

ORIGINAL ARTICLE

Skill development in reverse mentoring: Motivational processes of mentors and learners

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Building on Murphy's (2012) model of reverse mentoring, we examine the psychological processes that contribute to skill development in initiatives where knowledge is transferred from younger to older individuals. We employ a sample of younger mentors ($n = 457$) and older learners ($n = 293$) participating in a digital skills initiative to test parallel moderated mediation models. Our findings show extrinsic motivation plays a dominant role in the development of younger groups' mentoring skills, while older learners' digital skills development is primarily driven by intrinsic motivation. We also find positive affect and self-efficacy can serve as personal resources in this context, but only for mentors. Taken together, our results suggest motivational processes in reverse mentoring unfold differently for the two groups involved in the exchange. Recommendations for human resource practice, including specific guidelines for developing intergenerational learning initiatives, are discussed.

KEYWORDS

digital skills, intergenerational learning, (intrinsic and extrinsic) motivation, mentoring skills, positive affect, reverse mentoring, self-efficacy

1 | INTRODUCTION

The field of human resource (HR) management is increasingly embracing intergenerational learning, which refers to the interactions between members of different generations that result in individuals gaining new knowledge, skills, and values (Gerpott, Lehmann-Willenbrock, & Voelpel, 2017; Ropes, 2013). In a twist on the traditional top-down knowledge exchange, companies like Cisco, Microsoft, and Sodexo are encouraging their younger workers to share their knowledge and insights with their more senior counterparts (Earle, 2011; Microsoft, 2015; Sodexo, 2017). This new perspective, known as reverse mentoring, has been gaining momentum in practice and has reached a wide audience through popular publications such as the *Harvard Business Review* and *The New York Times* (e.g., Korkki, 2016; Meister & Willyerd, 2010). However, even though Murphy (2012) laid the theoretical foundation and presented a compelling case for the need for empirical research on reverse mentoring several years back, scholarly research on the subject is still practically nonexistent (Dunham & Ross, 2016).

With research on reverse mentoring lagging behind practice, it is high time for scholars to systematically examine this phenomenon and

equip HR practitioners with evidence-based recommendations. Findings from the related literature, particularly the recent empirical work on intergenerational learning (e.g., Gerpott et al., 2017), suggest that pairing younger and older individuals in reverse-mentoring initiatives could have important advantages for both members of the dyad. For instance, younger employees may gain respect, mentoring skills, and insights into business operations while also forming more positive attitudes about older people (Harvey, McIntyre, Thompson Heames, & Moeller, 2009; Penick, Fallshore, & Spencer, 2014). Older workers, on the other hand, may get access to novel knowledge, gain a global perspective, and expand their social networks (Murphy, 2012). Moreover, at a time when digital technology plays an increasingly dominant role in our lives, younger workers are particularly well positioned to share their technology-related knowledge and skills with their older, frequently less tech-savvy counterparts (Borghans & ter Weel, 2002; Chen, 2013; OECD, 2016).

Given the potential benefits of reverse mentoring, it is surprising that the psychology of this exchange remains almost entirely unexplored. In our matched two-sample study, we contribute to HR literature and practice by examining the motivational processes that drive career-relevant skill development in younger mentors (henceforth "mentors") and older mentees or learners (henceforth "learners") taking part in a digital skills initiative. Specifically, we add to this nascent

All the authors contributed equally to this study.

area of research by proposing a theoretical model of within-person processes, including intrinsic and extrinsic motivations, positive affect, and self-efficacy, which drive skill development in this context. We demonstrate that the two sources of motivation do not equally affect the performance of younger and older participants, with extrinsic motivation being a relatively more important driving force for mentors' skill development and intrinsic motivation being more salient for learners. Our model also provides preliminary evidence that positive affect and self-efficacy are personal resources that help translate motivation into successful skill development for the younger group. Taken together, these contributions offer a better understanding of the within-person processes underlying skill development in reverse-mentoring collaborations, particularly those intended to promote "digital fluency" (Colbert, Yee, & George, 2016) in the contemporary workplace.

In the section that follows, we use life span motivation theory and social-cognitive career theory to draw parallels and distinctions between younger mentors' and older learners' motivations as drivers of skill development. We further draw on the broaden-and-build theory of positive emotions and cognitive evaluation theory to examine the role of positive affect and self-efficacy in reverse mentoring. Our method section outlines the digital skills initiative at the center of this study and the measures employed. As described in our results section, we used structural equation modeling with latent interactions to analyze the data obtained from the two matched samples. We discuss our findings in terms of their contribution to the literature on intergenerational learning and provide specific guidelines on the design of reverse-mentoring initiatives intended to inform practice in this area.

2 | THEORETICAL BACKGROUND AND HYPOTHESES

Today, older workers less proficient in technology use share the workplace with the "digital workforce," consisting of young adults who have grown up with the devices of the digital age (i.e., "digital natives") and individuals who have readily adopted new technologies later in life (i.e., "digital immigrants") (Colbert et al., 2016; Prensky, 2001). A recent OECD study (, 2016) of adult skills showed that 32% of 55- to 65-year-old participants reported having no computer skills or failed the computer skills test, compared to 7% of 25- to 34-year-olds. Moreover, among 55- to 65-year-olds, 10% had intermediate computer skills and only around 1% had advanced skills; the numbers for 25- to 34-year-olds were considerably higher (35 and 10%, respectively) (OECD, 2016). This evident disparity in digital fluency creates opportunities for younger employees to help their older counterparts better adapt to the modern workplace through digital skills training.

Keeping with the basic premise of reverse mentoring, our theoretical model is built around younger mentors and older learners. Workplace interactions between members of different age groups have typically been studied using a generational perspective (see Costanza, Badger, Fraser, Severt, and Gade (2012) and Lyons and Kuron [2014] for reviews) and have also garnered significant attention from practitioners (e.g., Gurchiek, 2016; Macrae, 2017). While a number of studies have shown differences in work-related attitudes,

values, and motivations among Baby Boomers, members of Generation X, and members of Generation Y (e.g., Cagin, 2012; Smola & Sutton, 2002; Twenge, Campbell, Hoffman, & Lance, 2010), others have pointed to the prevalence of contradictory findings in this literature and its methodological limitations, including the potential confounding of generational, cohort, and age effects (Constanza, Badger Darrow, Yost, & Severt, 2017; Lyons & Kuron, 2014; Parry & Urwin, 2011). Moreover, a recent study has shown that using generational labels, specifically the "Baby Boomer" label, elicits negative stereotypes and promotes workplace discrimination (Cox, Young, Guardia, & Bohmann, 2018). In light of these concerns, we refrain from using generational labels in our article and instead use the terms "younger" and "older" workers to distinguish between the two groups in our study, consistent with the conceptualization of reverse mentoring as younger employees mentoring their older colleagues (Murphy, 2012).

