Supplemental Material

CBE—Life Sciences Education

McFarland *et al.*

McFarland JL, Price RM, Wenderoth MP, Martinková P, Cliff W, Michael J, Modell H, Wright A. Development and validation of the Homeostasis Concept Inventory.

Supplemental Materials

Contents

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Homeostasis Concept Inventory

Correct answers are highlighted in blue, bold text.

Please select the best answer for each of the following multiple-choice questions.

1. In organisms, like humans, homeostatic negative feedback mechanisms result in

   a. an unfavorable, or damaging effect on the body.
   b. a constant decrease in the regulated variable.
   c. equilibrium among body cells and fluids.
   d. maintenance of an internal variable within a 'normal' range of values.

A new species of deer is found in North America. Researchers establish that the concentration of X in the blood is maintained at a relatively constant level over time, even when the animal's external or internal environment changes.

2. Some disturbance causes the concentration of X to increase. What change will occur in the activity of a sensor that detects X? The sensory receptor will

   a. increase its firing rate from zero to the maximum possible firing rate.
   b. fire at a new rate proportional to the magnitude of X.
   c. not change its firing rate.

3. When any disturbance causes the value of X to decrease there will be a physiological response that causes X to

   a. increase back towards its normal value.
   b. decrease still further.
   c. stay constant at its new value.

4. A homeostatic control mechanism functions to maintain the concentration of X at a relatively constant level. This mechanism is functioning

   a. when the concentration of X gets too high
   b. when the concentration of X gets too low
   c. when the concentration of X gets too high or too low
   d. at all concentrations of X

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5. The body has a sensor that detects blood pressure, but does not have a sensor that detects heart rate. Which of the following remains relatively constant when the internal or external environment changes?

   a. heart rate
   b. blood pressure
   c. both
   d. neither

6. Normal body temperature of a healthy adult is about 37 degrees C. A fever occurs when the temperature set-point is elevated. Jasmine feels cold as she develops a fever because her body temperature at that time is

   a. less than 37 degrees C.
   b. increasing above 37 degrees C.
   c. less than the new set point temperature.

7. A homeostatic mechanism in the human body has a control center, also called an integrator, that is part of which organ system or systems?

   a. the endocrine system
   b. the nervous system
   c. the endocrine system, the nervous system, or both

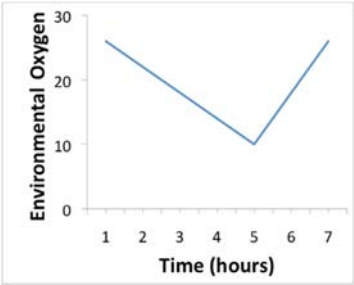
8. Plasma calcium concentration is maintained relatively constant even when calcium intake increases. Based on this information, one can conclude that

   a. plasma calcium must be needed for the normal function of many cells.
   b. the plasma calcium concentration must be controlled by the nervous system.
   c. there must be a mechanism to detect the concentration of calcium in the plasma

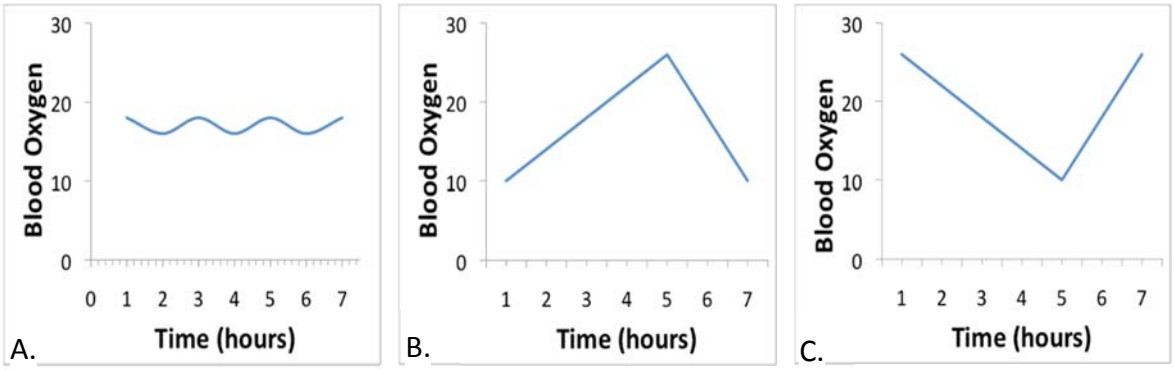
9. Baroreceptors detect blood pressure. Blood pressure is maintained relatively constant even when the internal or external environment changes. Under what conditions do the baroreceptors send signals to the brain?

