text or shapes in their CV to a specific color scheme. The participant suggested that this could be used to match the application to the branding colors of the company to which they are applying. This adaptation fits our definition of exploratory technology adaptation, as it requires that individuals modify a feature (applying the eye dropper to an external company website) in a way that they perceive as unusual or that departs from what is standard for the technology.

We decided to proceed to the controlled experiment and designed our manipulations by asking participants to adapt their use of technology, based on these two features, i.e., the use of unfamiliar fonts and the use of the eye dropper tool.

3.2 Online Experiment

Building on the pilot studies, we chose to persist with the creation of CVs for the task in the experiment. We decided to apply a quasi-experimental approach because of the inability to include a control group in our study. Our research model, just like ASTI, supposes that technology adaptations are required to prompt other adaptation and that these technology adaptations are either exploitative or exploratory. This renders a control group unattainable in our context, as the procedure for a no-adaptation group would not be comparable to our other test groups. Thus, we randomized all participants into two groups, one group in which we elicited exploitative technology adaptation and another in which we elicited exploratory technology adaptation.

3.2.1 Experimental Stimuli

We set up the experiment on a cloud-based subscription platform. The task for participants was to create a CV for a self-selected target company. When creating their CVs, participants assigned to Group A (the exploitative technology adaptation) were asked to use a font they had not used before in the word processor. Group B (the exploratory technology adaptation) participants were asked to use the "eye dropper" to pick a thematic color for their target company, and then apply this to their CV. For example, if a participant's target company were Coca-Cola, they could use the eye dropper to color their title in the same red color used by Coca-Cola. After completing the tasks, participants from both groups were guided to the same survey questions.

We performed a final pilot study with 60 subjects in total before the main experiment to assess the appropriateness of the experimental stimuli. Unlike the main experiment, participants were asked to express their opinions regarding the experimental stimuli at the end of the experiment. This process revealed multiple inappropriate wordings and misleading sentences, which we then corrected. We also reviewed every CV that was submitted to confirm whether subjects used the suggested features, i.e., a new font or the eye dropper, to format their CVs. For Group A, we confirmed that all submitted CVs contained unusual fonts. Likewise, for Group B, all submitted CVs included a color aligned with the thematic color of the participant's target company.

3.2.2 Instruments and Measures

We adapted measurement items for *perceived performance* (hereafter PERF), *personal innovativeness with IT, computer self-efficacy, experience, exploitative technology adaptation, exploitative task adaptation, exploratory technology adaptation, and exploratory task adaptation* from prior literature (Schmitz et al., 2016). Note that, consistent with ASTI, we define PERF as the extent to which an individual believes their behaviors are producing their desired outcomes. Hence, we refer to perceived performance, rather than performance, given that individuals may be limited in their ability to evaluate some performance outcomes and so must rely on their subjective judgement.

To complete our set of measurements, we used novel items for exploitative cognitive adaptation and exploratory cognitive adaptation, which were developed according to the core ideas in each construct and refined during pilot studies. Appendix A presents a more detailed account of this development of items and a full list of measures.

3.2.3 Participants and Experimental Procedures

We set up our online quasi-experiment on Credamo, a leading online platform for surveys and experiments. We attracted 547 participants for our online experiment, who were recruited over a two-week period. Among these participants, 15 submissions were dropped because of either failure to answer the attention check questions or extremely short completion time (less than one minute). This resulted in 532 valid responses for subsequent analysis.

The experimental procedures were as follows. Upon arrival, participants were presented with a welcome page that indicated the estimated time required for participation and gave each participant the option to proceed or quit. Next, each participant was asked to indicate a company for whom they would like to work, write down that company's website address, and visit their website. Afterward, we presented the scenario and the main task to the participants with the following text:

> *You have targeted a position at your dream company and communicated with the Head of Human Resources. The Head of Human Resources recommended you use a word processor, e.g., Microsoft Word, to create a two-page CV for initial screening. In the next pages, please follow the instructions and create this two-page CV using a word processor. For the sake of privacy protection, you can use a pseudonym for your name and contact information.*

Next, a randomization function assigned each participant to either Group A (the exploitative technology adaptation) or Group B (the exploratory technology adaptation). Participants in Group A were asked to use a font that they had not used before, and Participants in Group B were asked to use the eye dropper. Participants then submitted their CV and filled out the survey, which contained the same measures for both groups, i.e., survey items for all variables in the research model and survey items for relevant background information, such as *gender*, *age*, and *educational level*. The demographic distribution of the 532 participants is presented in Appendix Table A1.

4 Results

4.1 Manipulation Checks and Descriptive Analysis

Before running the formal analysis, we first conducted a randomization test to confirm the random assignment of experimental treatments. We looked for significant differences between the two groups in terms of age, gender, educational level, experience using a word processor, personal innovativeness with IT, and computer self-efficacy. Age and educational level were measured as ordinal variables, so we applied ordinal logistic regression to test whether there was a statistically significant difference between the two treatments. Gender was measured as a categorical variable, namely female, male, and non-disclosed. We used analysis of variance (ANOVA) to test for randomization. We applied a t-test to compare experience, personal innovativeness with IT, and computer self-efficacy between the two groups.

The p-values from all models were greater than 0.1, indicating no significant difference between two groups and confirming that participants were randomly assigned to each treatment. Table 1 presents an overview of the results.

Table 1. Randomization Checks

Variable	Statistical Model	Z/F/T-score	P-value
Age groups	Ordinal Logistic Regression	0.19 (Z-score)	0.851
Gender	ANOVA	0.12 (F-score)	0.543
Educational level	Ordinal Logistic Regression	-0.09 (Z-score)	0.928
Experience	T-test	0.777 (T-score)	0.438
Personal innovativeness with IT	T-test	-1.064 (T-score)	0.288
Computer self-efficacy	T-test	-0.002 (T-score)	0.999

We present descriptive statistics for our primary constructs (exploitative technology adaptation, exploitative task adaptation, exploratory technology adaptation, exploratory task adaptation, exploitative cognitive adaptation, exploratory cognitive adaptation, and PERF), internal consistency and discriminant validity of constructs in Table 2. The Cronbach's alpha scores and the composite reliability of all constructs were greater than the threshold value of 0.70, suggesting satisfactory internal consistency. The square root of the average variance extracted (AVE) of each latent variable was greater than the correlations between that latent variable and all other latent variables, which indicated adequate discriminant validity. The loadings and cross-loadings of measures are presented in Table 3. Moreover, the loadings of indicators on their respective latent variables were greater than their loadings on other latent variables, and the average loadings for these indicators on their respective latent variables was greater than 0.7, further demonstrating convergent and discriminant validity.

We next analyzed whether the experimental manipulations had succeeded in eliciting the intended types of technology adaptations across the two groups. Specifically, we expected participants assigned to Group A (use a new font) to score higher for exploitative technology adaptation, and participants from Group B (use the eye dropper) to score higher for exploratory technology adaptation. The results are reported in Table 4. The variable of our primary interest is *treatment*, a binary variable where 0 indicates Group A (use a new font) and 1 indicates Group B (use the eye dropper). The dependent variables of Models 1a, 2a, and 3a and Model 1b, 2b, and 3b were exploitative technology adaptation and exploratory technology adaptation, respectively. Only *treatment* was entered in Models 1a and 1b. The estimated coefficients were negatively significant for Model 1a and negatively significant for Model 1b, validating our manipulations of exploitative technology adaptation and exploratory technology adaptation. Models 2a and 2b included all control variables, including demographic information (age, gender, and educational level), personal innovativeness with IT, computer self-efficacy, and experience. The results were consistent. Models 3a and 3b reanalyzed the model, including only personal innovativeness with IT, computer self-efficacy, and experience as control variables by applying fixed effects on age, gender, and educational level. This also presented consistent results. As the two dependent variables for these tests— exploitative technology adaptation and exploratory technology adaptation—are potentially correlated, we reanalyzed our data using seemingly unrelated linear regression models to estimate the equations simultaneously and capture cross-equation correlations. The results are presented from Model 1c to Model 3d. Based on the Breusch-Pagan test, there are potential correlations in the error terms between models with different dependent variables. However, the results remained consistent. Collectively, these results support the effectiveness of the manipulations and suggest that individuals can distinguish the difference when self-reporting exploitative technology adaptation and exploratory technology adaptation.

Table 2. Descriptive Statistics, Internal Consistency and Discriminate Validity

Variable	**Min.**	***SD***	**Cron. alpha**	**Comp. rel.**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Exploitative technology adaptation	5.714	0.851	0.707	0.836	**0.794**						
Exploitative task adaptation	5.186	0.540	0.734	0.834	0.532	**0.748**					
Exploratory technology adaptation	4.432	1.501	0.868	0.919	0.408	0.382	**0.889**				
Exploratory task adaptation	5.351	0.848	0.780	0.860	0.403	0.622	0.373	**0.780**			
Exploitative cognitive adaptation	5.777	0.793	0.779	0.857	0.546	0.559	0.421	0.425	**0.775**		
Exploratory cognitive adaptation	5.249	1.045	0.844	0.895	0.604	0.576	0.644	0.472	0.604	**0.826**	
PERF	5.700	1.100	0.922	0.941	0.585	0.497	0.353	0.395	0.484	0.449	**0.873**

Note: Bold numbers show the square roots of the AVE values, while the off-diagonal elements are the correlations between the variables.

