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Quality of Learning Support for Mathematics in Transition to University.

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Abstract

We report on the development and validation of an instrument that measures students' perceptions of 'the quality and effectiveness of the learning support' (for mathematics) during their transition to university. This is achieved through quantitative analyses of students' survey data – including some predictive modelling with the measure - complemented with insights from interview data. The construct validation of the measure was performed using the *Rasch Rating Scale Model* (RSM). Results include fit and category statistics and the construct hierarchy which is presented

Calidad del apoyo para el aprendizaje de las matemáticas en la transición a la Universidad.

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Resumen

Este artículo muestra el desarrollo y la validación de un instrumento de medida de las percepciones de los estudiantes de secundaria acerca de, *la calidad y la eficacia del apoyo para el aprendizaje de las matemáticas*, en el proceso de transición a la educación superior. Para ello, se ha llevado a cabo un análisis cuantitativo de los datos obtenidos mediante un estudio de encuesta que, tomando algunos modelos de predicción, ha conjugado otros datos derivados de entrevistas. La validación de constructo de la medida se ha realizado mediante el RSM (*Rating*

with some extracts from interview data. The paper concludes with some educational implications and examples of how this measure can be used to give substantial practical results.

Key words: Higher Education, Transition, Mathematics education, STEM, Teaching and learning Quality, measurement, Rasch model.

Scale Model) de Rasch. Los resultados incluyen estadísticos de ajuste y de categorías, así como la jerarquización del constructo con algunos extractos de los datos de las entrevistas. El artículo finaliza aportando las principales implicaciones educativas que se derivan de este proceso, mostrando ejemplos de cómo esta medida puede ser utilizada para obtener resultados prácticos importantes sobre el apoyo en el aprendizaje de las matemáticas en los procesos de transición educativa.

Palabras clave: Educación superior, Transiciones, Educación matemática, Educación científico-tecnológica y matemática, Enseñanza y aprendizaje de calidad, Medida, Modelo de Rasch.

Introduction

This paper reports on an instrument that we have developed and validated to measure new undergraduate students perceptions of the effectiveness and quality of the support they receive for their learning of mathematics during their first year at university. The research project we draw on, "Mathematics learning, identity and educational practice: the transition into Higher Education"[1], aimed to understand how students can acquire a mathematical disposition and an identity that supports their engagement with Science, Technology, Engineering, Mathematics (STEM) in their pre-university and university education. In particular, we investigated how students' experiences of mathematics education practices interact with background social factors to shape their self-identity, dispositions, learning outcomes and their decision-making in transition into Higher Education (HE). Our focus is on learning outcomes for mathematics because of its importance to STEM as a whole in HE and hence to students' educational and socioeconomic life opportunities (Ball, Davies, David, & Raey, 2002; Boaler & Greeno, 2000).

We will explain how this measurement came to be needed in the context of researching widening participation in STEM and mathematically –demanding subjects in HE. We will then describe how the instrument was developed and then how the constructed measure was validated, including statistical indices with the aid of the Rasch model. We reveal the quality of the levels of scores, drawing on some of the interview data that accompanied our study. Finally we show how the measure has been used in some examples of modelling outcomes through some regression models. We argue that the result is that the instrument has proved fit for purpose in this context, i.e. in modelling effects of this and other variables on students' dispositions in HE. We will consider however how transfers to other contexts need careful consideration, and suggest how the measure may need to be developed for such purposes.

Background Literature and research questions

Students' transition to university and their first year experience have been extensively investigated in recent years because of their importance on students' life decisions and trajectories. An associated issue, which is the focus of this paper, is the widely known 'mathematics problem' in England (at least), which sees very few students to be well prepared to continue their studies from schools and colleges into courses in HE Institutions in mathematically demanding programmes.

A lot of studies on transitions dealt with the misalignment of students expectations, compared to the reality of university experience (e.g. Cook & Leckey, 1999; Jackson, Pancer, Pratt, & Hunsberger, 2000; Lowe & Cook, 2003; Pancer, Hunsberger, Pratt, & Alisat, 2000), whilst others focused on students preparation and the role of pre-university experiences (e.g. Hourigan & O'Donoghue, 2007). Completion prediction, based on a variety of factors, has also been a popular topic (D'Agostino & Bonner, 2009; Shah & Burke, 1999). Various studies explored identity development at university, and the effect of gender, ethnicity, social class, either as predictors or mediators of relevant difficulties encountered (e.g. Bell, Wieling, & Watson, 2007; Cassidy & Trew, 2004; Weiner-Levy, 2008). The literature generally shows that transition is often a 'threat' to progress, especially for certain students, and that efforts to align practices on either side of the transition can help (Alcock, Attridge, Kenny, & Inglis, 2014; Hoyles, Newman, & Noss, 2001).

From a pedagogical perspective, the literature has been dominated by a focus on approaches to learning, most often measured/conceptualised using the Study Process Questionnaire (Biggs, Kember, & Leung, 2001), and the resulting "deep vs surface approach to learning" framework. This framework has been popular (e.g. Baeten, Struyven, & Dochy, 2013; Chamorro-Premuzic, Furnham, & Lewis, 2007; Loyens, Gijbels, Coertjens, & Côté, 2013; Smyth, Mavor, Platow, Grace, & Reynolds, 2013) since it serves both as a useful metaphor for development of teaching and learning in HE and a research tool (Tormey, 2014). In general a deep approach to learning was found to be associated with positive academic outcomes. This framework has also been criticized by some scholars as being 'underdeveloped' (Howie & Bagnall, 2012) or oversimplified (Tormey, 2013). Tormey suggests that the "dominance of the model in the teaching and learning in HE literature may also have prevented the development of alternative, more useful frameworks for understanding learning in higher education" (Tormey, 2013, p.1).