   a. when blood pressure is not at its normal value.
   b. when blood pressure is increasing.
   c. when blood pressure is constant.
   d. at all levels of blood pressure.

10. An animal lives in a habitat where oxygen levels in the environment vary over time as shown below.



If oxygen level in the blood of the animal is regulated by a homeostatic mechanism, which of the figures above correctly shows oxygen levels in the blood of the animal over time?



The correct answer is a.

11. While watching TV, Sam eats a 6 frosted sugar cookies. As glucose is absorbed from Sam's digestive tract, there is a rise in his blood glucose concentration. Blood glucose is homeostatically maintained. Which of the following will occur FIRST? a change in the

    a. activity of the sensors that monitor blood glucose
    b. activity of effectors that lower blood glucose
    c. release of hormones that change blood glucose

12. Dora walks home on a freezing winter night and starts to shiver. What determines how much she will shiver?

    a. her body temperature
    b. the outside air temperature
    c. her set point temperature
    d. the difference between the set point temperature and her body temperature
    e. the difference between outside air temperature and her body temperature

13. Homeostatic systems require a sensor, a control center, also called an integrator, and an effector. The role of the effector is to directly change the

    a. value of the homeostatically regulated variable.
    b. value of the set point.
    c. magnitude of the signal from the sensor.
    d. activity of the control center or integrator.

14. In temperature regulation, the sweat gland is an effector that most directly causes a change in

    a. body temperature.
    b. the body's temperature set point.
    c. signals from the sensory receptors in the skin.
    d. the temperature control center, also called an integrator, in the brain.

15. Blood pressure is maintained relatively constant even when the internal or external environment changes. Effectors are parts of the body that receive signals from a control center. Which of the following is an effector in the system that maintains blood pressure?

    a. blood volume
    b. sensory receptors for blood pressure
    c. cardiac muscle
    d. the resistance that must be overcome for blood to flow

16. The control center, also called an integrator, receives signals from the sensors that are part of the mechanism and a set-point signal. Which of the following represents how the control center processes these two signals?

    a. (set-point signal) − (sensor signal)
    b. (set-point signal) + (sensor signal)
    c. (set-point signal) · (sensor signal)
    d. (set-point signal) ÷ (sensor signal)

17. Baroreceptors sense blood pressure. The baroreceptor nerves are cut so the signal from the baroreceptors is unable to reach the cardiovascular control center. After cutting the nerves, blood pressure will

    a. remain constant.
    b. decrease.
    c. increase.
    d. become equal to the set-point value.

18. Information from sensory receptors in homeostatic systems

    a. determines the set point.
    b. is sent to effectors.
    c. is sent to control centers, also called an integrators.
    d. stays in the receptor until the regulated variable changes back to normal.

19. In a homeostatic system the control center, also called an integrator, receives sensory information from receptors and

    a. determines what the body wants.
    b. determines the set point.
    c. processes the information and controls the behavior of the effector.
    d. transmits the sensory information unchanged to the effector.
    e. controls the activity of the sensory receptors.

20. Samira is watching a movie and eats 3 chocolate bars. As Samira's digestive tract absorbs the sugar, there is an initial increase in her blood glucose. When are blood glucose sensors signaling?

    a. before eating
    b. during eating
    c. while eating and digesting the chocolate bars
    d. all the time