Table 3. Loadings and Cross-Loadings of Measures

	Exploitative technology adaptation	Exploitative task adaptation	Exploratory technology adaptation	Exploratory task adaptation	Exploitative cognitive adaptation	Exploratory cognitive adaptation	Perf.
ITECH_1	**0.757**	0.369	0.154	0.278	0.404	0.293	0.362
ITECH _2	**0.774**	0.444	0.456	0.346	0.409	0.479	0.470
ITECH _3	**0.849**	0.452	0.358	0.335	0.483	0.443	0.519
ITASK_1	0.423	**0.785**	0.223	0.482	0.432	0.434	0.399
ITASK_2	0.302	**0.648**	0.481	0.450	0.326	0.432	0.308
ITASK_3	0.400	**0.740**	0.185	0.445	0.403	0.380	0.356
ITASK_4	0.454	**0.808**	0.283	0.483	0.498	0.477	0.395
RTECH_1	0.379	0.352	**0.899**	0.352	0.403	0.582	0.316
RTECH_2	0.317	0.299	**0.880**	0.310	0.327	0.559	0.273
RTECH_3	0.391	0.367	**0.889**	0.333	0.393	0.577	0.346
RTASK_1	0.310	0.497	0.267	**0.840**	0.351	0.354	0.322
RTASK_2	0.259	0.432	0.440	**0.641**	0.264	0.397	0.278
RTASK_3	0.288	0.444	0.236	**0.788**	0.292	0.333	0.288
RTASK_4	0.386	0.552	0.230	**0.835**	0.405	0.384	0.336
ICOG_1	0.411	0.454	0.296	0.312	**0.807**	0.465	0.367
ICOG_2	0.349	0.368	0.296	0.259	**0.726**	0.365	0.304
ICOG_3	0.446	0.479	0.273	0.378	**0.784**	0.459	0.389
ICOG_4	0.475	0.423	0.438	0.355	**0.780**	0.568	0.400
RCOG_1	0.399	0.441	0.570	0.389	0.442	**0.849**	0.348
RCOG_2	0.437	0.490	0.553	0.413	0.537	**0.839**	0.428
RCOG_3	0.433	0.510	0.472	0.383	0.540	**0.799**	0.306
RCOG_4	0.423	0.466	0.526	0.371	0.483	**0.814**	0.357
PERF_1	0.526	0.407	0.319	0.346	0.411	0.453	**0.886**
PERF_2	0.483	0.388	0.321	0.334	0.423	0.424	**0.856**
PERF_3	0.489	0.354	0.293	0.334	0.393	0.406	**0.884**
PERF_4	0.524	0.399	0.309	0.383	0.452	0.449	**0.884**
PERF_5	0.531	0.409	0.296	0.321	0.432	0.433	**0.855**

Table 4. Results Comparing Manipulations of Exploitative Technology Adaptation and Exploratory Technology Adaptation

Variables	**Linear regression models**					
	DV: exploitative technology adaptation			**DV: exploratory technology adaptation**		
	Model (1a)	**Model (2a)**	**Model (3a)**	**Model (1b)**	**Model (2b)**	**Model (3b)**
Treatment: *-0: New font* *-1: Eye dropper*	-0.174** (0.073)	-0.233*** (0.063)	-0.229*** (0.062)	0.604*** (0.128)	0.516*** (0.110)	0.497*** (0.108)
Control variables	No	Yes	Yes	No	Yes	Yes
Fixed effect	No	No	Yes	No	No	Yes
R^2	0.01	0.28	0.31	0.04	0.28	0.33
Variables	**Seemingly unrelated linear regression models**					
	DV: exploitative technology adaptation			**DV: exploratory technology adaptation**		
	Model (1c)	**Model (2c)**	**Model (3c)**	**Model (1d)**	**Model (2d)**	**Model (3d)**
Treat. *-0: New font* *-1: Eye dropper*	-0.174** (0.073)	-0.233*** (0.062)	-0.236*** (0.061)	0.604*** (0.127)	0.516*** (0.110)	0.509 (0.106)
Control variables	No	Yes	Yes	No	Yes	Yes
Fixed effect	No	No	Yes	No	No	Yes
R^2	0.01	0.29	0.34	0.04	0.29	0.35

Breusch-Pagan test of independence	Correlation coef. between two DVs	χ^2 (1)	*p*-value
Model (1c) vs. Model (1d)	0.47	118.173	<0.01
Model (2c) vs. Model (2d)	0.31	50.368	<0.01
Model (3c) vs. Model (3d)	0.26	36.00	<0.01
Note: *$p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$. (532 Observations)			

4.2 Hypothesis Testing

We analyzed the structural model to estimate the path coefficients in SmartPLS (version 4.1.0.0) using PLS-regression mode with bootstrap resampling. We selected PLS-regression mode because this approach allows the formative measurement of computer self-efficacy (CSE), consistent with recommendations in prior literature (Schmitz et al. 2016; Marakas et al., 2007). Results showed that (1) both exploitative technology adaptation (β = 0.546, p < 0.01) and exploratory technology adaptation (β = 0.644, p < 0.01) had a significant and positive effect on exploitative cognitive adaptation (R^2 = 29.9%) and exploratory cognitive adaptation (R^2 = 41.5%), respectively; (2) both exploitative cognitive adaptation (β = 0.561, p < 0.01) and exploratory cognitive adaptation (β = 0.474, p < 0.01) had a significant and positive effect on exploitative task adaptation (R^2 = 31.5%) and exploratory task adaptation (R^2 = 22.5%), respectively; and (3) both exploitative task adaptation (β = 0.320, p < 0.001) and exploratory task adaptation (β = 0.085, p < 0.05) had a significant and positive effect on PERF (R^2 = 29.4%). The full results are illustrated in Figure 2.

To test our hypotheses, we conducted a mediation analysis, based on a bootstrap test (with 5,000 bootstrap samples and 95% bias-corrected confidence intervals) to verify whether exploitative cognitive adaptation and exploratory cognitive adaptation mediate between exploitative technology adaptation and exploitative task adaptation, and exploratory technology adaptation and exploratory task adaptation, respectively. The results show that the indirect effect of exploitative technology adaptation through exploitative cognitive adaptation on exploitative task adaptation was positive and significant (95% CI = 0.161 to 0.265; p < 0.01) and the direct effect (Exploitative technology adaptation → Exploitative task adaptation) was still positive and significant (95% CI = 0.238 to 0.411; p < 0.01), implying a partial mediation effect. Therefore, H1 is supported. We also found a partial mediation effect for exploratory cognitive adaptation, where the indirect effect of exploratory technology adaptation through exploratory cognitive adaptation on exploratory task adaptation was positive and significant (95% CI = 0.173 to 0.328; p < 0.01), and the direct effect (Exploratory technology adaptation → Exploratory task adaptation) was still positive and significant (95% CI = 0.016 to 0.257; p < 0.05), thus supporting H2.

We applied two key strategies to check for common method bias. First, we followed guidance from prior literature (Kock, 2015; Lowry & Gaskin, 2014) to examine the variance inflation factor (VIF) of constructs in our inner model as a sign of common method bias in our structural model. The occurrence of a VIF exceeding 3.3 is proposed as an indication that a model may be contaminated by common method bias as well as pathological collinearity. The maximum value of the VIF in the inner model is 1.906, less than the threshold value (=3.3), suggesting our model does not suffer from problematic levels of common method bias. Second, we used a marker variable approach to detect common method bias. We included two items in the survey with no theoretical relationship with other items. We perceived social desirability and self-esteem bias to be possible sources of common method bias, so we measured individuals' behavioral intention to use (Venkatesh & Davis, 2000) recycling facilities (BIUR) to measure an unrelated socially desirable construct (both items loaded above 0.9). We applied the unrelated marker variable method by connecting the marker variables to all constructs and reanalyzing the structural model. The results demonstrate that each relationship remained significant, even with the addition of the marker variable. We present the comparison of path coefficients in Table 5 as supporting evidence.

In addition to the unrelated marker variable approach, we also used the CFA marker technique for a more stringent test (Williams et al., 2010). We ran an additional CFA with the marker variable, BIUR, followed by a baseline CFA model that constrained the correlations between BIUR and other variables to zero to establish baseline uncorrelated item loadings and error variances (see Table 6). We then ran Method-C to add paths from BIUR to each item of the substantive variables, while constraining these paths to be constant across the model. The lack of significant difference from the baseline model suggests no evidence of shared CMV between BIUR and indicators of the substantive model. We ran Method-U to remove the constraint that paths were constant from BIUR to indicators in the substantive model, allowing us to calculate of unique paths for each substantive variable. The lack of significant improvement suggests there is no evidence that CMV was different across indicators. Finally, we ran Method-R to constrain latent factor correlations to values from the baseline model. The lack of significant difference from Method-U suggests no evidence of CMV skewing relationships among substantive variables.

