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Article *in* Journal of Education and Work · June 2021

DOI: 10.1080/13639080.2021.1931668

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"This is an Accepted Manuscript of an article published online by Taylor & Francis in *Journal of Education and Work* on 06 June 2021, available online: https://doi.org/10.1080/13639080.2021.1931668"

Graduates’ Career Success Predicted by Mathematical and Affective Abilities, Effective Higher-Education Learning and Economic Contexts: A Bioecological Positivity to Success Model

This study posits a bioecological positivity to success (BEPS) model and examines how diverse bioecological factors predict graduates’ career success. The BEPS model with an emphasis on hard (e.g. science, technology, engineering and mathematics [STEM]) and soft (e.g. interpersonal and critical thinking) skills generate a hypothetical model: positive aspects of person (mathematical/hard and affective/soft abilities), process (effective hard and soft competencies learning in higher education) and proximal contexts (original family income and present employment status) predict graduates’ career success (job income and perceived extrinsic, intrinsic and autonomy satisfaction) in early adulthood. Gender, studying STEM, and study years are also included as predictors in the path analysis as control. Path analyses examine the model with cohort data from the Taiwan Education Panel Survey (TEPS) and its follow-up (TEPS-B), which are longitudinal studies of a group of young people (n = 2,700) since grade 7 till age 24-25 years old. Results reveal that soft skills and employment play the most significant roles in graduates’ career success. Hard skills play a minor role. Findings support the BEPS model and provide implications for educational practices and policymaking to emphasise on soft skills learning, employability and entrepreneurship education.

Keywords: bioecological theories; career success; higher education; hard and soft skills

Introduction

The massification trend in higher education challenges institutions in providing high quality teaching and in preparing their graduates for socio-economic development or career success (Hornsby and Osman, 2014). Notably, the influence of neoliberalism fundamentally transforms the role of higher education from ‘public good’ to ‘private good’, and the cultivation of ‘employability’ has become the primary concern of universities and higher education graduates (Marginson, 2016; Mok and Jiang, 2018). While global higher education discusses the significance of ‘employability’ for the graduates’, future career development and success, the factors in college students' education that contribute to a successful career remain in question. Therefore, going beyond the superficial emphasis on employability is necessary and the factors that may predict career success of higher education graduates are worth exploring. The current study aims to provide insights into the re-thinking of graduates' career success and institutional effectiveness.

To achieve the above goal, this study identifies longitudinal and bioecological factors that predict graduates' career success and provides corresponding educational provisions. Our analytical approach involves prediction, which allows for inferring causation or more broadly comprehension. At the least, longitudinal cohort data examined in this study can partially address the issue of cause and effect.

Defining Career Success of Higher Education Graduates

Extensive literature is available regarding the theories, models and factors of career success (Heslin, 2005; Suprk, Hirschi and Dries, 2019). Everett Hughes (1937, 1958) categorised career in *objective* and *subjective* aspects and set a foundation for research on career success. In particular, objective career success is measured by verifiable attainments such as income, promotions and occupational status, while subjective career success is evaluated by employee perceptions of career experiences (Heslin, 2005). The objective measures are commonly applied as the hallmarks for career success (Nicholson, 2000). With the operationalisation of career success as 'job satisfaction' (Thorndike, 1934) and its further studies (Locke, 1969), subjective criteria have entered the discourse of career success and job satisfaction has attracted research focus in recent decades (e.g. Hall, 2002; Waaijer et al., 2017).

In higher education, colleges and universities commonly use graduates' career success to measure institutional effectiveness (Kuh and Ewell, 2010). Various alumni survey use income as the fit-for-all measure of career success. However, such measure has been criticised due to its failure in capturing the complexity of graduates' employment in different disciplines and its ignorance of the connection between graduates' educational experiences, workplace engagement and well-being (Dumford and Miller, 2015). In addition, higher education graduates with different levels of credentials (as bachelor's, master's and doctorate) have different expectations regarding career success after entering the job market (Jackson, 2013; Waaijer et al. 2017).

Job satisfaction is increasingly used to investigate the career success of higher education graduates (e.g. Bender and Heywood, 2006; Sabharwal and Corley, 2009; Waaijer et al., 2017). For example, the work–preference model is developed to study job satisfaction from both extrinsic (e.g. income) and intrinsic (e.g. motivation) perspectives (Throsby, 1994, 2001). With this reference, Dumford and Miller (2015) suggest that job satisfaction of higher education institution graduates can be categorised into extrinsic and intrinsic aspects.

In the current study, the above categorisation is used to define career success as extrinsic (e.g. income and job security) and intrinsic (e.g. work reflecting personality, interest and values; opportunities to be creative; and contributions to the greater good) satisfaction (Dumford and Miller, 2015). In addition to extrinsic and intrinsic satisfaction, this study also considers the essence of job autonomy, which refers to the high work flexibility regarding contents, pace and procedure of completing tasks and allocation of work and casual time. Job autonomy is of value for young generations especially in this era of advanced development of information and communication technology (e.g. work at home through the Internet). Job autonomy, however, is a complex concept, which relates to personal creative traits (Orth and Volmer, 2017) and organizations' cooperative climate (Llopis and Foss, 2016). Young entrepreneurs or freelancers may have higher job autonomy but encounter stress and insecurity.