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R code

```
# R packages
library(lme4)
library(lmerTest)
library(psych)
library(psychometric)
library(ltm)
library(difR)
library(ggplot2)
library(WrightMap)
library(data.table)
library(corrplot)
library(mirt)
library(ShinyItemAnalysis)

# DATA
load(file = "dataHCI.RData")
load(file = "dataGrads.RData")
load(file = "dataTestretest.RData")
load(file = "dataPrePost.RData")
data(dataHCI)
attach(dataHCI)

# variable names
varsA  <- paste("A", 1:20, sep = "")
varsQR <- paste("QR", 1:20, sep = "")

# CRITERION VALIDITY
# graduate students (10), MEAN = 14.5, SD = 3.27
mean(dataGrads$total); sd(dataGrads$total)
# undergraduate students (669), MEAN = 12.13, SD = 3.65
mean(dataHCI$total); sd(dataHCI$total)
# comparison: total score graduate vs undergraduate,
# two-sample t-test, alternative greater, p-value 0.024
```

```
t.test(dataGrads$total, dataHCI$total, alternative = "greater")

# comparison: total score pre vs post,
# paired t-test, p-value 0.010
t.test(dataPrePost$score.pre, dataPrePost$score.post, paired = T)
# difference post-pre
dif <- dataPrePost$score.post - dataPrePost$score.pre
t.test(dif)
mean(dif, na.rm = T); sd(dif, na.rm = T)
# comparison: exposed (16) vs not exposed (45), difference pre vs post
# two sample t-test, alternative greater, p-value 0.048
pre <- dataTestretest[(dataTestretest$prepost == "pre"),]
post<- dataTestretest[(dataTestretest$prepost == "post"),]
difTestretest <- post$total - pre$total
t.test(dif, difTestretest , alternative = "greater")
mean(difTestretest ); sd(difTestretest)

# LINEAR MIXED EFFECT MODEL; using lme4 and lmerTest packages
data <- dataHCI
summary(lmer1 <- lmer(total ~ as.factor(yearc5) + gender + major +
                        profsch + ethn4 + age3 + EnglishF + level +
                        NprerH + typeS + typeSCH + (1|survey),
                      data = data))
anova(lmer1)

# remove nonsignifficant: NprerH, typeS, typeSCH, level, profSCH (one by one, here all at once)
summary(lmer2 <- lmer(total ~ as.factor(yearc5) + gender + major + ethn4 +
                        age3 + EnglishF + (1|survey),
                      data = data))
anova(lmer2)

# remove age3 (optimal mixed effect model)
summary(lmer3 <- lmer(total ~ as.factor(yearc5) + gender + major + ethn4 +
                        EnglishF + (1|survey),
                      data = data))
```

```
anova(lmer3)

BIC(lmer1, lmer2, lmer3)

# optimal fixed effects model (selection not shown here)
lmF <- lm(total ~ gender + major + as.factor(yearc5) + minority + EnglishF + typeSCH, data = data)
summary(lmF)

BIC(lmer1, lmer2, lmer3, lmF) # mixed-effect model fits better using BIC

# CONSTRUCT VALIDITY, UNIDIMENSIONALITY OF THE INSTRUMENT
# tetrachoric correlation heat-map
corP <- polychoric(dataHCI[,varsQR])
round(corP$rho,2)

# Exploratory factor analysis
# Optimal number of factors
VSS(dataHCI[,varsQR])
# BIC supports unidimensionality of the measure (1-factor solution)
# RMSEA 0.04 acceptable for 1-factor model

(FA1<-fa(dataHCI[,varsQR],nfactors=1))
(FA2<-fa(dataHCI[,varsQR],nfactors=2))
(FA3<-fa(dataHCI[,varsQR],nfactors=3))

fa.diagram(FA1)
fa.diagram(FA2)
fa.diagram(FA3)

# Higher order factor solution
(om.h <- omega(dataHCI[,varsQR], sl=FALSE))

# Scree plot
pca <- princomp(dataHCI[,varsQR], cor=TRUE)
plot(pca$sdev^2, type="b", pch=16, xlab="Component number", ylab="Eigenvalue")
```

```
round(
  cbind("Variance"=pca$sdev^2, "%"=100*pca$sdev^2/sum(pca$sdev^2),
        "Cumulative %"=100*cumsum(pca$sdev^2)/sum(pca$sdev^2)), d=2)

# RELIABILITY
# Pearson correlation coefficient, 0.77, CI = (0.62, 0.87)
cor.test(pre$total, post$total)

# Cronbach's alpha, 0.72, CI = (0.69, 0.75); using psych and psychometric packages
psych::alpha(dataHCI[,varsQR])
psychometric::alpha(dataHCI[,varsQR])

# ITEM ANALYSIS
# difficulties and discriminations; using psychometric package
item.exam(dataHCI[, varsQR], discr = T)

# IRT models - 1PL, 2PL, 3PL; using ltm package
fit1PL <- rasch(dataHCI[, varsQR])
fit2PL <- ltm(dataHCI[, varsQR] ~ z1)
fit3PL <- tpm(dataHCI[, varsQR])