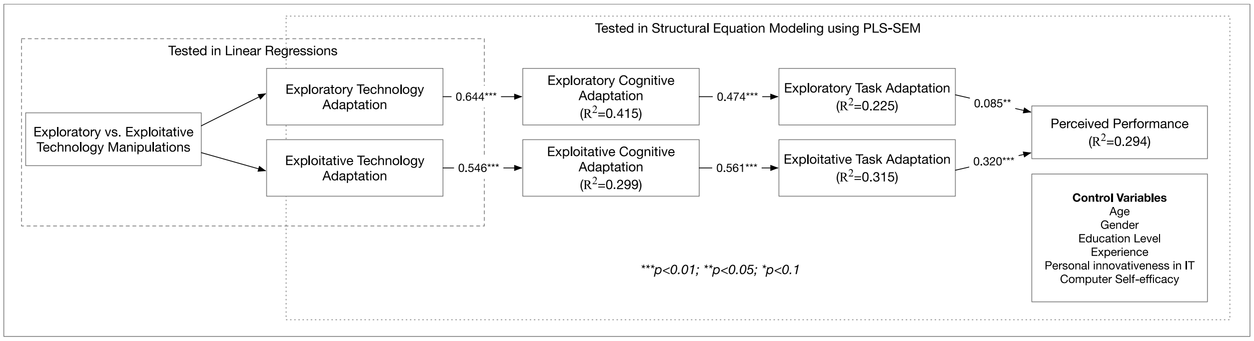


Figure 2. Research Model: Testing Results

Table 5. Results Comparing Manipulations of Exploitative Technology Adaptation and Exploratory Technology Adaptation

Path relationship	With marker variable		Without marker variable	
	Path coef.	*p*-value	Path coef.	*p*-value
Exploitative technology adaptation→ Exploitative cognitive adaptation	0.437	<0.001	0.546	<0.001
Exploitative cognitive adaptation→Exploitative task adaptation	0.420	<0.001	0.561	<0.001
Exploratory technology adaptation→Exploratory cognitive adaptation	0.570	<0.001	0.644	<0.001
Exploratory cognitive adaptation→Exploratory task adaptation	0.385	<0.001	0.474	<0.001
Exploitative task adaptation→PERF	0.252	<0.001	0.320	<0.001
Exploratory task adaptation→PERF	0.091	<0.05	0.085	<0.05

Table 6. Chi-Square, Goodness-of-Fit Values, and Model Comparison Tests

Model	χ^2	*df*	*CFI*
CFA	805.368	286	0.932
Baseline	1016.778	305	0.907
Method-C	990.171	288	0.908
Method-U	990.391	263	0.905
Method-R	996.388	267	0.905
Chi-square model comparison*	$\Delta\chi^2$	**Δdf**	**χ^2 Critical Value: 0.05****
Baseline vs. Method-C	26.607	17	27.587
Method-C vs. Method-U	0.22	25	37.652
Method-U vs. Method-R	5.947	4	9.488

Note: * If the value from $\Delta\chi^2$ is less than the value from "χ^2 Critical Value: 0.05"; there is no statistically significant difference between two models. **The values were obtained from the upper-tail critical values of χ^2 distribution with v degrees of freedom

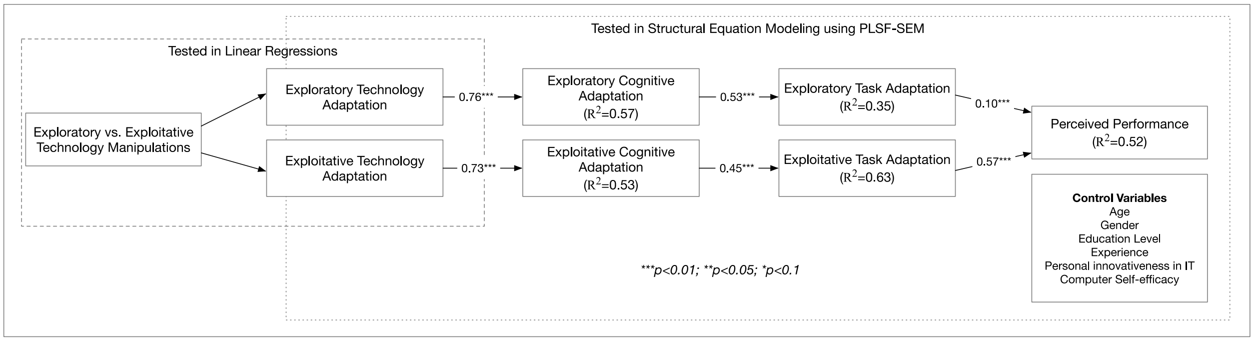


Figure 3. Robustness Check Using PLSF-SEM

To confirm the robustness of our findings, we employed factor-based PLS, also as known as PLSF-SEM, implemented by WarpPLS 8.0 (Kock, 2019) to corroborate our results. The results are consistent with the estimation from PLS-regression mode and are presented in Figure 3. Likewise, we also conducted a bootstrap test for mediation analysis, which also yielded consistent results. More specifically, we found that (1) both the indirect effect of exploitative technology adaptation through exploitative cognitive adaptation on exploitative task adaptation (product of coefficient = 0.326; $p < 0.01$) and the direct effect, from exploitative technology adaptation to exploitative task adaptation (coefficient = 0.405; $p < 0.01$), are positive and significant, implying a partial mediation effect; and (2) the indirect effect of exploratory technology adaptation through exploratory cognitive adaptation on exploratory task adaptation (product of coefficient = 0.399; $p < 0.01$) and the direct effect, from exploratory technology adaptation to exploratory task adaptation (coefficient = 0.084; $p > 0.242$), are also positive but insignificant, implying a full mediation effect.

Finally, we conducted a path comparison between two groups to further investigate the different paths of technocognitive structuration and their comparative effect on perceived performance. First, we examined whether the mediation effects differed between the two treatment groups: *exploratory vs. exploitative technology manipulation*. Specifically, we conducted a mediation analysis with the same settings as our hypotheses testing for each group, respectively. The results were consistent with the findings from the hypotheses testing, with one exception. For the exploratory technology adaptation group, we identified a full mediation effect instead of partial mediation. The indirect effect of exploratory technology adaptation through exploratory cognitive adaptation on exploratory task adaptation was positive and significant (95% CI = 0.282 to 0.470; $p < 0.01$), while the direct effect (Exploratory technology adaptation → Exploratory task adaptation) was insignificant (95% CI = -0.053 to 0.229; p = 0.195). Such findings echo the results of our robustness check with PLSF-SEM presented previously, implying that the mediation effect of cognitive adaptation is stronger for *exploratory* technology.

Since both mediation effects persist in both groups, we further conducted a multigroup comparison to assess the heterogeneity of exploratory adaptation and exploitative adaptation between the two groups. Although we manipulated technology features between the groups to emphasize exploitative and exploratory characteristics, both types of adaptations may coexist and intertwine when individuals engage in the given tasks. Therefore, the multigroup comparison can further untangle the heterogeneity in adaptation behaviors between different technological components and their implications for performance. The results revealed that the exploratory mediation effect in the exploratory group was stronger than that in the exploitative group, with a difference of 0.263 and a p-value of < 0.01. Additionally, the impact of exploratory adaptation on perceived performance in the exploratory group was stronger than in the exploitative group (difference = 0.086, $p < 0.05$). However, the heterogeneity of exploitative adaptation between the two groups was insignificant. Collectively, these results indicate that exploratory technologies are more likely to trigger task adaptation and elicit improvements in perceived performance.

4.3 Illustrative Qualitative Study

The controlled experiment demonstrated the hypothesized mediating effect of exploitative cognitive adaptation and exploratory cognitive adaptation. We supported these results with an illustrative qualitative study of 12 individuals, the purpose of which was to identify vignettes of how these mediating effects of exploitative cognitive adaptation and exploratory cognitive adaptation might play out in a naturalistic setting and over a longer time period. This qualitative study focused on wearable devices that could be linked to a smartphone's health and fitness app. Our focus on wearables in health and fitness combines some of the documented areas where technology is linked to changing ways of thinking, such as changing attitudes to body image (Aboody et al., 2020) and health (Hardey,

2019) and changing attitudes to social relationships (Dewa et al., 2019), information engagement (Liu et al., 2017), and technology addiction (He et al., 2017). Appendix C presents an overview of data gathering and analysis for these vignettes.

