On The Impact of Nonverbal Signalling in Online Teaching

Maria Osipenko[1*], Katrin Heller[2]
[1]Department of Business and Economics, Berlin School of Economics and Law, Berlin, Germany
[2]Berlin School of Economics and Law, Berlin, Germany
*Corresponding author, Email: osipenko@hwr-berlin.de

Abstract

Strategies that optimize teaching style and enhance teaching impact, especially in an online format, have captured the attention of researches in various fields. In an online lecture, instructors may communicate non-verbally (e.g., via highlighting) some important concepts in the script to draw attention to particular key elements for a given topic. The so-called signalling or cueing strategies, where visual (text-based or picture-based) cues draw attention to relevant parts of the material, come into play. In the present paper, we address the following research question: Do different usage patterns of nonverbal signalling cues, such as highlighting words and formulas, as well as making notes in lecture materials, have an impact on learning success in an online format? In our retrospective analysis of lecture notes and the contained nonverbal signalling cues against the probability of passing exam questions in quantitative online courses, we were able to confirm a significant positive effect of highlighting and colour coding of formulas and a significant negative impact of using many signalling tools simultaneously. The results are promising for recommending signalling strategies for course instruction in quantitative disciplines.

Keywords: non-verbal signalling, non-verbal cues, teaching strategy

1. Introduction

Strategies that optimize teaching style and enhance teaching impact, especially in an online format, have captured the attention of researches in various fields. Vikas and Mathur (2021) finds a significant impact of teaching effectiveness on overall learning outcomes (see also Emhardt et al. (2022), Ng and Przybylek (2021), Dixson et al. (2016), Cheng et al. (2014), and Tawil (2019).) According to Copeland et al. (2000), a lecturer's ability to identify key points, lecture clarity and comprehensibility are at core of lecture quality perception.

Kebritchi, Lipschuetz, and Santiague (2017) mention communication barriers when learning online, in the form of frequently missing verbal and nonverbal cues on the instructor and learner side. From the learner's point of view, verbal instructor cues can be transmitted through adequate educational technology usage in video lectures, while nonverbal information comes through instructor gestures when explaining the material.

In the present paper, we address the following research question: Do different usage patterns of nonverbal signalling cues, such as highlighting words and formulas, as well as making notes in the lecture materials, have an impact on learning success in an online format?

According to the empirically supported computational theory of visual attention (Bundesen, Vangkilde, and Petersen (2015)), visually perceived objects compete with each other to enter our visual short-term memory. It is assumed that this process is influenced by our subjective attention weights, determining which features of a visual object (denoted as *x*) are more important in our eyes for sorting it into a specific category (denoted as *i*). On the computational side, the phenomena is characterized by the so-called processing rate equation:

$$v(x,i) = \eta(x,i)\beta_i \frac{w_x}{\sum_t w_t}, \tag{1}$$

where $v(x,i)$ denotes the rate at which a visual categorization $x \in i$ takes place. $\eta(x,i)$ denotes the strength of sensory evidence for i, β_i is category-specific decision bias, and $\frac{w_x}{\sum_t w_t}$ is the relative attention weight for x related to the sum of all object weights.

The weight equation specifies:

$$w_x = \kappa_x \sum_j \eta\,(x,j)\pi_j$$

with $\pi_\cdot$ being the pertinence of category $\cdot$ and κ_x the local feature contrast of x (e.g., colour) as proposed by Nordfang, Dyrholm, and Bundesen (2012). That is, when $\pi_\cdot$ is fixed, the visual evidence in favour of a category $\eta(x,i)$ and the object contrast κ_x tend to increase the weights and support the encoding of the corresponding concepts into one's visual short memory. We can thus manipulate the appearance $\eta(x,i)$ and the contrast κ_x to leverage the resulting weight of x.

These attention weights play a crucial role in determining which object will be processed into the visual working memory. Due to limited processing capacity, the visually perceived objects compete with each other, and the objects with the highest weights have a higher likelihood to be processed. The following example includes three categories: high relevance text (*h*), low relevance text (*l*), formulas (*f*):

$$w_x = \kappa_x\{\eta(x,h)\pi_h + \eta(x,l)\pi_l + \eta(x,f)\pi_f\}$$

For text, $\eta(x, h)$ can be increased using text formatting and signaling via highlighting. If x is a formula, $\eta(x, h) = \eta(x, l) = 0$ and $\eta(x, f) = 1$ meaning that the formulas are always identified as such. However, in case of formulas, the category specific β_f in (1), quantifying the willingness to process the formulas, might be low, and thus contrasting signalling (κ_x) might be useful in increasing the associated relative weights to support the processing of the information.