Reverse-mentoring initiatives intended to promote competent technology use among older adults represent a new area of study (see Cotugna and Vickery [1998] and Leh [2005] for exceptions), though there exists a rich body of knowledge on technology acceptance and use more broadly (e.g., Turner, Kitchenham, Brereton, Charters, & Budgen, 2010). Users' attitudes toward and experience with technology have been studied extensively in the information systems and related literature, with the technology acceptance model (TAM) (Davis, 1989) playing a dominant role. TAM is primarily focused on factors that promote information technology acceptance, integrating knowledge on users' perceived usefulness and the ease of use of new technologies and their subsequent behavioral intentions to use them (Davis, 1989; King & He, 2006). In a notable extension of this model, Venkatesh, Morris, Davis, and Davis (2003) drew from various disciplines to propose a unified theory of technology acceptance, which also featured users' motivation and affect, though not in prominent roles. We explore these motivational processes and affective states in a unique context—a digital skills initiative targeted at older technology users. We begin with intrinsic and extrinsic motivations as drivers of skill development, then extend our theorizing by examining the mechanisms linking motivation and skill development.

2.1 | Motivation and skills in reverse mentoring

People are considered to be intrinsically motivated when they engage in work that is inherently interesting, meaningful, challenging, or enjoyable. Alternatively, they are considered to be extrinsically motivated when they engage in activities to obtain some goal that is separate from the work itself (Amabile, 1993). While intrinsic and extrinsic motivations are sometimes characterized as opposite ends of a single continuum (e.g., Ryan & Deci, 2000a), a recent meta-analysis spanning over 40 years of motivation research concluded that the two constructs should not be viewed as antagonistic, as they play a joint role in predicting important outcomes such as performance (Cerasoli, Nicklin, & Ford, 2014). Therefore, we considered them simultaneously.

Intrinsic motivation encompasses a natural inclination toward skill mastery, cognitive flexibility, and exploration, which promotes high levels of engagement in the activity and high-quality learning (Amabile, 1993). Accordingly, when younger mentors are intrinsically

motivated to engage in a task (i.e., mentoring their older colleagues), this should energize them, facilitate their skill acquisition, and ultimately result in higher perceptions of development of mentoring skills. Similarly, older learners who are intrinsically motivated to learn from their younger counterparts are primarily driven by a keen interest in acquiring a particular set of skills. Such intrinsic interest in exercising and extending one's capabilities tends to be associated with positive experiences and outcomes, including high levels of engagement in the activity and high-quality learning (Amabile, 1993; Ryan & Deci, 2000b). Hence, when it comes to digital skills training, high levels of intrinsic motivation should propel learners to engage with the task and thereby increase their comfort with using new technologies.

Frequently, however, people act not out of an intrinsic interest in a task, but because performing this task has some instrumental value (Ryan & Deci, 2000b). Such extrinsic motivation can lead to resistance and disinterest due to feelings of resentment, but this is not necessarily the case in situations where extrinsic goals are self-endorsed and important to individuals (Ryan & Deci, 2000a, 2000b). We examine whether mentors in our study who are driven by extrinsic factors (e.g., career reasons) may benefit from the process of reverse mentoring. We propose when younger mentors commit their time to advance their career prospects, which is a self-endorsed external goal that they choose to pursue willingly, extrinsic motivation can facilitate their involvement and persistence in the activity.

Learners participating in reverse mentoring may also be propelled by extrinsic reasons. Technology is ubiquitous in today's environment, putting members of older generations at a disadvantage (Borghans & ter Weel, 2002). As a result, learners may be driven to engage in digital skills training not only out of an inherent interest in acquiring skills, but also to remain employable and retain their earning potential. With financial motives likely diminished in later career stages, social pressures, such as family or work expectations, can also be meaningful external drivers for developing digital skills. While such external pressure can negatively influence performance, it can also energize individuals into action, as long as the task is not exceedingly difficult yet is instrumental in obtaining the desired outcome (Cerasoli et al., 2014; Gagné & Deci, 2005). Externally motivated learners would thus perceive satisfying outside expectations regarding their digital skills is contingent on actively engaging in reverse mentoring, which should facilitate their learning. Taken together, we propose:

Hypothesis 1: [Younger] Mentors' (a) intrinsic and (b) extrinsic motivations are positively related to their [mentoring] skill development.

Hypothesis 2: [Older] Learners' (a) intrinsic and (b) extrinsic motivations are positively related to their [digital] skill development.

2.2 | Life span changes in motivation

Motivation at work and motivation for learning change with age (Kanfer & Ackerman, 2004; Kanfer, Frese, & Johnson, 2017); correspondingly, so do the perspectives and interests that individuals hold

throughout their careers (Lent, Brown, & Hackett, 1994). Social-cognitive career theory suggests that interests in work-related activities and skill acquisition develop through repeated activity engagement and external reinforcements; while this process continues over the life span, it is much more fluid and formative in late adolescence and early adulthood (Lent et al., 1994). This means that feedback from the environment, including extrinsic rewards, exerts more influence early in one's career. This impact is further enhanced (or tempered) by one's perceptions of how their efforts relate to the achievement of outcomes. According to life span development theory, people adjust their self-regulatory and motivational processes in response to the changing opportunities and challenges they encounter at work and in other life domains (Heckhausen & Schulz, 1995; Heckhausen, Wrosch, & Schulz, 2010). Compared to their older counterparts, younger people have a higher perception of the utility of their performance (Kanfer & Ackerman, 2004). Consequently, they generally employ more proactive strategies to control external circumstances, which increases the motivating potential of extrinsic outcomes (Kooij, De Lange, Jansen, Kanfer, & Dikkers, 2011). Hence, we suggest that extrinsic, career-related motives drive mentors' engagement with reverse mentoring to a greater extent than their inherent interest in the activity.

Work-related interests tend to crystalize relatively early in one's career, but changing life and work circumstances, including technological innovations, can spark a reappraisal of those interests and the development of new competencies (Lent et al., 1994). Whether these competencies actually develop in later career stages, however, depends more on intrinsic rather than extrinsic factors. This is because the perceived utility of performance decreases with age, with older employees seeing less of a connection between their efforts and workplace rewards, rendering extrinsic motivators less powerful (Kanfer & Ackerman, 2004; Kooij et al., 2011). Instead, older individuals tend to engage in self-directed control strategies, focusing more on outcomes that are intrinsically rewarding, attainable, and under their control (Heckhausen & Schulz, 1995; Kooij et al., 2011). This is supported by meta-analytic findings, which demonstrate that the effectiveness of intrinsic motivation for achieving high performance tends to increase with age, while the potential of extrinsic motivation to drive results decreases with age (Kooij et al., 2011). Accordingly, while we expect extrinsic pressures do exert some influence on older learners' performance, intrinsic motives play a dominant role in driving their skill development. Thus, we propose:

Hypothesis 3a: Extrinsic motivation (relative to intrinsic motivation) is a stronger driver of skill development for [younger] mentors than for [older] learners.