Vignette 1 (change initiated by exploitative technology adaptation): Participant A is a former soccer player who initially used running and cycling to help recover from injury. Over time, he became passionate about long-distance running, triathlons, and adventure races. He has won multiple prestigious national races in Ireland. He has also competed internationally at the international elite Ultra Trail de Mont Blanc (UTMB) races, ranking in the top 100 of over 2,000 athletes. Participant A described a change initiated by exploitative technology adaptation that triggered an adaptation in his understanding of "rest days." He explained how he initially relied on one or two trusted measures to help gauge his need for rest. He later began expanding his use of measures and discovered that each measure added information that others missed. This expanded his use of features and broadened his understanding of what it means to be "rested" and to have "rest days":

> *Then I discovered the Body Battery (BB) feature in Garmin [exploitative technology adaptation], which actively measures holistically how rested/ready you are… I observed it for a while and even though the plan would say I should or shouldn't run and the body battery said the opposite. More often than not I'd agree with the battery. I started researching other Garmin features that indicate fatigue or readiness for training. Maybe each of these are flawed but I would look at them as a collective [exploitative cognitive adaptation]. My BB might say I'm ready to run but the other three might say otherwise. This is really valuable to me and contradicted the way I used to rely on a single measure. I learned from this that no one feature is perfect or even reliable. Groups of features and metrics collectively are really good, and now I use the watch and those collective measures as my Central Governor, as "True North" [exploitative task adaptation]. If the training plan says run but the watch says to rest, then I rest.*

Vignette 2 (change initiated by exploitative technology adaptation): Participant E is a former winner of the national Roller Derby in Austria. She participates in mini-Ironman events, as well as many separate running, cycling and swimming events in between. Participant E jointly manages an adventure tourism company that provides mountain tours. She uses and experiments with technology in plotting and tracking optimal adventure racing routes. Participant E noted that the training programs they use for professional sports teams have become more and more comprehensive and thorough, with new features continuously spreading through sports cultures by word of mouth. She explained:

> *We look at everything. The girls are constantly experimenting with all tech, particularly where they hear rivals are trying something [exploitative technology adaptation] … we analyze the data looking for places where the player or team may be doing something new, creative or ground breaking—something that might appear negative but that long term if done well might give us an advantage [exploitative cognitive adaptation] … The app designers want us to always maximize performance, and when we look at dips [in performance] we should be trying to improve them [exploitative task adaptation]*

Interestingly, just as the previous vignette highlighted a need to remain critical of individual measurements and features, Participant E also noted some concerns about athletes' tendency to adapt their cognitive structures to better align with specific tools and measures. She explained:

> *I've learned about the innate human need to rely on technology. Humans are competitive and these [wearables] give a great opportunity for that—to look at your teammate and see what they are doing and to push yourself … They will say to you "[Coach] I know this isn't what I should be doing" as they push out for a second or third run in a day just to top whatever WhatsApp group thing they have going*.

Vignette 3 (change initiated by exploratory technology adaptation): Participant B is a four-time 1500m champion runner with five gold and one silver national team medals over six years at the 5 Nations British and Irish Championships. He also qualified to represent Ireland in World Masters championships in Brazil in 2013, finishing fifth in the 1500m final. He achieved this after running his first cross country competition at age 34 and his first 1500m at 35. Participant B explained how he had been sponsored by a nutrition gel brand for his long-distance races. His performance was suffering for reasons he couldn't explain, so he began experimenting with the various features on his device to try and understand what he was missing. He explained:

> *I recorded what I and others in the group had eaten. I plotted the number of milliliters of the nutrition supplement at various points in the race. Usually that feature is used for taking photos at scenic points on the route [exploratory technology adaptation] … This level of analysis was key for endurance performance in [the race] when I think back … the tech showed [that] heat and altitude raised body temperature and heart rate so much the body couldn't digest food. After 85km, I kept vomiting and was on the verge of pulling out. I had my blood saturation and temperature taken in the tent and it showed my body was OK, it was just internal and mental.*

This realization led Participant B to think about nutrition in a different way when it came to long-distance racing:

> *My previous thinking was to keep getting carbs and sugar … I used the tech and data in conjunction with blood samples taken as I ran … Whenever I went into the heart rate red zone I found out I was burning carbs and sugar, not fat. This completely undermined what I had though previously [exploratory cognitive adaptation]. It showed that taking [the supplement] (sugar and carbs in gel form) was actually making the issue worse. But if I can get the body to train to burn fat first I wouldn't need to force to eat as much food [exploratory task adaptation].*

Vignette 4 (change initiated by exploratory technology adaptation): Participant H is the CEO of a company specializing in video analysis for sports, focusing on the Rugby Union market. She has undergraduate and postgraduate degrees in sports science, and she is a former international rugby player. She is also the director of women's rugby with a professional rugby club, where she governs the training and management of girls at all ages. She is also a member of the national rugby executive board. While training women's sports teams, Participant H began to grow frustrated by a perceived lack of consideration for female athletes:

> *App designers aren't aware of the specifics of female sports. All of the apps are designed with men in mind. Even where they have a tailored program for women, when we looked into it, it's usually just something really crude like "take the men's plan and knock 30% off" … Women's sport is in reality much more sophisticated. For example, while women's physiques might be on average less powerful in the short run, over a full sixty or seventy minute game or long race they tend to conserve energy and outperform.*

She noted that for women's sports, the standard measures could indicate different information than was presumably intended:

> *Girls drop out of sport around 15-18 years old. This is well known. What is not known is why. We've struggled with that for years ... It is why the men's teams dominate. They are no better, but more of the better ones stay playing. It's really puzzling to work out why girls drop at such a high rate. Well, technology is starting to give us some insight. We cannot see the girls that are overtraining [but] we can monitor their stress levels [exploratory technology adaptation]. We can analyze their presence or absence at training or when they finish early. We can analyze their injuries. With some specific teams they voluntarily allow analysis of their cycles. It turns out all of these things are in some way a predictor of drop outs [exploratory cognitive adaptation]. Another one is ranking or placing in runs/training. Some girls are very competitive and take it very badly when they go through a bad patch after a long record of good performance. So, we monitor all those things and where we see one or more of them dip we put an arm round them, ease back their training or do whatever it is helps to keep them motivated [exploratory task adaptation].*

5 Discussion and Conclusion

There is evidence that the continued use of digital technology not only coincides with cognitive adaptations but these cognitive adaptations also become more pronounced as technology is used and adapted more intensively (see, e.g., Introna, 2016; Chandler, 2019). One limitation of existing perspectives is that they often assume that the use of technology evolves in predictable ways, e.g., social media lead to polarization and new performance metrics lead to decreasing consideration of other, harder to measure criteria. This creates a disconnect with the sociotechnical theories that are often used to describe prolonged technology use, as those theories suggest that adaptation takes different forms according to the abilities and intent of the actor and the capabilities and constraints of the surrounding context (Jones & Karsten, 2008; Cecez-Kecmanovic et al., 2014; Sarker et al., 2019).

We argue that resolving this paradox requires that we understand the types of cognitive adaptations that occur as individuals adapt and integrate technology. Our research therefore complements and extends these theories of tool-related cognitive change and technology adaptation. Specifically, we extend adaptive structuration theory for individuals (ASTI) and propose a theory of technocognitive structuration. This theory presents a generalized model of technology-related cognitive adaptation in structuration episodes; a model which does not presuppose any specific tools, tasks, or contexts. Our findings demonstrate that adaptations may vary widely in form—for example, in our qualitative study, we observed that some users of mobile devices might use their camera to take pictures of scenic locations when out running, while other users might use the same feature to record their intake of nutrition. While such widely varying uses of technology are mediated by different cognitive adaptations, we show that these cognitive adaptations can be categorized into two different types: *exploitative cognitive adaptations* and *exploratory cognitive adaptations.* This study therefore has implications for research on technology adaptation and cognitive structures.

5.1 Implications for Research on Technology Adaptation

Technocognitive structuration builds on a long line of previous studies that have investigated adaptation behaviors in the context of digital systems. While some previous studies view social and material actors as equally responsible in the process of adaptation, such as actor network theory (Callon, 1986) or sociomateriality (Orlikowski & Scott, 2008), others treat human "intent" as a distinct and important influence (cf. Cecez-Kecmanovic et al., 2014). The theory of structuration is one such theory, as it assumes that intent and modality shape individuals' configuration of rules and resources as well as their ability to relate actions to overarching structures and outcomes (Giddens, 1984; Jones & Karsten, 2008).

As an extension of structuration theory, ASTI also assumes that individuals' intent plays an important role. As Schmitz et al. (2016, p. 668) explain:

> *From the perspective of ASTI, the spirit of a technology exists as an individual's understanding of that technology's capabilities and affordances… Adaptations may be subtle, adjusting within the realm of the current spirit, or may be dramatic with transformational consequences. This… is tied to how the user understands the technology as it is available in a given usage episode.*

Yet for ASTI and other theories of technology adaptation, the nature of this technology/task understanding and how this understanding changes as individuals make technology and task adaptations remains unclear. We argue that this has left a blind spot at the heart of these theories which obfuscates how the tools we use shape and are shaped by our internal mental environments (Vygotsky, 1978; Simon, 1988). By addressing this blind spot, we make two major contributions to research on technology adaptation.

