RESEARCH ARTICLE



Workplace learning in Crowdwork Questionnaire (WLCQ): Measuring self-regulated learning and skill development in online platform work

Anoush Margaryan¹ | Julian Albert² | Timothy Charlton-Czaplicki¹

¹Department of Digitalization, Copenhagen Business School, Frederiksberg, Denmark

²Oxford Internet Institute, The University of Oxford, Oxford, UK

Correspondence

Anoush Margaryan, Department of Digitalization, Copenhagen Business School, Frederiksberg, Denmark. Email: ama.digi@cbs.dk

Funding information

European Centre for the Development of Vocational Training; Alexander von Humboldt-Stiftung

Abstract

This paper addresses learning and development processes in online platform work. Specifically, it proposes a new instrument to survey and analyze self-regulated workplace learning in crowdwork, a type of online platform labor in which a global pool of workers are matched with clients through digital platforms to carry out remunerated tasks. Although workplace learning practices of workers in traditional, organisationally embedded jobs have been studied extensively, the findings cannot be transferred to describe and explain learning behaviors within crowdwork, which is fundamentally different from traditional work in that it is autonomous, radically distributed, and no organisationally provided training opportunities exist in crowdwork. To advance the understanding of workplace learning in crowdwork we reviewed the literature on workplace learning, platform work, and self-regulated learning to develop the Workplace Learning in Crowdwork Questionnaire, which we subsequently validated with 992 crowdworkers from six European countries on three

This is an open access article under the terms of the Creative Commons Attribution-NonCommercial License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited and is not used for commercial purposes. © 2022 The Authors. *International Journal of Training and Development* published by Brian Towers (BRITOW) and John Wiley & Sons Ltd.

crowdwork platforms. The instrument can be used by researchers to study the nature of (self-directed) workplace learning in online labor platforms. It can also be used by crowdworkers to self-reflect on their learning and development.

INTRODUCTION

The global uptake of crowdwork has increased in recent years (Kässi & Lehdonvirta, 2018), and up to 10 per cent of the EU adult population has worked on crowdwork platforms (Spencer et al., 2018). Although the terminology is in flux, broadly two types of crowdwork exist (Howcroft & Bergvall-Kåreborn, 2018; Margaryan, 2019a): location-independent, where the work occurs entirely remotely, within online labor platforms such as Upwork or People Per Hour, and location-dependent, where the work is coordinated online or via apps, but the actual delivery of service occurs offline, as in taxi-hailing services such as Uber or domestic help such as TaskRabbit. The focus of this paper is on location-independent, fully online crowdwork, with examples of tasks including software development, graphic design, professional services, and writing and translation. The uptake of crowdwork has recently gained further traction due to the COVID-19 pandemic (Spurk & Straub, 2020). Despite the increased uptake of crowdwork, crowdworkers' workplace learning behaviors are not well-understood (Lehdonvirta et al., 2018). While workplace learning practices of employees in organisationally embedded jobs have been studied extensively, demonstrating that deep and powerful learning takes place in everyday working life (Billett, 2001; Manuti et al., 2015; Skule, 2004), crowdwork is a fundamentally different form of organizing. Therefore, we cannot assume that crowdworkers' learning practices simply mirror those of employees in organisationally embedded jobs. Psychometrially refined instruments could help improve our understanding of workplace learning practices in crowdwork, but such instruments are presently scarce and incomplete.

At least two key characteristics differentiate workplace learning in crowdwork. First, crowdworkers are a freelance workforce operating outside conventional organizational structures. Rather than being employers, crowdwork platforms are intermediaries matching clients and workers, therefore platforms typically do not directly support workers in their learning. Consequently, crowdworkers do not have access to the sorts of formal or informal learning opportunities—training and mentoring, networking, and structured or incidental knowledge sharing—that exist in conventional jobs. Crowdworkers are solely responsible for organizing and managing their own learning, with no organisationally provided learning (Littlejohn & Margaryan, 2014). Self-regulated learning, therefore, is the main form of learning available to crowdworkers (Margaryan, 2019b). Crowdworkers aiming to improve their skills to secure more and better-quality tasks on competitive online labor platforms have to develop and strengthen their ability to self-initiate and self-direct their learning and development, for example, by scanning the horizon for in-demand skills or finding other people to learn with and from (Barnes et al., 2015; Cedefop, 2020).

Second, compared to organisationally embedded work, the nature of online platform labor is autonomous, radically distributed, and fragmented. Unlike in most conventional jobs,

of and

497

crowdwork tasks are conceptualized and designed to be undertaken autonomously rather than in teams, communities, or networks. Interdependencies that are inherent in conventional jobs are deliberately designed out of the workflow in crowdwork platforms. Furthermore, crowdworkers typically do not have a 'supervisor': the platforms deploy algorithms to intermediate the match between skills requested and offered on the platforms but do not interfere in the content of the work task or the relationship between the crowdworker and the client. Unlike in conventional work, there are no in-built opportunities for incidental knowledge sharing and informal learning from colleagues or others (Green et al., 2014). If crowdworkers wish to find others to learn with and from, they have to look elsewhere beyond the platform further increasing the importance of self-regulation in learning (Taylor & Joshi, 2019).

Finally, crowdwork also differs from other superficially similar modes of remote work, such as telework, coworking, or working from home. The latter are not distinct types of work but types of work arrangements where workers are to some extent embedded in organizations, for example through access to organizational training or knowledge-sharing opportunities. Taken together, these structural differences suggest that crowdworkers' learning practices may not mirror those of workers in conventional organizational jobs and not be adequately captured by existing instruments deserving independent analysis. Recent empirical research has begun to illuminate how crowdworkers organize and self-regulate their workplace learning. For example, they develop a range of skills through their platform work, including core skills in their professional field or transversal skills such as communication or self-marketing (Blaising et al., 2021). Additionally, nascent research reveals that crowdworkers undertake a range of individual and social learning activities and behavioral self-regulatory learning strategies to organize their workplace learning (Margaryan, 2019a, 2019b; Taylor & Joshi, 2019). As more people engage in crowdwork, a systematic understanding of the learning potential of this new type of work organization becomes increasingly important. To facilitate empirical research in this area, reliable, and rigorous instruments to survey and analyze crowdworkers' learning behaviors, in particular their self-regulated learning activities and learning strategies, are required. No such instruments specifically developed for crowdwork settings exist in the published literature.

The majority of extant instruments for measuring self-regulated learning have been developed in and for educational, formal learning contexts, such as schools and universities, to analyze the learning behaviors of students rather than workers (Sitzmann & Ely, 2011). A recent review found only a few validated instruments to scope self-regulated learning in the workplace, all of which are targeted at conventional organizational employment (Cuyvers et al., 2020). These instruments are not directly applicable to crowdwork, which differs from conventional employment in the absence of social infrastructures, task interdependencies, learning scaffolds, and the shift of responsibility for learning to individual workers (Littlejohn & Margaryan, 2014). The literature highlighted the importance of analyzing self-regulated learning in new work domains (Sitzmann & Ely, 2011) including crowdwork (Lehdonvirta et al., 2018).