Theoretical Basis

Bioecological models

Originating from the ecological theories of human development that emphasise the interaction among ecological systems (Bronfenbrenner, 1979, 1989), 'the bioecological model, together with its corresponding research designs, is an evolving theoretical system for the scientific study of human development over time' (Bronfenbrenner and Morris 2006, p. 794). Later, the bioecological model focuses on longitudinal changes of four elements: person, process, context and time. According to bioecological theory, individual lives are embedded or shaped by historical times and events, especially transitions over different stages of events, study and career development (Bronfenbrenner and Morris, 2006).

Positive affect to success (PAS) hypothesis

The PAS hypothesis is that 'positive affect engenders success' (Lyubomirsky, King and Diener, 2005, 803). Positive affects include long-term happiness and short-term, frequently experienced positive emotions (e.g. joy, interest and pride).

A bioecological positivity to success (BEPS) model

According to the aforementioned two theories, this study posits a BEPS model (Figure 1) that highlights the person, process, context and time (developmental) factors that contribute to career success. While the BEPS model serves as a theoretical framework, detailed factors related to career success are also addressed for further model elaboration.

<Insert Figure 1 here.>

Factors Relating to Career Success

Factors suggested by the BEPS model

According to bioecological theory, individual lives are shaped by historical times and events, especially transitions over different stages of events, study and career development (Bronfenbrenner and Morris, 2006). When the factors relevant to career success are investigated from the perspective of the BEPS model with four aspects (person, process, context and time), the skills (hard and soft) are found closely related to the first two aspects.

The person aspect covers the hard and soft abilities that the graduates are equipped with for their career development, while the process aspect investigates whether graduates have effective learning and training of relevant hard and soft competencies. The context aspect refers to economic status inheritance, including graduates' original family income and present job status. Finally, the time aspect includes distal factors since birth or temporary ones but still likely influence career success, such as graduates' gender, department choice and study year.

Gender serves as a contextual control because gender is a socio-cultural construct playing a different role for career success in different cultures. Gender also interacts with department choices (or disciplines), playing a role in career success. For example, although females are generally less satisfied than their male counterparts for most disciplines, one research (Bender and Heywood, 2006) shows that this is not true for other fields (e.g. computers and mathematics). Another study that compared genders, males are less satisfied in the fields of science and health but not in social science and engineering (Sabharwal and Corley, 2009).

Economists identify the intergenerational transmission of economic success by genetics (e.g. IQ) and environment (e.g. wealth, parenting and schooling), with the latter as more critical (Bowles and Gintis, 2001, 2002; Heckman and Mosso, 2014). General research of career success investigates various factors, including gender (e.g. Bender and Heywood, 2006; Sabharwal and Corley, 2009), nationality (e.g. Sabharwal, 2011), personality (e.g. Seibert and Kraimer, 2001), mentorship (Nick et al., 2012) and employment status (Wilkin, 2013). In particular, research explores factors regarding recent college graduates, including institutional-related factors, course quality, work experience, skill development, graduate identity, demographic characteristics and job search strategies (Jackson, 2013).

Hard and soft skills

A particular focus is paid to 'skills' as the natural factors contributing to career success. Compared with their peers, highly skilled graduates have more chances to receive higher pay and get promoted, especially when their skills trained in higher education match the demands of their job positions (Mavromaras et al., 2010).

Skills are divided into hard and soft aspects. Employee hiring generally depends on candidates' technical/hard and affective/soft skills (Laker and Powell, 2011; Litecky, Arnett and Prabhakar, 2004). This dichotomy is consistent with the emphasis of teaching hard and soft skills in educational systems. Hard skills refer to cognitive abilities, including those in mathematics and information and communications technology (ICT) and problem solving. Soft skills cover social, emotional and affective factors that can be categorised into three groups as 'approach to learning and work, interpersonal skills, and social skills' (Savitz-Romer, Rowan-Kenyon and Fancsali 2015, p. 19).

The emphasis of these two aspects of skills on educational attainment and career success changes with the times. In the first three industrial revolutions, hard skills attracted more attention in education and workplace. For example, higher education concentrates on STEM (science, technology, engineering and mathematics) and industries focus on technological skills. However, with the advent of the Fourth Industrial Revolution featuring artificial intelligence (AI) and autonomous robotics brings the fear of "technological unemployment," because AIs and robots are forecast to eliminate a significant number of job positions in various industries (World Bank 2016). However, it is still arguable how the Fourth Industrial Revolution will impact the labour market, and both optimistic and pessimistic perspectives co-exist (Marengo 2019; Ra et al. 2019). In the current literature, the optimistic views are increasingly taking the lead (Ra et al. 2019) as the existing estimates of the impact of AIs and automation on future work are criticized by the flaws in data collection on employable skills for specific job positions (Frank et al. 2019).

Despite the discussions on the impacts of Fourth Industrial Revolution, a growing trend emphasises soft skills such as interpersonal communications, which are playing a significant role in liberal arts education (Colvin, 2015). In particular, social, emotional and affective skills are increasingly connected to career success (Savitz–Romer et al., 2015). The significance of soft skills is also empirically approved in the workplace because they can facilitative the improvement of higher-level cognitive skills (Ra et al. 2019). For instance, in the technological giant, Google, its Project Oxygen of human resources survey indicates that human skills are the tops skills for successful employees (Davidson, 2019).

Research Questions

The proposed BEPS model and related literature suggest that diverse bioecological factors predict graduates' career success. Career success as the outcome is represented in both objective (job income) and subjective (job satisfaction) aspects. The predictors include positive factors in person (hard and soft abilities), process (effective hard and soft competencies learning in higher education) and proximal context (original family income and present employment status), controlling for developmental contexts (gender, department choice in higher education and study years). The two research questions addressed in this study are as follows.