An alternative framework for transition was suggested by Wingate (2007) focusing on developing and supporting 'learning to learn'. A combination of factors has also been considered in studies, including 'student-student' interactions as beneficial, and inaccessible lectures associated with problematic progression (Chamorro-Premuzic et al., 2007; Scanlon, Rowling, & Weber, 2007; Weiner-Levy, 2008). In response to these findings, various scholars and practitioners have started implementing 'intervention' supportive mechanisms to facilitate the transition for students. The list of these efforts is growing, including texting (Harley, Winn, Pemberton, & Wilcox, 2007), peer mentoring support (Bodycott, 1997; Heirdsfield, Walker, & Walsh, 2005), use of technology, and other internet-based tools (Chaisanit, Trangansri, & Meeanan, 2012; Han, Nelson, & Wetter, 2014; Harnisch & Taylor-Murison, 2012; Schworm & Gruber, 2012), social study networks (Peat, Dalziel, & Grant, 2000) and tutorial programmes to enhance collaboration (Karantzas et al., 2013).

Even though some of these efforts are generic, most of the previous work in widening participation/access to HE is either not directly applied to mathematics or else is relatively under-researched, especially in respect to supporting transitions. For mathematics, it is now acknowledged, at least for pre-university contexts, that some

mathematical classroom and institutional practices can make a difference to students' identities as mathematics learners; Boaler (1999) found that more discussion-based, collective and 'equitable' pedagogy helped certain students to align themselves positively with mathematics. All this is consistent with our earlier finding that transmissionist teaching can have a negative effect on students' mathematics dispositions at the end of their pre-university courses (Pampaka, Williams, Hutcheson, et al., 2012) which for some students meant deciding not to go into mathematically demanding (STEM) subjects.

None of the previously reported research however attempted to measure students' perceptions of the quality/effectiveness (on their learning) of the learning support (for mathematics) in place during their first year at University, and how this is related with other aspects of the transitional experience (e.g. teaching experiences before and after). As part of our study in transition to mathematically demanding courses we anticipated the need for such an instrument; in response to this need, we present here the development and validation of an instrument that captures students' perceptions of this support. This is achieved through the quantitative analysis of students' surveys, justified further by interview data. We also employ this measure further to model its effect on students' developing dispositions. In particular, we aim to answer these two questions:

RQ1: Does the instrument provide a valid measure of the construct of students' perceptions of 'the quality/effectiveness of the learning support' (for mathematics) in place during the first year at University? (hereafter we call the construct MathSupport@Uni)

RQ2: What evidence is there that this measure is fit for purpose in predictive modelling, e.g. in associations with other learning outcome measures?

Methodological Framework

Context of the study

The wider project on which this study draws employed a mixed methodological framework involving longitudinal surveys, student biographical interviews and case studies of practice. The survey allowed us to model dispositions (and other outcomes) over time, considering the effect of pedagogy and other transition-related variables, as well as their interaction with background factors. The individual biographical interviews (with linked case study data) allowed us to trace students' trajectories of identity, their dispositions and choices, and how these draw on their experiences of mathematics educational practices and their learning outcomes (Black et al., 2010; Williams, 2012; Williams et al., 2009).

For the current paper we draw on data from the survey and some biographical interviews to present the results of the validation of the new constructed measure, and then use it in further modelling of disposition outcome variables believed to be crucial to our focus on students' engagement and disengagement with mathematics. The longitudinal student survey took place at three data points (DPs hereafter), with resulting sample as shown in Figure 1:

- DP1: at/just before the beginning of their university course (2008),
- DP2: later in the first year (February to May 2009), and
- DP3: early in their second year (October 2009 to January 2010).

Our sample was drawn from selected STEM programmes (exceptions being in Education, and Medicine) in five HE institutions[2].

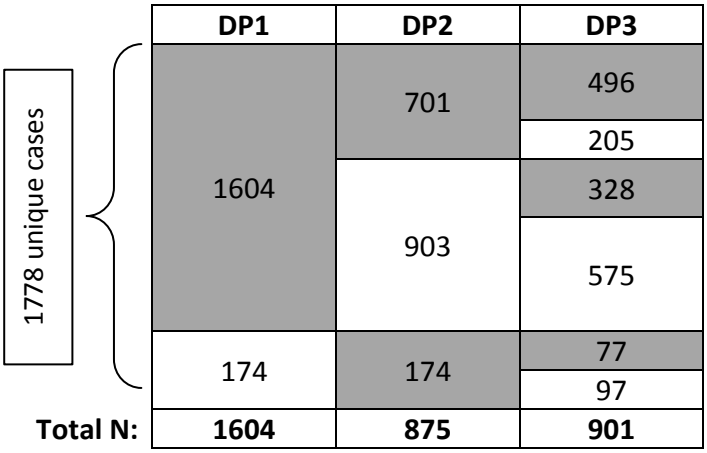

Figure 1. Sample description at each time point (with missing data)

Instrumentation

In our pilot case study work we identified mechanisms designed to support students learning mathematics during their transition to university, included support centres, tutoring sessions and other formal groups. In order to quantify the quality of these provisions, in addition to more standard modes of learning delivery in place (such as lectures) we constructed an instrument to be added to the students' questionnaire. To our knowledge there is as yet no existing similar measure that would serve this purpose, therefore, we collected some relevant items to develop the instrument (Table 1), based on pilot and initial case study findings.