First, we highlight the existence of exploitative cognitive adaptation and exploratory cognitive adaptation. These measurable constructs, linked to changes in technology-related behaviors, provide an important stepping stone to understanding the cognitive impact of digital technologies. This not only adds depth and consistency to existing perspectives on technology adaptation, particularly ASTI, it also better equips those perspectives to address contemporary social issues. Many studies across different fields have highlighted the types of harmful cognitive structures that can result from continued technology use and what mechanisms might be used to address them (e.g., He et al., 2017; Knight & Tsoukas, 2019; Moravec et al., Dennis, 2019; Saiphoo & Vahedi, 2019). Technocognitive structuration can help us understand the evolution of those cognitive structures within the context of continued technology use and adaptation.

Second, we show that adaptations in cognitive structures mediate the impact of feature discovery on behavioral change. The separability of individuals' internal worlds from their material surroundings is a topic of ongoing debate among theories of technology adaptation (Markus & Silver, 2008; Cecez-Kecmanovic et al., 2014). Some scholars prefer to treat human and material agencies as co-constituted in the materialist entanglement of practice (cf. Orlikowski & Scott, 2008; Poole, 2009). Others assume that structures only really persist in the internal worlds of individuals, with technology adaptations reflecting but never truly embodying these structures (Pickering, 1993; Jones & Karsten, 2008; Rerup & Feldman, 2011). We provide evidence that adaptation in these distinct internal cognitive structures are not only rationalizations of practice; rather, they are a necessary enabler of adaptation and changing task-related outcomes.

5.2 Implications for Research on Cognitive Structures

A large body of research has studied the formation and adaptation of cognitive structures. This research has become established in many social sciences, including fields such as marketing (Ng & Houston, 2009), management (Shaw, 1990), relationship studies (Murray & Holmes, 199), and even IS (Evermann, 2005). A common feature of this rich, multidisciplinary body of research on cognitive structures is the assumption that individuals engage in cognitive adaptation as a response to feedback from their environment. Yet just as the previous section argued that existing literature on technology adaptations does not adequately ground them in cognitive changes, so too we argue that existing literature on cognitive adaptations does not adequately link them to the changing use of technology—in particular, digital technology.

This lack of connection between cognitive and technology adaptation is not because IS research has not considered the impact of cognition processes on individuals' relationship with technology. Rather, it is because cognitive adaptation is often theorized as either a preexisting context for technology acceptance, or an outcome of technology use. For example, Beaudry and Pinsonneault (2005) present a coping model of adaptation, which offers powerful insights about how individuals adopt different strategies towards technology (benefits maximizing, self-preservation, etc.), based on their perceptions of whether that technology is a threat or opportunity and their perceived degree of control over how it is used. However, that model does not explain the "back and forth" between technology adaptation and cognitive adaptation and how individuals' perceptions change based on how they use the technology.

The inability of existing theory to model task, technology, and cognitive adaptation in an integrated fashion is problematic, given that individuals often approach problem solving and communication in different ways when they use different tools (Cybulski et al., 2015; McGrath et al., 2016). We argue that it does not, therefore, make sense to position cognitive adaptation as an input and/or output of technology and task adaptation, given these adaptations are interdependent. Moreover, by positioning cognitive adaptation as an input and/or output of technology and task adaptation, we risk obscuring the possible acceleration of cognitive adaptation associated with digital technologies. This potential for accelerated cognitive adaptation is significant, as these technology-enabled shifts in thinking styles could be long-lasting, especially as cognitive adaptations are often accompanied by measurable physiological changes. For example, different brain regions appear to activate when people use physical vs. digital tools, such as cash vs. digital payment methods (Ceravolo et al., 2019), and there are signs that social media addiction creates enduring anatomical changes in individuals' brain structures (He et al., 2017). Understanding the interdependency of task, technology, and cognitive adaptations is thus essential, given that the reach of digital technologies into our daily lives is likely to increase due to our increasing reliance on digital communication, data-driven decision-making, AI and augmented intelligence, and the growing popularity of blended systems that rely on immersive environments and wearable devices.

5.3 Implications for Practice

This study has significant managerial implications. Existing research has demonstrated that the adaptation of technology is common and often productive. Technocognitive structuration highlights that technology adaptation is also connected with cognitive adaptation. This finding provides support for organizational initiatives that invest in conceptual technology training to complement task-related training. Moreover, building on our observations that cognitive adaptations mediate the impact of technology adaptations on task adaptations, we argue that organizations should consider expanding conceptual training practices. For example, organizations may wish to encourage conceptual discussions among peers to propagate situated task-specific cognitive structures, rather than expecting individuals to cognitively "connect the dots" as they observe the external technology and task-related actions of others.

Understanding the cognitive impacts of extended technology use is also important for the designers of digital technologies. Designers often seek to design systems that are compatible with users' existing cognitive structures so that technologies can quickly meet users' expectations and minimize their cognitive burden (Brown et al., 2014; Hu et al., 2017; Grimes et al., 2021). This requirement is summarized by Krug's (2000) famous book on user experience entitled "*Don't Make Me Think*. However, our quantitative findings suggest that users may improve their perceived performance when they make exploratory cognitive adaptations that modify their cognitive structures. We also observed this trend in the qualitative data, presented here as vignettes, where athletes reported stronger perceived performance when their technology adaptations led them to actively critique the assumed reasoning behind technological capabilities. Conversely, athletes and coaches reported lower improvements in perceived performance when they embraced the intuitive logic of these expertly designed systems. For example, in our qualitative data, we encountered athletes who discovered newly available social comparison metrics in their wearable devices. In many respects, these social comparison capabilities represented a design success. They provided an easy to understand basis for adaptation among athletes, which led the athletes to embed the wearables further into their fitness-related tasks. Yet, according to their coach, those adaptations also caused the athletes to overtrain and exhaust themselves, because, following the logic of the systems, they began treating the amount of training as a goal, rather than their performance in the actual sport.

We do not claim that designers should completely abandon the goal of making systems easy to use or intuitive. Instead, the theory of technocognitive structuration suggests that while designers must consider how to match and extend users' existing cognitive structures to some degree, they must also consider how their designs can avoid restricting users to these specific structures. Implementing this approach may mean that designers should present capabilities in a way that avoids prescribing an interpretation, e.g., favoring the presentation of raw data rather than summaries. It may also mean actively encouraging reflection among users, e.g., by prompting users to consider what they hope to achieve as they evolve their use of a technology. This desire to avoid imposing strict cognitive structures may become especially important if technologies like AI continue to grow, as such technologies often impose particular ways to understand systems and evaluate actions (Liao et al., 2020; Fügener et al., 2021; Jussupow et al., 2021; Jia et al., 2024). Enabling exploratory cognitive adaptations may also be important for cybersecurity, as the effectiveness of cybersecurity systems often requires that users remain vigilant in the face of creative and ever-changing attack strategies, which are designed to target gaps in users' understanding (Dhillon et al., 2021). These gaps in understanding are likely to grow as more devices become integrated into users' customized sociotechnical systems—devices such as wearables, the internet of things, and emotion-sensing technologies—and the resulting complexity makes it harder to predict and counteract specific vulnerabilities with "designed" cognitive adaptations.

This study also has implications for policymakers, regulators, and moderators interested in harmful cognitive structures connected with technology use, such as delusions or addictions. Our growing reliance on technology is commonly described as a double-edged sword (Schultze & Leidner, 2002; Lee et al., 2018; Benlian, 2020). On the positive side, new technologies can help us share information, become more productive, stay connected with family and friends, and support flexible work arrangements. On the negative side, continued technology use is often associated with self-destructive and/or socially harmful behaviors (Knight & Tsoukas, 2019; Moravec et al., 2019; Saiphoo & Vahedi, 2019; Yui et al., Hui, 2019). This is somewhat paradoxical, given that we are supposedly continuously adapting these technologies to make them more useful (DeSanctis & Poole, 1994; Jones & Karsten, 2008). Harmful tools should therefore give way to better alternatives, or at least systems that provide better outcomes to the individuals adapting them (cf. Bostrom et al., 2009; Bernardi, 2017).

Understanding the episodic dynamics by which these structures are formed can help us understand possible remedies or intervention windows. For example, policymakers, regulators, and moderators may wish to investigate whether individuals tend to form harmful cognitive structures when they are exposed to a combination of technology features and task demands, or when they engage in specific technology/task adaptations. This could allow policymakers, regulators, and moderators to become more proactive and to identify and test the ways that continued technology use can impact individuals' cognitive structures.