The purpose of this paper is to provide a validated instrument to survey and analyze crowdworkers' learning behaviors—the Workplace Learning in Crowdwork Questionnaire (WLCQ). The instrument is based on a combination of items adapted from an extant questionnaire validated in a conventional, employment-based knowledge-work (Fontana et al., 2015) and newly developed items derived from the latest empirical research on crowdwork. This paper describes the development and validation of the WLCQ. First, we

discuss the theoretical foundations of the instrument and our approach to item generation and content validation. Then, we summarise the psychometric validation of the internal structure of three key scales on workplace learning behavior on two samples with n = 527 and n = 465workers across three platforms. We validate the internal structure of the instrument by considering factor structure, scale reliability, and measurement invariance across theoretically relevant groups including the geographic location of the worker (Northwestern Europe [Germany, UK, Finland] and Southeastern Europe [Romania, Spain, Italy]), their level of financial dependence on the platform (primary/secondary source of income) and their occupational specialization (creative and multimedia/writing and translation). First, different economic/welfare regimes-in Europe, typified by countries located in the northwest and southeast—have been shown to pose differential enablers and barriers to workplace learning (e.g., Ashton, 2004) and measurement invariance for workers active in different welfare regimes can inform comparisons and policy on vocational development on a supranational level. Second, workers' financial dependence on platforms has been linked with the precarity of work (Anwar & Graham, 2020), affecting other factors such as time spent crowdworking. Measurement invariance between various degrees of platform dependency is thus important for research investigating differential learning behaviors of full-time and occasional crowdworkers, for instance. Last, workers' specializations impact their selection of types of crowdwork tasks (e.g., Rainbird et al., 2004). In addition to having a robust internal structure, it is important that the new instrument enables opportunities for advancing the theory of self-regulated workplace learning. To this end, we present some notable deviations from the SRL theory we uncovered, which illustrate how the WLCQ contributes novel theoretical insights.

DEVELOPMENT OF THE WLCQ

The structure of the WLCQ is grounded in a three-dimensional conceptualization of workplace learning: *what workers learn, how they learn, and with whom they learn* (Margaryan, 2019a). Correspondingly, the instrument includes sets of items and scales that operationalize the three conceptual dimensions. First, a set of items to scope *what crowdworkers learn* in the workplace, in particular, *what* skills they develop through crowdwork. Second and third, the instrument includes scales to analyze *how* and *with whom crowdworkers learn*, specifically to scope the individual and social workplace learning activities and self-regulatory learning strategies crowdworkers undertake to develop their skills. Typically instruments measuring workplace learning focus on only one or two dimensions (Cuyvers et al., 2020), so in addition to the unique focus on crowdwork, the three-dimensional structure we use further increases the originality of our instrument. In the following section, we present the broader literature underpinning the instrument. The full questionnaire is available in the Supporting Information Material enclosed.

What is learned through crowdwork: Skill categories (SDEV)

To scope *what* is learned through crowdwork, the WLCQ originally included a set of items on 10 *skill categories* that crowdworkers have been empirically shown to develop through their work on platforms (Cedefop, 2020). Specifically, the skill development (SDEV) scale is based on an inductive analysis of 77 in-depth interviews with crowdworkers from four leading crowdwork platforms (detailed in Cedefop, 2020). Each item reflects a particular skill category



developed through crowdwork, including, for example, core technical skills, or transversal skills such as communication or learning to learn. Most SDEV items reflect established skill categories (Buchanan et al., 2017), with the exception of two crowdwork-specific categories: *skills related to bidding for projects on platforms* (e.g., self-promotion or using search engine optimisation techniques) and specific *skills required for freelance work more generally*, such as handling taxation.

Each skill category is presented as a statement linked to the specific platform and providing examples of the skill category: 'Through work on < platform name >, I developed my communication skills (e.g., handling customers, handling cultural differences, presentation skills, email etiquette, etc.)'. The frequency of skill development is measured by a four-point Likert scale ranging from 'never' to 'daily'. SDEV measures the frequency of development of each skill item rather than the respondents' agreement with the item, therefore a neutral option that a five-point Likert scale would capture is not required (Clark & Watson, 1995).

How and with whom people learn in crowdwork: Individual and social workplace learning activities and self-regulated learning strategies

To measure *how* crowdworkers learn and *who they learn with*, the WLCQ comprises two sets of scales: (i) workplace learning activities (WLA) and (ii) self-regulated learning strategies (SRLS) including planning, implementation, and reflection strategies. Adopted from the *Self-Regulated Learning at Work Questionnaire or SRLWQ* developed for traditional work settings (Fontana et al., 2015), both scales cover individual and social workplace learning activities and SRLS.

WLA scale

The original WLA scale contained 11 items covering social and individual, as well as formal and informal workplace learning activities synthesized from the literature as detailed in Fontana et al. (2015). The original WLA scale was modified to fit the crowdwork context. First, three new items were added to scope learning from free online courses, paid online tutorials, and online fora, which have become increasingly popular in the years following the publication of the SRLWQ and are known mechanisms through which crowdworkers learn (Cedefop, 2020). Second, some extant items were reworded to suit the crowdwork context (e.g., 'Asking colleagues for advice' was reworded to 'Asking others for advice' since crowdworkers do not work in teams) and some original items were disaggregated (e.g., 'Working alone or with others to develop solutions to problems'—into 'Working alone to complete my [Platform] projects' and 'Collaborating with others to complete my [Platform] projects'). These adaptations resulted in a 15-item WLA scale covering individual and social learning activities. Similar to the SDEV scale, WLA is measured through a four-point Likert scale analyzing the frequency of use of WLA, ranging from 'never' to 'daily' during the past 3 months.

SRLS scale

The SRLS items were adapted from the original SRLWQ instrument (Fontana et al., 2015) with relatively minor revisions. The SRLS scale is underpinned by Zimmerman's Cyclical Phases

Model postulating that individuals self-regulate their learning through *forethought, performance*, and *self-reflection* (Zimmerman, 2006). Each phase encompasses various subprocesses, such as goal setting, strategic planning, self-evaluation, or reaching out to others for feedback. The original SRLS scale included 42 items to scope the range and usage frequency of SRL subphases/processes of Zimmerman's model. It was adapted by removing duplicate items or items that were considered too general. One item was added to reflect an SRL strategy specific to crowdwork which had emerged from a previous empirical study of crowdworkers (Cedefop, 2020): 'Before joining [Platform], I signed up to other platforms to test and learn how to be successful in online work'. The resultant SRLS scale included 35 items reflecting a mix of individual and social SRL strategies.

Finally, in addition to SDEV, WLA, and SRLS scales, the instrument scopes a set of specific individual and contextual factors: the task categories workers specialize in (e.g., software development, administrative support), the complexity and requisite skill variety of tasks, personal motives to undertake crowdwork, and key demographic variables (e.g., age, gender, education, hours worked on the platform, and attitude to freelance work.

CONTENT VALIDITY OF THE WLCQ

To establish the content validity of the scales, three mechanisms were used: interviews with crowdworkers, expert review, and a pilot. Specifially, the content validity of the new SDEV scale was established through an inductive analysis of 77 in-depth interviews with crowdworkers from four leading global platforms, whereby the interviewees were asked to describe all the skills they developed and used in crowdwork; from these interviews, the 10 categories of skills which formed the SDEV scale were inductively devised (the interview methodology is described in Cedefop, 2020). Further, to ensure that the instrument effectively targets the concepts under investigation, we subjected the WLCQ to a peer-review by researchers on crowdwork and crowdworkers' learning (n = 6). This resulted in adding crowdwork-specific items and further refinement of items (e.g., the inclusion of more granular options for platform experience). Finally, the instrument was adjusted based on feedback from a small-scale pilot including post-survey interviews with crowdworkers (n = 6). In response, we added clarifying examples to scale items that included jargon such as 'formal processes' and other information, for instance on data usage, in clearer terms.

