Measuring the Semantic Priming Effect Across Many Languages

Erin M. Buchanan1, Kelly Cuccolo2, Tom Heyman3, Niels van Berkel4, Nicholas A. Coles5, Aishwarya Iyer6, Kim Peters7, Anna E. van ’t Veer3, Maria Montefinese8, Nicholas P. Maxwell9, Jack E. Taylor10, Kathrene D. Valentine11,275, Patrícia Arriaga12, Krystian Barzykowski13, Leanne Boucher14, W. M. Collins14, David C. Vaidis15,276, Balazs Aczel16, Ali H. Al-Hoorie17, Ettore Ambrosini18,277, Théo Besson19, Debora I. Burin20,278, Muhammad M. Butt21, A. J. Benjamin Clarke22, Yalda Daryani23, Dina A. S. El-Dakhs 24, Mahmoud M. Elsherif25,279, Maria Fernández-López26, Paulo R. d. S. Ferreira27, Raquel M. K. Freitag28, Carolina A. Gattei29,280, Hendrik Godbersen30, Philip A. Grim II31, Peter Halama32, Patrik Havan33, Natalia C. Irrazabal34, Chris Isloi35, Rebecca K. Iversen36, Yoann Julliard37, Aslan Karaaslan38,281, Michal Kohút39, Veronika Kohútová40, Julija Kos41, Alexandra I. Kosachenko42, Tiago J. S. d. Lima43,282, Matthew HC Mak44, Christina Manouilidou45, Leonardo A. Marciaga46, Xiaolin M. Melinna47, Jacob F. Miranda48, Coby Morvinski49, Aishwarya Muppoor50, F. E. Müjdeci51, Yngwie A. Nielsen52, Juan C. Oliveros53, Jaš Onič41, Marietta Papadatou-Pastou54, Ishani Patel55, Zoran Pavlović56, Blaž Pažon41, Gerit Pfuhl57,283, Ekaterina Pronizius58, Timo B. Roettger59, Camilo R. Ronderos60, Susana Ruiz-Fernandez61, Magdalena Senderecka62, Çağlar Solak63, Anna Stückler64, Raluca D. Szekely-Copîndean65,284, Analí R. Taboh66,285, Rémi Thériault67, Ulrich S. Tran58, Fabio Trecca68,112, José Luis Ulloa69, Marton A. Varga70, Steven Verheyen71, Tijana Vesić Pavlović72, Giada Viviani73, Nan Wang74, Kristyna Zivna75, Chen C. Yun76, Oliver J. Clark77, Oguz A. Acar78, Matúš Adamkovič79,286, Giulia Agnoletti80,287, Atakan M. Akil81,288, Zainab Alsuhaibani82, Simona Amenta83, Olga A. Ananyeva84, Michael Andreychik85, Bernhard Angele86,289, Danna C. Arias Quiñones87, Nwadiogo C. Arinze88, Adrian D. Askelund89,290, Bradley J. Baker90, Ernest Baskin91, Luisa Batalha92, Carlota Batres87, Maria S. Beato93, Manuel Becker94, Maja Becker95, Maciej Behnke96,291, Christophe Blaison97, Anna M. Borghi98,292, Eduard Brandstätter99, Jacek Buczny100, Nesrin Budak101, Álvaro Cabana102, Zhenguang G. Cai103, Enrique C. Canessa104,293, Ignacio Castillejo105, Müge Cavdan106, Luca Cecchetti107, Sergio E. Chaigneau108, Feria X. W. Chang109, Christopher R. Chartier110, Sau-Chin Chen111, Elena Cherniaeva84, Morten H. Christiansen112,294, Hu Chuan-Peng113, Patrycja Chwiłkowska114, Montserrat Comesaña115, Chin Wen Cong116, Casey Cowan117, Stéphane D. Dandeneau118, Oana A. David119, William E. Davis120, Elif G. Demirag Burak121, Barnaby J. W. Dixson122,295, Hongfei Du123,296, Rod Duclos124, Wouter Duyck125, Liudmila A. Efimova84, Ciara Egan117, Vanessa Era126,297, Thomas R. Evans127,298, Anna Exner128, Gilad Feldman129, Katharina Fellnhofer130, Chiara Fini131, Sarah E. Fisher132, Heather D. Flowe133, Patricia Garrido-Vásquez134, Daniele Gatti135, Jason Geller 136, Vaitsa Giannouli137, Anna S. Gorokhova84, Lindsay M. Griener138, Dmitry Grigoryev139, Igor Grossmann140, Mohammadhesam Hajighasemi141, Giacomo Handjaras142, Cathy Hauspie125, Zhiran He143, Renata M. Heilman144, Amirmahdi Heydari145, Alanna M. Hine117, Karlijn Hoyer146, Weronika Hryniszak147,299, Janet H.