# IRT models comparison, 3PL model is the best
anova(fit1PL, fit2PL)
anova(fit2PL, fit3PL)

# Item parameters for the optimal 3PL model
summary(fit3PL)

# item fit statistics for 3PL model
# calculation takes a bit longer here
item.fit(fit3PL, simulate.p.value = T)

# IRT models with mirt package
fit1PLmirt <- mirt(dataHCI[, varsQR], model = 1, itemtype = "2PL",
```

```
        constrain = list((1:length(varsQR)) + seq(0, (length(varsQR) - 1)*3, 3)), SE=TRUE)
fit2PLmirt <- mirt (dataHCI[, varsQR], model = 1, itemtype = "2PL", SE=TRUE)
fit3PLmirt <- mirt (dataHCI[, varsQR], model = 1, itemtype = "3PL", SE=TRUE)

# IRT models comparison, 3PL model is the best
anova(fit1PLmirt, fit2PLmirt)
anova(fit2PLmirt, fit3PLmirt)

#item coefficients under the optimal model
coef(fit3PLmirt, simplify=T, IRTpars = TRUE)

# item fit statistics for 3PL model
itemfit(fit3PLmirt)

# FAIRNESS
# DIF by gender
data <- dataHCI[, varsQR]
group <- dataHCI[, "gender"]
# remove students who did not specify gender
group[dataHCI[, "gender"]=="none"] <- NA
data <- data[complete.cases(group), ]
group <- abs(c(na.omit(group)) - 2)
# logistic regression DIF method; using difR package
difLogistic(data, group, focal.name = 1, p.adjust.method = "BH")

# DIF by English language status
group <- dataHCI[, "EnglishF"]; group <- as.numeric(group == "yes")
data <- dataHCI[, varsQR]
# logistic regression DIF method; using difR package
difLogistic(data, group, focal.name = 1, p.adjust.method = "BH")

# DIF by Ethnic group
group <- dataHCI[, "ethn4"]
summary(group)
data <- dataHCI[, varsQR]
```

```
score <- apply(data, 1, sum)
LRval <- pval <- c()
# logistic regression DIF method with several focal groups
for (i in 1:20){
 # null model
 fit0 <- glm(data[, i] ~ score, family = "binomial")
 # alternative model
 fit1 <- glm(data[, i] ~ score + group + score*group, family = "binomial")
 LRtest <- anova(fit0, fit1, test = "LRT")
 # LR-test statistics
 LRval <- c(LRval, LRtest$Deviance[2])
 # p-values
 pval  <- c(pval, LRtest$`Pr(>Chi)`[2])
}
# adjusted p-values; using Benjamini-Hochberg correction
# none of items detected as DIF
LRval
p.adjust(pval, method = "BH")
```

```
# ABSTRACT VS APPLIED
item <- 1:20
i.type <- c("Abstract", "Abstract", "Abstract", "Abstract", "Applied", "Applied",
        "Abstract", "Applied", "Applied", "Applied", "Applied",
        "Applied", "Abstract", "Applied", "Applied", "Abstract",
        "Applied", "Abstract", "Abstract", "Applied")
i.type <- as.factor(i.type)
difc <- item.exam(dataHCI[, varsQR], discr = T)[, "Difficulty"]
i.types <- data.frame(item, i.type, difc)
# comparison: difficulty of abstract vs applied questions
# two sample t-test, p = 0.132
t.test(difc ~ i.type)
mean(difc[i.type == "Abstract"]); sd(difc[i.type == "Abstract"])
mean(difc[i.type == "Applied"]); sd(difc[i.type == "Applied"])
```

```
# FIGURES
# settings for graphics
theme1 <- theme_bw() +  theme(axis.line  = element_line(colour = "black"),
                        panel.grid.major = element_blank(),
                        panel.grid.minor = element_blank(),
                        panel.background = element_blank(),
                        legend.title = element_blank(),
                        legend.position = c(0, 1),
                        legend.justification = c(0, 1),
                        legend.background = element_rect(fill = "transparent"),
                        legend.key = element_rect(colour = "white"))

# Figure 1: boxplots
# graduate vs undergraduate
df <- data.frame(score = c(dataGrads$total, dataHCI$total),
                 group = c(rep("Graduate", nrow(dataGrads)),
                           rep("Undergraduate", nrow(dataHCI))))
df$group <- relevel(df$group, "Undergraduate")
p1 <- ggplot(df, aes(x = group, y = score)) +
  geom_boxplot(aes(x = group, y = score,
                   fill = group),
               alpha = 0.7) +
  geom_point(position = position_jitter(width = 0.2)) +
  xlab("") +
  ylab("Total score on HCI") +
  scale_fill_manual(values = c("#B79F00", "#F564E3"))
p1 + theme1 + theme(legend.position = "none")