Internal structure and instrument validity

Data collection and sampling

Data were collected through an online survey on three crowdwork platforms: *Fiverr, Upwork*, and *PeoplePerHour*. Participants were paid 8–9 EUR for about 20–25 min of their time. We defined eligible participants as workers of at least 18 y.o., who were registered on at least one target platform and had already completed one or more projects. We limited participation to those who had recently worked in one of six European countries: Finland, Germany, the UK, Italy, Romania, and Spain. Crowdworker population size is unknown since statistics on the size of the crowd-workforce are rarely made public and only non-probabilistic population estimates are available (e.g., Spencer et al., 2018). We collected two samples (Table 1).

501

	Responde	nts	Age		Work experie	nce	Female gender	Primary income
Scale	n	%	M	SD	Μ	SD	%	%
Clerical and data entry	58 31	11 7	36 41	10 12	9 10	4 4	66 52	21 10
Creative and multimedia	96 179	18 38	34 32	10 11	9 6	4 5	54 36	19 20
Professional Services	62 22	12 5	35 43	9 14	9 10	5 4	44 18	29 5
Sales and marketing support	64 32	12 7	33 34	9 9	8 8	4 5	45 28	31 16
Software dev & tech.	70 51	13 11	38 36	10 13	10 9	4 5	21 14	17 16
Writing and translation	168 134	32 29	35 35	10 12	8 8	5 5	61 64	43 23
No data	8 16	2 3	41 33	11 12	10 5	5 5	38 31	25 31

TABLE 1 Sociodemographic characteristics of participants.

Note: The values are presented in the following format EQ-Sample | PA-Sample.

For sample one (n = 527), we employed equal-quota (EQ) sampling on two platforms where collaboration with the platform owners could initially not be agreed upon. Researchers randomly identified eligible workers through the platforms' search functions while keeping response quotas for gender and country of work constant. To prevent self-selection bias, the survey was not posted publicly, but randomly identified workers were directly invited to participate in the survey as a paid project. For EQ sampling, the response rate was around 20 per cent. Sample two was collected through platform-assisted (PA) sampling (n = 465). Platform representatives assisted in distributing the survey to a randomly selected subgroup of eligible workers. The response rate for the PA sample is unknown since the data were deemed business-sensitive and not disclosed by platforms.

PSYCHOMETRIC EVALUATION METHODOLOGY

We evaluate the internal structure of key scales (SDEV, WLA, and SRLS) based on a two-phase exploratory and confirmatory scale development process adapted from Clark and Watson (1995) and Hinkin (1998) and by testing for measurement invariance across selected demographic groups. The analysis was performed in R using the 'lavaan', 'boot', and 'semTools' packages. An exploratory factor analysis, EFA (using iterated principal axis factor analysis, polychoric correlations, and Promax oblique rotation) was performed to identify a latent variable structure. Items with skewed response distributions, low levels of correlation to other scale items, or problematic cross-loadings were deleted at the outset unless a theoretical justification suggested otherwise.

We performed CFA using the robust WLSMV estimator that is suitable for the analysis of ordinal data that does not rely on normally distributed variables (Flora & Curran, 2004). Reliability of the final scales was measured as the degree of intercorrelation of items by calculating ordinal coefficient alpha, α , and the average variance extracted (AVE). We additionally report coefficient omega, ω , calculated using the model-implied covariance matrix in the denominator. We evaluated convergent validity by assessing the size of the factor loadings (>0.5), AVE (>0.5), and the measures of internal consistency, α and ω (>0.7) (Hair

et al., 2019). Discriminant validity was established using the correlation heterotrait-monotrait ratio (HTMT) using 0.85 as the threshold (Henseler et al., 2015).

Last, we iteratively tested for measurement invariance (MI) using multiple-group confirmatory factor analysis (MG-CFA) following the approach for ordinal data outlined by Svetina et al. (2020). We tested MI for geography (NW Europe, n = 602; SE Europe, n = 390), task category (creative and multimedia, n = 275; writing and translation, n = 302), and dependence on the platform (primary n = 201 or nonprimary source of income n = 791).

A more detailed description of the methodology is available as a Supporting Information File.

RESULTS AND DISCUSSION

Skill categories scale (SDEV)

A scree-test on the reduced polychoric correlation matrix and parallel analysis both suggested a three-factor structure underlying the EQ sample. The EFA yielded a simple structure explaining more than half of the observed variance (Table 2).

Latent factor PA1 of the resulting model describes *core and subject-matter skills* which are central to being successful in an area of expertise such as core technical skills or analytical thinking. Factor PA2 represents *professional skills*, such as crowdworkers' ability to

SDEV iten	a	Factor loading				
Item	Description	PA1	PA2	PA3		
PA1: Gene	ral and subject matter ^a					
SD01	Analytical skills	0.70	0.18	-0.14		
SD02	Computer literacy	0.67	0.15	-0.11		
SD03	Learning skills	0.65	-0.15	0.37		
SD04	Core technical skills (e.g., web development)	0.40	-0.11	0.20		
PA2: Profes	ssional ^b					
SD05	Personal dispositions (e.g., confidence)	0.05	0.81	0.03		
SD06	Communication skills (e.g., email etiquette)	0.05	0.54	0.23		
SD07	Organisational skills (e.g., time management)	0.24	0.52	0.13		
PA3: Crow	dworking-specific ^c					
SD08	Skills in being a freelancer	0.04	-0.02	0.70		
SD09	Skills in obtaining work on platforms	-0.09	0.15	0.68		

TABLE 2 Results from an exploratory factor analysis of the SDEV scale (EQ-sample).

Note: Factor loadings above 0.40 are in bold. Item codes refer to the final questionnaire in the appendix. Cumulative proportion of variance explained for.

Abbreviation: SDEV, skill development.

^aPA1: 0.21.

^bPA2: 0.40.

^cPA3: 0.56.



FABLE 3	Results of confirmatory	factor analysis for	r models of SDEV	(PA-sample).
----------------	-------------------------	---------------------	------------------	--------------

	χ^2		RMSEA			
Model	Value	df	Value	90% CI	SRMR	CFI
One-factor model ^a	206.643**	27	0.121**	[0.106, 0.137]	0.056	0.952
Two-factor model ^b	173.380**	26	0.112**	[0.096, 0.128]	0.051	0.961
Three-factor model ^c	94.761**	25	0.078*	[0.062, 0.095]	0.042	0.981

Abbreviation: SDEV, skill development.

^aAll items load onto a single factor representing a worker's general propensity for skill development during crowdwork.

^bSDEV has two underlying latent variables, one capturing skill categories specific to crowdwork (Cedefop, 2020) and another for those categories that are traditionally included in taxonomies of workplace skill development (Eraut, 2004).

^cEFA-derived three-factor model.

p < 0.01; p < 0.001

communicate or their personal dispositions like confidence or creativity. Factor PA3 captures *crowdwork-specific skills* around succeeding as a freelancer as well as obtaining work on platforms.

One scale item—'Through work on [Platform Name], I developed foreign language skills' failed to load on any latent factor and was dropped. In crowdwork, foreign language learning is both a core skill for some crowdworkers such as translators, but also a more general means to successfully bid for tasks and client communication on predominantly English-speaking international platforms. The complexity of the item could be due to confounding these two applications in one item.

Dropping this item leads to a construct with only two latent variables. Following the 'twoindicator rule' (Hair et al., 2019, p. 671) we specified both loadings to be equal in the measurement model. The EFA solution was tested against two theory-derived alternative models in the PA sample (Table 2), one assuming a unidimensional and the other a two-factor structure (Table 3).

The three-factor solution demonstrated the best-fit indices meeting the criteria of CFI > 0.90 (Hair et al., 2019, p. 640), RMSEA < 0.8 and SRMR < 0.8 (Hu & Bentler, 1999). All standardised parameter estimates (>0.67) are statistically significant and AVE exceeds 0.5 for each latent construct (Table 4).