Code	Item Description
WorkFellow	I have learnt a lot from working with my fellow students on the maths for my course.
FollowLectures	I can follow the maths in most of my lectures.
TeachSupport	I find that the teachers generally respond to my needs in the maths teaching I have received.
UseTechnology	I have learnt a lot from using technology for maths during my course.
OnlineSupport	I have learnt a lot from using on-line support for maths during my course.
Comparison	I preferred the school/pre-university teaching to the teaching this year at university.
Lectures	I have benefitted a lot from maths lectures.
Tutorials	I have benefitted a lot from maths tutorials.
InformalGroup	I have learnt a lot from working with my own informal group of colleagues outside of organised classes/ tutorials/ workshops. (only at DP3)
OtherSpecialProvisions	I have learnt a lot from special provision provided for my particular maths needs.

Table 1. The Items of the Instrument: 'InformalGroup' was added at DP3

These items were presented to the students in the form of a 5 point Likert scale (strongly disagree, disagree, neutral, agree, strongly agree) and the instruction: "Please tell us what you think of the support you have had for learning maths in your course/ programme so far"[3].It should also be noted that the final item was followed by a sub-section where students were asked to report on the particular 'special provisions', as shown below:

If applicable, please tick one or more 'special provisions', and/or add your own 'other' special maths provision that has been important to your studies this year.
☐ Special tutoring
☐ Learning support unit
☐ Contact with lecturers outside lectures
☐ Small group teaching
☐ Special workshops
☐ Peer mentoring
☐ Other (please specify) .....

Figure 2. Extra 'special provisions'

The investigation of these open ended responses at DP2, led to the introduction of a new item at DP3, as shown in Table 1 ("InformalGroup").

Analytical Considerations

In this section we detail the analytical approach of responding to the questions. The first research question deals with the construction (already presented) and validation of the measure of 'perceived support', while the second deals with the use of this validated measure in further statistical modelling.

Validation refers to the accumulation of evidence to support validity arguments. Our psychometric analysis for this purpose is conducted within the Rasch measurement framework and therefore we follow the guidelines summarised by Wolfe and Smith Jr, (2007a, 2007b) based on Messick's (1989) validity 'definitions'. The Rasch model was selected because it provides the means for constructing unidimensional interval measures from raw data and because the total raw score is sufficient for estimation of measures. Models of the Rasch family are governed by certain assumptions, the most important of which are unidimensionality, local independence, and common item discrimination. In its simplest form (i.e. for dichotomous responses) the model proposes a mathematical relationship between a person's 'ability', the 'difficulty' of the task, and the probability of the person 'succeeding' on that task (Wright, 1999). For the analysis and results reported in this paper we employed the Rating Scale Model, which is an extension of the simple Rasch model to rating scale observations like ours (i.e. in Likert type response format). The model allows the item difficulty of each question or statement to be based on the way in which an appropriate group of subjects actually responded to that question in practice: thus the 'difficulty' of an item is established by virtue of the degree to which 'higher ability' (i.e. high scores on the construct) are required to 'succeed' (i.e. in our case agree with) that item. Thus, here, the model establishes the relative difficulty of each item stem in recording the development of the disposition from the lowest to the highest levels the instrument is able to measure (Andrich, 1999; Bond & Fox, 2001; Wright & Mok, 2000). Analysis was performed with the Winsteps software (Linacre, 2014) and the following statistics will guide our exploration for this paper: (a) Item fit statistics to indicate how accurately the data fit the model (b) category Statistics to justify "communication validity" (Lopez, 1996), (c) Differential item functioning (DIF) to check for validity across different sub-groups (Thissen, Steinberg, & Wainer, 1993) and (c) Person – item maps and the item difficulty hierarchy to provide evidence for substantive, content and external validity.

After the measures' validation these scores were added to the survey dataset together with background and other outcome variables for the students of our sample. The survey data analysis employed Generalised Linear Modelling (GLM) of these learning outcome variables over different time intervals (Hoffman, 2004; Hutcheson, Pampaka, & Williams, 2011; Hutcheson & Sofroniou, 1999). Variable selection was based

on procedures where the emphasis is on selecting 'useful' models that incorporate theoretical judgements as well as statistical criteria applied to the sample data (Agresti, 1996; Weisberg, 1985). To this end, we have avoided selecting models based entirely on statistical criteria and automated procedures such as step-wise selection and all-subsets selection.

Validation Results

The sample

The validation results are based on the students who responded (even partly) at this section of the questionnaire during DP2 and DP3, split as follows for some relevant background variables:

Variable	Categories	DP2	DP3
Gender	Male	351 (56.2%)	464 (52.3%)
	Female	274 (43.8%)	424 (47.7%)
Mathematically Demanding (MD) Course	Yes	507 (81.1%)	518 (58.3%)
	No	118 (18.9%)	370 (41.7%)
	Total	**625**	**888**

Table 2. Validation Sample Description

It should be noted that under the 'MD' course classification there were students from Mathematics courses (including combined degrees), Engineering (Electrical and Mechanical) courses as well as Physics and Chemistry. The Non Mathematically demanding courses include Medicine and Social Sciences and some educationally-related degrees.

The measurement validation was performed at various levels, considering both DP2 and DP3 available data separately (i.e. students' responses to this part of the questionnaire) as well as the combined responses of the students at both DPs. The main purpose of the latter, when following a psychometric approach, is to also establish the measure's invariance over time. Therefore, results presented in this section will be based on this analysis[4].

Construct Validity: Checking for Unidimensionality

Fit statistics (i.e. Infit and Outfit mean-squares, MNSQ) are used in the Rasch context to check fulfilment of unidimensionality assumption and to flag items that may be problematic in this respect. In a 'perfect' measure these statistics should be 1, but an acceptable range is within 0.6 to 1.4 depending on the analysis. For the purposes of this paper we took any value above 1.3 as possible cause for investigation.