(1) What are the effects of the bioecological factors on graduates' job income? (Model 1 in Figure 2)

(2) What are the effects of the bioecological factors on graduates' job satisfaction?

<Insert Figure 2 here.>

Method

Data Source and Sample

Cohort data from the Taiwan Education Panel Survey (TEPS) (Chang, 2001–2007) for adolescence and its follow-up (TEPS-B) (Kuan, 2017) for adulthood were obtained from the Survey Research Data Archive, Taiwan. Data for TPES were collected from grade-7 students (born in 1988/1989) and their parents (n = 20,055) beginning 2001. Follow-ups were carried out until 2007 during the students' grades 9, 11 and 12. TEPS-B further followed up a sub-sample of the cohort at their ages of 24–25 years in 2014 (n = 2,722). The sub-sample is a probability sample of the original TEPS sample of junior high (7^{th}-9^{th} grade) students. This sub-sample of students enrolled in the original TEPS sample of senior high schools, which were the sampled schools of another cohort (born in 1984/1985) surveyed by TEPS at the same time as the junior-high sample (Kuan, 2017). The sub-sample is also the only TEPS panel that offers information on the surveyed young people since grade 7 and onward.

The data analysis results were inferred to the original grade-7 student population using sampling weights provided by TEPS-B. Cases without weights (due to incomplete data in relevant variables) were removed, yielding a final sample size of 2,700. All further analyses were conducted by activating the weight and thus all findings could be inferred to the original grade-7 student population (n = 20,055).

Measures

A total of 14 measures were used, including four for the outcome (career success) and ten for predictors, as listed below.

Outcome: Career success

(1) Job income: Monthly salary in the latest job

(2) – (4) Perceived job satisfaction in extrinsic, intrinsic and autonomy aspects

Positive person predictors

(5) Hard (cognitive) ability: Grade-7 mathematical ability, which captures basic formal/abstract cognitive abilities (traditional academic intelligence or IQ) starting from adolescence

(6) Soft (affective) ability: Positive affect or positivity towards jobs and interpersonal relationships, which captures basic affective abilities (or emotional intelligence), including those related to employment, salient only after having jobs starting from early adulthood for most people in Taiwan

Positive process predictors

(7) Hard competencies: Effective science, technology, engineering and mathematics (STEM) learning in higher education

(8) Soft competencies: Effective emotional, developmental, and interpersonal learning in higher education

Positive contextual (economic) predictors

(9) Original family income: Parental reports on family income when the students were at grade-7

(10) Current employment status: Employed or unemployed because the outcome measures asking about the current/last job (Appendix) and thus this measure becomes essential as a proximal context

Time/developmental predictors/controls

(11) Gender (for person)

(12) Department choices: Domain choice in the latest degree (Study STEM vs. non-STEM)

(13) Interaction between gender and department choices

(14) Total study years (for context)

Except for original family income, gender and the measures with data collection time presented in the above list, all data were reported by the student participants at ages 24–25 (i.e. TEPS-B). The measurements used in this study, variables in the datasets, item content, scales and data preparation before the formal analysis are presented in Appendix.

Data Analysis

The two hypotheses were examined by path analysis using structural equation modelling (SEM) with the R software Version 3.6.1 (R Core Team, http://www.R-project.org), RStudio Version 1.2.5001, and related R packages.

Step 1. Calculate means, standard errors, and correlations for the 14 measures with activated weight using R jtools, weights, and survey packages.

Explaining correlations. The large sample size of this study could easily lead to a significant result. As such, a supplementary criterion was used to evaluate the effect size of a correlation coefficient, with absolute value of < 0.350 indicating a low relationship, 0.360–0.670 for a moderate relationship and > 0.680 for a high relationship (Taylor, 1990).

Step 2. Predict Income (Model 1) and three job satisfaction outcomes (Model 2) by (SEM) path analysis with activated weight using R lavaan and **lavaan.survey packages.**

All the 14 measures were transformed to manifest or observed variables and then to z scores before path analysis. The reason for z-score use is to reduce multicollinearity in regression analysis especially for the interaction term (e.g. Measure 13; Appendix) (Aiken, West and West, and Reno, 1991). Using SEM rather than linear regression analysis is to reflect the actual situation that the predictors and the outcomes between the three satisfaction measures are correlated (Figure 2).

Explaining path analysis (SEM) results. All path models in SEM (or multiple regression formulated as a SEM), unless setting constraints, are saturated or just-identified and have a zero degree of freedom (Raykov, Lee, Marcoulides, and Chang, 2013). It is because a saturated path model has exactly the number of free parameters equal to the total number of regression beta coefficients, measure variances, and covariances between the predictors and between the outcomes (Figure 2). As such, in the context of SEM path analysis, it is inappropriate to evaluate a saturated path model's fit to empirical data using the traditional model fit indices, such as a below 0.800 root mean square error of approximation (RMSEA), and a larger than 0.900 comparative fit index (CFI) or Tucker–Lewis index (TLI)) (Hair, Black, Babin and Anderson, 2010).