Adequate levels of α (>0.7) further indicate construct reliability and convergent validity. Levels of ω are equally satisfactory (>0.78) for all factors apart from the crowdwork-specific factor PA2 (0.66 [0.58, 0.72]), for which convergent validity is called into question. We consider the important theoretical association between the items composing PA2 as sufficient evidence to assume validity despite relatively low ω . We identified adequate discriminant validity by assessing the HTMT ratio between the constructs (<0.82).

For SDEV, we established measurement invariance across participants *from two European regions*, with varying levels of platform dependence and task specialisations. For the two groups of workers located in Northwestern/Southeastern Europe, the configural model showed adequate fit (RMSEA = 0.070, CFI = 0.984, SRMR = 0.038). Adding further constraints on thresholds, $\Delta \chi^2(9) = 14.544$, p = 0.104; factor loadings, $\Delta \chi^2(6) = 7.5064$, p = 0.277; and intercepts, $\Delta \chi^2(6) = 4.662$, p = 0.588, did not significantly worsen the fit. For the two groups of workers with *varying levels of financial dependence on the platform*, the configural model again demonstrated adequate fit (RMSEA = 0.072, CFI = 0.983, SRMR = 0.040). Adding constraints

TABLE 4	Internal	consistency	measures	for	SDEV
---------	----------	-------------	----------	-----	------

5			
Subscale	ω	α	AVE
EQ-sample: ^a			
PA1: Professional skills	0.80 [0.77, 0.83]	0.85 [0.82, 0.87]	0.65
PA2: Crowdworking skills	0.62 [0.53, 0.68]	0.67 [0.58, 0.74]	0.51
PA3: General skills	0.72 [0.68, 0.76]	0.76 [0.71, 0.79]	0.46
PA-sample: ^b			
PA1: Professional skills	0.83 [0.80, 0.86]	0.88 [0.85, 0.91]	0.72
PA2: Crowdworking skills	0.66 [0.58, 0.72]	0.72 [0.64, 0.78]	0.56
PA3: General skills	0.78 [0.74, 0.82]	0.82 [0.77, 0.85]	0.54

Note: 95 per cent confidence intervals in brackets.

Abbreviations: AVE, average variance extracted; SDEV, skill development.

 $^{\rm a}N = 527.$

 ${}^{\rm b}N = 465.$

on thresholds, $\Delta \chi^2(9) = 6.789$, p = 0.659, and factor loadings, $\Delta \chi^2(6) = 6.396$, p = 0.380 did not significantly worsen the model fit. For the two groups of workers *specialised in design and writing/translation*, the configural model showed adequate fit (RMSEA = 0.068, CFI = 0.986, SRMR = 0.039). The model with equal thresholds (proposition 4) did not significantly worsen the fit, $\Delta \chi^2(9) = 5.647$, p = 0.775.

WLA scale

One item—'Learning by working alone to complete my [Platform] projects'—was deleted because only half of the interitem correlations were within a recommended interval of 0.15 and 0.50 (Clark & Watson, 1995). The median response to this item indicated that respondents worked autonomously on a daily basis. Velicer's MAP and a scree-test provided evidence for a three-factor EFA solution with a simple structure (Table 5).

The factors are representative of three established forms of workplace learning. Factor PA1 typifies *deliberate practice* (Ericsson et al., 1993), a form of expertise development according to which professionals learn through systematic practice, self-study, and receiving formative feedback on their performance from experts. Deliberate practice further includes activities such as *learning by trial-and-error* or *seeking knowledge and help* (e.g., in online communities). In our sample, 57 per cent of respondents reported engaging in deliberate practice daily, compared to 11 per cent for social and 8 per cent for formal learning activities. Factor PA2 reflects *formal work-related learning* such as undertaking paid and unpaid online courses or attending physical workshops. In the case of crowdwork, formal learning opportunities are all external to the platform workplace, and each worker themselves self-initiates and organizes their own participation in these formal learning activities. Although a worker's decision to participate in formal learning activities is self-directed and self-regulated, the activities themselves are organized and directed by others, such as an educational institution or a training provider. Finally, factor PA3 represents *social learning* undertaken largely in interaction with others.

NAL OF	505
ing and	

TABLE 5	Results from an exploratory factor analysis of the WLA scale	(EQ-sample)).	
WLA iter	n	Factor 1	oading	
Item	Description	PA1	PA2	PA3
PA1: Deli	perate Practice ^a			
LA03	Following new developments in my field	0.74	0.16	-0.16
LA12	Thinking deeply about my work	0.74	0.00	-0.03
LA01	Acquiring new information	0.72	-0.09	0.09
LA11	Finding a better way to do a task by trial and error	0.61	-0.09	0.17
LA04	Performing tasks that are new to me	0.57	-0.09	0.25
LA09	Reading articles/books to acquire knowledge	0.55	0.36	-0.24
LA14	Learning from online community forums	0.48	0.18	-0.05
LA13	Receiving feedback on my projects	0.41	-0.08	0.13
PA2: Form	nal Learning ^b			
LA07	Taking free online courses	0.07	0.78	0.00
LA08	Using paid online tutorials	0.05	0.76	-0.01
LA06	Attending a training course/workshop	-0.11	0.73	0.22
PA3: Socia	al Learning ^c			
LA05	Asking others for advice	-0.09	0.03	0.77
LA02	Collaborating with others	0.01	-0.02	0.71
LA10	Observing/replicating other people's strategies	0.12	0.24	0.46

Note: Factor loadings above 0.40 are in bold. Item codes refer to the final questionnaire in the appendix. The cumulative proportion of variance is explained below.

Abbreviation: WLA, workplace learning activities.

^aPA1: 0.23.

^bPA2: 0.39.

^cPA3: 0.50.

Examples include learning with/from fellow crowdworker through *collaboration* or *replication* of others' behaviors and strategies.

In the PA sample, we tested the model fit of the three-factor EFA solution against two alternatives: a unidimensional model as described by Fontana et al. (2015) and a two-factor model differentiating between informal and formal learning (Table 6).

CFA supported the three-factor EFA solution, which demonstrated the relatively best fit compared to the alternatives. All standardized parameter estimates reach the threshold of 0.5 bar giving feedback (0.48). Despite this, the item was retained for its theoretical relevance to the *deliberate practice* concept, where the giving and receiving of feedback are central. Measures of reliability (Table 7) are overall acceptable, though *social learning* (PA3) demonstrates insufficient internal consistency in the PA sample. This calls into question the convergent validity of this factor. Social learning strategies exist but are not prevalent in crowdwork contexts (47 per cent reported undertaking at least one activity involving *collaboration, asking for advice* or *observation, and replication* at least weekly). Other previous

	χ^2		RMSEA			
Model	Value	df	Value	90% CI	SRMR	CFI
One-factor model ^a	536.909***	77	0.115***	[0.106, 0.124]	0.102	0.878
Two-factor model ^b	367.676***	76	0.092***	[0.083, 0.101]	0.082	0.923
Three-factor model ^c	322.565***	74	0.086***	[0.076, 0.096]	0.076	0.934

 TABLE 6
 Results of confirmatory factor analysis for models of WLA.

^aAll items load onto a single factor representing propensity for workplace learning.

^bIn the two-factor model items are loaded onto two factors representing formal and informal learning activities, two dimensions originally considered by Fontana et al. (2015)

^cThe three-factor model is based on the EFA results and items are loaded onto three factors representing deliberate practice, formal learning, and social learning.