-w. Hsiao148, Guanxiong Huang149, Keiko Ihaya150, Ewa Ilczuk151, Tatsunori Ishii152, Andrei Dumbravă153,300, Katarzyna Jankowiak154, Xiaoming Jiang155,301, David C. Johnson156,302, Rafał Jończyk154,303, Juhani Järvikivi157, Laura Kaczer158, Kevin L. Kamermans159, Johannes A. Karl160, Alexander Karner161, Pavol Kačmár162, Jacob J. Keech163, M. Justin Kim164,304, Max Korbmacher165,305, Kathrin Kostorz58, Marta Kowal166, Tomas Kratochvil167, Yoshihiko Kunisato168, Anna O. Kuzminska169, Lívia Körtvélyessy170, Fatma E. Köse171,306, Massimo Köster172, Magdalena Kękuś173, Melanie Labusch174,307, Claus Lamm58, Chaak Ming Lau175, Julieta Laurino158, Wilbert Law176,308, Giada Lettieri177, Carmel A. Levitan178, Jackson G. Lu179, Sarah E. MacPherson180, Klara Malinakova181, Diego Manriquez-Robles182, Nicolás Marchant108, Marco Marelli183, Martín Martínez184, Molly F. Matthews185, Alan D. A. Mattiassi186, Josefina Mattoli-Sánchez187, Claudia Mazzuca188, David P. McGovern160, Zdenek Meier189, Filip Melinscak161, Michal Misiak190,309, Luis C. P. Monteiro191, David Moreau192,310, Sebastian Moreno193, Kate E. Mulgrew194, Dominique Muller195,311, Tamás Nagy196, Marcin Naranowicz197, Izuchukwu L. G. Ndukaihe198, Maital Neta199,312, Lukas Novak200, Chisom E. Ogbonnaya201, Jessica Jee Won Paek202, Aspasia E. Paltoglou203,313, Francisco J. Parada204, Adam J. Parker205, Mariola Paruzel-Czachura206,314, Yuri G. Pavlov207, Saeed Paydarfard208, Dominik Pegler58, Mehmet Peker209, Manuel Perea210,315, Stefan Pfattheicher64, John Protzko211, Irina S. Prusova84, Katarzyna Pypno-Blajda206, Zhuang Qiu212, Ulf-Dietrich Reips213, Gianni Ribeiro214,316, Luca Rinaldi215,317, S. C. Roberts190,318, Tanja C. Roembke216, Marina O. Romanova84, Robert M. Ross217, Jan P. Röer218, Filiz Rızaoğlu219, Toni T. Saari220, Erika Sampaolo107, Anabela C. Santos221, F. Çağlar Sarıçiçek222, Kyoshiro Sasaki223, Frank Scharnowski58, Kathleen Schmidt224, Amir Sepehri141, Halid O. Serçe225, A. T. Sevincer226, Cynthia S. Q. Siew109, Matilde E. Simonetti227, Miroslav Sirota228, Agnieszka Sorokowska229, Piotr Sorokowski229, Ian D. Stephen230, Laura M. Stevens231, Suzanne L. K. Stewart232, David Steyrl58, Stefan Stieger233, Anna Studzinska234, Mar Suarez93, Anna Szala235,319, Arnaud Szmalec125,236, Daniel Sznycer237, Ewa Szumowska238,320, Sinem Söylemez239, Bahadır Söylemez240, Kaito Takashima241, Christian K. Tamnes242, Joel C. R. Tan109, Chengxiang Tang243, Peter Tavel244, Julian Tejada245, Benjamin C. Thompson246, Jake G. Tiernan160, Vicente Torres-Muñoz247, Anna K. Touloumakos248, Bastien Trémolière249,321, Monika Tschense250, Belgüzar N. Türkan251, Miguel A. Vadillo105, Caterina Vannucci107, Michael E. W. Varnum252, Martin R. Vasilev253, Leigh Ann Vaughn254, Fanny Verkampt255, Liliana M. Villar256,322, Sebastian Wallot257, Lijun Wang258, Ke Wang259, Glenn P. Williams260, David Willinger261, Kelly Wolfe262,323, Alexandra S. Wormley252,324, Yuki Yamada263, Yunkai Yang264, YUWEI ZHOU265, Mengfan Zhang58, Wang Zheng266, Yueyuan Zheng267, Chenghao Zhou268, Radka Zidkova244, Nina M. Zumbrunn160, Ogeday Çoker269, Sami Çoksan270,325, Sezin Öner271, Asil A. Özdoğru272,326, Seda M. Şahin51, Dauren Kasanov273, & Savannah C. Lewis274,327