In this context of the saturated SEM path model, the regression coefficients obtained are still robust and trustworthy (Heyder, Kessels, and Steinmayr, 2017) especially using z scores or resulting in standardized regression coefficients (betas). The beta (standardized estimate) can be explained as a correlation between the outcome and the predictor controlling for all of the other predictors in the model. The value of beta can be directly explained like correlations: *r*s = 0.100 small, *r*s = 0.300 medium, and *r*s = .500 large effect sizes (Cohen, 1992). The relative relationships of the predictors with the outcome, therefore, can be inferred by comparing the absolute values of the betas of the predictors in a model. R squares are used to explain the total variance of the outcome to be examined by all of the predictors included in the path model.

Results

Correlations Between the Measures

Following general practice, we checked for potential multicollinearity in the regression (including path) analysis, which would result in non-trustworthy parameter estimates. Correlations between predictors that were larger than 0.900 serve as one indicator of multicollinearity, while smaller correlations indicate fewer such problems (Hair, Black, Babin, Anderson and Tatham, 2006).

In the current study, the correlations between predictors were between −0.098 and 0.479, all below 0.900 (Table 1). In addition, all the correlations were small except for two moderate ones (0.479 between hard ability and study year; 0.385 between hard and soft competencies). The results together with the use of SEM (allowing for correlations between predictors) revealed few multicollinearity problems in the parameter estimates.

<Insert Table 1 here.>

Predicting Job Income

Research Question 1 was explored using Model 1 (Figure 2; Table 2). The predictors could explain 9.1% of the total variance of job income, as shown by the R-square value of Model 1 (0.091; Table 2). The results showed that the current/last monthly salary (income) of the adults aged 24–25 could be significantly predicted by their current job status as being employed (beta = 0.202), soft ability (0.133) and hard ability (0.115), in descending order.

<Insert Table 2 here.>

Although not the focus of this study, females had fewer incomes than males (beta = −0.064) and could indicate gender inequality. The adults with longer study years had fewer incomes (−0.108). The result is inconsistent with the conservation of resources theory and empirical research finding that low education level is related to low salary (Ng and Feldman, 2014). One likely reason for this finding is that the participants were still in their early adulthood (ages 24–25 years) and several may still be studying and engaging in part-time or less demanding jobs. These results justify the need to include these measures (gender and study years) as predictors as controls, which serve as conditions in explaining the effects of the focused predictors in the path model (cf. Data Analysis/Step 3/ Explaining path analysis (SEM) results/the second paragraph).

Predicting Job Satisfaction

Model 2 (Figure 2) was used to answer Research Question 2. Model 2 accounted for extrinsic satisfaction by 17.3%, intrinsic satisfaction by 15.3% and autonomy satisfaction by 10.8% (Table 2).

The adults' extrinsic satisfaction was significantly predicted by employment (beta = 0.278) and soft ability (0.249), in descending order (Table 2). Their intrinsic satisfaction was significantly predicted by their soft ability (0.270), soft competencies learning in higher education (0.144), employment (0.128), and hard ability (0.046). The adults' autonomy satisfaction was positively predicted by soft ability (0.238) and employment (0.171). Autonomy satisfaction was also negatively predicted by the students' hard ability (−0.061).

Regarding the control variables, the adults who studied STEM had lower perceived autonomy satisfaction (beta = −0.071; Table 2) than their peers. This result is consistent with the negative effect of hard (mathematical) ability on autonomy satisfaction. Furthermore, study years positively predicted intrinsic satisfaction (0.060). The results showed that formal education related to intrinsic job satisfaction. The reasons for these significant, though small, effects are unknown and deserve future research.

Discussion

The BEPS Model Addresses Objective and Subjective Career Success

This study posits a BEPS model (Figure 1) based on bioecological theories (Bronfenbrenner, 1979, 1989; Bronfenbrenner and Morris, 2006) as a theoretical framework to investigate how graduates' career success is predicted by longitudinal person, process and context factors using path analyses. The respective investigation of two path models for career success in terms of job income and perceived job satisfaction (including extrinsic, intrinsic and autonomy satisfaction) successfully identifies significant predictors, all in descending order, for career success.

(1) Significant predictors for job income are employment, soft ability and hard ability;
(2) Significant predictors for extrinsic satisfaction are employment and soft ability;
(3) Significant predictors for intrinsic satisfaction are soft ability, effective soft competencies learning in higher education, employment and hard abilities; and
(4) Significant predictors for autonomy satisfaction are soft ability and employment but lower hard ability.

In summary, soft skills and employment play the largest roles in graduates' career success. It is because they both have positive effects on the four representations of career success (income, extrinsic satisfaction, intrinsic satisfaction, and autonomy satisfaction). Hard skills play minor roles. Parental family income fails to play any role. Although control variables are not the focus of this study, several significant roles are worthy of attention.

In summary, the findings generally support the BEPS model and provide implications for educational practices and policymaking. These major findings are further discussed with existing literature as follows.

Soft Skills Matters more than Hard Skills

Personal soft ability significantly predict all the aspects of career success and effective soft competencies learning in higher education predicts intrinsic satisfaction, whereas hard ability significantly predicts only income, intrinsic satisfaction and autonomy satisfaction, and hard competencies learning significantly predict none. The findings are consistent with previous research that soft skills are increasingly highly connected to career success (Davidson, 2019; Savitz-Romer et al., 2015) and the global trend of emphasising soft skills learning given the fourth industrial revolution (Colvin, 2015).