***p < 0.001.

Subscale	ω	α	AVE
EQ-sample ^a			
PA1: Deliberate Practice	0.82 [0.80, 0.85]	0.85 [0.82, 0.87]	0.43
PA2: Formal Learning	0.76 [0.72, 0.80]	0.83 [0.80, 0.86]	0.63
PA3: Social Learning	0.68 [0.60, 0.72]	0.74 [0.68, 0.78]	0.49
PA-sample ^b			
PA1: Deliberate Practice	0.82 [0.79, 0.85]	0.85 [0.82, 0.87]	0.42
PA2: Formal Learning	0.82 [0.78, 0.86]	0.89 [0.85, 0.91]	0.74
PA3: Social Learning	0.60 [0.50, 0.67]	0.65 [0.57, 0.72]	0.40

TABLE 7 Internal consistency measures for WLA.

Note: 95 per cent confidence intervals in brackets.

Abbreviations: AVE, average variance extracted; WLA, workplace learning activities.

 $^{\rm a}N = 527.$

 ${}^{\rm b}N = 465.$

surveys (Margaryan, 2019a, 2019b) corroborate the presence of social learning in crowdwork and justify the theoretical composition of the factor, therefore, these items were retained. Discriminant validity of the WLA scale was established by examining the HTMT ratios between the latent constructs (<0.80).

Similar to SDEV, for WLA, we demonstrated measurement invariance across workers who specialise in design and writing or translation, European geographies, and levels of platform dependence. For the two occupational groups, the configural model showed adequate fit (RMSEA = 0.069, CFI = 0.953, SRMR = 0.069). Adding constraints on thresholds, $\Delta \chi^2(14) = 15.817$, p = 0.325, and factor loadings, $\Delta \chi^2(11) = 11.797$, p = 0.379, did not significantly worsen model fit. For participants from the two European regions, the configural model indicated adequate fit (RMSEA = 0.074, CFI = 0.950, SRMR = 0.063) which did not change significantly for adding constraints on thresholds, $\Delta \chi^2(14) = 17.877$, p = 0.212; factor loadings, $\Delta \chi^2(11) = 14.133$, p = 0.226; and intercepts, $\Delta \chi^2(11) = 19.618$, p = 0.051. Similarly, for the two levels of platform dependence, the



Items LS35, LS01, LS23, and LS23 (refer to the full questionnaire) were excluded from the scale because they correlated with fewer than half of all other items within the range of 0.15–0.50. Three further items, LS06, LS18, and LS22, failed to load during subsequent EFA and were

configural model showed adequate fit (RMSEA = 0.070, CFI = 0.956, SRMR = 0.063) which did not significantly change once the three constraints were added, $\Delta \chi^2(14) = 16.047$, p = 0.311; $\Delta \chi^2(11) = 10.241, p = 0.509; \Delta \chi^2(11) = 14.277, p = 0.218.$

SRLS scale

dropped. Two of the three items originally hypothesized to be part of the *self-efficacy* subprocess of SRL failed to load adequately. On re-examining the items we concluded that the limited selection of items in the original scale is inadequate to capture the complex and multifaceted aspects of self-efficacy, such as the perceived experiences of handling challenging situations during crowdwork and crowdworkers' confidence in their learning abilities and subsequent improvement of outcomes. More importantly, self-efficacy represents a set of 'beliefs' and as such reflects the 'affective' aspect of self-regulated learning (Zimmerman, 2006) rather than capturing specifically behavioral aspects that the new WLCQ instruments is focused on. Therefore, we drop the items associated with the self-efficacy construct and propose that in the future, crowdworkers' self-efficacy beliefs are measured through a separate scale.

After removing problematic items, scree plot and parallel analysis suggested a seven-factor EFA solution (Table 8).

The resulting structure is largely in line with Zimmerman's SRL model, with some noteworthy deviations. The forethought phase of the SRL model comprises task analysis, captured by short- and long-term goal setting (PA2) and self-motivational beliefs including intrinsic task value/interest (PA5). The performance phase in Zimmerman's model, during which the individual executes the work task and simultaneously engages in the learning process, is constituted by subprocesses of self-control and self-observation. Our EFA results (Table 8) hint at potentially a more nuanced structure of this phase. Traditional SRL self-control strategies (e.g., time management) or task strategies (e.g., note-taking or organization of thoughts through diagrams) still load as one latent factor (PA6). However, our analysis suggests that in crowdwork self-observation (PA1) may be characterized by more action-driven-in particular adaptation-focused-strategies than in Zimmerman's model developed in formal learning settings, where self-observation strategies tend to be conceptualized as mostly mental self-tracking and physical self-recording of one's progress towards learning goals. In addition, one latent factor appears to load on both workers' self-control and self-observation strategies, which in our data show explicit continuity of learning from workers' past experiences to present tasks and future opportunities. This latent factor is interpreted as *learning transfer* (PA3), a phenomenon well-researched in educational psychology (Perkins & Salomon, 1992) which denotes learners' ability to apply knowledge and skills across contexts (e.g., from university to the workplace) and time horizon (such as from past to present experiences). The third phase in Zimmerman's model, self-reflection, is characterized by processes of selfjudgement, the evaluation of one's own performance, and self-reaction, the drawing of adaptive inferences. Both subprocesses were confirmed through our analysis as represented as latent factor PA4 (Table 8).

Finally, latent variable PA7, composed of items measuring social SRLS involving other workers, cannot be matched to one of Zimmerman's phases exclusively. The scale items under ,

Training

FABLE 8	Results from an	Exploratory	Factor A	Analysis	of the SR	LS Scale	(EQ-sampl	le).
---------	-----------------	-------------	----------	----------	-----------	----------	-----------	------

SRLS It	em	Factor loading	ng					
Item		Description	PA1	PA2	PA3	PA4	PA5	PA6
PA1: Sel	lf-observation ^a							
LS10	Changing my strategies	0.79	0.11	0.08	0.03	-0.01	-0.18	-0.03
LS09	Adapting learning strategies to each project	0.70	-0.09	0.13	0.00	0.03	-0.01	0.02
LS12	Using different strategies for each thing	0.63	-0.22	0.06	0.02	-0.04	0.02	0.17
LS07	Choosing the best strategy	0.62	0.27	-0.25	0.14	-0.01	0.00	0.06
LS08	Using strategies that have worked in the past	0.55	0.13	0.07	-0.09	0.00	0.02	0.00
LS11	Changing my learning goals	0.54	0.20	0.03	0.03	-0.01	0.00	-0.03
PA2: Go	al setting ^b							
LS04	Planning how I'll achieve my learning goals	0.02	0.84	-0.12	0.13	-0.03	0.06	0.03
LS02	Setting short-term learning goals	-0.03	0.72	0.06	-0.10	0.03	0.16	-0.06
LS05	Regularly reviewing progress	0.06	0.72	0.01	0.10	0.01	0.06	0.01
LS03	Setting long-term learning goals	0.19	0.58	0.11	-0.17	-0.06	0.10	-0.03
PA3: Tra	ansfer of skills and knowledge C							
LS19	Applying lessons learned	0.14	-0.18	0.86	-0.07	-0.10	0.10	-0.09
LS13	Using what I learn in my future jobs	0.00	0.13	0.78	-0.20	0.02	-0.13	0.12
LS32	Thinking about impacts on other projects	-0.16	-0.01	0.51	0.22	-0.01	0.04	0.15
LS20	Treat new information as a starting point	0.20	-0.17	0.42	0.10	0.08	0.30	-0.15
LS15	Learnings related to what I already know	0.06	0.07	0.31	0.30	0.11	0.13	-0.11
PA4: Sel	If-reflection ^d							
LS28	Thinking about what I have learned	0.12	0.02	-0.13	0.91	0.01	0.05	-0.06
LS29	Bigger picture of my professional development	-0.08	0.15	0.31	0.63	-0.09	-0.06	0.03
LS27	Asking myself if there were better ways to do it	0.18	-0.02	-0.07	0.60	0.05	0.08	-0.01
PA5: Ta	sk value/interest ^e							
LS26	Preferring challenging projects	0.00	-0.02	-0.07	-0.05	0.94	0.05	-0.01
LS25	Projects that require me to learn something new	-0.02	-0.05	-0.02	0.04	0.93	0.01	-0.03
LS14	Important for me to learn new things	0.05	0.17	0.31	0.02	0.44	-0.21	0.10