# pre vs post
df <- melt(dataPrePost, id.vars = 'id', measure.vars = c('score.pre','score.post'))
levels(df$variable) <- c("Pre", "Post")
p2 <- ggplot(df, aes(x = variable, y = value)) +
  geom_boxplot(aes(x = variable, y = value,
```

```
                fill = variable),
            alpha = 0.7) +
  geom_point(position = position_jitter(width = 0.2)) +
  xlab("") +
  ylab("Total score on HCI") +
  scale_fill_manual(values = c("#00FF00FF", "#0080FFFF"))
p2 + theme1 + theme(legend.position = "none")

# exposed vs not exposed
df <- data.frame(value = c(dif, difTestretest),
                 variable = c(rep("Exposed", length(dif)),
                              rep("Not exposed", length(difTestretest))))
p3 <- ggplot(df, aes(x = variable, y = value)) +
  geom_boxplot(aes(x = variable, y = value,
                   fill = variable),
               alpha = 0.7) +
  geom_point(position = position_jitter(width = 0.2)) +
  xlab("") +
  ylab("Difference in total score on HCI") +
  scale_fill_manual(values = c("#FF8000FF", "#FF00FFFF"))
p3 + theme1 + theme(legend.position = "none")


# Figure 2: density plots
# relevel of variables
levels(dataHCI$typeS) <- c("Allied", "Science", "Mixed")
dataHCI$typeS <- relevel(dataHCI$typeS, "Science")
dataHCI$major <- as.factor(dataHCI$major)
levels(dataHCI$major) <- c("Other", "Science")
dataHCI$major <- relevel(dataHCI$major, "Science")

# planned majors
hist0 <- ggplot(dataHCI, aes(total, fill = major)) +
  geom_density(aes(y = ..density..,
                   color = major,
```

```
            linetype = major),
          position = "identity",
          alpha = 0.5,
          size = 1) +
 xlab("Total score on HCI") +
 ylab("Density") +
 scale_y_continuous(expand = c(0, 0), limits = c(0, 0.16))
hist0 + theme1
# course type
hist1 <- ggplot(dataHCI, aes(total, fill = typeS)) +
 geom_density(aes(y = ..density..,
            color = typeS,
            linetype = typeS),
          position = "identity",
          alpha = 0.5,
          size = 1) +
 xlab("Total score on HCI") +
 ylab("Density") +
 scale_y_continuous(expand = c(0, 0), limits = c(0, 0.16))
hist1 + theme1
# institution type
hist2 <- ggplot(dataHCI, aes(total, fill = typeSCH)) +
 geom_density(aes(y = ..density..,
            color = typeSCH,
            linetype = typeSCH),
          position = "identity",
          alpha = 0.5,
          size = 1) +
 xlab("Total score on HCI") +
 ylab("Density") +
 scale_y_continuous(expand = c(0, 0), limits = c(0, 0.16))
hist2 + theme1

# Figure 3: difficulty and discrimination
DDplot(dataHCI[, varsQR])
```

```
# Figure 4: Wright map
# detaching package psych
detach(package:psych, unload = TRUE)
# 1PL IRT model
fit1PL <- rasch(dataHCI[,varsQR])
factor.scores(fit1PL)
# estimated ability
thetas1PL <- factor.scores(fit1PL)$score.dat[, "z1"]
# estimated difficulty
diffclt1PL <- summary(fit1PL)$coef[1:20, "value"]
# ordered difficulty
diffclt1PLordered <- diffclt1PL[order(diffclt1PL)]


wrightMap(thetas = thetas1PL,
        thresholds = diffclt1PLordered,
        item.side = itemClassic,
        item.prop = 0.5,
        label.items = order(diffclt1PL),
        thr.lab.text = order(diffclt1PL),
        dim.names = "",
        oma = c(0, 2, 0, 2))


# Figure 5: IRT models
# ICC
ICC <- plot(fit3PL,
         type="ICC")
# IIC
IIC <- plot(fit3PL,
         type="IIC",
         ylab = "Item information")
# TIF
TIF <- plot(fit3PL,
```

```
        type="IIC",
        item = 0,
        ylab = "Test information",
        main = "Test Information Function")

# Figure 6: tetrachoric correlation heatmap
corrplot(corP$rho, method="shade", ord="hclust", rect.col = "black", cl.lim=c(-0.1,1), cl.length=12)

# Figure 7: abstract vs applied
AA_box <- ggplot(i.types, aes(x = i.type, y = difc)) +
  geom_boxplot(aes(x = i.type, y = difc,
                   fill = i.type),
               alpha = 0.7) +
  geom_point(position = position_jitter(width = 0.2)) +
  xlab("") +
  ylab("Difficulty") +
  scale_y_continuous(expand = c(0, 0), limits = c(0, 1)) +
  scale_fill_manual(values = c("gold", "#FF00FFFF"))
AA_box + theme1 + theme(legend.position = "none")
```