5.4 Limitations and Implications for Future Research

We aimed to consider a range of empirical contexts when constructing our empirical analysis, particularly in the development of our measurements. Nevertheless, in order to experimentally test our hypotheses, we had to study adaptation in a narrow, controlled context. This made sense as a starting point, as we had to establish the fundamental premise of our research model. However, examining other technologies and individual groups would likely add further nuance to the theory of technocognitive structuration. Such research may also be able to make distinctions about the types of cognitive adaptations that are more or less desirable and the potential for cognitive adaptations to impair individuals' ability to accurately evaluate their performance. It would be particularly interesting to examine cognitive adaptations when new tools are introduced into knowledge-intensive and highly specialized professional environments. Possible examples include the use of AI in health systems, the use of automated information retrieval systems in formal auditing processes, and the introduction of open source software tools in private organizations, to name only a few.

We also acknowledge some methodological limitations related to time and naturalism. Our experimental approach provided a compelling basis for causal inference. It also provided validation for our assumptions that individuals have some capacity to self-report cognitive adaptations. We supported our experimental data with qualitative illustrations. These illustrations provide additional reassurance that the proposed types of cognitive adaptations also occur in naturalistic settings, and over prolonged periods of technology use and adaptation. Nonetheless, extended observation of structuration episodes across more diverse contexts, and even longer timelines, may reveal additional patterns. For example, the process of adaptation may often be iterative, with larger adaptations emerging from multiple smaller cycles of adaptation. There may also be contexts where individuals are not well-equipped to self-report adaptations, as when later cognitive adaptations distort each individual's reimaginings of past structures. Future research may wish to combine self-reports of cognitive adaptation with other measurements. For example, it may be possible to design NeuroIS studies that can measure physiological and neurological changes (Dimoka et al., 2012; Riedl, Davis, and Hevner, 2014), and link these with the different types of cognitive adaptation proposed by technocognitive structuration.

We further acknowledge theoretical limitations, which arise because we build the theory of technocognitive structuration on ASTI, and thus also on structuration and AST. ASTI, structuration theory, and AST generally focus on adaptations that have been repeated and become persistent, rather than the fleeting structures that individuals have trialed and abandoned. The manner in which these fleeting structures are abandoned may reveal important theoretical constraints or considerations for cognitive adaptation that are not obvious in persistent structures.

Finally, our focus was on the deliberate use of technology by intentional users with the potential to consciously reflect on their behaviors. We made no distinction between explicit and tacit knowledge in cognitive structures. These types of knowledge often influence behaviors differently (Alavi & Leidner, 2001), suggesting that they may play different roles in task-related cognitive structures. We consider this an exciting possibility, and we call for future research to explore it further.

5.5 Conclusion

This study presents a theory of technocognitive structuration. Technocognitive structuration integrates existing research on adaptative structuration theory for individuals (ASTI) with existing research on cognitive structures. The integration of these theories reveals that exploitative and exploratory cognitive adaptations mediate how individuals translate technology adaptations into task adaptations. Technocognitive structuration can therefore help us understand how and when individuals change their cognitive structures as they interact with technology and adapt it to fit their needs. This added understanding is likely to become more important as individuals become more dependent on digital technologies such as data analytics, AI, digital communication channels, immersive environments, and wearable technologies.

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Appendix A

Overview of Demographics

Table A1. Demographic Distribution of Experiment Participants

Variable	Frequency (Percentage%)
Gender	
Male	225 (42.29%)
Female	297 (55.83%)
Undisclosed	10 (1.88%)
Age	
<20	29 (5.45%)
21-30	310 (58.27%)
31-40	146 (27.44%)
41-50	27 (5.08%)
51-60	10 (1.88%)
>60	10 (1.88%)
Education	
Lower secondary education	1 (0.19%)
Upper secondary education	12 (2.26)
Vocational degree	63 (11.84%)
Bachelor's degree	338 (63.53)
Master's degree	109 (20.49)
PhD	9 (1.69)

Developing Survey Items for Exploitative Cognitive Adaptation and Exploratory Cognitive Adaptation

Exploitative cognitive adaptation is defined as *the process when an individual modifies existing cognitive structures to integrate new features, without changing the associations among familiar features.* Based on this definition and the earlier theoretical discussion of *exploitative cognitive adaptation*, we developed four individual items. Each item shared a focus on technology and task-specific cognitive adaptations that (1) were intentional (2) resulted in a more elaborate cognitive structure. We further noted different styles in the ways individuals might self-report *exploitative cognitive adaptation*, which we needed to accommodate in the measurement of the construct. First, we noted that an individual could find it easier to describe *exploitative cognitive adaptation* as a process of extending a cognitive structure, or alternatively as a process of decomposing a cognitive structure, depending on how hierarchically that individual had constructed their previous cognitive structure. Second, because individuals' internal worlds are influenced by both internal reflection and social interaction, we noted that an individual could describe *exploitative cognitive adaptation* as a process of introspection (the individual recognizes something they believe is important) or of social anticipation (the individual recognizes something they believe others will view as important). We therefore created four survey items that could capture these different styles of describing *exploitative cognitive adaptation* (see Table A2).

Table A2. Survey Items for Exploitative Cognitive Adaptation

Survey item	Extending vs. decomposing cognitive structure	Introspection vs. social anticipation of possibilities
I tried hard to learn more about what specific things to consider in a CV	Decomposing	Introspection
I looked for additional information so that I can think more about what to include in a CV	Extending	Introspection
I tried my best to learn more about what employers might expect to see in a CV	Extending	Social anticipation
I learned about the finer points of making a CV	Decomposing	Social anticipation

Exploratory cognitive adaptation is defined as *the process when an individual modifies a cognitive structure to include new features, and this modification changes the associations among familiar features*. Based on this definition and the earlier theoretical discussion of *exploratory cognitive adaptation*, we once again developed four individual items. Each item shared a focus on technology and task-specific cognitive adaptations that (1) were intentional (2) resulted in a cognitive structure with new associations for previously familiar features. We also once again noted differences in the styles individuals might self-report *exploratory cognitive adaptation*, which we needed to accommodate in the measurement of the construct. First, we noted that, depending on how much experience an individual possesses with a specific task/technology and how much they interact with other individuals in related contexts, that individual may perceive that their cognitive adaptation has resulted in a structure that is either unique for them personally, or unique in general. Second, because *exploratory cognitive adaptation* will likely create some sense of instability for an individual, that individual could describe a cognitive adaptation in terms of the creation of new associations in their cognitive structure, or the destruction of existing associations. Similar to the measurement of *exploitative cognitive adaptation*, we therefore created four survey items that could capture these different styles of describing *exploratory cognitive adaptation* (see Table A3).

Table A3. Survey Items for Exploratory Cognitive Adaptation

Survey item	**Cognitive structure is unique to individual or unique in general**	**Creation vs. destruction of associations**
I changed my views on how to create a CV	Unique to individual	Creation of new associations
I developed a unique understanding of how to create a CV	Unique in general	Creation of new associations
I made an effort to reconcile different ideas on how to create a CV	Unique to individual	Destruction of existing associations
I tried my best to think outside the box about what a CV should include	Unique in general	Destruction of existing associations

Table A4. Measurement Items

Perceived performance: 1-7: *strongly disagree* to *strongly agree* (Schmitz et al. 2016; Moore & Benbasat, 1991)	
PERF1	Using my word processor technology enables me to process text documents more quickly.
PERF 2	Using my word processor technology improves the quality of how I process text documents.
PERF 3	Using my word processor technology makes it easier to process text documents.
PERF 4	Using my word processor technology enhances my effectiveness at processing my text document.
PERF 5	Using my word processor technology gives me greater control over how I process text documents.
Exploitive technology adaptation: 1-7: *strongly disagree* to *strongly agree* (Schmitz et al. 2016)	
ITECH1	I have experimented with new features on my word processor technology.
ITECH2	I have changed the settings/preferences on my word processor technology to alter the way I interact with it.
ITECH3	I have taken advantage of the ability to adapt my word processor technology so I could use it as it was intended to be used.
Exploratory task adaptation: 1-7: *strongly disagree* to *strongly agree* (Schmitz et al. 2016)	
RTASK1	I have developed a way of using my word processor technology which deviates from the standard usage.
RTASK2	I have used at least one feature or capability of my word processor technologies in an unusual manner which the creator does not encourage.
RTASK3	I have modified something in my word processor technology to use it in a non-standard way.
Exploitive cognitive adaptation: 1-7: *strongly disagree* to *strongly agree* (novel scale)	
ICOG1	I tried hard to learn more about what specific things to consider in a CV.
ICOG2	I looked for additional information so that I can think more about what to include in a CV.
ICOG3	I tried my best to learn more about what employers might expect to see in a CV.
ICOG4	I learned about the finer points of making a CV.
Exploratory cognitive adaptation: 1-7: *strongly disagree* to *strongly agree* (novel scale)	
RCOG1	I changed my views on how to create a CV.
RCOG2	I developed a unique understanding of how to create a CV.