Hypothesis 3b: Intrinsic motivation (relative to extrinsic motivation) is a stronger driver of skill development for [older] learners than for [younger] mentors.

2.3 | How motivation drives skill development

We propose positive affect, which captures the experience of pleasant feelings, such as excitement and enthusiasm (Cropanzano, Weiss,

Hale, & Reb, 2003), can help explain the relationship between intrinsic motivation and skill development. Unsurprisingly, engaging in activities that are perceived as interesting and enjoyable tends to evoke favorable affective experiences; positive affect is thus considered a consequence of intrinsic motivation (Grant & Berry, 2011; Vallerand & Ratelle, 2002). In our study, mentors who are intrinsically driven have keen interest in mentoring their older colleagues. In this context, getting the opportunity to actually help people improve their digital skills is inherently meaningful and should promote feelings of excitement and positive mood. Similarly, intrinsically motivated learners in our study have keen interest in developing their digital skills. As a result, the process of learning should facilitate their absorption in the activity and evoke positive feelings (Cropanzano et al., 2003), thereby increasing positive affect. Taken together, for both younger mentors and older learners, experiencing positive mood during reverse mentoring should bode well for their performance.

In accordance with the broaden-and-build theory of positive emotions (Fredrickson, 2001), positive affective states boost personal resources and expand people's "thought-action repertoires" by spurring the desire to explore and gain new knowledge and experiences. In this sense, we suggest positive moods play an important role in the context of reverse mentoring, as they energize individuals to engross themselves in the interaction and set the stage for effective knowledge exchange. Support for this comes from studies showing that positive affect leads to increased cognitive flexibility (Nadler, Rabi, & Minda, 2010), improved task performance (Erez & Isen, 2002), and better problem solving (Ashby, Isen, & Turken, 1999), which can be particularly valuable when mentoring others. Positive moods are also associated with higher training success (Konradt, Filip, & Hoffmann, 2003) and increased working memory capacity in older adults (Carpenter, Peters, Västfjäll, & Isen, 2013), which should facilitate learners' digital skills acquisition.

In sum, we propose that when people are intrinsically driven to engage in reverse mentoring, this promotes feelings of enthusiasm and excitement, which, in turn, facilitates knowledge transfer. In other words, we argue that, for both mentors and learners, positive affect mediates the link between intrinsic motivation and their skill development.

Hypothesis 4: Positive affect mediates the relationship between (a) [younger] mentors' and (b) [older] learners' intrinsic motivation and skill development.

We further posit the impact of intrinsic motivation on positive affect is enhanced when individuals have high self-efficacy, which refers to people's belief in their ability to successfully perform a specific task (Bandura, 1986). Support for this hypothesis can be gleaned from cognitive evaluation theory, which addresses some of the contingencies of intrinsic motivation (Deci & Ryan, 1985). Intrinsic motivation pertains to activities that are inherently interesting, satisfying, meaningful, or challenging (Amabile, 1993). However, to sustain this motivation, individuals need to feel competent in their actions, or, in other words, need to have high perceptions of self-efficacy (Deci & Ryan, 1985). Accordingly, we argue the impact of intrinsic motivation on positive affect is stronger for individuals with higher self-efficacy

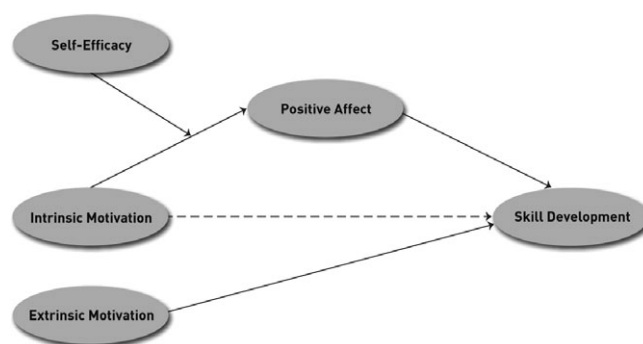


FIGURE 1 Hypothesized relationships in the conceptual model. Notes: Mentoring self-efficacy and skill development for younger mentors, computer self-efficacy, and digital skills development for older learners

perceptions. Specifically, when mentors have low perceptions of mentoring ability, their intrinsic motivation may not elicit the same level of positive affect. Similarly, when learners do not feel confident in their digital skills, this should lessen any gains in positive mood derived from their intrinsic interest in learning. Considered in concert with the proposed mediated paths, our theoretical model culminates in two moderated mediation hypotheses:

Hypothesis 5: (a) [Younger] Mentors' and (b) [older] learners' self-efficacy enhances the indirect effect of intrinsic motivation on skill development through positive affect.

Our conceptual model is depicted in Figure 1.

3 | METHOD

3.1 | Design, participants, and procedure

Our two-sample study is based on a nationwide reverse-mentoring initiative in a European country, in which younger mentors helped older learners develop digital skills such as general computer use, word processing, file management, Internet browsing, emailing, social media, and smartphone use skills. The voluntary initiative—both younger mentors and older learners signed up voluntarily to participate and were not compensated nor charged for joining—recruited participants through an online and media campaign and intense fieldwork by more than 100 local coordinators of the initiative. At each of the initiative's locations (there were 230 locations across the country), multiple mentors were assigned to multiple learners; approximately 5,000 older learners and 3,250 younger mentors participated altogether. The overall average age of participants was 64 years for learners and 23 years for mentors. The majority of participants were women, accounting for 67% of learners and 57% of mentors, respectively.

During the week-long initiative, younger mentors used various approaches to help older learners develop their digital skills. Specifically, through guided practice and one-on-one interactions, mentors shared their knowledge; offered hands-on assistance, guidance, and feedback; and provided encouragement and support when learners

encountered problems or experienced frustration. These behaviors closely correspond with the core functions of mentors in reverse mentoring (Murphy, 2012). During breaks between sessions, participants were able to socialize and develop relationships with their fellow learners and their mentors. Overall, this reverse-mentoring initiative was highly structured, with the younger mentors receiving online training and detailed instructions prior to its start.