Preliminary analysis considered all items (Table 1) presented under the aforementioned section of the questionnaire as defining the measure of 'perceived support'. The scoring of the item "comparison" had to be reversed for this analysis, so as all items will point to a higher value for 'perception of support' at university. This analysis showed the "comparison" item to be misfitting (with infit and outfit mean-square values larger than 1.4), indicating mis-behaviour of this item under the constructed measure. A possible explanation of the misfit for this item may be the fact that it was the only item whose scoring was reversed for analysis, which is sometimes problematic. Also it

was considered that reflecting and comparing with previous experiences constitutes an aspect of perceived transitional experience that is not experienced in the same way as the target construct. Hence it was decided to delete this item from the measure and all analyses reported here exclude it[5].

The item analysis results of the constructed measure are shown in Table 3.

ENTRY NUMBER	TOTAL SCORE	TOTAL COUNT	MEASURE	MODEL S.E.	INFIT MNSQ	INFIT ZSTD	OUTFIT MNSQ	OUTFIT ZSTD	PT-MEASURE CORR.	PT-MEASURE EXP.	EXACT MATCH OBS%	EXACT MATCH EXP%	ITEM
1	4829	1410	-.04	.03	1.20	5.0	1.19	4.7	.64	.63	45.1	47.2	WorkFellow
2	5198	1400	-.51	.04	1.19	4.6	1.12	3.0	.48	.61	53.0	50.6	FollowLectures
3	4555	1350	.08	.03	.70	-8.6	.71	-8.4	.66	.62	57.0	47.2	TeachSupport
4	4069	1370	.66	.03	.90	-2.8	.91	-2.3	.63	.64	45.7	43.6	UseTechnology
5	4384	1371	.32	.03	1.21	5.2	1.20	4.9	.59	.64	43.1	45.6	OnlineSupport
6	4668	1329	-.13	.04	.69	-8.9	.68	-9.0	.73	.62	58.4	48.6	Lectures
7	4486	1276	-.13	.04	1.04	1.0	1.03	.7	.69	.63	48.7	48.7	Tutorials
8	583	159	-.85	.10	1.16	1.3	1.14	1.2	.49	.59	50.3	49.9	InformalGroup
9	1260	428	.60	.06	1.05	.8	1.11	1.7	.58	.63	50.0	43.2	OtherSpecialProvisions
MEAN	3781.3	1121.4	.00	.04	1.02	-.3	1.01	-.4			50.2	47.2	
S.D.	1564.1	448.6	.46	.02	.19	5.1	.19	4.9			4.9	2.5	

Person separation=1.54, reliability=0.7; Item separation=8.66, reliability=0.99

Table 3. Item Measurement Report

In this case, Rasch analysis showed acceptable fit for all the items suggesting that they could constitute a single dimension scale, which we called 'students' perceptions of the quality of the learning support (for mathematics) in place during their first year at University' (MathSupport@Uni). This 'healthy' measure is further investigated next.

Communication Validity: Checking Rating Scale functioning

Rating scales and their response formats serve as tools with which the researcher communicates with the respondents, a function defined by Lopez (1996) as 'communication validity'. Examining category statistics is essential within the Rasch measurement framework in order to confirm the appropriateness of the Likert scale used and its interpretation by the respondents. A well-functioning scale should, at least, present ordered average measures, and ordered step calibrations (Linacre, 2002) with acceptable fit statistics, as shown here (see Table 4 and/or Figure 3). In the probability plot of Figure 3, the four thresholds (i.e. boundary between category 1 and 2, 2 and 3, 3 and 4, 4 and 5) are denoted with arrows superimposed on the probability curves of each category. These seem to be ordered and provide evidence of a well-functioning scale.

SUMMARY OF CATEGORY STRUCTURE. Model="R"

CATEGORY LABEL	OBSERVED SCORE	COUNT	%	OBSVD AVRGE	SAMPLE EXPECT	INFIT MNSQ	OUTFIT MNSQ	STRUCTURE CALIBRATN	CATEGORY MEASURE	
1	1	632	6	-1.23	-1.26	1.03	1.04	NONE	(-3.02)	1
2	2	1392	14	-.48	-.43	.94	.92	-1.67	-1.44	2
3	3	2940	29	.16	.18	.92	.93	-.87	-.21	3
4	4	3849	38	.84	.79	.93	.95	.21	1.37	4
5	5	1280	13	1.47	1.56	1.15	1.09	2.32	(3.51)	5
MISSING		3299	25	.50						