RCOG3	I made an effort to reconcile different ideas on how to create a CV.
RCOG4	I tried my best to think outside the box about what a CV should include.
Exploitive task adaptation: 1-7: *strongly disagree* to *strongly agree* (Schmitz et al. 2016)	
ITASK1	I try hard to figure out ways to process text documents using my current word processor technology.
ITASK2	I frequently attempt to stop existing ways of processing text documents because of how I use my word processor technology.
ITASK3	I strive to find ways to process text documents faster with features of my word processor technology.
ITASK4	Overall, I am doing my best in taking advantage of the various features of my word processor technology to better understand how to process text documents.
Exploratory task adaptation: 1-7: *strongly disagree* to *strongly agree* (Schmitz et al. 2016)	
RTASK1	I try hard to figure out new places and settings to process text documents that were not possible without my word processor technology.
RTASK2	I strive to take on new ways to process text documents by using my word processor technology.
RTASK3	My fitness technologies have allowed me to frequently attempt new ways to process text documents; ways I could not do in the past.
RTASK4	Overall, the use of my word processor technology has enabled me to try new and different ways to process text documents.
Personal innovativeness with word processor technologies: 1-7: *strongly disagree* to *strongly agree* (Schmitz et al. 2016; Agarwal & Prasad 1998)	
PITT1	If I heard about new technologies for processing text documents, I would look for ways to experiment with them.
PITT2	Among my peers, I am usually the first to try out new technologies for processing text documents.
PITT3	In general, I am keen to try out new technologies for processing text documents.
PITT4	I like to experiment with new technologies for processing text documents.
Computer self-efficacy with word processor technologies: 1-7: *not confident* to *totally confident* (novel formative scale following Schmitz et al., 2016; Marakas et al. 1998; Marakas et al.2007)	
CSE1	I believe I have the ability to create text documents using a word processor.
CSE2	I believe I have the ability to create tables in text documents in a word processor.
CSE3	I believe I have the ability to insert pictures into text documents in a word processor.
CSE4	I believe I have the ability to select a professional design template in a word processor.
CSE5	I believe I have the ability to change the layout of my text documents (e.g., page orientation, margins change etc.) in a word processor.
CSE6	I believe I have the ability to add shapes and graphics in a word processor.
Experience with wearable fitness technology: How long have you been using word processing technologies (months)? (Schmitz et al., 2016)	

Appendix B: Data Gathering and Analysis for Illustrative Qualitative Study

The illustrative qualitative study was conducted to provide naturalistic, evocative illustrations of the mediating role of *exploitative cognitive adaptation* and *exploratory cognitive adaptation*. With this goal in mind, we sought out a variety of participants, and we sought to observe their behaviors over a prolonged period of time.

12 participants (see Table B1) were selected using a purposeful sampling designed to (1) focus on individuals who would be likely to engage in adaptation and (2) include a diverse range of sports, roles, levels of achievement, and levels of seniority and experience. We selected participants across popular sports, such as sprint racing, endurance/adventure racing (e.g., Ultra Trail de Mont Blanc 130km event), multi-sport racing (e.g., triathlons), rugby, and soccer as well as some niche sports such as roller derby. We included beginners who started their sport later in life, along with elite athletes who had won either national or international sporting titles. We also ensured a mix of amateur and professional athletes. This strategy of diversity also enabled a form of "member-checking," thus addressing the limitations of analytical transferability (Lincoln & Guba 1985).

We conducted semi-structured interviews from June 2018 to November 2021 (Table B2) with follow-up interviews spread across the duration of the study to elicit evidence at various stages of adaptation. In addition, we conducted interviews with some participants immediately before and after key sporting events in their career. The interview protocol was based on the research model in Figure 1, though discussion was also allowed to deviate in the interests of elaborating on each participant's context and preferences. This reflexive approach (Rubin & Rubin, 2011; Wengraf, 2001) provided real-time clarification and expansive discussions to illuminate factors of importance (Oppenheim, 2000; Yin, 2017). All interviews were professionally transcribed, proofread, and annotated. In any cases of ambiguity, we sought clarification from the corresponding participant through telephone or email.

We supported interview data with analysis of participants' performance data from their fitness watches and apps dating as far back as 2015. This included data on the participants' overall training and event activities by month and year (e.g. Figure B1), by event (e.g., Figure B2) and also allowed analysis of different variables such as heart rate, speed, elevation at specific points during these events (Figure B3). This allowed us to then interview the participants about various adaptations over a month or year, right through to before, after, or during specific points of a sporting event. These additional sources of evidence allowed us to develop "converging lines of inquiry" and strengthen the validity and robustness of our interview findings (Dubé & Paré 2003; Yin, 2017). These extra sources of data were particularly critical in this study where participants are discussing not just the sport that often forms part of their core identity, but also sensitive, emotive issues around success or failure in that sport. Also, this data helped to address well-documented dangers of collecting autobiographical temporal data such as events, dates, and sequences (Ancona et al., 2001; Stafford, 2009). To further improve overall validity and reliability, we maintained an "audit trail" to ensure interview data was substantiated by the athlete's wearable data, where possible.

Table B1. Profile of Interview Participants

Participant	Description	Gender	Period studied
A	*Former soccer player who used running and cycling to help recover from injury. Now he focuses on long-distance running (e.g., 130km races), multi-sports (e.g., triathlons), and adventure races and has won many prestigious national races in Ireland. He has also competed internationally at a number of the international elite Ultra Trail de Mont Blanc (UTMB) races, ranking in the top 100 of over 2,000 athletes.*	Male	2015 to 2021
B	*Four-time 1500m champion runner with five gold and one silver national team medals over six years at the 5 nations British and Irish Championships. Qualified to represent Ireland in World Masters championships in Brazil in 2013, finishing 5th in the 1500m final. He achieved this after running his first cross-country competition at age 34 and his first 1500m at 35.*	Male	2019 to 2021
C	*Started training at 35 with no previous history of distance running. He started training for races of 5km, then 10km, and then half marathons. He is a university researcher in the area of fitness technology and time.*	Male	2015 to 2021
D	*Competitor in national and international endurance races for over 20 years. Competitions include cycling (she is a winner of a 2,113km cycle race), mountain biking (Everesting Challenge), multiday team adventure racing (World's Toughest Race, Eco-Challenge Fiji, ITERA), and long solo adventure races (The Race). This athlete is well regarded as one of the top endurance athletes in Ireland, often winning or placing in the top 10.*	Female	2015 to 2021
E	*Winner of the National Roller Derby in Austria. She does mini-Ironman events and many separate running, cycling, and swimming events in between. She jointly manages an adventure tourism company that provides mountain tours. She uses and experiments with technology in plotting and tracking optimal adventure racing routes.*	Female	2020 to 2021
F	*Competes mostly in endurance races, mainly trail-running, but she has also competed in multiday team races (e.g., ITERA) and solo multisport adventure races. She has also hiked in the Italian and French Alps, Scotland, and Wales and has also climbed Kilimanjaro. With respect to trail running, this athlete has competed in races up to 130km in length in Scotland, Ireland, Wales, and Italy.*	Female	2015 to 2021
G	*Chartered physiotherapist with a master's in sports medicine. She started running at age eight and hasn't gone a week without a run since then. She has been on the National Irish Marathon Mission panel since 2014. She placed second in the 2015 Dublin City Marathon and she has numerous sub-three hour marathons.*	Female	2021
H	*Worked as an athletic performance coach with a professional provincial rugby team, winning two European Cup titles. He worked with the Irish Sevens team that competed in the World Cup held in Dubai. He was also team manager for Rowing at the Rio and Tokyo Olympics where the women's team won a bronze medal. He has personally competed in international rowing, Ironman and multiday ultra-running events including the Marathon des Sables.*	Male	2020 to 2021
I	*Started running in his early 40s. He has a methodical approach based on experimentation of fitness plans and technology. He has used this to build his competence and compete in full marathons, competing twice in both the NYC and Berlin marathons.*	Male	2015 to 2021
J	*A fitness/yoga instructor who experiments with wearables and uses technology to evaluate different fitness regimes and techniques. She runs "for fun."*	Female	2019 to 2021
K	*CEO of a company specializing in video analysis for sports, focusing on the Rugby Union market. She has a post-grad degree in sports science and is a former international rugby player. She is also the director of women's rugby with a professional rugby club where she governs the training and management of girls of all ages; she is on the national rugby executive board.*	Female	2020 to 2021
L	*Runs 5km, 10km, and half marathons. He is a researcher in information systems and experiments with the use of technology for fitness and other personal use.*	Male	2020 to 2021