Our sampling frame included 1,650 mentors and 515 learners who were invited to complete our questionnaire at the end of the initiative. They were recruited with an invitation letter and participated by either filling out the online questionnaire (available only to mentors) or the paper-and-pencil questionnaire (available to mentors and learners). After the gathered data were checked for quality and consistency, 457 responses from mentors (28% response rate) and 293 responses from learners (57% response rate) were adequate for further analysis. In the final sample, the average age was 27.5 ($SD = 9.7$) for mentors and 64.7 ($SD = 7.3$) for learners, and mentors and learners were 71 and 70% female, respectively. The mentors had 6.5 years ($SD = 7.9$) of work experience on average, with only 18.2% having no work experience. Most of the learners were retirees with extensive work experience, though 8.7% were still employed.

3.2 | Measures

All variables reported here were measured on a 5-point Likert-type scale. The scales used in the study were part of a larger questionnaire, minimizing any potential item context effects (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Every scale featured a time-anchor, thus eliciting responses from participants that referred to the time before, during, and after the initiative. Because younger mentors and older learners assumed different roles in the initiative, separate role-specific scales were used for each group of respondents.

Intrinsic and extrinsic motivations were measured by asking participants why they had decided to join the digital skills initiative. For mentors, the scales were adapted from Ryan and Connell (1989) to reflect their role. Two three-item scales were used for measuring their intrinsic and extrinsic motivations for joining the initiative and mentoring older learners. Sample items included, "Because I enjoy mentoring others" and "Because taking part in this initiative will look good on my CV." For learners, motivation was measured using the Learning Self-Regulation Questionnaire, which is intended for older learners (Black & Deci, 2000). It was adapted to reflect their motivation to join the initiative and develop digital skills. Two three-item scales were used to measure their intrinsic and extrinsic motivation. Sample items included, "Because it is fascinating to learn about new technologies" and "Because I might get an official certificate at the end of the training." All scales were time-anchored in the period *before* the initiative.

Task-specific self-efficacy of participants was measured by adapting the *teaching self-efficacy scale* (Schwarzer & Hallum, 2008) for younger mentors and the *computer self-efficacy scale* (Compeau & Higgins, 1995) for older learners. The four-item mentoring self-efficacy scale for mentors included items such as "I am confident that, even in case of an unexpected situation, I would find a way to bring the mentoring session to a close." With the three-item computer self-efficacy scale, we asked learners how confident they were when interacting

with a computer in various situations. A sample situation included, "When there was no one around to tell me what to do." Again, the scales were anchored in the time period *before* the event.

Positive affect was assessed with the same measure in both groups of participants. We used three items from the PANAS scale (Watson, Clark, & Tellegen, 1988). The items related to participants' positive feelings *during* the mentoring sessions, such as feeling "excited" and "enthusiastic."

Skill development was measured by assessing whether the participants believed that their skills had improved as a result of taking part in the initiative. The items were based on Kirkpatrick and Kirkpatrick (2006). For mentors, a sample item included, "After taking part in the initiative, I am more confident in my mentoring skills." For learners, a sample item was, "After taking part in the initiative, I am more confident in my digital skills." In both cases, the scales related to participants' perceptions *after* the event.

We ran confirmatory factor analyses (CFAs) to assess reliability and discriminant validity of the constructs. The CFA results of the proposed five-factor measurement model demonstrated excellent fit with the data in both samples and high standardized factor loadings, which ranged from 0.620 to 0.845 for mentors and from 0.560 to 0.995 for learners. Moreover, the five-factor measurement model fit indicators (comparative fit index [CFI] = 0.979, root mean square error of approximation [RMSEA] = 0.034, and standardized root mean square residual [SRMR] = 0.042 for mentors; CFI = 0.972, RMSEA = 0.040, and SRMR = 0.049 for learners) were superior to those of the single-factor model (CFI = 0.443, RMSEA = 0.164, and SRMR = 0.149 for mentors; CFI = 0.397, RMSEA = 0.176, and SRMR = 0.152 for learners), as well as to those of alternative (nested) models for both groups (see Appendix A for details).

We also included theoretically relevant control variables that have previously been shown to influence learning and performance (e.g., Cerasoli et al., 2014; Colquitt, LePine, & Noe, 2000; Noe, Tews, & Marand, 2013) or were important to include to account for the reverse-mentoring context of this study. In line with recent recommendations, we tried to include as few control variables as possible to preserve degrees of freedom and prevent potential biases (Bernierth & Aguinis, 2016; Bernierth, Cole, Taylor, & Walker, 2018). We included gender, age, past participation in the initiative, and work experience for mentors, and gender, age, past participation in the initiative, current employment status, and the educational level for learners.

Gender (coded 1-male, 2-female) was added for both groups (mentors and learners) due to the predominantly female composition of both samples and, more broadly, the population participating in the initiative, given that reverse mentoring is conceptually gender-neutral (Murphy, 2012). Similarly, age (measured in years) was also added for both groups, consistent with recent evidence that skill-development potential changes with age (OECD, 2016), and to account for within-group variability in age in the two groups. Because this initiative takes place annually, past participation in the initiative (coded 1-past participation, 2-no past participation) was added to account for participants' familiarity with the focal activity (i.e., mentoring for mentors and digital skills training for learners). Further, we included variables on current and past work activity in our model. We asked mentors about their cumulative work experience (in years) and learners about their

TABLE 1 Descriptive statistics, reliabilities, and bivariate correlations

Variable (group)	<i>M</i>	<i>SD</i>	1	2	3	4	5	6	7	8	9
Younger mentors											
1. Intrinsic motivation	4.34	.59	(.80)								
2. Extrinsic motivation	2.81	1.02	.031	(.72)							
3. Mentoring self-efficacy	4.23	.60	.295**	.027	(.79)						
4. Positive affect	4.26	.66	.446**	.105*	.314**	(.72)					
5. Mentoring skill development	3.66	.85	.207**	.414**	.027	.267**	(.83)				
6. Gender	1.71	.46	.070	.050	-.059	.156**	.166**				
7. Past participation	1.78	.42	-.116**	.031	-.013	-.023	-.015	-.027			
8. Work experience	6.46	7.87	.097	-.203**	.144**	-.008	-.170**	-.088	-.179**		
9. Age	27.54	9.67	.101*	-.270**	.119*	-.038	-.232**	-.060	-.224**	.893**	
Older learners											
1. Intrinsic motivation	4.56	.41	(.67)								
2. Extrinsic motivation	2.86	1.03	.174**	(.82)							
3. Computer self-efficacy	2.54	.91	-.002	-.092	(.74)						
4. Positive affect	4.14	.72	.428**	.072	.086	(.83)					
5. Digital skill development	3.86	.71	.319**	.197**	.161**	.281**	(.68)				
6. Gender	1.70	.46	.131*	-.116	.003	.171**	.017				
7. Education	2.27	.63	-.193**	-.221**	.208**	-.080	.026	-.063			
8. Past participation	1.84	.37	-.100	-.098	-.124	-.082	-.158**	.021	-.105		
9. Age	64.76	7.30	-.075	.006	.014	-.075	-.022	-.166**	.231**	-.146*	
10. Currently employed	1.91	.28	-.099	.065	-.035	-.018	.019	.021	.058	-.061	.428**

Notes: Descriptive statistics are based on (aggregated) observed variables; $n(\text{Mentors}) = 457$; $n(\text{Learners}) = 293$. Scale reliabilities are provided in parentheses on the diagonal. * $p < .05$; ** $p < .01$.

current employment status (coded 1=employee, 2=retired).¹ Finally, we included learners' educational level (coded 1 = elementary school, 2 = high school, 3 = undergraduate degree, 4 = graduate degree) due to the expected higher variability of educational attainment in this group of participants.