INTERNATIONAL JOURNAL OF 509

TABLE 8 (Continued)

SRLS Item		Factor loading							
Item		Description	PA1	PA2	PA3	PA4	PA5	PA6	
PA6: Sel	lf-control strategies ^f								
LS17	Blocking time in my calendar	-0.07	0.37	-0.02	0.05	-0.07	0.63	-0.01	
LS16	Making notes or diagrams	-0.10	0.04	0.22	-0.05	-0.05	0.62	-0.02	
LS33	Writing up private notes and not sharing	-0.10	0.01	-0.10	0.11	0.11	0.60	0.07	
PA7: Social learning strategies ^g									
LS31	Sharing what I have learned	0.05	-0.02	0.07	-0.04	-0.04	-0.02	0.84	
LS34	Writing up notes and share these with others	0.02	0.03	-0.21	-0.15	0.11	0.44	0.58	
LS30	Considering how learning may interest others	-0.02	0.01	0.12	0.32	-0.07	-0.08	0.52	
LS21	Asking others for help	0.00	-0.02	0.09	-0.09	-0.03	0.19	0.45	

Note: Factor loadings above 0.40 are in bold. Item codes refer to the final questionnaire in the appendix. The cumulative proportion of variance is explained below.

^aPA1: 0.11.

^bPA2: 0.21.

^cPA4: 0.38.

^dPA5: 0.45.

^ePA6: 0.52.

^fPA7: 0.58.

^gPA3: 0.30.

PA7 include *help-seeking*, *note-taking*, and *sharing experiences with others*, suggesting the factor is simultaneously lodged in the *performance* and *self-reflection* phases. Although Zimmerman's model recognizes that the SRL subprocesses often involve other people (referred to as 'significant others'), the social SRL processes are not conceptualized as a distinct set of strategies within the original model.

Using the PA-sample, the seven-factor model suggested by EFA (Table 8) is tested against two alternatives (Table 9): a unidimensional model of SRL strategies, and a representation of Zimmerman's three cyclical phases of SRL.

CFA results indicate that the EFA-derived seven-factor model has a statistically significant better fit than the alternative models. All items load significantly on the hypothesized latent factors. As shown in Table 10, the majority of SRL subscales demonstrate adequate internal consistency, justifying the continuation of scale development.

PA6 (self-control) demonstrates ω values slightly below the commonly acceptable cut-off in both samples. However, the construct is retained due to its theoretical significance. Convergent validity is indicated by statistically significant factor loadings (<0.54) and acceptable AVE values for all factors apart from PA7 (social learning), which falls slightly below the threshold. We proceed under the assumption of convergent validity based on the theoretically justified cohesion between the items composing PA7. Discriminant construct validity is also indicated based on the HTMT ratios between the latent constructs (<0.75).

TABLE 9	Results of	confirmatory	factor	analysis	for	models	of SI	RLS.
---------	------------	--------------	--------	----------	-----	--------	-------	------

	χ^2		RMSEA			
Model	Value	df	Value	90% CI	SRMR	CFI
One-factor model ^a	2526.838***	299	0.128***	[0.123, 0.133]	0.110	0.760
Three-factor model ^b	9622.949***	325	0.116***	[0.112, 0.121]	0.103	0.804
Seven-factor model ^c	1201.708***	329	0.076***	[0.072, 0.081]	0.068	0.912

Abbreviations: SRLS, self-regulated learning strategies.

^aIn the one-factor model SRL is interpreted a unidimensional scale with a single latent trait representing general propensity for self-regulated learning.

^bIn the three-factor model SRLS are modelled along the three cyclical phases of self-regulated learning (Zimmerman, 2006) forethought, performance and self-evaluation-without accounting for the self-regulatory subprocesses.

^cThe seven-factor model is based on the EFA results.

***p < 0.001.

ABLE 10 Internal consistency measures for SRLS.						
Subscale	ω	α				
EQ-sample ^a						
PA1: Self-observation	0.83 [0.80, 0.85]	0.85 [0.83, 0.87]				
PA2: Goal-setting	0.84 [0.81, 0.86]	0.87 [0.85, 0.89]				
PA3: Transfer of skills & knowledge	0.76 [0.72, 0.79]	0.80 [0.77, 0.83]				
PA4: Self-reflection	0.81 [0.77, 0.84]	0.84 [0.80, 0.87]				
PA5: Task value/interest	0.85 [0.81, 0.88]	0.84 [0.80, 0.87]				
PA6: Self-control strategies	0.64 [0.57, 0.69]	0.71 [0.65, 0.76]				
PA7: Social learning	0.71 [0.67, 0.75]	0.76 [0.72, 0.80]				
PA-sample ^b						
PA1: Self-observation	0.84 [0.82, 0.87]	0.86 [0.83, 0.89]				
PA2: Goal-setting	0.87 [0.85, 0.89]	0.91 0[.88, 0.92]				
PA3: Transfer of skills & knowledge	0.78 [0.74, 0.81]	0.82 [0.78, 0.85]				
PA4: Self-reflection	0.80 [0.75, 0.83]	0.84 0[.79, 0.87]				
PA5: Task value/interest	0.83 [0.79, 0.86]	0.82 [0.77, 0.85]				
PA6: Self-control strategies	0.68 [0.62, 0.74]	0.75 [0.70, 0.80]				
PA7: Social learning	0.73 [0.67, 0.77]	0.75 [0.70, 0.80]				

TABLE 10	Internal	consistency	measures	for	SRLS
----------	----------	-------------	----------	-----	------

Note: 95 per cent confidence intervals in brackets.

Abbreviations: AVE, average variance explained; SRLS, self-regulated learning strategies.

 $^{a}N = 527.$

 ${}^{b}N = 465.$

For SRLS, we were able to show measurement invariance across the three tested groupings. For the two occupational groups, the configural model showed adequate fit (RMSEA = 0.066, CFI = 0.935, SRMR = 0.069) which did not significantly change once constraints on thresholds, $\Delta \chi^2(28) = 28.084$, p = 0.46; loadings, $\Delta \chi^2(21) = 29.284$, p = 0.11; and intercepts, $\Delta \chi^2(21) = 21.048$,

AVE

0.50 0.64 0.45 0.66 0.73 0.46 0.46

0.54 0.72 0.47 0.64 0.70 0.51 0.47



p = 0.46, were subsequently added. For the workers located in either Northwestern or Southeastern Europe, the configural model demonstrated adequate fit (RMSEA = 0.068, CFI = 0.931, SRMR = 0.063) which did not significantly worsen when constraints were added for thresholds, $\Delta \chi^2(28) = 30.214$, p = 0.353; and factor loadings, $\Delta \chi^2(21) = 22.401$, p = 0.377. Last, for the two groups with varying financial dependence on crowdwork, the configural model demonstrated adequate fit (RMSEA = 0.064, CFI = 0.940, SRMR = 0.063) which was not significantly worsened by adding additional constraints, $\Delta \chi^2(28) = 37.353$, p = 0.111; $\Delta \chi^2(21) = 23.027$, p = 0.343; $\Delta \chi^2(21) = 30.740$, p = 0.078.