The greater emphasis on hard skills compared with soft skills has long persisted in K-12 and higher education curricula. Given the limited school times and tight schedules for diverse disciplines, schools and teachers sacrifice soft skills teaching to provide students with more opportunities for hard skills training. In fact, soft skills learning can be independent courses or naturally infused into hard skills (e.g. ICT and mathematics) courses. Furthermore, most teaching approaches or pedagogies aiming to develop higher-order student thinking or skills (e.g. project or problem-based, service and collaborative learning) focus on soft skills (e.g. deep, system, creative and critical thinking) (Davidson and Major, 2014).

The present findings indicate that both hard and soft skills are positive factors but the latter account for more aspects of career success than the former, thereby justifying further emphasis on soft skills in K-12 and higher education curricula. The case that education designs over-emphasise hard skills at the expense of soft skills can be transformed into transdisciplinary curricula such as STEAM, of which "A" stands for arts (Jho, Hong and Song, 2016), maker space and service learning. Future pedagogies can further focus on a simultaneous co-learning of both hard and soft skills.

Employment Matters Persistently for Career Success: Re-define 'Employment'

Employment is a robust approach to career success for both job income and different forms of job satisfaction. The global trend of massification of higher education in developed countries raises issues and debates on over-qualification, employability and gaps between formal education and actual jobs (Hornsby and Osman, 2014; Marginson, 2016; Mok and Jiang, 2018). Formal education excels at preparing the next generations with basic and core hard skills (e.g. language, mathematics and science) and soft skills (e.g. creativity, critical thinking and interpersonal interactions) for future lives using past cultural heritage, knowledge and artefacts. However, formal education is criticised for its fixed, inertia system and curricula that overly relies on cultural heritage, which may not well update and adapt itself to the fast-changing society driven by modern ICT development. Needless to say, AI development may replace numerous current jobs and unforeseen jobs may be created. Thus, the present appears to be a suitable time to re-define "employment," as addressed below.

Employment with old vs. new jobs in content

Employment in today’s society, therefore, not only involves the traditional industry where companies hire employees but also many entrepreneurs who create new ones. The proportions of traditional and new companies are likely to change gradually along the way towards the prevalence of AI-infused businesses. Governments and higher education institutions may need to invest in “employment” in at least two aspects, equally introducing traditional companies and supporting their undergraduate students in creating start-ups.

Employment in uncertain lifestyles of job types

Given the advance of AI, one side effect of the changing proportions of traditional and new jobs is that the expiration dates of any old jobs are unpredictable. The uncertainty of job duration becomes a crisis for people with a fixed work mindset, such as Taiwan with Confucian-culture values academia, including formal education degrees. Parents normally support their children along the direct path from K-12 to higher education. However, this direct path may not be a blessing but a drawback for their children’s future career success. Employment along the trajectory of formal education may be a necessity for the next generations’ career success (e.g. starting from primary or secondary education or at least starting from undergraduate stages). Changing this culturally imprinted mindset may not be easy but deserves early preparation through mass education (e.g. social media).

Family Income Fails to Predict Career Success

The findings that original family income fails to predict graduates’ career success in early adulthood are inconsistent with literature that states the intergenerational transmission of economic success (Bowles and Gintis, 2001, 2002). However, the positive, though very weak, correlations between family income and two indicators of career success (e.g. job income and intrinsic satisfaction) (Table 1) slightly support the intergenerational transmission of economic success. The seemingly paradoxical findings can be explained as the weak relationships between original family income in adolescent and job income or intrinsic satisfaction in adulthood are spurious and can be ignored when other essential predictors are included in the model. In particular, hard ability and study years have significant correlations with family income.

The findings demonstrate that career success can be determined by controllable factors such as personal hard and soft abilities and employment, more than by relatively uncontrollable, born-into backgrounds (e.g. original family income). The BEPS model thus addresses inspiring stories of career success more than singularly emphasising the socio-economic status of graduates' original families.

Minor Findings: Effects of the Control Variables

In addition to the focused person, process and context factors or predictors, this study examines the path models including three extra controlling factors: gender, department choices (field of study: study vs. not study STEM), the interaction between gender and study STEM, and study years. The findings show that gender and study years predict career success, while department choices fail to predict any such indicators.

Gender inequality in job income

Inequality remains between genders in Taiwan, favouring male graduates in their salary but not job satisfaction. This finding partially replicates related previous studies in Scotland, where male faculty members have higher salaries and job satisfaction (Sabharwal and Corley, 2009; Ward and Sloane, 2000). Low salary and 'career success' among females remain an issue to address and resolve by policymakers.

Department choices' vague role

Department choices (in terms of study STEM or not) fail to be an effective predictor for income, extrinsic satisfaction, and extrinsic satisfaction but is a negative, significant predictor for autonomy satisfaction. The result suggests that study STEM does mean higher career success than study non-STEM, especially in Taiwan.

One reason for the non-significant results may be due to the fact that both STEM and non-STEM actually represent diverse fields (cf. Appendix: Measure 12). For example, both engineering and mathematics are part of STEM but engineering faculty members may have a higher income than their mathematics colleagues. This income discrepancy may, in turn, influence job satisfaction (Sabharwal and Corley, 2009). Future research can use more detailed categories of department and job types and relate the categories to career success.

The reason for the significant, negative result (studying STEM predicts lower autonomy satisfaction), is uncertain. Job autonomy appears to relate to personal innovative behaviour and creative self-efficacy (Orth and Volmer, 2017) and organizations' cooperative climate emphasizing knowledge sharing behaviour (Llopis and Foss, 2016). Future research can explore this effect further by incorporating factors of personal and organizational behaviours. For example, a hypothesis may be whether STEM jobs are less creative especially within companies emphasizing competitiveness for young STEM employees in Taiwan.