4 | RESULTS

Descriptive statistics, Cronbach's alphas, and bivariate correlations for all variables and both groups of participants are presented in Table 1. We tested our hypotheses by estimating structural equation models (SEMs) because they perform superiorly to other approaches when measurement error is present. Specifically, we used procedures for estimating latent path models and the most current approaches for examining latent variable interactions (i.e., latent moderated structural equations or LMS method; Cheung & Lau, 2017; Sardeshmukh & Vandenberg, 2016) in Mplus 7.4 (Muthén & Muthén, 1998-2015).

The results in Table 2 show that both intrinsic ($\gamma = .202$, $p < .01$) and extrinsic ($\gamma = .515$, $p < .001$) motivations related positively to younger mentors' skill development; hypotheses 1a and b were thus supported. We also found support for hypothesis 2a, with intrinsic motivation having a strong impact on older learners' digital skills development ($\gamma = .472$, $p < .001$) and marginal support for hypothesis 2b, which proposed that extrinsic motivation is associated with learners' skill development ($\gamma = .136$, $p < .1$).

Cumulatively, the results reported before also provide initial support for hypotheses 3a and b. The role of extrinsic motivation (relative to intrinsic motivation) is clearly, and even in absolute terms

(comparison of standardized coefficients: $.515 > .202$), more important for the skill development of mentors when compared to learners (comparison of standardized coefficients: $.136 < .472$), for whom intrinsic motives prevail. Nevertheless, we conducted a 95% bias-corrected confidence interval (CI) overlap test for ratios of standardized coefficients of extrinsic relative to intrinsic motivation (Cumming, 2009). There was no overlap between the two intervals (the interval was [11.88, 1.12] for mentors and [0.41, 0.00]² for learners) and the interval for mentors was positioned higher than the interval for learners. This offers support for hypothesis 1. Analogously, the stronger role of intrinsic motivation relative to extrinsic motivation for learners in our data (the interval of the ratio was [688, 0.98] for learners and [0.89, 0.08] for mentors) offers support for hypothesis 1.

Hypothesis 4a stated that positive affect mediates the relationship between mentors' intrinsic motivation and their skill development. Based on the model results shown in Table 2, we can establish that intrinsic motivation was significantly related to positive affect ($a = .470$; $p < .001$); at the same time, positive affect was positively related to skill development ($b = .136$, $p < .05$), with intrinsic motivation controlled for. Further, our results show that the 95% bias-corrected CI (based on 1,000 random samples) of the indirect effect of intrinsic motivation on skill development through positive affect ($ab = .064$) excluded zero [0.006, 0.140]. This provides support for hypothesis 4a. However, because the direct path remained significant ($c' = .202$), with the 95% bias-corrected CI excluding zero [0.053, 0.345], we can conclude positive affect partially mediated the relationship between mentors' intrinsic motivation and their skill development.

TABLE 2 Latent path model coefficients for mentors and learners

Antecedent		Consequent					
		Positive affect (M)			Skill development (Y)		
		Coeff.	SE	p	Coeff.	SE	p
Younger mentors							
Gender		.135	.049	.006	.132	.053	.012
Past participation		.095	.050	.058	.050	.055	.362
Age		-.175	.108	.106	-.252	.117	.032
Work experience		.135	.108	.212	.112	.116	.334
Intrinsic motivation	<i>a</i>	.470	.050	.000	<i>c'</i>	.202	.071
Extrinsic motivation		-	-	-		.515	.060
Positive affect		-	-	-	<i>b</i>	.136	.069
<i>R</i> ² = .257				<i>R</i> ² = .413			
Older learners							
Gender		.089	.058	.127	-.041	.069	.545
Education		.007	.059	.906	.166	.068	.014
Age		-.091	.065	.164	-.147	.076	.051
Currently employed		.027	.063	.668	.099	.075	.187
Past participation		-.109	.057	.056	-.162	.068	.018
Intrinsic motivation	<i>a</i>	.478	.064	.000	<i>c'</i>	.472	.093
Extrinsic motivation		-	-	-		.136	.077
Positive affect		-	-	-	<i>b</i>	.081	.086
<i>R</i> ² = .255				<i>R</i> ² = .382			

Notes. Estimation is maximum likelihood. Standardized coefficients are shown. M = mediator; Y = dependent variable. Model fit indicators for mentors: $\chi^2 = 175.1$, $df = 89$; RMSEA = .048; CFI = .947; SRMR = 0.068. Model fit indicators for learners: $\chi^2 = 184.74$, $df = 99$; RMSEA = .057; CFI = .926; SRMR = 0.066. CFI = comparative fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

On the other hand, we did not find support for hypothesis 4b, which proposed that positive affect mediates the link between learners' intrinsic motivation and digital skills development. Although the path from intrinsic motivation to positive affect was statistically significant ($a = .478$; $p < .001$), the path from positive affect to skill development was not ($b = .081$; $p = .345$). In addition, the 95% bias-corrected CI of the indirect effect ($ab = .039$) included zero [–0.054, 0.163]. This precludes us from concluding that positive affect mediated the relationship between learners' intrinsic motivation and their digital skills development.