Table 4. Category statistics for the MathSupport@Uni Measure

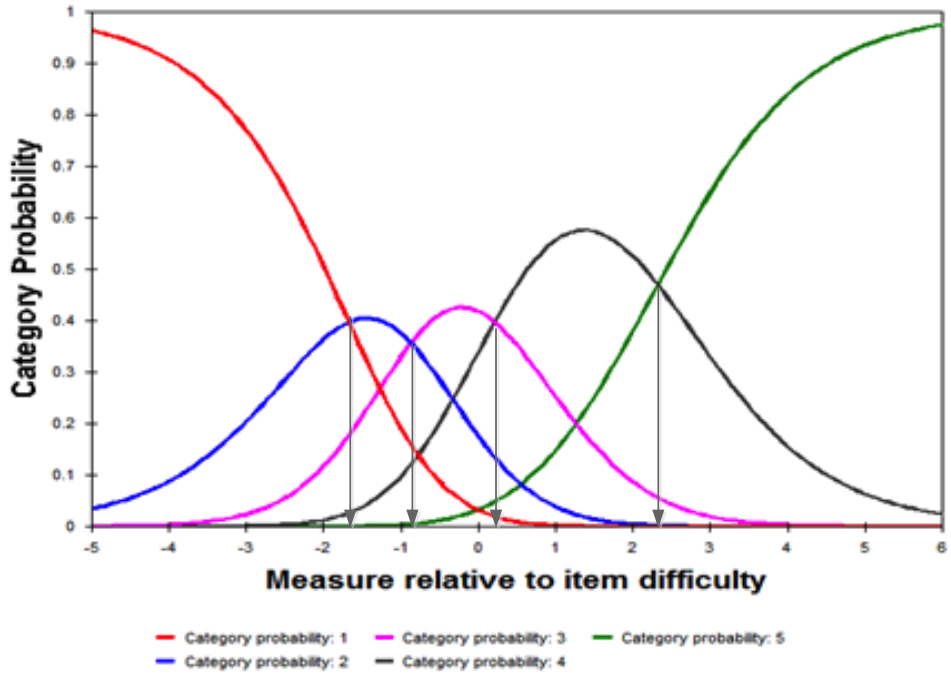

Figure 3. Category probability curves

Measurement invariance: Differential Item Functioning

When a measure is intended for use with different subject groups or for different occasions, it is also important to establish its invariance across groups (or occasions): Only if the item calibrations are invariant from group to group can meaningful comparisons of person measures be made (Wright & Masters, 1982). A statistical way to inform this process is to check for Differential Item Functioning (DIF), which is a serious threat to the validity of items and tests/instruments when used with different groups and could indicate a source of item bias. DIF measurement may be used to reduce this source of test invalidity and allows researchers to concentrate on other explanations for group differences in test scores (Thissen et al., 1993). For this analysis we are primarily concerned with time (data point, DP) and gender DIF, and then for differences based on the subject area the students are attending[6]. Figure 4 presents the result of this analysis in regards to time (DP), with the points showing how the item measures differ at the two DPs. The stars indicate statistically significant differences, even though the prevalent cut-off value of concern in DIF analysis is the difference in logit (to be larger than 0.5). In our case the differences are small but worth mentioning: at DP2 students find it harder to report agreement with 'following lectures' and 'teachers' support' compared to DP3 (since the scores on these items are larger, thus more difficult to agree, see Figure 5). The opposite happens regarding benefits from lectures: students at the second year find it harder to endorse compared to first year students. A difference was also signified as significant for gender regarding the 'tutorials' item: this item was harder for male students to endorse.

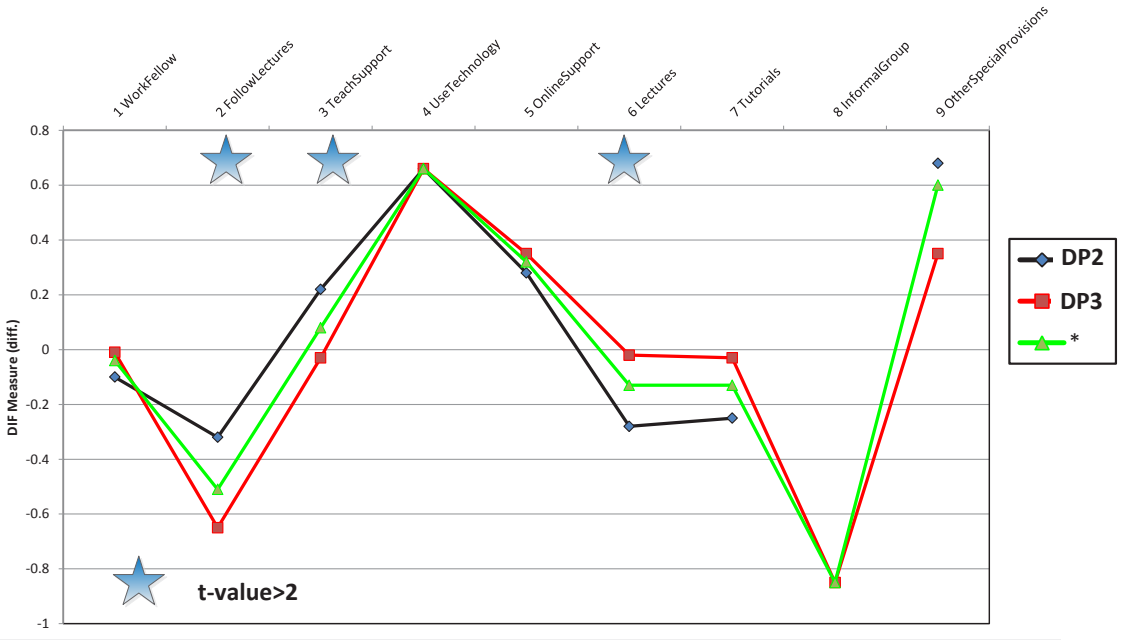

Figure 4. Differential Item Functioning, by time (DP)

The Rasch Hierarchy and Students' Voice

Figure 5 shows the resulting measurement scale (on the left) of students' scores and items' difficulties. At the left end of the figure the logit scale is shown; this is the common measurement scale for both items and persons (i.e. students). At the left side of the map the students' distribution in the scale is shown (each # represents 11 students, each "." represents 1 to 10 students). The higher the place of a student in that scale the more highly they feel their learning was effectively supported in transition (first year HE). On the right hand side of the students' 'histogram' the items that constitute the scale are presented, ranging from the easiest to report agreement with (bottom) to the most difficult. The description of the items that correspond to each code can be found in Table 1.