CONTRIBUTIONS AND IMPLICATIONS FOR THEORY AND PRACTICE

Our paper has implications for at least two fields of research: workplace learning in online platform work and self-regulated learning theory.

Implications for workplace learning and development in crowdwork

The paper contributes original empirical evidence on workplace learning and skill development in a relevant new phenomenon—online crowdwork platforms—which, despite their rapidly increasing uptake around the world, not least in the context of the ongoing COVID-19 pandemic (Spurk & Straub, 2020), remain under-researched. The focus on crowdworkers' learning as a distinct type of workplace learning behavior is warranted because online platform settings are different from conventional organizational settings in terms of task interdependences, lack of organizational scaffolds for learning, training, and incidental knowledge sharing, as well as the overall shift of responsibility for learning to workers.

Our study makes two distinct contributions to the nascent research on workplace learning in crowdwork. First, we contribute a new typology of skills developed through crowdwork. The typology comprises nine different skill sets, including seven skill types across core/technical and transversal skills categories well-established in the literature, and two skill types specific to crowdwork settings that are new in the literature. Our findings contribute important evidence that despite the structural constraints inherent in online platform work and the lack of organizational support for learning and development, crowdworkers engage extensively in selfregulated learning and skill development through their daily work on the platforms. Second, we contribute to the literature by showing that the workplace learning behavior in crowdwork takes at least three forms: deliberate practice (largely individual learning by engaging in challenging work tasks, practicing systemically, and receiving formative feedback from clients); social learning (learning through knowledge sharing, help-seeking, and help giving) and to a lesser extent self-initiated formal learning (deciding to participate in instructional courses or workshops). Of these, deliberate practice appears to be the most frequent type of learning behavior amongst crowdworkers, likely because of the autonomous nature of this study and crowdworkers' 'just-in-time' approach to learning due to cost-benefit considerations when deciding on the investment of time in learning. However, both social learning and self-initiated formal learning also are a part of learning practices in crowdwork. Future research should examine if these learning behavior types are replicated in other crowdwork platforms and among other types of platform workers.

Contributions to self-regulated learning theory

Our findings make an empirically grounded theoretical contribution by pointing toward at least three key conceptual differences between the structure of SRL in online platform work and the structure advanced in the literature. First, the three phases postulated in the literature appear to be less distinct and more closely intertwined in crowdwork settings, probably due to the largely ad hoc, experiential nature of learning in crowdwork. This further validates findings from some recent studies from organisationally based work contexts. Namely, Cuyvers et al. (2020; 2021) problematized the notion of distinct phases in SRL and empirically illustrated through a longitudinal, multiple case study design the interrelated, dynamic nature of SRL in the workplace, with no evidence found for distinct phases. Also, an earlier, smaller-scale, exploratory study by Margaryan et al. (2013) suggested that SRL processes in the workplace are iterative and fluid rather than delineated into discrete stages as postulated by the phase models. One noteworthy example is *social learning strategies*, which in crowdwork take place both in the performance and self-reflection phases, whereas in Zimmerman's model they are postulated to occur in the performance phase only.

The second deviation from extant SRL theory we surfaced is that the *performance* phase, when applied to crowdwork, appears to fail to account for an important subphase at the intersection of *self-control* and *self-observation strategies* that concerns *learning transfer*, which requires aspects of both subprocesses. This category includes *planning ahead for the application of newly acquired skills in future jobs*, an element of the *forethought* phase, suggesting these two phases are also closely interconnected in crowdwork settings and concurrent during task execution.

Our third theoretical contribution is the identification of SRL processes that appear to be *particularly prominent* in crowdwork: action-oriented adaptation, goal setting, continuous transfer of learning, self-reflection, intrinsic value of tasks, self-control, and social learning strategies. Although most of these SRL processes are postulated in Zimmerman's model, one of them—continuous transfer of learning—is a new contribution emerging from our study. Taken together, our findings suggest that although multiprocess explanations of SRL hold in crowdwork settings, the phase models may have to be reconsidered when applied to the (crowd) workplace.

Implications for practice

The WLCQ can be used by crowdworkers to support self-reflection on their learning and development. Our data suggest that the respondents recognized and valued the developmental function of the survey. Potentially the WLCQ can be designed as a web-based, interactive tool to be included within the platforms' interfaces or offered as an open tool that workers can use to plan and reflect on their learning.

Our study also has implications for platform owners. The majority of crowdwork tasks and workflows are currently designed to be carried out autonomously and the complex interdependences typically found in organisationally embedded work are deliberately designed out of crowdwork. However, our study demonstrates that, despite these structural constraints, crowdworkers adopt social learning activities and strategies. Platforms could consider how workplace learning and development could be incorporated as an explicit dimension of the workflows, conceptually, and practically, for example, by enabling functionality for workers to

513

find and select tasks that fit their learning goals or structurally supporting them in engaging in social learning and knowledge sharing practices. Platforms could utilize the WLCQ to enhance workers' user experience by offering better professional development perspectives as well as improving their business models, fostering learning, productivity, and well-being in crowdwork.

CONCLUSIONS, LIMITATIONS, AND FURTHER RESEARCH

We presented a new instrument, the WLCQ, to survey and analyze workplace learning behaviors in crowdwork, an emergent and growing form of online platform work. Our analyses demonstrated the internal validity and reliability of the scales surfacing some important deviations from theory which contribute novel insights into the nature of self-regulated workplace learning in a new form of work and warrant further research. Analysis of measurement invariance showed the models underpinning the instrument performed adequately across groups differentiated by their geography, primary category of work, and financial dependence on the platform.

The WLCQ contributes an original instrument to survey and analyze self-regulated workplace learning in crowdwork. The originality of the instrument is three-fold. First, the WLCQ addresses conceptual and methodological gaps in our understanding of workplace and self-regulated learning in crowdwork and the lack of currently available instruments to survey and analyze these behaviors in a systematic and reliable way, well-documented in recent reviews (Cuyvers et al., 2020; Lehdonvirta et al., 2018; Sitzmann & Ely, 2011). Second, the WLCQ allows us to empirically test and adjust extant theory on workplace and self-regulated learning expanding and adding nuance to existing phase models of SRL as well as contributing a typology of skills developed through crowdwork.

Our study has at least three limitations that do not invalidate our findings but limit their generalisability. First, we only validated the internal structure of the WLCQ and used only one measurement occasion per participant. Future research should seek to additionally demonstrate convergent and discriminant validity with other external learning constructs and theoretically relevant variables, as well as include test-retest reliability analysis to establish temporal reliability. Second, our sampling strategy may suffer from economic self-selection (Lehdonvirta et al., 2020), whereby workers' opportunity costs may shape our findings. While the financial compensation offered to respondents was reasonably high compared to similar studies (about \$9.50 for 20-25 min of work), it remains relatively more attractive to lower-paid than higher-paid crowdworkers. Higher-paid crowdworkers may therefore be underrepresented in our study. On crowdwork platforms, a higher rate is often assumed to signal higher skill, and it is plausible that higher-paid crowdworkers may adopt qualitatively and quantitatively different learning behaviors than lower-paid workers. Third, the validation of the WLCQ instrument is limited to respondents who worked from a small number of EU countries. Although our sampling strategy was designed to include a diverse set of countries representative of the main types of economic regimes in Europe, the generalisability of our findings to other countries is unknown. Future research should extend the sample to other geographies, for instance, middle- and low-income countries.