Hypothesis 5a proposed that mentors' self-efficacy enhances the indirect effect of intrinsic motivation on their skill development through positive affect. We tested this proposition by employing the procedure for testing moderated mediation suggested by Preacher, Rucker, and Hayes (2007) and Hayes (2015) and extending it to latent variables by building on Sardeshmukh and Vandenberg (2016) and Cheung and Lau (2017). After previously finding support for the mediating role of positive affect for mentors, we also established (see Table 3) that the interaction effect between intrinsic motivation and self-efficacy was significant for this group of respondents ($a_3 = -.320$;

TABLE 3 Model coefficients for the conditional process model for mentors

Antecedent	Consequent				
	Positive affect (M)		Skill development (Y)		
	Coeff. (95% CI)	p	Coeff. (95% CI)	p	
Gender	.148 (.048, .242)	.003	.213 (.010, .384)	.023	
Past participation	.107 (.027, .202)	.016	.074 (–.089, .240)	.368	
Age	–.006 (–.018, .004)	.256	–.018 (–.036, –.003)	.028	
Work experience	.004 (–.008, .018)	.531	.010 (–.013, .030)	.350	
Intrinsic motivation <i>a</i> ₁	.409 (.276, .578)	.000	<i>c'</i>	.367 (.092, .662)	.008
Extrinsic motivation	–	–	.447 (.297, .608)	.000	
Positive affect	–	–	<i>b</i>	.204 (–.008, .411)	.068
Mentoring self-efficacy <i>a</i> ₂	.251 (.145, .361)	.000			
Intrinsic motivation * mentoring self-efficacy <i>a</i> ₃	–.320 (–.631, –.041)	.033			

Notes. Estimation is maximum likelihood, unstandardized coefficients, five integration points, bootstrapping based on 1,000 random samples, multiple independent runs. Standard model-fit indicators are not available for latent interaction models; thus, we list information criteria (Loglikelihood = –7,206.61; AIC = 14,543.22; BIC = 14,804.906). AIC = Akaike Information Criterion; BIC = Bayesian Information; Criterion CI = confidence interval.

95% CI = [-0.631, -0.041]). However, in contrast to our predictions, the interaction was negative.

Following Preacher et al.'s (2007) recommendation, we operationalized high and low levels of the moderator (i.e., mentoring self-efficacy) as one SD above and below its mean score. We then calculated the conditional indirect effect estimates, their bias-corrected bootstrap CIs, and significance values for low, mean, and high conditions. Our results indicate that the conditional indirect effect was stronger and significant in the low (.149; 95% CI = [0.007, 0.354]) and mean (.083; 95% CI = [0.003, 0.181]) self-efficacy conditions, but was weaker and not significant in the high self-efficacy condition (.018; 95% CI = [-0.032, 0.133]). In addition, we calculated the recently proposed index of linear moderated mediation (Hayes, 2015). The index was negative and significant (-.065; 95% CI = [-0.213, -0.002]), meaning that the indirect effect of intrinsic motivation on the development of mentoring skills through positive affect is a decreasing function of mentoring self-efficacy. These results confirm the existence of a moderated mediation mechanism, but not in the predicted direction, which means that hypothesis 5a was not supported.

After establishing that positive affect did not mediate the relationship between learners' intrinsic motivation and digital skills development, we could not find support for hypothesis 5b. The interaction term between learners' intrinsic motivation and computer self-efficacy was also not significant ($a_3 = -.140$; 95% CI = [-0.591, 0.172]), meaning that the two necessary conditions for hypothesis 5b were not satisfied. Moreover, the index of linear moderated mediation was not significant (-.013; 95% CI = [-0.164, 0.025]). Thus, hypothesis 5b was not supported.

5 | DISCUSSION

Interest is mounting in how intergenerational collaboration can be utilized to promote digital fluency among older workers, while simultaneously boosting career-relevant skills in their younger, more tech-savvy counterparts (Chen, 2013; Colbert et al., 2016; Murphy, 2012). In our study, we examined the motivations and skill development of younger mentors and older learners in the context of reverse mentoring. We found both intrinsic and extrinsic motivations increased mentors' and learners' perceptions of skill development, though extrinsic motivation (relative to intrinsic motivation) was a stronger driver of skill development for the younger group. We further showed positive affect mediated the effect of intrinsic motivation on skill development in mentors, but only for those with low levels of mentoring self-efficacy. We did not find support for any mediating or moderating effects in our sample of learners. In sum, the results of our two-sample study suggest the motivational process of younger mentors is more complex and features positive affect and extrinsic motivation in prominent roles, whereas the motivational process of older learners is relatively straightforward, with intrinsic motivation having a more direct impact on subsequent digital skills development. These findings advance reverse-mentoring scholarship in several ways.

Our conceptual model provides insight into the within-person processes driving individuals' skill development in reverse-mentoring collaborations, an area that has thus far received limited attention.

Importantly, we highlight how extrinsic motivation, despite often being presented as an impoverished form of motivation (Ryan & Deci, 2000b), can be used to explain variation in younger mentors' and older learners' skill development. Unsurprisingly, however, this effect is much more pronounced in the younger group. Younger people seek out opportunities to develop their skills, in reverse-mentoring initiatives or otherwise, to enhance their career prospects. This proactive approach to controlling external circumstances is indicative of the prominent role that extrinsic outcomes play at this life stage (Heckhausen et al., 2010; Heckhausen & Schulz, 1995; Kooij et al., 2011). Our results are consistent with prior findings showing extrinsic values, including the perceived importance of money and status, are more pronounced in younger generations (Twenge et al., 2010).

On the other hand, we only found marginal support for the role of extrinsic motivation in older learners' digital skills development. Even though societal pressures, including expectations regarding lifelong learning and the constant upgrading of skills, can be strong external motivators (Gagné & Deci, 2005), we suggest these pressures may be tempered by learners' perceptions that these goals are not under their control. Instead, older individuals are more likely to pursue outcomes that they perceive as intrinsically rewarding and attainable (Heckhausen et al., 2010; Kooij et al., 2011).

When examining the psychological mechanisms that unfold in reverse mentoring, we positioned positive affect as the linchpin that links individuals' intrinsic motivation and skill development. We found support for this mediating effect in our sample of mentors, which is consistent with previous studies showing the beneficial effects of positive mood on cognitive functioning (Erez & Isen, 2002; Nadler et al., 2010) and quality of learning outcomes (Fredrickson, 2001; Konradt et al., 2003). Surprisingly, we did not find support for this effect in learners. It appears that intrinsically driven older adults become engaged in learning irrespective of whether this experience is pleasant or not. We speculate that the reason for this may lie in age differences in attitudes toward work and learning. Specifically, older adults, compared to their younger counterparts, put greater value on hard work and grit and tend to score higher on work centrality (Cogin, 2012; Lyons & Kuron, 2014); thus, they may be more likely to persevere at the task at hand even when this does not evoke positive feelings.

Our unexpected finding with regard to moderated mediation in the sample of younger mentors also warrants further discussion. We found positive affect mediated the effect of mentors' intrinsic motivation on their skill development, but only for those who came to the initiative with low-mentoring self-efficacy perceptions. In other words, experiencing positive affect during the initiative was not a significant factor for mentors who had high self-efficacy; instead, their perceptions of development of mentoring skills were directly impacted by their intrinsic and extrinsic motivations. Considered in concert with our findings regarding older learners, we may tentatively conclude positive affect is only beneficial for mentors with low self-efficacy, as such positive affective experiences may compensate for their lack of confidence in their abilities. In line with the broaden-and-build theory of positive emotions (Fredrickson, 2001), it appears younger employees rely on positive affect as a personal resource to better cope with low confidence and self-doubt in novel situations.