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Table 1. The questions in the HCI are either abstract or applied

The wording of abstract questions may use variable X to indicate that they may refer to any particular system. Applied questions refer to particular physiologically regulated variable, as specified. The HCF is the Homeostasis Conceptual Framework (McFarland et al 2016).

HCI Item	Item Type	Regulated variable	Corresponding critical components and constituent ideas in HCF (HCF row number)
1	Abstract	Unspecified	Negative feedback (H2, H2.1)
2	Abstract	X	Sensor (H3, H3.3)
3	Abstract	X	Negative feedback (H2, H1.2)
4	Abstract	X	Homeostasis / stable internal environment (H1.7)
5	Applied	Blood pressure	Sensor (H3)
6	Applied	Temperature	Control center: set-point (H4.5)
7	Abstract	Unspecified	Control center: integrator (H4.1)
8	Applied	Calcium	Sensor (H3)
9	Applied	Blood pressure	Sensor (H3.4)
10	Applied	Oxygen	Homeostasis / stable internal environment (H1.2, H2)
11	Applied	Glucose	Sensor (H3.1, H3.3)
12	Applied	Temperature	Control center (set-point) (H4.5, H4.6)
13	Abstract	Unspecified	Effector (H5.3, H5.2)
14	Applied	Temperature	Effector (H5.2, H5.3)
15	Applied	Blood pressure	Effector (H5.1, H5.2)
16	Abstract	Unspecified	Control center (H4.5)
17	Applied	Blood pressure	Control center (H4.5, H4.6, H4.2)
18	Abstract	Unspecified	Control center & Sensor (H4.2)
19	Abstract	Unspecified	Control center integrator (H4.6, H4.2)
20	Applied	Glucose	Sensor (H3.4, H1.7)

Table 2. Item parameter estimates and standard errors (SE) in the 3-parameter IRT model

Because there are three parameters for each item, discrimination (a), difficulty (b), and guessing (c), the model uses 60 parameters in total. Note that, in most cases, the value of the guessing parameter is quite small, indicating that students in this sample were rarely guessing. Item fit statistics (S-X2, see Ames and Penfield, 2015) are included indicating that all items fit well.