Interaction between gender and department choices' weak effects

Suggested by related research (Bender and Heywood, 2006; Sabharwal and Corley, 2009), this study include interaction between gender and study STEM as a predictor. Although the interaction between gender and study STEM has a small, significantly positive correlation with income, this measure fails to be a significant effect in all the four aspects of career success in path analysis.

The reason may be that the effects are unstable especially with the fact that both STEM and non-STEM contain diverse fields. The slight positive correlation between income and the interaction between gender and study, however, still calls for further research on whether studying STEM favours females.

Study years as only a control

Study years negatively predict job income but positively predict intrinsic satisfaction. High achievers in academic fields can be expected to engage in postgraduate study during their early adulthood, which leads to speculation that using study years as a predictor is merely for control purposes, especially for job income.

For job satisfaction, study years positively predict intrinsic satisfaction. This finding suggests that people pursuing postgraduate education reflects their tendency to pursue personal growth. Future research can focus on studying relationships between study years and job satisfaction or motivation types (e.g., intrinsic and extrinsic motivations) (Cerasoli, Nicklin and Ford, 2014).

Contributions and Limitations of this Study

Contribution. The proposed BEPS model successfully assists in identifying long-term multiple bioecological factors relating to workability in terms of objective and subjective career success. Examining empirical data using the BEPS model reveals that workable personal, process and contextual factors (especially soft skills and employment) have greater roles than non-workable contextual factors (e.g. original family income). The BEPS model serves as a framework to incorporate diverse substantial factors and to guide scientific methodologies for future research to delve into life-long factors for career success.

Limitations. This study investigates participants in their early adulthood. Unobserved heterogeneity would have shaped both outcomes (e.g. income) and predictors between the gap years. For example, the effects of study years need explanation with caution because academically high achievers may still be studying for their postgraduate degrees, which is thus proper to be explained as controls in path analysis. Effective predictors are expected to vary for later adulthood.

Further, longitudinal data are used as observational cohort data in the model. Many measures might have changed in an unknowable manner, such as hard and soft abilities. For example, this study uses mathematical abilities in grade 7 to represent hard ability. Future research can formulate a more complex path or SEM model with several phases, including predictors of the same measure collected from multiple phases (e.g. original family income in adolescence and early adulthood).

Using an existing dataset to examine the posited BEPS model (Figure 1) is a convenient and cost-effective choice. However, measure selection with proper item content and numbers remains an issue. For example, this study used EFA, which chose only two items for the measure of hard competencies (Appendix) but at least 4 items for a measure are a proper practice for a latent construct in SEM's measurement model.

Some special findings deserve future research to validate for different samples and cultures. For example, reasons for the result that both hard ability and studying STEM negatively predict autonomy satisfaction are unknown. Personal traits, organisational climate, and cultures may state this result.

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Appendix. Details of the Measures

Measure	Variable name in the dataset	Items	Scale range	Data preparation
Outcome				
1. Income (monthly salary)	cpn14e19_1	What is the average monthly income of your [current/last] job?	0–300,000 NTD	
Perceived satisfaction		Do you agree with the following statement in describing your [current/last] job?		Reverse coding; EFA
2. Extrinsic satisfaction	cpn14e22_5–7	3 items, e.g. Your income is high.	1=SA ~ 5=SD	Mean score
3. Intrinsic satisfaction	cpn14e22_4;8–12	6 items, e.g. Your job gives you the opportunity to grow or learn something new.	1=SA ~ 5=SD	Mean score
4. Autonomy satisfaction	cpn14e22_1–3	3 items, e.g. You can decide or change your work content or progress.	1=SA ~ 5=SD	Mean score
Predictor				
Person: Hard vs. soft abilities				
5. Hard ability (Mathematical ability)	w1m3p	Grade-7 mathematics standardised cognitive test	−2.740 to 2.570; mean = −.0376,	

			standard deviation= 1.002 IRT scores	
6. Soft ability (positivity)	cpn14e26_1–7	Do you agree with the following statements in describing yourself? 7 items, e.g. Even if it takes a long time for the work to slowly see the results, you can maintain consistent performance.	1=SA ~ 5=SD	Reverse coding; EFA; Mean score
Process: Hard vs. soft competencies from effective learning in university		How much benefit does your undergraduate study provide regarding the following knowledge or skills?”		Reverse coding; EFA
7. Hard competencies	cpn14b12b_4–5	2 items: Make good use of computers and information technology; Analyse mathematical, scientific or statistical problems		Mean score
8. Soft competencies	cpn14b12b_1–2;6–10	7 items, e.g. self-understanding; independent learning		Mean score
Context: Economic status				
9. Family income (original family income)	w1p515	Parent self-report when students at grade 7, “What is the total income of your family every month?”	1 = <20,000NTD ~ 6 = >200,000NTD	
10. Employment (present job status)	cpn14e18	A derived variable based on self-report of the last job status	1= employed, 2 = unemployed	Reverse coding
Time/Developmental controls				
11. Gender (female) (control for person)	w1s502		1 = male; 2 = female	
12. Study STEM (Department choice; control for process)	cpn14b4g_x	Category of expertise in the latest degree (e.g. social sciences, medicine and technology)	2 = STEM (including agriculture and medicine); 1 = social sciences and humanities	recording
13. Gender*Study STEM	Not available	Interaction between gender and study STEM	Gender times Study STEM.	computing
14. Study year (total study year; control for context)	cpn14b1	What is your highest level of education (including what you are studying now)? (e.g. high school, master and Ph.D.)	middle school = 9 years, general university = 16 years, PhD = 22 years	Re-coding