5.1 | Implications for practice

The interplay among mentors' motivation, affect, and self-efficacy perceptions described before offers useful guidelines on how to approach younger people's skill development in practice. When developing a skill, individuals with lower levels of self-efficacy are particularly likely to benefit from a pleasant atmosphere that facilitates the experience of positive emotions such as contentment, interest, connectedness, and pride (Fredrickson, 2001). On the other hand, those with higher self-efficacy are more likely to respond positively to extrinsic incentives, because they have a higher expectancy that their efforts will allow them to attain their desired outcome (Vroom, 1964). Hence, managers should emphasize both positive moods and career-relevant outcomes, such as recognition, promotion, and monetary rewards (Kanfer & Ackerman, 2004), when working with their younger employees. According to our findings, this coexistence of a positive climate and extrinsic motivators creates the right conditions for younger people to thrive.

In contrast to their younger counterparts, older individuals primarily rely on intrinsic motivation when learning new skills, with extrinsic motivation assuming a markedly diminished role. This presents a challenge to managers, because extrinsic tools commonly employed in human resource management, either in the form of rewards or pressures, cease to be effective. This problem is compounded by the fact that older workers are less willing to participate in skills training or career-development activities in the first place (Ng & Feldman, 2012). One suggestion for dealing with this has been to provide older workers with jobs and tasks that are interesting and worthwhile (Kooij et al., 2011). Similarly, we recommend that practitioners champion a workplace that is intrinsically motivating to older employees by giving them meaningful tasks and designing training interventions that align with their interests.

Successful examples of reverse mentoring, such as the initiative described in the present study, pave the way for the introduction of organizational initiatives that benefit both cohorts of participants and, at the same time, account for the diverse needs of younger people in the early stages of their professional lives and older people in the later stages of their careers (Chaudhuri & Ghosh, 2012; Murphy, 2012). We suggest such initiatives are particularly likely to be effective under certain conditions.

5.1.1 | Initiative setup and recruitment

Based on our findings and the emerging literature on intergenerational learning, we encourage HR practitioners looking to support their older employees in upgrading their digital skills to create reverse-mentoring programs in the workplace. We advise that these programs be formal in nature for the following reasons. First, to engage older employees, the initiative should be highly structured and interactive, with opportunities for frequent feedback, which creates a more favorable learning environment for adult learners (Wolfson, Cavanagh, & Kraiger, 2014). Second, to attract younger employees and help formalize the reverse-mentoring process, organizations could put in place a system that tracks and rewards their participation in reverse mentoring (e.g., mentoring certificate, promotion opportunities, etc.) and provide them with training in basic mentoring skills. This is in line with our

results showing that extrinsic motivators and the potential for advancing career-relevant skills are central to younger mentors' involvement in such initiatives.

We also advise these programs be voluntary in nature. This is vital to attract older learners who are intrinsically interested in updating their digital skills. Moreover, for the sake of protecting their self-concept, older adults tend to avoid career-development activities where the risk of failure is perceived to be high (Kanfer & Ackerman, 2004; Wolfson et al., 2014); interacting with technology is one such anxiety-provoking situation. However, participating in digital skills training voluntarily is less likely to threaten older learners' self-concept, which could facilitate their initial involvement and subsequent engagement in the initiative. These participants can then serve as intergenerational learning ambassadors for their less intrinsically oriented counterparts and those colleagues who may avoid such initiatives due to fear of failure.

For younger mentors, voluntary participation is more likely to evoke pleasant and positive affective experiences, which, as shown in this study, can compensate for lower confidence in one's ability to mentor. Also, from a strategic talent management perspective, the voluntary nature of this program would allow the organization's management to identify high potential—younger employees with ambition and intergenerational sensibility—for future leadership roles. These proactive individuals can likewise serve as intergenerational learning ambassadors and thereby promote reverse mentoring among their peers.

5.1.2 | Intergenerational learning

Reverse mentoring is a novel approach to intergenerational collaboration in organizations, and we hope our findings help HR practitioners develop or refine their programs to capitalize on participants' motivational processes. We should note, however, the reverse-mentoring initiative at the core of this study was inherently a one-way process, with knowledge transfer flowing from the younger, more tech-savvy group to their older, less tech-savvy counterparts. Organizational scholars are now stressing intergenerational learning should be viewed as bidirectional or reciprocal, because individuals from both groups are likely to benefit from the exchange (Knight, Skouteris, Townsend, & Hooley, 2014; Ropes, 2013). While not empirically examined in our study, we expect that even a digital skills initiative, where there is a significant imbalance in expert (i.e., digital) knowledge, can produce positive outcomes beyond younger employees' mentoring and older employees' digital skills, as both groups bring unique expert, social, and practical knowledge to the table (Gerpott et al., 2017).

For organizational scholars, this expanded view of intergenerational learning opens up numerous avenues for future research. Practitioners, on the other hand, can use such initiatives to create norms about knowledge sharing and intergenerational collaboration in their organizations (Gagné, 2009). To gain widespread acceptance of intergenerational learning initiatives, however, intervention developers (e.g., HR managers) should enlist early participants—the aforementioned intergenerational learning ambassadors—to help spread the word (Dearing, 2009). When it comes to the diffusion of innovations

in organizations, the first people to adopt the innovation (the so-called innovators and early adopters) are crucial to bringing attention to it and facilitating its spread (Rogers, 2003). We expect, in a digital skills initiative like the one described in this study, the first group of mentors and learners to sign up would play a central role in helping diffuse this intervention among their colleagues. Importantly, for the older group, this process of attracting participants through diffusion has an added benefit. Namely, spreading acceptance of this initiative is directly linked to the spread of digital skills knowledge in the organization, with older employees who adopt this innovation (i.e., reverse mentoring) also becoming late adopters of another one (i.e., technology knowledge).

5.2 | Limitations and future research

Our findings are subject to certain limitations that can be addressed in future research. First, our study design was cross-sectional, meaning that we collected all data at one point in time; any causal inferences are thus tentative. To address this, we obtained evidence of concomitant variation and we established temporal precedence by using a strong theoretical foundation and by carefully wording our measures to separate them chronologically with time anchors (Preacher & Hayes, 2008). Such use of retrospective reporting for some of our scales is a limitation, but we tried to mitigate this concern by using established, valid measures with adequate reliability, asking respondents to recall events from the immediate past (i.e., 5 days prior), informing them of the aim and usefulness of the research, and assuring them of the confidential nature of their responses. These steps follow guidelines for improving the validity of retrospective reports, making this a viable method for data collection when researchers are unable to take multiple measures over time (Miller, Cardinal, & Glick, 1997). Nonetheless, replicating our study using experimental or longitudinal designs would help alleviate this concern further.