Item	Coefficient estimates						Item fit statistics		
	Discrimination (a)	SE (a)	Difficulty (b)	SE (b)	Guessing (c)	SE(c)	$S\text{-}X^2$	df	p-value
1	1.09	0.37	-0.32	0.67	0.30	0.21	13.77	12	0.32
2	0.78	0.34	-1.23	1.84	0.17	0.58	17.66	12	0.13
3	2.42	0.87	-0.71	0.38	0.46	0.16	11.88	9	0.22
4	0.34	0.11	1.19	0.72	0.00	0.10	15.32	13	0.29
5	0.71	0.16	0.38	0.35	0.00	0.10	11.79	11	0.38
6	1.54	0.44	0.86	0.14	0.11	0.06	16.13	11	0.14
7	0.21	0.09	-0.85	1.18	0.00	0.11	21.44	13	0.06
8	1.09	0.14	-0.98	0.13	0.00	0.01	17.13	11	0.10
9	0.44	0.10	0.64	0.23	0.00	0.01	15.24	13	0.29
10	3.93	2.06	0.56	0.12	0.49	0.04	17.74	11	0.09
11	1.06	0.44	-1.08	1.31	0.21	0.51	4.03	11	0.97
12	2.25	0.74	0.56	0.16	0.36	0.06	13.59	12	0.33
13	4.27	1.63	0.34	0.12	0.37	0.05	19.82	11	0.05
14	3.08	1.16	0.00	0.20	0.51	0.07	12.96	10	0.23
15	2.02	0.60	0.82	0.13	0.24	0.05	8.52	12	0.74
16	1.55	0.38	0.06	0.24	0.23	0.10	11.56	12	0.48
17	1.61	1.49	2.81	1.03	0.27	0.03	14.37	13	0.35
18	1.85	0.24	-1.13	0.10	0.00	0.00	8.12	10	0.62
19	1.39	0.18	-1.24	0.13	0.00	0.02	16.60	11	0.12
20	0.95	0.34	-1.06	1.18	0.07	0.48	8.83	12	0.72

Table 3. Three sets of DIF analyses assess the fairness of all 20 items with respect to gender, English language status and ethnicity

This DIF analysis was based on a logistic regression that compared two models: a null model that assumed no DIF, and alternative model that assumed DIF. We used a likelihood-ratio test (LR-value) to determine whether the difference between the models was significant at the 0.05 level. We used the Benjamini-Hochberg correction to account for the fact that we are conducting multiple comparisons. Because all of the p-values exceed 0.05, none of the items functioned differently.

Item	DIF analysis with logistic regression					
	Gender		English		Ethnicity	
	LR-value	p-value	LR-value	p-value	LR-value	p-value
1	6.54	0.21	4.25	0.25	12.30	0.53
2	0.12	0.94	4.13	0.25	9.01	0.66
3	0.40	0.94	8.31	0.09	11.03	0.55
4	3.03	0.55	1.72	0.62	19.85	0.16
5	1.36	0.85	3.07	0.36	7.64	0.76
6	2.69	0.58	3.06	0.36	6.87	0.78
7	0.38	0.94	1.24	0.72	13.75	0.46
8	1.72	0.77	0.24	0.89	20.87	0.16
9	3.33	0.55	4.78	0.24	10.98	0.55
10	2.43	0.59	4.74	0.24	10.18	0.61
11	5.00	0.33	0.93	0.78	9.39	0.66
12	6.32	0.21	0.25	0.89	7.46	0.76
13	3.23	0.55	7.44	0.10	18.02	0.18
14	0.26	0.94	0.59	0.85	17.07	0.21
15	0.43	0.94	0.54	0.85	19.71	0.16
16	0.21	0.94	10.19	0.09	18.38	0.18
17	0.55	0.94	1.65	0.62	5.55	0.85
18	0.27	0.94	7.95	0.09	21.52	0.16
19	9.70	0.10	8.94	0.09	12.42	0.53
20	9.18	0.10	4.69	0.24	11.89	0.53