ACKNOWLEDGEMENTS

The development and validation of the WLCQ were made possible through funding from the Alexander von Humboldt Foundation and the European Centre for the Development of

514

Vocational Training (Cedefop). The authors would like to thank the crowdwork platforms and workers for participating in the survey and colleagues for helpful comments and assistance in the development of the instrument and the paper: Vili Lehdonvirta, Otto Kässi, Laura Larke, Sian Brooks, Susanne Klausing, Gretta Corporaal, Huw Davies, Alex Wood, and Ujwal Gadiraju. The authors are grateful to the Editor-in-Chief Prof. Dr. Matthias Pilz and three anonymous reviewers for the improvements suggested.

ORCID

Anoush Margaryan https://orcid.org/0000-0002-1740-8104 Julian Albert https://orcid.org/0000-0002-1134-1359 Timothy Charlton-Czaplicki https://orcid.org/0000-0002-8003-1979

REFERENCES

- Anwar, M. A., & Graham, M. (2020). Between a rock and a hard place: Freedom, flexibility, precarity and vulnerability in the gig economy in Africa. *Competition & Change*, 1–22.
- Ashton, D. N. (2004). The political economy of workplace learning. In H. Rainbird, A. Fuller, & A. Munro (Eds.), Workplace learning in context (pp. 37–53). Routledge.
- Barnes, S.-A., Green, A., & de Hoyos, M. (2015). Crowdsourcing and work: Individual factors and circumstances influencing employability. *New Technology, Work and Employment*, 30(1), 16–31.
- Billett, S. (2001). Learning in the workplace: Strategies for effective practice. Allen & Unwin.
- Blaising, A., Kotturi, Y., Kulkarni, C., & Dabbish, L. (2021). Making it work, or not: A longitudinal study of career trajectories among online freelancers. *Proceedings of the ACM on Human-Computer Interaction*, 4, 1–29.
- Buchanan, J., Finegold, D., Mayhew, K., & Warhurst, C. (2017). The Oxford handbook of skills and training (1st ed.). Oxford University Press.
- Cedefop. (2020). Developing and matching skills in the online platform economy. (Reference Series No. 3085). Publications Office https://data.europa.eu/doi/10.2801/588297
- Clark, L., & Watson, D. (1995). Constructing validity: Basic issues in objective scale development. *Psychological Assessment*, 7(3), 309–319.
- Cuyvers, K., Donche, V., & van den Bossche, P. (2021). Unravelling the process of self-regulated learning of medical specialists in the clinical environment. *Journal of Workplace Learning*, 33(5), 375-400.
- Cuyvers, K., Van den Bossche, P., & Donche, V. (2020). Self-regulation of professional learning in the workplace. *Vocations and Learning*, *13*(2), 281–312.
- Eraut, M. (2004). Informal learning in the workplace. Studies in Continuing Education, 26(2), 247-273.
- Ericsson, K., Teschromer, C., & Krampe, R. T. (1993). The role of deliberate practice in the acquisition of expert performance. *Psychological Review*, *100*(3), 363–406.
- Flora, D. B., & Curran, P. J. (2004). An empirical evaluation of alternative methods of estimation for confirmatory factor analysis with ordinal data. *Psychological Methods*, 9(4), 466–491.
- Fontana, P., Milligan, C., Littlejohn, A., & Margaryan, A. (2015). Measuring self-regulated learning in the workplace. *International Journal of Training and Development*, 19(1), 32–52.
- Green, A., de Hoyos, M., Barnes, S.-A., Baldau, B., & Behle, H. (2014). *Exploratory research on Internet-enabled* work exchanges and employability. EC Institute for Prospective Technological Studies.
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variancebased structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135.
- Hinkin, T. R. (1998). A brief tutorial on the development of measures for use in survey questionnaires. Organizational Research Methods, 1(1), 104–121.
- Howcroft, D., & Bergvall-Kåreborn, B. (2018). A typology of crowdwork platforms. Work, Employment and Society, 33(1), 21–38.
- Hu, L.-T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1–55.



- Kässi, O., & Lehdonvirta, V. (2018). Online labour index. Technological Forecasting & Social Change, 137, 241–248.
- Lehdonvirta, V., Margaryan, A., & Davies, H. (2018). Literature review: Skill formation and skill matching in online platform work. Cedefop. https://www.cedefop.europa.eu/files/crowdlearn_literature_review.pdf
- Lehdonvirta, V., Oksanen, A., Räsänen, P., & Blank, G. (2020). Social media, web, and panel surveys: Using nonprobability samples in social and policy research. *Policy & Internet*, 1–22.
- Littlejohn, A., & Margaryan, A. (Eds.). (2014). Technology-enhanced professional learning. Routledge.
- Manuti, A., Pastore, S., Scardigno, A., Giancaspro, M., & Morciano, D. (2015). Formal and informal learning in the workplace: A research review. *International Journal of Training and Development*, 19(1), 1–17.
- Margaryan, A. (2019a). Workplace learning in crowdwork: Comparing microworkers' and online freelancers' practices. Journal of Workplace Learning, 31(4), 250–273.
- Margaryan, A. (2019b). Comparing crowdworkers' and conventional knowledge workers' self-regulated learning strategies in the workplace. *Human Computation*, *6*(1), 83–97.
- Margaryan, A., Littlejohn, A., & Milligan, C. (2013). Self-regulated learning in the workplace. International Journal of Training and Development, 17(4), 245–259.
- Perkins, D. N., & Salomon, G. (1992). Transfer of learning, *Encyclopedia of Education* (2nd ed.). Pergamon Press. Rainbird, H., Fuller, A., & Munro, A. (Eds.). (2004). *Workplace learning in context*. Routledge.
- Sitzmann, T., & Ely, K. (2011). A meta-analysis of self-regulated learning in work-related training and
- educational attainment: What we know and where we need to go. Psychological Bulletin, 137(3), 421-442.
- Skule, S. (2004). Learning conditions at work: A framework to understand and assess informal learning in the workplace. *International Journal of Training and Development*, 8(1), 8–20.
- Spencer, N., Huws, U., Syrdal, D., & Holts, K. (2018). Work in the European gig economy. https://uhra.herts.ac. uk/bitstream/handle/2299/19922/Huws_U._Spencer_N.H._Syrdal_D.S._Holt_K._2017_.pdf
- Spurk, D., & Straub, C. (2020). Flexible employment relationships and careers in times of the COVID-19 pandemic. *Journal of Vocational Behavior*, *119*, 119.
- Svetina, D., Rutkowski, L., & Rutkowski, D. (2020). Multiple-group invariance with categorical outcomes using updated guidelines: An illustration using M *plus* and the lavaan/sem tools packages. *Structural Equation Modeling: A Multidisciplinary Journal*, 27(1), 111–130.
- Taylor, J., & Joshi, K. D. (2019). Joining the crowd: The career anchors of information technology workers participating in crowdsourcing. *Information Systems Journal*, 29(3), 641–673.
- Zimmerman, B. J. (2006). Development and adaptation of expertise: The role of self-regulatory processes and beliefs. In A. Ericsson, N. Charness, P. Feltovich, & R. Hoffman (Eds.), *The Cambridge handbook of expertise and expert performance* (pp. 705–722). Cambridge University Press.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Margaryan, A., Albert, J., & Charlton-Czaplicki, T. (2022). Workplace learning in Crowdwork Questionnaire (WLCQ): Measuring self-regulated learning and skill development in online platform work. *International Journal of Training and Development*, 26, 495–515. https://doi.org/10.1111/ijtd.12268