Second, we relied entirely on self-report measures, meaning that common method variance (CMV) could have biased our results (Podsakoff et al., 2003). However, we employed both procedural and statistical remedies to mitigate this threat. Specifically, we used scales with established construct validity, explained study procedures clearly, and preserved the anonymity and confidentiality of data. Additionally, we obtained evidence of discriminant validity by running CFAs (Conway & Lance, 2010; Podsakoff et al., 2003). Lastly, in our study we focused on path models with latent interactions, where significance cannot be an artifact of common variance (c.f., Podsakoff, MacKenzie, & Podsakoff, 2012).

Third, our study positioned intrinsic and extrinsic motivations as antecedents of skill development in reverse mentoring, but was particularly focused on understanding the psychological mechanisms that underlie these relationships. Future research could unpack the specific aspects of intrinsic or extrinsic motivation that are driving individuals to develop skills in this context. For instance, one motivating factor that could be examined is the need for belongingness or relatedness, which is a basic psychological need that is thought to facilitate intrinsic motivation (Baumeister & Leary, 1995; Gagné & Deci, 2005; Ryan & Deci, 2000a). The dynamics of reverse mentoring could help satisfy this need, as mentoring relationships have been identified as

one example of a high-quality connection that energizes people and helps them thrive (Dutton & Heaphy, 2003). Similarly, extrinsic motivation could also be examined in more depth (e.g., Gagné et al., 2015), which would help practitioners further tailor the interventions that we outlined before.

Fourth, we conceptualized affect as an *a posteriori* average perception of affective states experienced during the reverse-mentoring initiative. Future studies could employ alternative research designs (e.g., diary studies) that would enable researchers to measure affect at regular intervals, thereby accounting for the daily fluctuations in affective experiences. Moreover, people also react to their coworkers' displays of emotion. Research could thus explore such concepts as emotional contagion and group affect (Collins, Lawrence, Troth, & Jordan, 2013) to investigate how group experiences may impact reverse mentoring. Finally, while positive affect helped account for the link between younger mentors' intrinsic motivation and skill development, this does not preclude the existence of other mediators (Preacher & Hayes, 2008). For example, engagement, which is characterized by vigor, dedication, and absorption (Schaufeli & Bakker, 2004), may be particularly relevant in this context, as its affective and cognitive dimensions convincingly link intrinsic motivation and skill acquisition.

6 | CONCLUSION

The present study adds to the emerging body of literature on intergenerational learning by showing how age differences in digital fluency can be utilized to facilitate older learners' digital skills development and enhance younger mentors' mentoring skills at the same time. In testing our theoretically derived model of the motivational processes involved in reverse mentoring, we found considerable differences in factors that drive younger and older individuals' skill development, including (intrinsic and extrinsic) motivation, positive affect, and self-efficacy. Organizations should consider such differences when designing formal or informal initiatives that are meant to capitalize on intergenerational collaboration and, ultimately, foster HR development in today's age-diverse organizations.

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ENDNOTES

¹As evident from the results reported in Tables 2 and 3, there were no significant effects for either cumulative work experience or current employment status in any of our models. This allows us to generalize our findings to reverse-mentoring situations that include older workers with rich work experience and younger mentors with or without work experience.

²Instead of the (negative) lowest interval value for extrinsic motivation for learners (−.036), we used .001.

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APPENDIX A: FIT STATISTICS FOR NESTED MEASUREMENT MODELS

Model (group)	$\chi^2(df)$	CFI	RMSEA	SRMR	Diff
Younger mentors					
Full measurement model	142(94)	.979	.034	.042	
Model I—Four-factor model ^a	479(98)	.835	.092	.101	***
Model II—Four-factor model ^b	427(98)	.858	.086	.061	***
Model III—Four-factor model ^c	266(98)	.927	.061	.058	***
Model IV—Four-factor model ^d	536(98)	.810	.099	.079	***
Model V—Three-factor model ^e	548(101)	.806	.098	.073	***

APPENDIX A (Continued)

Model (group)	$\chi^2(df)$	CFI	RMSEA	SRMR	Diff
Model VI—Three-factor model ^f	779(101)	.707	.121	.131	***
Model VII—Three-factor model ^g	806(101)	.695	.124	.121	***
Model VIII—Two-factor model ^h	1,105(103)	.566	.146	.140	***
Model IX—Two-factor model ⁱ	912(103)	.650	.131	.098	***
Single-factor model ^j	1,393(105)	.443	.164	.149	***
Older learners					
Full measurement model	118(80)	.972	.040	.049	
Model I—Four-factor model ^a	443(84)	.735	.121	.101	***
Model II—Four-factor model ^b	232(84)	.891	.078	.075	***
Model III—Four-factor model ^c	304(84)	.837	.095	.109	***
Model IV—Four-factor model ^d	335(84)	.815	.101	.097	***
Model V—Three-factor model ^e	402(87)	.768	.111	.121	***
Model VI—Three-factor model ^f	483(87)	.708	.125	.142	***
Model VII—Three-factor model ^g	398(87)	.771	.111	.120	***
Model VIII—Two-factor model ^h	600(89)	.623	.140	.142	***
Model IX—Two-factor model ⁱ	604(89)	.620	.141	.142	***
Single-factor model ^j	908(90)	.397	.176	.152	***

Notes. df = degrees of freedom; CFI = comparative fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; diff = difference in chi-square. All models are compared to the relevant full measurement model. Model descriptors (Mentors; Learners):

^aIntrinsic and extrinsic motivations were combined in one factor.

^bPositive affect and intrinsic motivation were combined in one factor.

^cSkill development and extrinsic motivation were combined in one factor.

^dTask-relevant self-efficacy, and intrinsic motivation were combined in one factor.

^eSkill development and extrinsic motivation were combined into one factor along with positive affect and intrinsic motivation into another factor.

^fExtrinsic and intrinsic motivations were combined into one factor along with skill development and task-relevant self-efficacy into another factor.

^gPositive affect and intrinsic motivation were combined into one factor along with skill development and task-relevant self-efficacy into another factor.

^hPositive affect and intrinsic motivation were combined into one factor along with skill development, task-relevant self-efficacy, and extrinsic motivation into the other factor.

ⁱSkill development and extrinsic motivation were combined into one factor along with positive affect, intrinsic motivation, and task-relevant self-efficacy into the other factor.

^jAll variables were combined into a single factor.

*** $p < .001$.