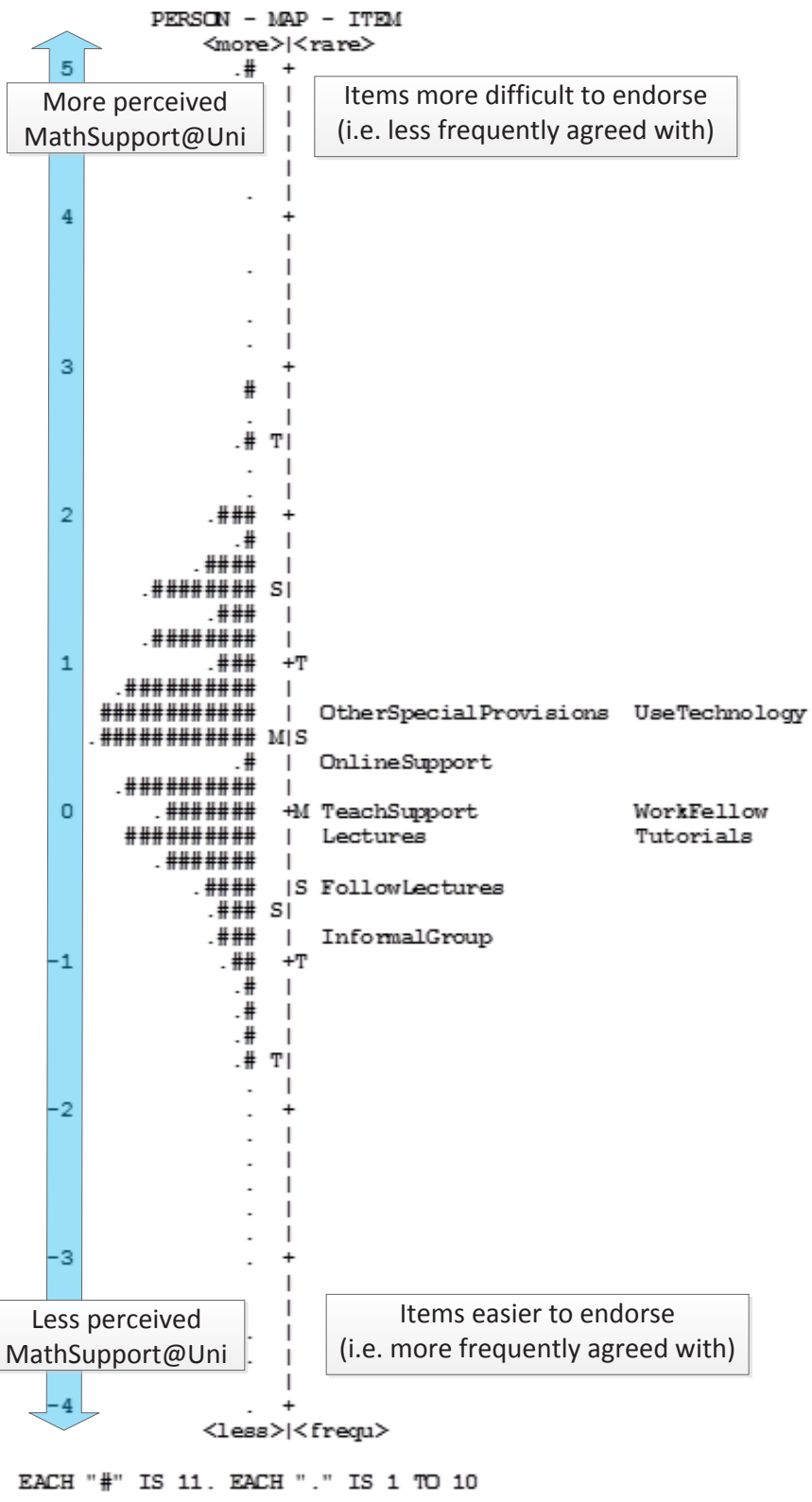

Figure 5. The person-item map hierarchy

The positioning of the items on the scale seems to accord with qualitative evidence provided by both interviews with students as well as their open-ended comments on the questionnaires. The following provide some justification of the 'difficulty' of the items as students were finding it harder to support their learning from 'mechanisms/ practices' located on the top of this scale, such as online or with the help of technology, and were more frequently benefiting from lectures (maybe because they did not have alternatives):

- **Technology and On-line:**
- "It's difficult….we are doing Maths Lab as well under this programming. You know, everything is involved, is involved with Maths. Everything is Maths".
- **"**I was on the internet all of yesterday and to be honest I found that learning maths on a computer doesn't work"
- "I find learning statistics online a difficult, impersonal and ineffective way to learn. It does not answer any questions and often creates more. It is bewildering and does not give me confidence in my abilities."
- **WorkFellow:** "I think that the best help that I can get is just find someone who's eagerly as stuck as I am and who wants a study partner effectively. Someone who I know more than them in some parts and they know more than me in other parts and, you know, just once we've shared we can get through."
- **Lectures and TeachSupport:**
- "It's a massive change from college, but I don't feel there's a problem with it anymore because, the lecturers are really, really helpful like they ask if anyone's got any questions … you can ask questions in the lectures if you need to."
- "You don't really work with other students at all, we don't use computers or online tools at all either. I benefit from Maths tutorials and lectures because they're the only kind of teaching you can get here apart from looking up everything by yourself!"
- "Lectures are too fast and hard to follow. Seminars examples are massively time consuming and I spend a long time getting the wrong answer. Examples are only really helpful when the solutions are present. I have found the only good use of time is looking back at examples and solutions on the system simultaneously which leaves almost no incentive to do the work for seminar deadlines/attend seminars."
- **InformalGroup:** "I've got a group of other friends I mean, generally when I'm in sort of the X department I have another group of friends, …we go out often and have coffees and manage to sit in the coffee bar and do a bit of work and that sort of thing. It's good, it's really nice."