1 Analytics, Harrisburg University of Science and Technology, Harrisburg, USA

2 Independent Researcher, Alma, USA

3 Methodology and Statistics Unit, Institute of Psychology, Leiden University, Leiden, The Netherlands

4 Department of Computer Science, Aalborg University, Aalborg, Denmark

5 Center for the Study of Language and Information, Stanford University, Stanford, USA

6 Department of Psychology, Christ University, Bangalore, India

7 University of Exeter Business School, University of Exeter, Exeter, United Kingdom

8 Department of Developmental and Social Psychology, University of Padova, Padova, Italy

9 Psychology, Midwestern State University, Wichita Falls, Texas, United States

10 Department of Psychology, Goethe University Frankfurt, Frankfurt am Main, Germany

11 General Internal Medicine, Massachusetts General Hospital, Boston, United States

12 Department of Psychology, Iscte-Instituto Universtário de Lisboa, Cis\_Iscte, Lisbon, Portugal

13 Institute of Psychology, Faculty of Philosophy, Jagiellonian University, Krakow, Poland

14 Department of Psychology and Neuroscience, Nova Southeastern University, Fort Lauderdale, USA

15 UFR de Psychologie, CLLE, Université de Toulouse, CNRS, Toulouse, France

16 Institute of Psychology, ELTE, Eotvos Lorand University Budapest, Hungary

17 Royal Commission for Jubail and Yanbu, Jubail Industrial City, Saudi Arabia

18 Department of Neuroscience, University of Padova, Padova, Italy

19 Laboratoire de Psychologie Sociale, Université Paris Cité, F-92100 Boulogne-Billancourt, France

20 Facultad de Psicología, Universidad de Buenos Aires - CONICET, Argentina

21 Department of Psychology, Government College University, Lahore, Lahore, Pakistan

22 Department of Linguistics, Thammasat University, Pathum Thani, Thailand

23 Department of Psychology, University of Tehran, Tehran, Iran

24 College of Humanities and Sciences, Prince Sultan University, Riyadh, Saudi Arabia

25 Department of Psychology, University of Birmingham, Birmingham, United Kingdom

26 Department of Basic Psychology, University of València, València, Spain

27 Instituto de Psicologia, Universidade Federal de Uberlândia (UFU), Uberlândia, Brasil

28 Departamento de Letras Vernáculas, Universidade Federal de Sergipe, São Cristóvão, Sergipe, Brazil

29 Universidad Torcuato Di Tella, Escuela de Gobierno, Buenos Aires, Argentina

30 FOM University of Applied Sciences, Essen, Germany

31 Computer and Information Sciences, Harrisburg University of Science and Technology, Harrisburg, PA, USA

32 Centre of Social and Psychological Sciences, Slovak Academy of Sciences, Bratislava, Slovakia

33 Institute of Experimental Psychology, Centre of Social and Psychological Sciences, Slovak Academy of Sciences, Bratislava, Slovak Republic