In an online lecture, an instructor may communicate (e.g., via highlighting) some important concepts non-verbally to draw attention to particular key aspects of a topic. The visual attention model above predicts, in this case, higher attention weights for a contrasted concept and thus a higher rate for encoding, keeping all other weights equal. Attention weights for objects with high visual evidence in favour of a category should substantially increase through visual contrasts (e.g., formulas). However, contrasting too many elements possibly deteriorates the increase in their relative weights and results in a lower likelihood of processing the relevant content.

The above aligns with the so-called signalling or cueing principle of van Gog (2014), where visual (text-based or picture-based) cues are added to draw attention to relevant parts of the material. The cueing principle is especially relevant in case of a learning environment, where learners most likely lack prior knowledge of a subject. In a more comprehensive framework of cognitive theory of multimedia learning (Mayer (2014)), the first stage refers to selecting the relevant part from the materials to organize them later into a coherent representation under restrictions of limited processing capacity. The effectiveness of this first stage is enhanced via signalling. Bautista, Maradei, and Pedraza (2022) provides references to studies where using signalling features reduced cognitive load and improved student performance.

In this paper, we conduct an observational study to assess the usefulness of text-based signalling in lecture notes for topics in introductory and intermediate statistics courses during three online semesters taught by a single instructor in a higher education setting. To measure learning success, we employ the transfer test approach. That is, our response variable relates to the topic specific exam scores.

Our research hypotheses are:

- Signalling nonverbal cues from the instructor result in an increased probability of passing the associated exam parts.

- The strength of the signalling effect differs across different objects such as text and formulas.

- An excessive amount of cues may distract and even result in a decreased probability of passing the associated exam parts.

In our analysis, we assume that other verbal lecture parts (such as verbal explanations and printed media/ script) remained the same across different semesters. Moreover, our analysis rests on the assumption that higher attention weights enhance learning and result in a higher probability of passing the respective exam parts at the end of the course. We find data-based evidence that colour coding and highlighting formulas indeed increase the probability of passing the associated exam questions. We also discover that using too many nonverbal cues can exhibit a negative effect on the later probability.

2. Data

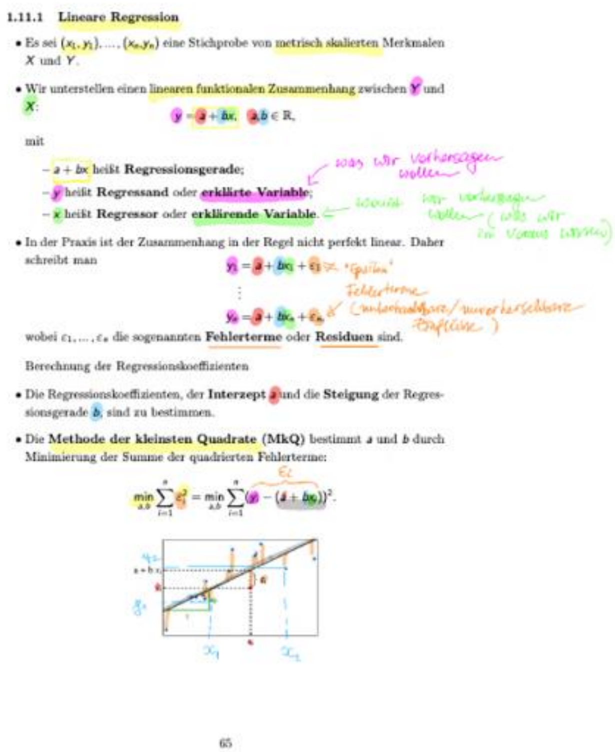
We retrospectively extract features from the lecture notes of three semesters and two courses on statistics. Figure 1 shows an example page of such lecture notes with nonverbal cues. The annotated scripts in PDF format of the courses Statistics 1 and Statistics 2 offered during two winter terms and one summer term in 2020 and 2021 constituted the raw data. Each course contains ten topics, for which the acquired competencies are tested in the final exam. In total, we have 63 data points corresponding to the individual topics.

To extract the contained textual cues, we manually collect the following 12 variables per topic:

- number of highlighted words
- number of highlighted formulas
- number of words in handwritten notes
- number of arrows drawn by hand

The descriptive statistics for the collected **explanatory variables** are given in Table 1.

Figure 1: An example of lecture notes



1.11.1 Lineare Regression

- Es sei $(x_1, y_1), \ldots, (x_n, y_n)$ eine Stichprobe von metrisch skalierten Merkmalen X und Y.
- Wir unterstellen einen linearen funktionalen Zusammenhang zwischen Y und X:

$$y = a + bx, \quad a, b \in \mathbb{R},$$

mit

- $a + bx$ heißt **Regressionsgerade**;
- y heißt **Regressand** oder **erklärte Variable**; was wir vorhersagen wollen
- x heißt **Regressor** oder **erklärende Variable**.

- In der Praxis ist der Zusammenhang in der Regel nicht perfekt linear. Daher schreibt man

$$y_1 = a + bx_1 + \varepsilon_1$$
$$\vdots$$
$$y_n = a + bx_n + \varepsilon_n$$

Fehlerterme

wobei $\varepsilon_1, \ldots, \varepsilon_n$ die sogenannten **Fehlerterme** oder **Residuen** sind.

Berechnung der Regressionskoeffizienten

- Die Regressionskoeffizienten, der **Interzept** a und die **Steigung** der Regressionsgerade b, sind zu bestimmen.
- Die **Methode der kleinsten Quadrate (MkQ)** bestimmt a und b durch Minimierung der Summe der quadrierten Fehlerterme:

$$\min_{a,b} \sum_{i=1}^{n} \varepsilon_i^2 = \min_{a,b} \sum_{i=1}^{n} \overbrace{(y_i - (a + bx_i))}^{\varepsilon_i}{}^2.$$

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We also collect the total number of pages and words for each topic and course, as well as the total number of printed formulas to standardize the collected values to make the topics comparable. Additionally, we label the challenging topics with a dummy variable **"topic complexity"** to control for the varying complexity of the topics.

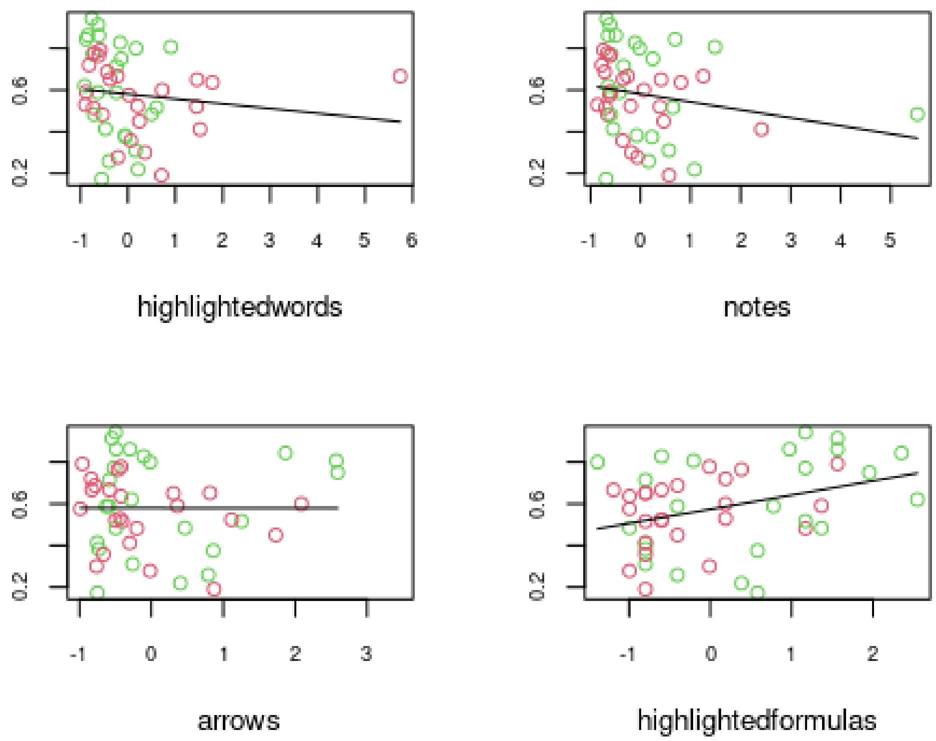
To make the topics comparable, we first scale the variables "**highlighted words**" and "**notes**" to the total number of words and pages, and the variable "**arrows**" to the total number of pages. Subsequently, we standardize the collected variables over all topics.

Table 1: Summary statistics for the variables highlighted words, notes, arrows, and highlighted formulas.

		pages	words	formulas	highlighted words	notes	arrows	highlighted formulas
minimum		1.00	80.00	0.00	14.00	10.00	3.00	0.00
maximum		30.00	1660.00	24.00	367.00	830.00	223.00	20.00
mean		10.41	760.63	8.37	152.67	271.57	71.30	7.05
standard deviation		6.48	377.52	5.94	81.94	170.96	48.55	5.08
skewness		0.86	0.44	0.60	0.70	1.06	1.13	0.67

For each pre-processed topic, we identified the exam questions, that allow inferring the problem-solving skills of students linked to the topic. Then, we counted the total number of students who attempt to answer the exam questions, and the number of students who passed, that is, scored more than the half of the points for their solution to the exam questions. The resulting proportion of passed is our **response**.

Figure 2: Scatterplots of explanatory variables against the response (ratio of students who passed the exam question associated with the given topic). The green points correspond to introductory statistics course, the red points correspond to intermediate statistics course.



The effects of explanatory variables on the response in the form of the proportion of students who passed the exam question associated with the given topic, seem to be homogeneous across the introductory and intermediate level, as shown in the scatter plots of the response against the standardized explanatory variables in Figure 2.

3. Methods and Results

To assess the effects, we fit a binomial regression to the data using the logit link. Formally, our model is specified as:

$$ln \frac{p(x_1, \ldots, x_k)}{1 - p(x_1, \ldots, x_k)} = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k, \quad (2)$$

where $p(x_1, \ldots, x_k)$ denotes the conditional probability of passing the topic-associated exam question and $x_1, \ldots, x_k$ are the explanatory variables. In our first model specification, these are the number of highlighted words, notes, arrows and formulas used in the topic lecture notes, respectively. We conduct the estimation via maximum likelihood using the function **glm (generalized liner model)** with family *binomial* and link *logit* in R Statistical Software (R Core Team (2023)).

The estimation results are presented in Table 2. Only the dummy variable "**topic complexity"** and "**highlighted formulas"** attain significant effects. Whereas the topic complexity reduces the probability of passing the associated exam question, the number of highlighted formulas increases this probability. We are not able to confirm significant effects of other explanatory variables: "**highlighted words"**, "**notes"**, and "**arrows"**.

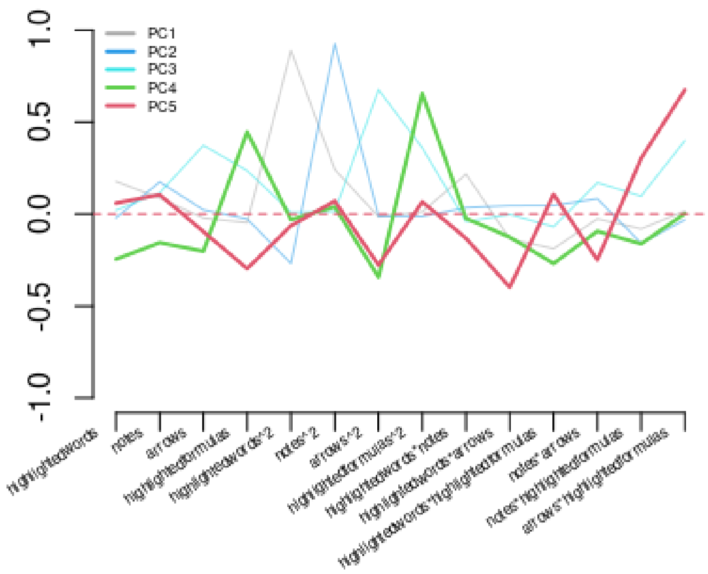
Table 2: The estimation results of binomial regression on signalling cues contained in the lecture notes.

Variable	Estimate	Standard error	*z* value	*p* value
intercept	-0.43	0.06	-7.35	0.00
topic complexity	-0.36	0.10	-3.65	0.00
highlighted words	0.04	0.07	0.55	0.58
notes	-0.06	0.06	-0.99	0.32
arrows	-0.01	0.06	-0.23	0.82
highlighted formulas	0.13	0.06	2.30	0.02

To account for interaction terms between the variables with the small sample size at hand, we now reduce the dimension of the extended data basis containing the original variables and their interaction terms including the quadratic terms. Here we use principal component analysis utilize the resulting principal component scores as explanatory variables in our model in (2).

The resulting principal component loadings are presented in Figure 3. The first five principal components (PC) on Figure 3 explain more than 75% of the total variation. Therefore, we take the first five principal components (PC1 through PC5) for our subsequent analysis in a binomial regression model. The resulting coefficient estimates are reported in Table 3 below.

Figure 3: Principal component (PC) weights for the variables



PC4 and PC5 exhibit significant effects on the probability to pass the associated exam question. The interpretation of the significant PCs in the model is the following (see Figure 3):

- PC4 "Signalling with colour coded formulas while sparing other cues": this component increases whenever the amount of colour coded formulas and the square of it lies above the average. In Figure 3, we see high positive weights for the corresponding variables. At the same time, negative weights are given to the amount of highlighted words, notes, arrows, and the square of arrows and the interaction terms of colour coded formulas with arrows, notes, and highlighted terms. That is, the corresponding component falls smaller (or gets even negative) if the respective variables have high values.

- PC5 "Distracting with the combination of formula cues, arrows and notes": this component increases, when the interaction terms of highlighted formulas with notes and arrows fall large, and it decreases whenever the number of colour coded formulas, the square of arrows, and the interactions between arrows, notes and highlighted words increase. The corresponding positive and negative weights for these variables are shown in Figure 3.

Table 3: The estimation results of binomial regression on the first five principal components obtained from signalling cues in the lecture notes and their interaction terms.

Variable	Estimate	Standard error	*z* value	*p* value
intercept	-0.42	0.06	-7.23	0.00
topic complexity	-0.37	0.10	-3.68	0.00
PC1	-0.01	0.01	-1.00	0.58
PC2	-0.03	0.02	-1.26	0.32
PC3	-0.02	0.03	-0.64	0.82
PC4	0.06	0.03	2.30	0.02
PC5	-0.09	0.04	-2.49	0.01

Overall, PC4 has a significant positive effect, aligning with the recommendations of van Gog (2014) concerning the colour coding of key concepts, whereas PC5 exhibits a significant negative effect, supporting the competition-of-visual-objects principle of the theory of visual attention as in Bundesen, Vangkilde, and Petersen (2015). Moreover, the negative effect of PC5 dominates the positive effect of PC4, showing that parsimonious use of signalling tends to result in better learning outcomes.

4. Conclusion

In our retrospective analysis of lecture notes and the contained nonverbal signalling cues against the probability of passing exam questions in a quantitative teaching field, we were able to confirm a significant positive effect of highlighting and colour coding of formulas and a significant negative impact of using many signalling tools simultaneously.

We extracted nonverbal signalling features directly from lecture notes by counting the number of signalling cues, such as highlighted text and formulas, and compute their interaction terms. In our first model specification, we simply used the extracted features without the interaction terms as explanatory variables in a logistic regression model for the response, which is the ratio of students who passed the associated exam parts to all participants. However, only the effects of highlighting formulas appeared to be significant in the model.

For our second model specification, we applied Principal Component analysis to reduce the dimension of the data augmented with variable interaction and quadratic terms. This allowed us to obtain the principal components of the data, which quantify the signalling strategies used in the lecture notes in a more comprehensive way. Subsequently, we used logistic regression of the response, which is the ratio of students who passed the associated exam parts to all participants, to assess the role of the signalling strategies for student performance. Significant results were obtained for the following two principal components: the first one, where a positive score indicates the strategy “Signalling with colour coded formulas while sparing other cues” and the second one, where a positive score corresponds to the situation “Distracting with the combination of formula cues, arrows and notes”. The first mentioned strategy had a significant positive impact on student performance, whereas the second one had a significant negative impact on the student performance.

The significant positive impact of the strategy “Signalling with colour coded formulas while sparing other cues” supports the cueing principle and fosters a better student performance in our analysis. In this sense, our results align with the importance of cueing principle stressed in van Gog (2014), Mayer (2014), and Bautista, Maradei, and Pedraza (2022). Furthermore, as the case “Distracting with the combination of formula cues, arrows and notes” had a significant negative impact on student perception as measured by the exam score, our results confirm the distraction hypothesis that using too many signalling cues can be counterproductive. That way we confirm the applicability of the computational theory of visual attention in Bundesen, Vangkilde, and Petersen (2015) with our findings regarding the negative impact of many signalling cues used simultaneously. Overall, the results are promising for recommending signalling strategies in the teaching of quantitative disciplines.

Nevertheless, one should generalize our results with great caution, since our sample size is rather small, only one teaching person is considered, and the underlying assumption of homogeneous and representative student groups is restrictive (Moos et al (2006)). These limitations point to future study directions. The analysis can be extended to a larger sample size and a wider teacher and student palette.

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