In sum, the measure is at least consistent with the interviews: we thematically coded all interviews and were reassured that the main themes there were captured in the items, especially after the addition of 'InformalGroup', that was a very significant element of the students' support for their learning.

GLM Results - Educational Significance

As already mentioned, the resulting validated measures (i.e. students' scores on this logit scale, see Figure 5) are then added back to the student datasets for further analysis. For this particular measure we had to perform a further adjustment during matching in order to minimise the effect of the missing data problems shown in Figure 1: we used

as a primary measure students' scores at DP2 and if not available (i.e. missing at DP2) we used their DP3 score (assuming they completed this DP). Apart from background information, the dataset also included other measures, such as mathematics disposition and disposition to complete their chosen course, mathematics self-efficacy, perception of transitional gap and positivity towards transition. Information about the construction of these measures is reported elsewhere (Pampaka, Williams, & Hutchenson, 2012; Pampaka & Williams, 2010; Pampaka et al., 2013; Pampaka, Williams, Hutcheson, et al., 2012).

The survey data analysis then employed GLM of learning outcomes at year 2 (in this case dispositions@DP3). Although it is not possible to specify the precise details of the selection of our final models due to the iterative nature of the process, the basic procedure we employed was to identify different variables of interest, under each of the relevant groups, shown in Figure 6 (i.e. previous dispositions, process and background variables) and select variables in the data that best represented these.

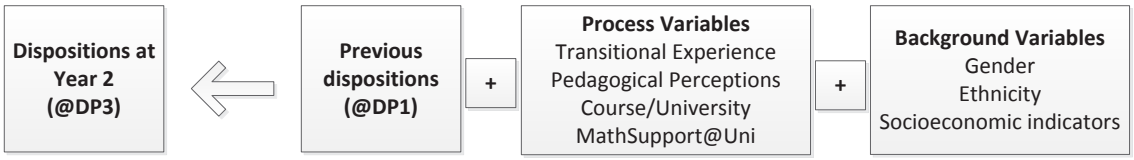

Figure 6. Modeling framework for dispositions

Models were constructed on the basis of theoretical considerations and tested for violations of the regression model assumptions. The final models we present here regard the developing mathematics dispositions of students during their second year at university, as well as their dispositions to complete their chosen courses, at the same time (DP3). They are both 'value added' models of dispositions, or in other words model of changing dispositions, since the corresponding disposition at previous data point (i.e. DP1) is accounted for in the model. Gender and ethnicity are used as control variables in the models.

Modeling mathematical disposition at DP3 (2nd year HE)

Table 5 presents a model for the value added to students' mathematical disposition, which accounts for about 58% of the variance in the response variable. Gender and ethnicity do not appear to have a significant effect (but are left in the model as controls). Some institutional effects are also signified as important (e.g. between Modern, Northern and Riverside Universities compared to the reference university category – City), which could be relevant to the sample composition on these universities. However, since we also account for the Mathematical demand of the courses and MathSupport@Uni, interpretation of university effects on the change of dispositions goes beyond of the scope of this paper. The positive coefficient of the Mathematically demanding (MD) courses dummy variable (in combination to the reference category – non MD), indicates that students in MD courses tend to score about 0.4 logits higher than non-MD students in the maths disposition measure at DP3. What is more interesting though is the effect of MathSupport@Uni, indicating that with a logit increase in this measure (i.e. the more highly the students felt their learning was effectively supported during their first HE year HE) the score of their maths disposition tend to increase by almost 0.2 logits (almost double the effect of their mathematics self-efficacy during the transition).

Variables	Coefficient B	s.e.	t value	p	F	p
MHEdisposition@DP1	0.56	0.04	15.51	<0.001	240.6	<0.001
MSE@DP1	0.12	0.04	3.29	0.001	10.88	0.001
Mathematically Demanding – YES	0.40	0.16	2.46	0.014	6.04	0.014
Gender – Male	0.19	0.11	1.75	0.08	3.05	0.081
Ethnicity – White	-0.11	0.11	-0.95	0.343	0.9	0.342
University [City]					3.14	0.008
- Hillside	0.49	0.33	1.49	0.136		
- Modern	0.78	0.35	2.26	0.024		
- Northern	1.12	0.34	3.35	<0.001		
- Riverside	0.71	0.31	2.31	0.021		
- Other	0.46	0.45	1.01	0.314		
MathSupport@Uni	0.18	0.05	3.57	<0.001	12.75	<0.001

Notes: F (11, 613) = 77.61, $p < 0.001$, $R^2 = 0.582$ (Adjusted $R^2 = 0.575$)

Table 5. A regression model for mathematical disposition at the second HE year (DP3)

Modeling disposition to finish course at DP3 (2nd year HE)

Finally, Table 6 presents a model for the value added to students' disposition to finish their chosen courses, which accounts for about 17% of the variance in the response variable.

Variables	Coefficient B	s.e.	t value	p	F	p
HEdisposition@DP1	0.35	0.05	7.77	<0.001	60.44	<0.0001
Gender – Male*	-0.33	0.16	-2.13	0.034	2.99	0.085
MathSupport@Uni*	-0.19	0.11	-1.7	0.089	0	0.997
Ethnicity – White	-0.27	0.16	-1.68	0.094	2.82	0.094
Positivity@Transition	0.18	0.06	2.92	0.004	8.54	0.004
MathSupport@Uni X Gender	0.30	0.14	2.17	0.031	4.69	0.031

Notes: F (6,402) =15.01, $p < 0.001$, $R^2 = 0.183$ (Adjusted $R^2 = 0.171$)
**Gender and MathSupport@Uni variables' coefficients, even though are given in the table are not interpreted given the significant effect of their interaction*

Table 6. A regression model for disposition to finish course at DP3

The model indicates significant (positive) effects of the Positivity@Transition and the interaction between gender and MathSupport@Uni, which are better illustrated and interpreted with the effect plots of Figure 7. The Positivity@Transition effect is easier to interpret: for every logit increase in this variable (i.e. the more positive the students were about their transition at University) students' score in their measure of disposition to complete their chosen course increases by about 0.2 logits. The MathSupport@Uni has a different effect for male and female students, as shown by the different direction of the plot in Figure 7. For female students, the higher they perceived the teaching and learning support at university, the lower they score on their disposition to finish their chosen course. For male students the effect is positive.