34 Departamento de Psicología, Universidad de Palermo - CONICET, Buenos Aires, Argentina

35 Unaffiliated Researcher, London, UK

36 Department of Philosophy, Classics, History of Art and Ideas (IFIKK), University of Oslo, Oslo, Norway

37 LIP/PC2S, Univ. Grenoble Alpes, Univ. Savoie Mont Blanc, 38000 Grenoble, France

38 Department of Psychology, Izmir Katip Celebi University, Izmir, Türkiye

39 Department of psychology, Faculty of Philosophy and Arts, University of Trnava, Trnava, Slovakia

40 Faculty of Philosophy and Arts, University of Trnava, Trnava, Slovakia

41 Department of Comparative and General Linguistics, Faculty of Arts, University of Ljubljana, Ljubljana, Slovenia

42 Department Of Psychology, Ural Federal University, Ekaterinburg, Russian Federation

43 Department of Social and Work Psychology, University of Brasília, Brasília, Brazil

44 Department of Psychology, University of Warwick, Coventry, United Kingdom

45 Department of Comparative and General Linguistics, Faculty of Arts, University of Ljubljana, Ljubljana, Slovenia

46 Department of Applied Mathematics, Illinois Institute of Technology, Chicago, IL, United States

47 The School of Optometry, The Hong Kong Polytechnic University, Hong Kong, Hong Kong SAR, China

48 Psychology Department, California State University, East Bay, Hayward, United States

49 Department of Management, Ben-Gurion University of the Negev, Be’er Sheva, Israel

50 Department of Psychology and Neuroscience, Nova Southeastern University, Fort Lauderdale, Florida, United States

51 Department of Psychology, Middle East Technical University, Ankara, Turkey

52 Department of Linguistics, Cognitive Science and Semiotics, Aarhus University, Aarhus, Denmark

53 Department of Psychology, Universidad Católica del Maule, Talca, Chile

54 Department of Primary Education, National and Kapodistrian University of Athens, Athens, Greece

55 College of Psychology, Nova Southeastern University, Fort Lauderdale, United States

56 Department of Psychology, University of Belgrade, Faculty of Philosophy, Belgrade, Serbia

57 Department of Psychology, UiT The Arctic University of Norway, Tromsø, Norway

58 Department of Cognition, Emotion, and Methods in Psychology, Faculty of Psychology, University of Vienna, Vienna, Austria

59 Department of Linguistics and Scandinavian Studies, University of Oslo, Oslo, Norway

60 Department of Philosophy, Classics, History of Art and Ideas, University of Oslo, Oslo, Norway

61 Department of Psychology, Brandenburg University of Technology Cottbus-Senftenberg, Cottbus-Senftenberg, Germany

62 Centre for Cognitive Science, Jagiellonian University, Krakow, Poland

63 Department of Psychology, Manisa Celal Bayar University, Manisa, Turkey

64 Department of Psychology and Behavioural Sciences, Aarhus University, Aarhus, Denmark

65 Department of Social and Human Research, Romanian Academy, Cluj-Napoca, Romania

66 CONICET - Universidad de Buenos Aires, Instituto de Física Interdisciplinaria y Aplicada (INFINA), Buenos Aires, Argentina

67 Department of Psychology, Université du Québec à Montréal, Montréal, Canada

68 TrygFonden’s Centre for Child Research, Aarhus University, Aarhus, Denmark

69 Programa de Investigación Asociativa (PIA) en Ciencias Cognitivas, Centro de Investigación en Ciencias Cognitivas (CICC), Facultad de Psicología, Universidad de Talca, Talca, Chile

70 ELTE Eotvos Lorand University, Budapest, Hungary

71 Department of Psychology, Education and Child Studies, Erasmus University Rotterdam, Rotterdam, The Netherlands

72 Faculty of Mechanical Engineering, University of Belgrade, Belgrade, Serbia

73 Department of Developmental Psychology and Socialisation, Department of Developmental Psychology and Socialisation, University of Padua, Padua, Italy