Note: SA = strongly agree; SD = strongly disagree; EFA = exploratory factor analysis used as a data reduction technique to combine several items as a mean score and an observed measure in path analysis; STEM = science, technology, engineering and mathematics

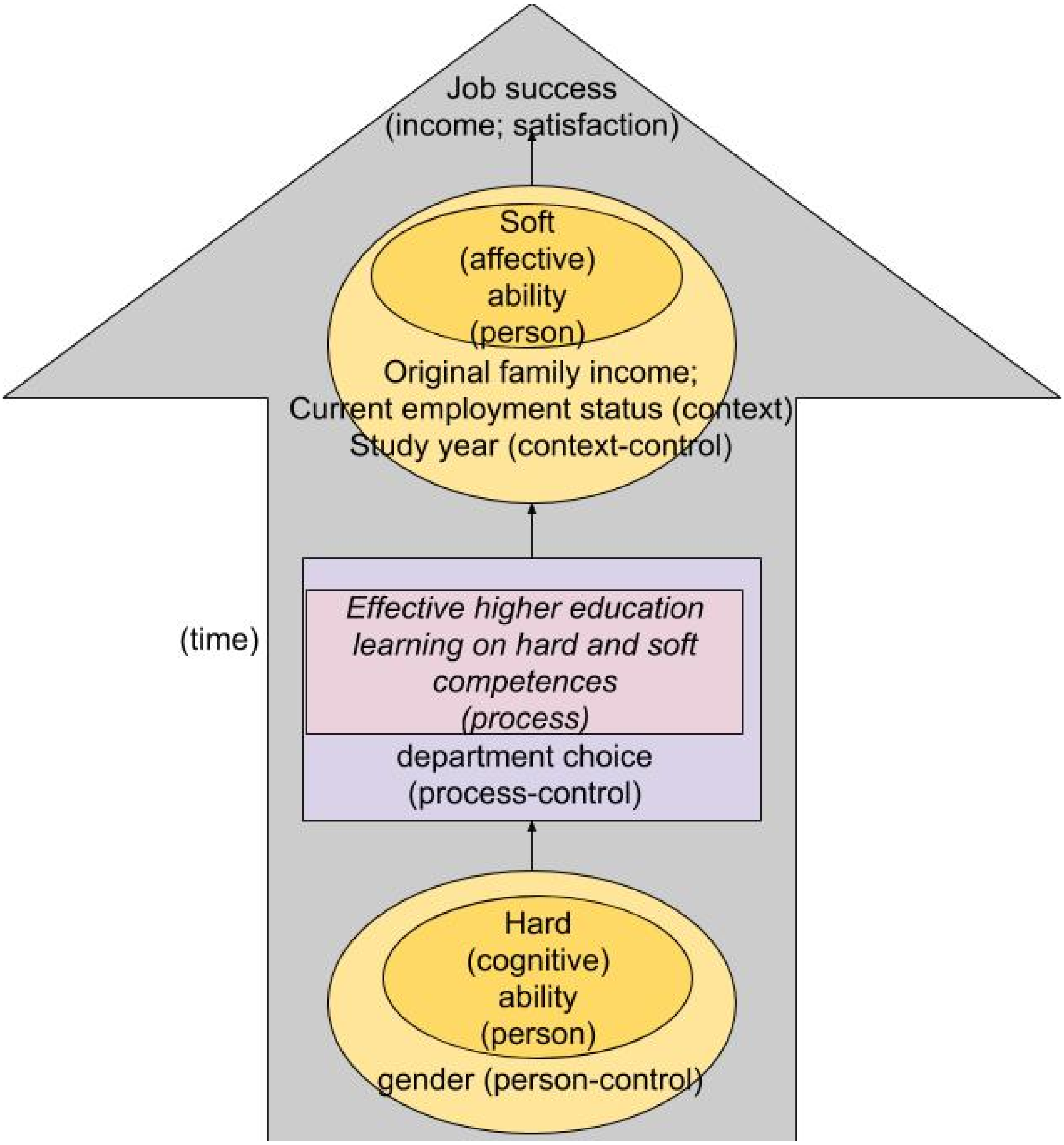
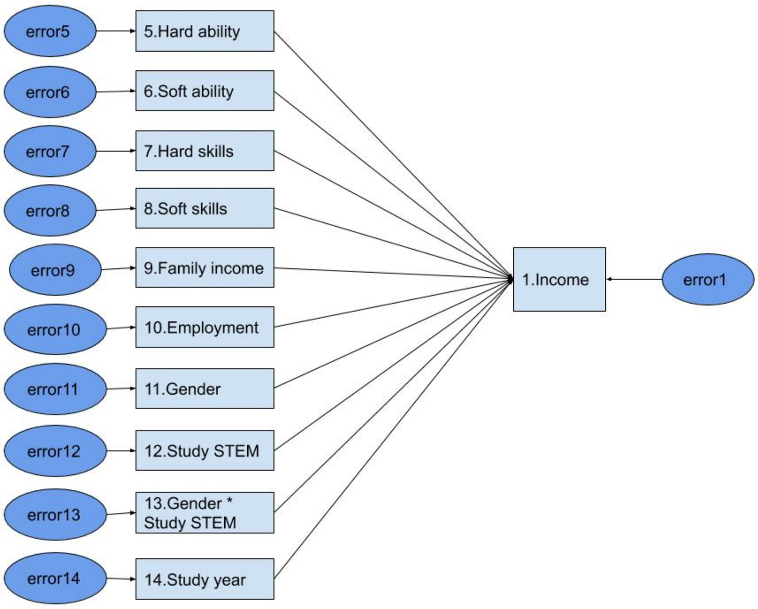


Figure 1. The bioecological positivity to success model

Model 1.



Model 2.

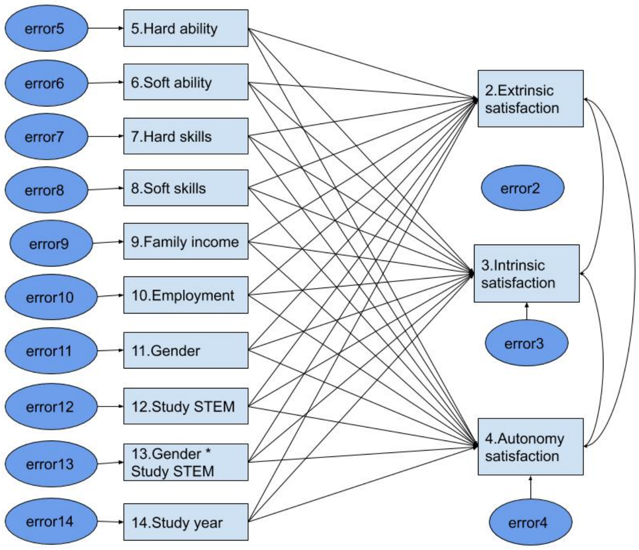


Figure 2. The two path models examined using SEM. Covariances (two arrows lines) between every two predictors (Measures 5-14) are omitted in both Model 1 and Model 2 to reduce the complexity in the graphs.

Table 1. Descriptive Statistics and Correlations for the Measures

		Mean	Standard error	Correlations												
				1.Income	2.Extrinsic satisfaction	3.Intrinsic satisfaction	4.Autonomy satisfaction	5.Hard ability	6.Soft ability	7.Hard competencies	8.Soft competencies	9.Family income	10.Employment	11.Gender (female)	12. Study STEM	13.Gender* study STEM
1	Income	29884.000	355.980													
2	Extrinsic satisfaction	3.139	0.018	0.268*												
3	Intrinsic satisfaction	3.409	0.015	0.074*	0.450*											
4	Autonomy satisfaction	3.335	0.018	0.061*	0.305*	0.378*										
5	Hard ability	0.124	0.020	0.044*	-0.039	0.087*	-0.041*									
6	Soft ability	3.880	0.010	0.153*	0.283*	0.316*	0.278*	-0.039*								
7	Hard competencies	2.527	0.017	-0.002	0.074*	0.149*	0.059*	0.111*	0.144*							
8	Soft competencies	2.592	0.014	-0.026	0.102*	0.233*	0.057*	0.078*	0.232*	0.385*						
9	Family income	2.624	0.022	0.053*	-0.017	0.051*	0.017	0.244*	-0.019	-0.009	0.022					
10	Employment	1.811	0.009	0.187*	0.293*	0.116*	0.177*	-0.095*	0.111*	-0.019	-0.017	-0.065*				
11	Gender(female)	1.515	0.011	-0.081*	-0.024	0.047*	0.007	0.023	0.004	-0.16*	0.129*	-0.037	0.030			
12	Study STEM	1.438	0.011	0.015	-0.008	0.022	-0.058*	0.063*	-0.006	0.248*	-0.098*	0.018	-0.049*	-0.293*		
13	Gender*Study STEM	-0.267	0.022	0.052*	0.027	0.031	-0.008	-0.007	0.032	-0.088*	0.017	0.032	-0.008	-0.013	-0.08*	
14	Study years	16.208	0.020	-0.072*	-0.078*	0.119*	-0.012	0.479*	-0.006	0.124*	0.097*	0.243*	-0.158*	0.020	0.097*	-0.028

Note. * $p < .05$. The Appendix shows the full names and detailed information on the measures.

Table 2. Path Analysis Results

	Models	Model 1 (salary)	Model 2 (perceived satisfaction)		
		1.Income	2.Extrinsic satisfaction	3.Intrinsic satisfaction	4.Autonomy satisfaction
	Covariance				
3	Intrinsic satisfaction		0.379^{*}		
4	autonomy satisfaction		0.221^{*}	0.309^{*}	
	Beta				
5	Hard ability	0.115^{*}	0.006	0.046^{*}	-0.061^{*}
6	Soft ability	0.133^{*}	0.249^{*}	0.270^{*}	0.238^{*}
7	Hard competencies	-0.013	0.027	0.048	0.051
8	Soft competencies	-0.039	0.051	0.144^{*}	-0.014
9	Family income	0.017	0.013	0.031	0.026
10	Employment	0.202^{*}	0.278^{*}	0.128^{*}	0.171^{*}
11	Gender(female)	-0.064^{*}	-0.030	0.044	-0.008
12	Study STEM	0.015	-0.005	0.020	-0.071^{*}
13	Gender*Study STEM	0.038	0.029	0.031	-0.016
14	Study years	-0.108^{*}	-0.044	0.060^{*}	0.017
	R-Square	*0.091*	*0.173*	*0.154*	*0.108*

Note. * $p < .05$. The regression coefficients are completely standardised solutions (betas). The Appendix shows the full names and detailed information on the measures.