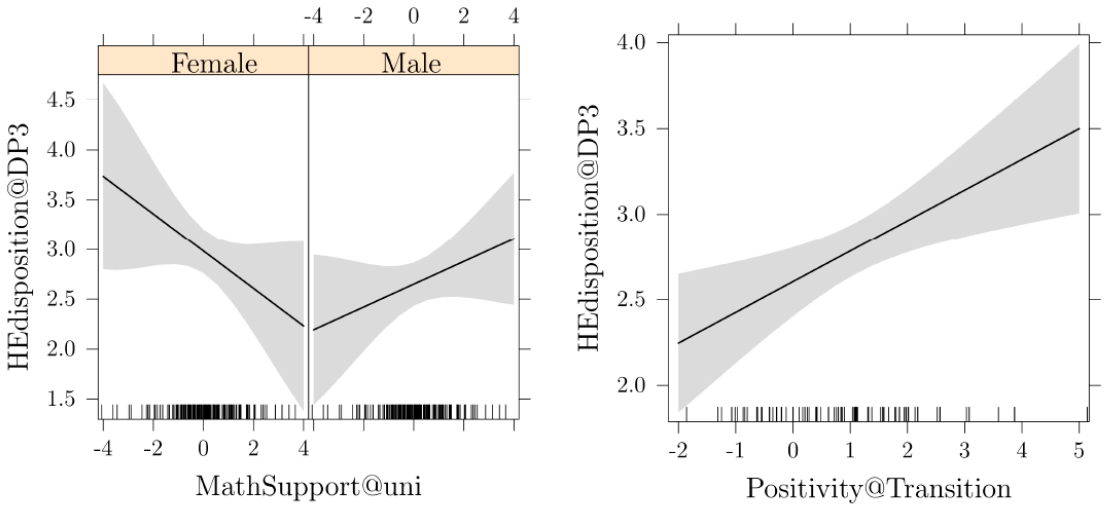

Figure 7. Effect plots for the linear model of disposition to complete course at DP3

Conclusion and discussion

We conclude that there is some sound basis for the valid use of this measure in predictive modelling. In the limited context of English universities and the study of the student experience of transition we argue that the instrument has proved robust. We have revealed a selection of models in which this measure proves of interest. We are aware of course of the limitations of the instrument and the work that would be needed to make the instrument fit for purpose in other contexts, even translating between languages is an onerous task, never mind between educational cultures.

However, we have also revealed here the methodology we used to establish this robustness in practice, and would draw attention to the aspects of the work we think is crucial. First there must be a theoretical, or at least robust, argument that such a construct might be fit for the study purposes. Second the items must be designed to match a hypothetical construct of conceptual significance, and ideally a range of items that covers a relevant domain (here the range of support experiences students speak of in interviews). If possible, the items should be expressed in words that are close to those students would use (e.g. in interviews). Then the sampling is an issue, and the need to consider subgroups in the validation of the instrument may lead to requirements on specific subsamples (by gender, backgrounds of various kinds, in our case the length of time studying and the subjects being studied at university and so on).

Then the scoring validity, item fit, and differential item functioning results need to be explored and declared. We announced these fit for our purposes, but it may be in other contexts that even these misfit values might be considered a threat, depending on the precise significance required in the models to be explored.

So far measures like these have been found useful in other contexts as well. Working with colleagues in Norway for example we have tested the comparability of such measures with the Nordic educational system (Pampaka, Pepin, & Sikko, forthcoming). Beyond some complications in regards to comparability of some of these measures across context (DIF, especially in regards to pedagogical measures) independent analysis of the use of these measures indicated some common relationships between the constructed measures in these two contexts: we found, for instance that higher perceived quality of

learning support was associated with less transmissionist teaching at university (as per students' perception); in addition higher MathSupport@Uni was also associated with more positive transitional experience (Pampaka et al., forthcoming).

A final observation: in much recent work we have found it necessary to construct such measures in order to robustly reveal the effects of important constructs. Even more significantly, we have had to build robust measures of learning outcomes not usually measured (Pampaka & Williams, 2010; Pampaka et al., 2013). Measures like this are important for modelling important effects on important learning outcomes: in our case the effect of support on the quality of student learning, and in other cases the effects of different teaching on students dispositions to learn (Pampaka, Williams, & Hutchenson, 2012; Pampaka, Williams, Hutcheson, et al., 2012).

The danger in avoiding this work – laborious as it is – is that important outcomes and important causes are never countenanced in research and then ignored in meta-analyses and policy. Evidence-based policy then draws wholly false conclusions from research, because there is no 'robust' research to respond to.

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[1] www.transmaths.org

[2] In UK, pre-university education is associated with the second year of post-secondary education (in colleges) when students get their A levels (A2) in various subjects.

[3] At DP3, students were asked to report retrospectively "Please tell us what you think of the support you received for learning mathematics in your course/programme last year…"

[4] More detailed results, including separate analyses per data point can be accessed at www.transmaths.org/support

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