74 Department of Linguistics, the Chinese University of Hong Kong, Hong Kong, China

75 Olomouc University Social Health Institute, Palacky University Olomouc, Olomouc University Social Health Institute, Olomouc, Czech republic

76 School of Psychology, Nanjing Normal University, Nanjing, China

77 Faculty of Health and Education, Manchester Metropolitan University, Manchester, United Kingdom

78 King’s Business School, King’s College London, London, United Kingdom

79 Institute of Social Sciences CSPS, Slovak Academy of Sciences, Košice, Slovakia

80 Escuela de Gobierno, Universidad Favaloro, Buenos Aires, Argentina

81 Doctoral School of Psychology, ELTE Eötvös Loránd University, Budapest, Hungary

82 College of Languages and Translation, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh, Saudi Arabia

83 Department of Psychology, University of Milano-Bicocca, Milan, Italy

84 Laboratory for Psychology of Social Inequality, HSE University, Moscow, Russian Federation

85 Department of Psychological and Brain Sciences, Fairfield University, Fairfield, CT, United States

86 Department of Psychology, Bournemouth University, Poole, UK

87 Department of Psychology, Franklin and Marshall College, Lancaster, USA

88 Psychology, Alex Ekwueme Federal University, Ndufu-Alike, Nigeria

89 Nic Waals Institute, Lovisenberg Diaconal Hospital, Oslo, Norway

90 Department of Sport, Tourism and Hospitality Management, Temple University, Philadelphia, USA

91 Department of Food, Pharma, and Healthcare, Saint Joseph’s University, Philadelphia, PA, USA

92 School of Behavioural and Health Sciences, Australian Catholic University, Strathfield, Australia

93 Faculty of Psychology, University of Salamanca, Salamanca, Spain

94 Psychological Assessment, University of Marburg, Germany, Marburg, Germany

95 CLLE, Université de Toulouse, CNRS, Toulouse, France

96 Department of Psychology and Cognitive Science, Adam Mickiewicz University, Poznan, Poland

97 Laboratoire de Psychologie Sociale, Université Paris Cité, Paris, France

98 Department of Dynamic and Clinical Psychology, and Health Studies, Sapienza University of Rome, CNR, Rome, Italy

99 Department of Economic Psychology, Johannes Kepler University Linz, Linz, Austria

100 Department of Experimental and Applied Psychology, Vrije Universiteit Amsterdam, Amsterdam, The Netherlands

101 Department of Psychology, Middle East Technical University, Ankara, Türkiye

102 Universidad de la República, Montevideo, Uruguay

103 Department of Linguistics and Modern Languages, The Chinese University of Hong Kong, Hong Kong, Hong Kong SAR, China

104 Facultad de Ingeniería y Ciencias, Universidad Adolfo Ibánez, Viña del mar, Chile

105 Departamento de Psicología Básica, Universidad Autónoma de Madrid, Madrid, Spain

106 Experimental Psychology, Justus Liebig University Giessen, Giessen, Germany

107 Social and Affective Neuroscience Group, IMT School for Advanced Studies Lucca, Lucca, Italy

108 Center for Social and Cognitive Neuroscience, School of Psychology, Universidad Adolfo Ibáñez, Santiago, Chile

109 Department of Psychology, National University of Singapore, Singapore, Singapore

110 Department of Psychology, Ashland University, Ashland, USA

111 Department of Human Development and Psychology, Tzu-Chi University, Haulien, Taiwan

112 School of Communication and Culture, Aarhus University, Aarhus, Denmark

113 School of Psychology, Nanjing Normal University, Nanjing, China

114 Psychology and Cognitive Science Department, Adam Mickiewicz University, Poznań, Poland

115 Basic Psychology, Psycholinguistics Research Line, CIPsi, School of Psychology, University of Minho, Portugal, Braga, Portugal

116 Independent Researcher, Malaysia

117 School of Psychology, University of Galway, Galway, Ireland

118 Psychology, Memorial University of Newfoundland, St.John’s, Newfoundland and Labrador, Canada

119 The International Institute for the Advanced Studies of Psychotherapy and Applied Mental Health, Babes-Bolyai University, Cluj-Napoca, Romania

120 Department of Psychology, Wittenberg University, