

## ABSTRACT

1 Poor quality medicines represent an expanding global public health threat facilitated  
2 by the Internet. A recent survey showed that one in five students have used modafinil  
3 to enhance learning ability mainly purchased from Internet sources. The aim of this  
4 work was to develop on-the-spot and simple methods for the quantification of modafinil  
5 in generic medicines using Fourier transform-infrared (FTIR), near-infrared (NIR) and  
6 Raman spectroscopy along with partial least square regression (PLSR). Modafinil  
7 tablets were measured in intact form using NIR and Raman and in powdered form  
8 using FTIR, NIR and Raman. Additionally, powder mixtures of crushed modafinil  
9 tablets and excipient(s) were prepared either by diluting the crushed tablets with  
10 excipient(s), or sequentially adding excipient(s) to the crushed tablets. Three PLSR  
11 models were constructed in Matlab 2014a from powder mixtures and two from intact  
12 and powdered tablets. For FTIR and Raman spectroscopy, PLSR models based on  
13 tablets gave linear calibration curve with correlation coefficient ( $r^2$ ) values above 0.94  
14 and a root mean square error of calibration (RMSEC) below 0.96% m/m. Conversely,  
15 the PLSR model based on powder sequential addition gave the highest accuracy using  
16 the NIR spectra ( $r^2 = 0.99$ , RMSEC = 1.15% m/m). The latter model showed accuracy  
17 in predicting the concentration of the active pharmaceutical ingredient in modafinil  
18 generic medicines proving their authenticity. The overall results showed that the  
19 combination of the three spectroscopic methods with PLSR offered a rapid technique  
20 for authenticating generic modafinil medicines.

21

22 Keywords: Counterfeit medicines; infrared; near-infrared; Raman; spectroscopy;  
23 quantification; authentication; partial least square regression.

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## 1. Introduction

26 Poor quality medicines represent a global threat to the public health that can result in  
27 treatment ineffectiveness, drug resistance, increased morbidity and mortality rate,  
28 economic loss and problems to the healthcare system [1,2]. Poor quality medicines  
29 can be degraded, substandard or counterfeit medicines [3]. Degraded medicines  
30 include those, which deteriorate from the poor-quality storage (humidity, temperature  
31 and light). Substandard medicines are those that encounter accidental defects in the  
32 manufacturing process and fail to fulfil the products' specifications. Counterfeit  
33 medicines are medicines which "are deliberately and fraudulently mislabelled with  
34 respect to identity and/or source" [4].

35 The Internet plays a major role in the spread of poor quality medicines, which could  
36 be over the counter products, prescription medicines, drugs of abuse and  
37 supplementary products [5-7]. This is partly due to the fact that the market of  
38 counterfeit online medicines is in continuous expansion [8]. According to the World  
39 Health Organisation (WHO), 50% of the medicines sold through illegal online  
40 pharmacies are counterfeits [9]. Thus, in 2013 the Interpol closed down over 9600  
41 illegal online pharmacies and seized over 9.6 million prescription medicines that were  
42 worth over \$41.1 million [10]. In this respect, the purchase of a counterfeit medicine  
43 could impose a public safety issue especially in case of drugs of abuse where  
44 medicines are frequently bought.

45 Smart drugs were one of the top classes that sales have increased (up to 50%) over  
46 the last decade and has been facilitated by the Internet (International Narcotics Control  
47 Board, 2016). Smart Drugs such include nootropics that have become particularly  
48 popular among students and healthcare professionals who have been under pressure

49 of study/work [11,12]. Students and healthcare professionals have utilised nootropics  
50 for enhancement of the memory and learning abilities [13-15]. There are several  
51 different nootropics on the market e.g. adderall, dexedrine, ephedrine,  
52 methylphenidate, modafinil and piracetam. Modafinil has the same stimulant effects of  
53 nootropics however it has less abusive tendencies and side effects [13,14].

54 Modafinil is sold under the brand name Provigil [16], and comprises modafinil as the  
55 active pharmaceutical ingredient (API), and the following excipients: croscarmellose  
56 sodium, lactose monohydrate, magnesium stearate, maize starch and povidone.  
57 Nonetheless, the excipients in generic modafinil are not always known and this  
58 variation influences the process of authentication of branded and generic modafinil.  
59 Thus, when authenticating a branded medicine, the test medicine needs to match the  
60 physical and chemical properties of the reference medicine [17]. Generic medicines  
61 however only need to prove that they contain the exact API at the correct concentration  
62 in relation to the reference medicine [18]. Consequently, a quantitative approach in  
63 authenticating generic modafinil medicines is favoured.

64 The literature reported conventional methods for quantification of the API in modafinil,  
65 which range from simple spectrophotometric to chromatographic methods. A  
66 spectrophotometric method was reported for the quantification of modafinil in solid  
67 dosage forms and underlined measurement of the absorbance of modafinil at its  
68 maximum wavelength (236 nm) [19]. Chromatographic methods utilised mainly  
69 reverse phase high performance liquid chromatography (RP-HPLC) [19-22], and thin  
70 layer chromatography (TLC) [23]. The aforementioned techniques offered, sensitivity,  
71 selectivity and precision yet they were time-consuming, destructive and required  
72 extensive sample preparation. On the contrary, spectroscopic techniques including  
73 Fourier transform infrared (FTIR), near-infrared (NIR) and Raman spectroscopy have

74 shown to be quicker, simpler and mobile [24-33]. When combined with multivariate  
75 regression analysis spectroscopic techniques offered rapid, on-spot and non-  
76 destructive quantification of APIs medicines [17,32]. To the best of our knowledge, no  
77 spectroscopic methods have yet been employed for quantification of modafinil in  
78 tablets.

79 Therefore, this work aimed at developing methods for the on-spot quantification of  
80 modafinil in generic medicines using FTIR, NIR and Raman spectroscopy along with  
81 PLSR.

82

## 83 **2. Materials and Methods**

### 84 2.1. Materials

85 Standard reference material including glucose, lactose, magnesium stearate,  
86 maize starch, microcrystalline cellulose, modafinil, povidone, sodium  
87 carboxymethylcellulose and sucrose were purchased from Sigma-Aldrich.

88 Eight modafinil generic batches of doses 100 and 200 milligrams (mgs) were  
89 bought from four Internet websites (Table 1). The percentage mass per mass (%  
90 m/m) of modafinil in the tablets was in the range of 57.6 – 72.7% m/m.

91 Reference analysis of modafinil API and tablets was performed using reverse  
92 phase-high performance liquid chromatography (RP-HPLC) by adopting the  
93 procedure given by Rao et al. 2007 [34].

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95

96

## 97 2.2. Sample Preparation

98 Four types of samples were considered in this study. The first type included intact  
99 tablets, which were removed from the packaging and used 'as received' without  
100 any treatment. The second type comprised powdered tablets which had been  
101 crushed in a mortar, homogenised and stored in 4 mm glass vials. The third type  
102 of samples comprised powders of pure substances (API and excipients) and the  
103 fourth type included powdered mixtures that were prepared by mixing crushed  
104 modafinil tablets with excipient(s).

105 Three modafinil mixtures were prepared and included: M1 (modafinil lactose  
106 dilution), M2 (modafinil excipients dilution) and M3 (modafinil excipients sequential  
107 addition) (Table 2). M1 (modafinil lactose dilution) was prepared by adding aliquots  
108 of lactose (major excipient in modafinil tablets) to crushed modafinil tablets to get  
109 a % m/m of modafinil in the range of 9.59 – 62.5% m/m. Similarly, M2 was prepared  
110 by adding aliquots of different excipients (one at a time) to crushed modafinil tablets  
111 to get 15.4 – 52.9% m/m of modafinil. A third approach was adopted in mixtures  
112 (M3) which was made by adding excipients (one at a time) sequentially to aliquots  
113 of crushed modafinil tablets to get 15.9 – 62.5% m/m.

114

## 115 2.3. Instrumentation

116 FTIR spectra were recorded using the Bruker Alpha mobile-FTIR equipped with a  
117 single reflection pure diamond attenuated total reflectance (ATR) crystal sample  
118 interface. The spectral range of the instrument was 500 – 6000  $\text{cm}^{-1}$ . NIR spectra  
119 were recorded employing the JDSU microNIR 1700 pro-spectrometer equipped  
120 with linear variable filter (LVF) dispersing element and 128-pixel cooled InGaAs

121 photodiode array detector. Spectra were measured over the wavelength range of  
122 900 – 1700 nm. Raman spectra were recorded using the Rigaku FirstGuard  
123 handheld Raman spectrometer equipped with 1064 nm laser power, thermoelectric  
124 cooling and charge coupled device detector. Spectra were collected over the  
125 wavenumber range of 250 – 2000  $\text{cm}^{-1}$ .

126

#### 127 2.4. Spectroscopic measurements

128 For FTIR measurements, a few milligrams from powdered samples or pure  
129 substances were measured by placing them in direct contact with the ATR crystal.  
130 Homogeneous preparations of samples were prepared using a Vortex mixer before  
131 each measurement. Four spectra were measured per sample such that a new  
132 aliquot was changed after each measurement. Each spectrum was the sum of 16  
133 scans at a resolution of 4  $\text{cm}^{-1}$ . For NIR and Raman measurements, intact tablets  
134 were measured 'as received' by placing them in direct contact with the  
135 spectrometers. Four spectra were taken from each tablet on both sides; such as  
136 two spectra were taken from each side rotating the tablet after each measurement.  
137 In addition, powders were measured through glass vials (after mixing with Vortex  
138 mixer) by placing them in direct contact with the instruments. Each spectrum was  
139 the sum of 32 scans for NIR and three scans for Raman respectively.

140

#### 141 2.5. Data treatment

142 Spectra from the three instruments were exported to Matlab 2014a for analysis.  
143 Spectral pre-treatment was made using multiplicative scatter correction second  
144 derivative (MSC-D1). The similarity between spectra was assessed using

145 correlation in wavelength space (CWS) method. In this respect, a correlation  
146 coefficient (r) value greater than or equal to 0.95 showed similarity. In addition,  
147 quantitative models were developed using partial least square regression (PLSR).  
148 PLSR has been considered as ideal in this case where univariate regression had  
149 not been possible. This was because the absorbance and scattering intensities in  
150 FTIR/NIR and Raman differed according to the physicochemical properties of the  
151 measured samples and not proportional to the concentration of the analyte of  
152 interest (Burns and Ciurczak, 2007) [35]. In this respect, PLSR offered a  
153 multivariate approach for quantifying the APIs in the aforementioned products.  
154 PLSR models predicted the concentrations of the different mixtures and/or  
155 products from multiple variables (absorbance intensities of scattering intensities  
156 measured at the full wavelength range). PLSR models find components (latent  
157 variables) in the absorbance and/or scattering intensities that relate to the  
158 concentrations. A PLSR model eventually assigns loadings (small and large) to the  
159 aforementioned latent variables. Latent variables with small loadings are rejected  
160 and vice versa. This is done by finding factors that capture variation among the  
161 data such that each factor is added as one at a time. In this sense, the first factor  
162 capture the highest variance, the second factor the second highest variance and  
163 so on. The following equations illustrate a PLSR model [36-37]:

$$164 \quad X = T.P + E$$

$$165 \quad c = T. q + f$$

166 Such as  
167 X absorbance or scattering intensities at different wavelengths  
168 c concentrations  
169 q loading vector  
170 T spectral score vector  
171 p spectral loading vector

### 172 **3. Results and Discussion**

173 The present study explored a swift quantification of medicines purchased from  
174 several Internet sources using handheld instruments. This was first study that had  
175 utilised quantitative PLSR models (non-destructive) with portable handheld FTIR,  
176 NIR and Raman spectroscopy, as well as a powder form of formulations with FTIR  
177 for the quantification of modafinil in branded and generic tablets. The  
178 aforementioned PLSR models were not limited to conventional dilution models; but  
179 also included more complex mixtures based on standard and sequential additions  
180 of constituents to crushed tablets.

181 Eight modafinil products (from different batches) were purchased from four  
182 websites. The eight products were selected based on assessing the differences of  
183 authenticity of products between websites as well as within each website. Four of  
184 these products had a label claim of modafinil 100 mg; while the remaining four had  
185 a label claim of modafinil 200 mg. The concentration range of modafinil in the four  
186 products was 57.6 – 72.7% m/m (Table 1). The tablets were compared in relation  
187 to the major constituents (API and excipients) expected to be present in branded  
188 and generic modafinil tablets. Excipients present in branded modafinil tablets  
189 (Provigil) include lactose monohydrate (main excipient), pregelatinised maize  
190 starch, croscarmellose sodium, povidone K29/32 and magnesium stearate [15].  
191 The excipient content of generic tablets may be variable and not always known  
192 [23], therefore additional excipients were measured including glucose, maize  
193 starch, microcrystalline cellulose, sodium carboxymethylcellulose and sucrose.  
194 The spectra of modafinil tablets were compared to the spectra of the API,  
195 excipient(s) and caffeine using the three techniques.

196

197 3.1. FTIR, NIR and Raman activity of modafinil tablets

198 Prior to spectral evaluation the FTIR, NIR and Raman activity of modafinil tablets  
199 and their main constituents had been investigated. When comparing the three  
200 spectroscopic techniques in relation to medicines' identification, it is well known  
201 that APIs are more Raman active whereas excipients are more IR/NIR active  
202 where the Raman activity of excipients is often masked by fluorescence [24]. If the  
203 medicine contains high concentrations of an excipient then the Raman activity of  
204 the medicine could be masked by the fluorescence exhibited by the excipient. One  
205 way of overcoming fluorescence of excipients was by using a longer wavelength  
206 laser such as 1064 nm, and that had been adopted in the current work.

207 The FTIR, NIR and Raman spectra of the medicinal products were compared to  
208 those of the API (modafinil) and the major excipient (lactose monohydrate) in  
209 modafinil tablets. Modafinil API was present in high amounts in all of the measured  
210 products (57 – 72% m/m) which minimised the effect of the excipients [24]. This  
211 was confirmed in the spectra of modafinil products, its API and lactose using the  
212 three techniques (Fig. 1). In this respect, the modafinil tablets' spectra showed  
213 representation of the modafinil API rather than lactose. The FTIR spectrum of  
214 modafinil tablet (Fig. 1a) showed higher similarity for the API spectrum ( $r = 0.95$ )  
215 than the lactose spectrum ( $r = 0.82$ ). Likewise the modafinil tablet NIR spectrum  
216 showed higher representation for the API spectrum ( $r = 0.99$ ) than lactose  
217 spectrum ( $r = 0.77$ ). The modafinil Raman spectrum showed higher similarity for  
218 the API spectrum ( $r = 0.95$ ) but dissimilarity to the lactose spectrum ( $r = 0.01$ ). This  
219 could be attributed to the strong Raman activity of modafinil API that had not been

220 affected by the fluorescence of lactose. Subsequently, the high representation of  
221 the API in the tablets' spectra contributed to the accuracy of quantification of  
222 tablets. Crushing the tablets into powders was needed to facilitate data collection  
223 and while this process may affect the physical properties of the powder (such as  
224 the particle size), our observations showed that the spectroscopic data were not  
225 affected. Some properties such as polymorphic nature of API are likely to be  
226 affected if strong physical processing was applied however, in our experiments we  
227 used gentle processing to ensure minimal energy is applied on tablets. Such  
228 delicate processing avoids any polymorphic changes (such as recrystallization or  
229 amorphous form formation). The particles should be representative of the tablets  
230 content regardless of the size of generated particles; hence reproducibility was not  
231 affected by sample preparation.

232

### 233 3.2. PLSR model construction

234 PLSR was applied to the MSC-D1 FTIR, NIR and Raman spectra over the full  
235 wavenumber/ wavelength in each technique. Four models were created using the  
236 FTIR spectra and five models were created using the NIR and Raman spectra  
237 (Table 3).

238 FTIR models included: FTIRM1 (modafinil lactose dilution), FTIRM2 (modafinil  
239 excipients dilution), FTIRM3 (modafinil excipients sequential addition) and FTIRM4  
240 (modafinil powdered tablets model). FTIRM1, FTIRM2 and FTIRM3 were  
241 constructed using a calibration validation (C: V) ratio of 2:1. Moreover, the  
242 calibration ranges used were 9.49 – 62.5, 15.4 – 52.9 and 15.9 – 62.5% m/m

243 respectively. The modafinil powdered tablet model (FTIRM4) was constructed with  
244 a C: V ratio of 3:1, four factors and a range of 54.9 – 62.4% m/m.

245 NIR models included NIRM1 (modafinil lactose dilution), NIRM2 (modafinil  
246 excipients dilution), NIRM3 (modafinil excipients sequential addition), NIRM4  
247 (modafinil powdered tablets model) and NIRM5 (modafinil intact tablet model).  
248 NIRM1, NIRM2 and NIRM3 were constructed with a C: V ratio of 2:1, and had  
249 calibration ranges of 9.49 – 62.5, 15.4 – 52.9 and 15.9 – 62.5% m/m respectively.  
250 In addition, NIRM4 and NIRM5 were created with a C: V ratio of 3:1 and calibration  
251 range of 54.9 – 62.5% m/m respectively.

252 The Raman models used were: RamanM1 (modafinil lactose dilution), RamanM2  
253 (modafinil excipients dilution), RamanM3 (modafinil excipients sequential addition),  
254 RamanM4 (modafinil powdered tablets model) and RamanM5 (modafinil intact  
255 tablet model). RamanM1, RamanM2 and RamanM3 were made with a C: V ratio  
256 of 2: 1, and had calibration range of 9.49 – 62.5, 15.4 – 52.9 and 15.9 – 62.5%  
257 m/m respectively. Furthermore, RamanM4 and RamanM5 were constructed with a  
258 C: V ratio of 3:1 and calibration range of 54.9 – 62.5% m/m respectively.

259

### 260 3.3. PLSR model validation

261 The linearity of the models was evaluated by internal validation criteria calculated  
262 using the calibration and internal validation sets. For internal validation, the criteria  
263 considered were the regression correlation coefficient ( $r^2$ ), root mean square error of  
264 calibration (RMSEC) and root mean square error of prediction (RMSEP) of the internal  
265 validation set. The  $r^2$  and RMSEC were calculated by interpreting the relationship  
266 between the predicted concentration and the nominal concentration of the calibration

267 set. Likewise, the RMSEP was calculated by interpreting the relationship between the  
268 predicted concentration and the nominal concentration of the validation set. If the  
269 model was a good fit, the relationship would be linear and an  $r^2$  value close to 1 would  
270 be obtained. There was no optimal value for the RMSEC and RMSEP however, the  
271 lower they were the more accurate was the model. A more accurate judgement was  
272 made by evaluating the relative standard error of prediction (RSEP); which was  
273 calculated as the percentage of the ratio of RMSEP to the mean value of the prediction  
274 set. A threshold value of  $\pm 5\%$  was taken for RSEP.

275 For FTIR models, the highest accuracy was observed for FTIRM1 (modafinil powdered  
276 tablet model), which showed  $r^2$  values of 0.98 and 0.97 for the calibration and  
277 validation sets respectively (Table 2). FTIRM1 also showed the high precision among  
278 the models with close RMSEC and RMSEP values, which were 0.52 and 0.78% m/m  
279 respectively. Moreover, the RSEP value of FTIRM4 was 1.33%. The worst model in  
280 relation to accuracy and precision among the FTIR models was FTIRM2. Thus, this  
281 model showed very low  $r^2$  values which were 0.51 and 0.49 for both the calibration  
282 and validation sets respectively. Moreover, the model showed high RMSEC, RMSEP  
283 and RSEP values of 11.2% m/m, 11.6% m/m and 29.8% respectively. This indicated  
284 that although the model was repeatable, it had low precision as the error values were  
285 not satisfactory. Similarly, FTIRM3 (modafinil excipients dilution) showed close  
286 RMSEC and RMSEP values of 6.57 and 4.63% m/m respectively; yet, high RSEP  
287 value of 13.55%. FTIRM3 showed low accuracy of calibration with  $r^2$  value of 0.75.  
288 The same pattern was observed with FTIRM4 that had close values of RMSEC (6.29%  
289 m/m) and RMSEP (7.03% m/m) and high RSEP value (19.8%). The lower accuracy  
290 in models based on mixtures rather than tablets could be attributed to the small amount  
291 of measurements (few milligrams) taken per sample. In this respect, the higher the

292 complexity of the sample (as the case of powdered tablets), the more representation  
293 of the sample was in the FTIR spectrum.

294 NIR models showed the highest accuracy for NIRM3 (modafinil excipients sequential  
295 addition) which gave  $r^2$  values for the calibration and validation sets of 0.99 and 0.99  
296 respectively (Table 3). NIRM3 showed high precision with RMSEC and RMSEP values  
297 of 1.15 and 1.21 correspondingly. Moreover, it showed an RSEP value of 3.45%.  
298 Additionally, the two tablet based models showed high precision but slightly lower  
299 accuracy than NIRM3. These included NIRM4 (modafinil powdered tablet model) and  
300 NIRM5 (modafinil intact tablet model) which had  $r^2$  values of calibration of 0.77 and  
301 0.69 individually. Both models were highly precise and showed RMSEC values below  
302 2% m/m and RSEP values below 4%. The remaining two powder models (NIRM1 and  
303 NIRM2) showed slightly lower accuracy but very poor precision. Thus, the  $r^2$  values of  
304 calibration for NIRM1 (modafinil lactose dilution) and NIRM2 (modafinil excipients  
305 dilution) were 0.72 and 0.84. Both of these models showed good repeatability with  
306 very close RMSEC and RMSEP values. Thus, NIRM1 showed RMSEC and RMSEP  
307 values of 8.45 and 8.82% m/m respectively. Likewise, NIRM2 showed RMSEC and  
308 RMSEP values of 5.26 and 5.25% m/m but had very poor external precision in the  
309 range of 15 – 23%.

310 Raman models showed the highest accuracy/precision for RamanM4 (modafinil  
311 powdered tablet model) and Raman M5 (modafinil intact tablet model) (Table 3). The  
312 aforementioned two models showed  $r^2$  value of calibration of 0.98 and 0.94. In  
313 addition, the RMSEC and RMSEP values for RamanM4 were 0.54 and 0.82% m/m,  
314 whereas for RamanM5 these values were 0.96 and 0.91% m/m respectively.  
315 RamanM4 provided a more precise model as it showed ten times lower RSEP value  
316 (1.4%) than RamanM5 (12.1%). The models based on powdered mixtures gave lower

317 accuracy and precision than tablet based models. In this sense, RamanM1 (modafinil  
318 lactose dilution), RamanM2 (modafinil excipients dilution) and RamanM3 (modafinil  
319 excipients sequential addition) had low  $r^2$  values of calibration which were 0.70, 0.84  
320 and 0.76 respectively. The three aforementioned models had high RSEP values which  
321 were in the range of 17 – 24%. All three models showed close agreement between  
322 their RMSEC and RMSEP values (Table 3).

323

#### 324 3.4. Prediction of modafinil in generic tablets

325 Test sets of powdered and intact tablets were used to examine the external predictive  
326 ability of the models. The predicted value was converted into label claim and the  
327 percentage label claim of each product was assessed. The pharmacopoeia acceptable  
328 deviation of the API for tablets is usually  $\pm 5\%$  of the label claim in order to allow  
329 variation in production, degradation during shelf life of the product and accuracy of the  
330 analytical method. In this work the range was extended to  $\pm 30\%$  of the label claim to  
331 compensate for difficulty in setting up a calibration in the spectra and account for the  
332 noise generated by the instrument/spectral algorithms [16].

333 For powdered tablets, all the eight products were predicted through the powdered  
334 dilution models (Table 4). In this respect, the best predictive ability was observed for  
335 NIRM3 which showed a mean prediction of 98.2% label claim (RSD = 2.35%) for all  
336 batches. This was followed by FTIRM3 and NIRM1, which showed mean prediction  
337 values of 97.9 and 97.2% label claim respectively. Additionally, FTIRM2 and NIRM2  
338 showed good predictive ability with values of 91.1 and 90.2% label claim respectively.  
339 The remaining models (FTIRM1, RamanM1, RamanM2 and RamanM3) exhibited poor  
340 predictive ability below 70%.

341 RamanM2 and RamanM3 showed better prediction for intact tablets (Table 5). Thus,  
342 the mean prediction of intact tablets using the two models were 108 and 84% label  
343 claim respectively. Moreover, NIRM2 showed good predictive ability for intact tablets  
344 with a mean prediction of 103% label claim. The remaining models included NIRM1,  
345 NIRM3 and RamanM1 had poor prediction above 130% label claim.

346

347

#### 348 **4. Conclusions**

349 The findings demonstrated that the combination of handheld FTIR, NIR and Raman  
350 spectroscopy with PLSR offered a rapid method for quantifying modafinil in branded  
351 generic medicines with minimal sample preparation. NIR and Raman techniques were  
352 non-destructive, however FTIR required powdering the tablets prior to measurement.  
353 In comparison to NIR, FTIR and Raman showed that models based on tablets were  
354 more accurate than those based on powder mixtures. Among the powder mixture  
355 models, modafinil excipients sequential addition offered the highest accuracy and  
356 precision for the quantification of powdered tablets using FTIR and NIR spectroscopy.  
357 Modafinil excipient dilution models offered the highest accuracy and precision for the  
358 quantification of intact tablets using NIR and Raman spectroscopy. Consequently, the  
359 choice of the powder model depended to a degree, on the technique used as well as  
360 the sample quantified. Subsequently, this may represent a challenge in the  
361 generalisability of the method to other nootropics that could be of different  
362 concentration and have different formulation. Hence, future work should consider the  
363 accuracy of quantification for different formulation types (tablets, capsules, caplets)  
364 and/or closely related analogues of drugs.

365

366

367 **List of abbreviations:**

368 Active pharmaceutical ingredient (API)

369 Correlation in Wavelength Space (CWS)

370 Fourier transform-infrared (FTIR)

371 High performance liquid chromatography (HPLC)

372 Near-infrared (NIR)

373 Partial least square regression (PLSR)

374 Relative standard error of calibration (RSEC)

375 Relative standard error of prediction (RSEP)

376 Root mean square error of calibration (RMSEC)

377 Thin layer chromatography (TLC)

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379

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485 Poisons.

486

## 487 **List of tables**

488 **Table 1.** Modafinil tablets purchased from the Internet

Website number	Batch number	Dose (mg)	Modafinil concentration (% m/m)
1	1a	100	57.6
1	1b	100	62.9
2	2a	200	65.9
2	2b	200	72.7
3	3a	200	63.8
3	3b	200	66.3
4	4a	100	57.7
4	4b	100	62.8

489

490 **Table 2.** Details of the powdered mixtures prepared

DN	Modafinil tablet amount (mg)	Diluent	Diluent amount (mg)	Total weight (mg)	API (% m/m)
M1V1	201.3	LAC	0	201.3	62.5
M1V2	181.6	LAC	19.6	201.2	56.4
M1V3	168.5	LAC	32.6	201.1	52.4
M1V4	159.5	LAC	43.3	202.8	49.1
M1V5	151.2	LAC	53.1	204.3	46.2
M1V6	129	LAC	71.7	200.7	40.2
M1V7	110.9	LAC	90.6	201.5	34.4
M1V8	99.3	LAC	98.9	198.2	31.3
M1V9	81	LAC	119.9	201	25.2
M1V10	71.8	LAC	129.7	201.5	22.3
M1V11	50.8	LAC	150	200.8	15.8
M1V12	30.6	LAC	170.7	201.3	9.5
M1V13	0	LAC	199.6	199.6	0
M2V1	169.6	LAC/ POV	30.6	200.2	52.9
M2V2	163	LAC/POV/ MgS	52.4	215.4	47.3
M2V3	121.9	LAC/ POV/ MgS/ MAI	79.4	201.3	37.8
M2V4	104.1	LAC/POV/ MgS/MAI/ MCC	97.2	201.3	32.3
M2V5	76.8	LAC/MCC/ NaCMC	134.9	211.7	22.7
M2V6	51.8	LAC/POV/ MgS/MAI/ MCC/NaCMC	158.9	210.7	15.4
M3V1	201.3	0	0	201.3	62.5
M3V2	180.3	LAC	43.2	223.5	50.1

M3V3	134.4	POV	78.8	213.1	39.4
M3V4	100.7	MgS	97.2	197.8	31.8
M3V5	87.2	MAI	128	215.2	25.3
M3V6	71	MCC	149.1	220.1	20.2
M3V7	52.7	NaCMC	154.5	207.2	15.9

491 DN: dilution number, M1: modafinil lactose dilution, M2: modafinil excipients dilution, M3: modafinil  
492 excipients sequential addition, LAC: lactose, POV: povidone, MgS: magnesium stearate, MAI: maize  
493 starch, MCC: microcrystalline cellulose, NaCMC: sodium carboxymethylcellulose.

494

495 **Table 3.** Results of the PLSR models constructed using the three techniques

Model number	F	C:V ratio	r <sup>2</sup> calib	RMSEC (% m/m)	r <sup>2</sup> valid	RMSEP (% m/m)	RSEP (%)
FTIRM1	3	25:11	0.98	0.52	0.97	0.78	1.33
FTIRM2	1	12:60	0.51	11.24	0.49	11.61	29.9
FTIRM3	1	14:70	0.75	6.57	0.93	4.63	16.5
FTIRM4	4	60:20	0.84	6.29	0.80	7.03	19.8
NIRM1	1	25:11	0.72	8.45	0.70	8.82	23.3
NIRM2	1	12:60	0.84	5.26	0.84	5.25	15.2
NIRM3	3	14:70	0.99	1.15	0.99	1.21	3.45
NIRM4	1	60:20	0.77	1.77	0.69	2.05	3.51
NIRM5	1	48:16	0.69	1.91	0.76	1.71	2.85
RamanM1	1	25:11	0.70	8.49	0.80	6.74	19.0
RamanM2	1	12:60	0.84	5.52	0.83	6.57	17.8
RamanM3	1	14:70	0.76	7.62	0.83	9.16	23.9

RamanM4	4	60:20	0.98	0.54	0.95	0.82	1.40
RamanM5	4	48:16	0.94	0.96	0.93	0.91	12.1

496 FTIRM1, NIRM1 and RamanM1: modafinil lactose dilution, FTIRM2, NIRM2 and RamanM2: modafinil  
 497 excipients dilution, FTIRM3, NIRM3 and RamanM3: modafinil excipients sequential addition, FTIRM4,  
 498 NIRM4 and RamanM4: modafinil powdered tablets model, NIRM5 and RamanM5: modafinil intact tablet  
 499 model. C:V: calibration:validation ratio, F: number of factors, r<sup>2</sup>: correlation coefficient, RMSE:root mean  
 500 square error.

501

502

503

504 **Table 4.** Results of the predicted powdered tablets

	Predicted label claim (%)							
	1a	1b	2a	2b	3a	3b	4a	4b
BN								
Dose (mg)	100	100	200	200	200	200	100	100
FTIRM1	24.9	57.7	49.4	43.8	70.2	49.4	28.1	42.6
FTIRM2	98.5	96.4	86.8	87.8	88.0	87.5	91.2	92.9
FTIRM3	105	104	93.1	94.1	94.6	93.9	98.4	100
NIRM1	100	98.6	95.3	95.2	95.9	93.4	101	98.3
NIRM2	92.0	89.5	88.8	88.4	89.6	87.1	94.4	91.4
NIRM3	97.6	94.7	99.2	99.2	101	96.9	101	96.0
RamanM1	91.1	60.7	55.4	55.8	56.0	55.2	59.1	60.6
RamanM2	74.0	46.2	44.9	44.9	44.9	44.5	46.7	48.7
RamanM3	80.6	65.9	64.0	63.2	65.8	64.0	67.5	68.4

505 BN: Batch number

506

507 **Table 5.** Results of the predicted intact tablets

	Predicted label claim (%)					
	2a	2b	3a	3b	4a	4b
BN						
Dose	200	200	200	200	100	100
(mg)						
NIRM1	134	135	137	136	133	133
NIRM2	107	107	108	110	95.4	89.1
NIRM3	144	145	148	150	125	118
RamanM1	186	188	170	182	205	210
RamanM2	101	106	97.6	104	119	122
RamanM3	77.9	81.0	72.5	77.7	94.5	100.9

508 BN: Batch number

509

510 **Figure legend**

511 Fig. 1. MSCD1 treated (a) FTIR spectrum modafinil tablets, (b) FTIR spectrum of pure  
512 modafinil, (c) FTIR spectrum lactose monohydrate, (d) NIR spectrum modafinil tablets,  
513 (e) NIR spectrum of pure modafinil, (f) NIR spectrum lactose monohydrate, (g) Raman  
514 spectrum modafinil tablets, (h) Raman spectrum of pure modafinil and (i) Raman  
515 spectrum lactose monohydrate measured using the Bruker Alpha FTIR, JDSU  
516 microNIR and Rigaku handheld Raman instruments respectively.