Table B2. Data Collection Information

Participant	Technology used	Period of collection	Interviews	Supporting data sources
A	Ambit3 Vertical watch, FBLive	2015 to 2021	6 interviews between 2015 and 2021 including 3 targeted interviews the 2 days before and the day after the 180km UTMB race in Chamonix 2019.	Analysis of fitness app data from 2018 to 2021. Particular attention paid to altitude measures given A's races were mainly extreme mountain racing. Ongoing analysis of A's Facebook posts and blog/race report website
B	Garmin watch and app	2019 to 2021	8 interviews incl. 6 targeted interviews the day before and after each of 3 1500m national races in 2019	Analysis of all B's fitness app data from 2019 to 2021
C	Garmin watch/ app	2015 to 2021	4 interviews	Analysis of all C's fitness app data from 2018 to 2020
D	Garmin Fenix watch, Strava,	2015 to 2021	3 interviews including 2 targeted immediately before or after: Eco-Challenge Fiji 2019 ITERA2019 ITERA 2018	Analysis of all D's fitness app data from 2018 to 2021. Particular attention paid to altitude measures given D's races were mainly mountain racing in extreme environments. Ongoing analysis of D's Facebook posts and blog/race report website
E	Garmin Forerunner,	2020 to 2021	2 targeted interviews before and after Roller Derby Tournament 2020	No supporting data
F	Ambit3 Vertical watch,	2015 to 2021	4 interviews including 2 targeted interviews the morning of and day after the "Kerry Way" 80km race.	Analysis of all F's fitness app data from 2015 to 2021
G	Garmin Forerunner, Strava	2021	2 general interviews in 2021	No supporting data
H	Garmin Forerunner, Strava	2020 to 2021	1 general interview 2020	Analysis of Strava data only. Some gaps in data and events not logged, but these were noted and discussed in interview.
I	Polar watch and app	2015 to 2021	3 interviews including 2 targeted interviews the morning of and day after NYC marathon 2019	Analysis of all I's fitness app data for 6 month period in 2019
J	Coros watch/ app	2019 to 2021	1 interview in 2021	No supporting data
K	Polar watch/ app	2020 to 2021	1 interview in 2021	No supporting data
L	Coros watch/ app	2020 to 2021	1 interview in 2021	No supporting data

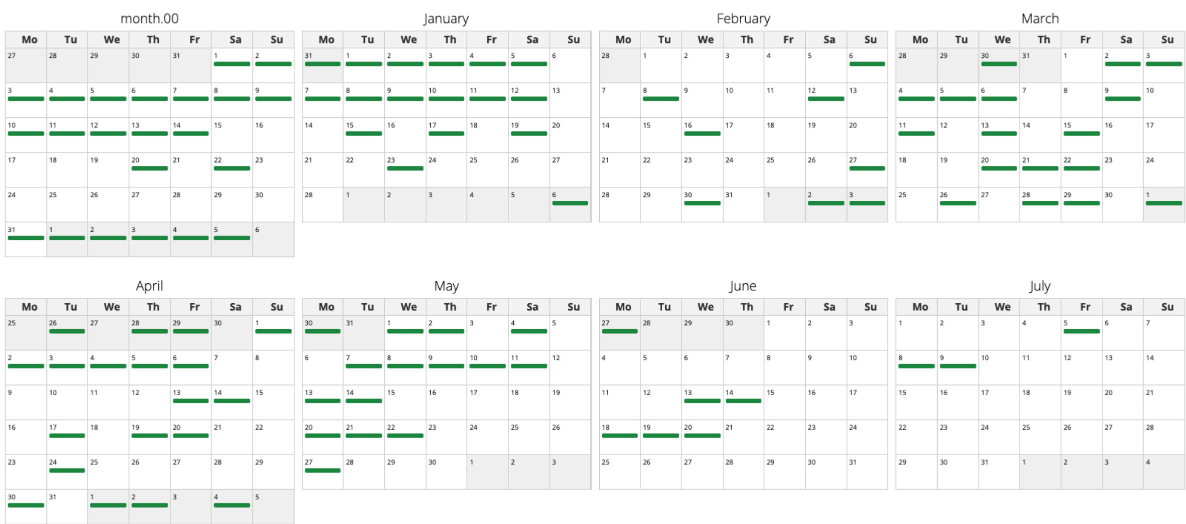

Figure B1. Data on Overall Calendar of Activity

Figure B2. Data on Single Events: Patterns of High/Low Performance

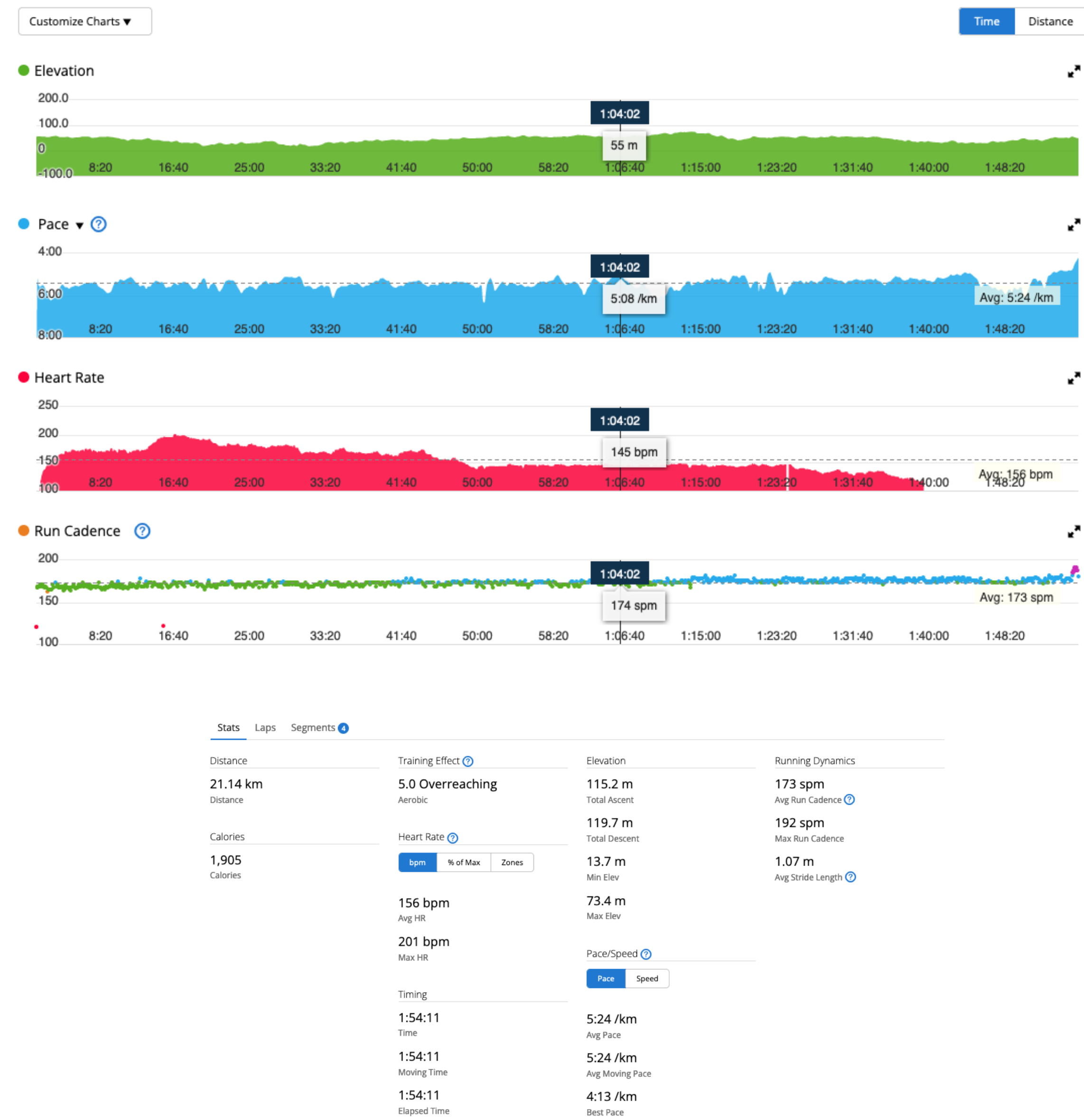

Figure B3. Multidimensional Data on Specific Time Points During Event

The first step of our data analysis was to familiarize ourselves with the data by reading through the interview notes, and data taken from the participant's fitness devices and blog posts or race reports. This was important to ensure internal validity or "credibility" (Golafshani, 2003; Yin, 2008; Thomas & Magilvy, 2011), as it brought the context of each participant to the forefront of the analysis. Next, we began trying to describe each story with the constructs and relationships in the research model. This meant differentiating the semantic content of interactions, which could be easily described within the structure of the research model, and the latent domain-specific and intent-related constituents (cf. Boyatzis, 1998; Maki & Buchanan, 2008). Third, we continuously reviewed emerging vignettes and discussed alternative interpretations. This helped to ensure internal validity, as it forced us to consider alternative logics that could better explain each adaptation. Fourth, we selected four vignettes that we felt were most illustrative.

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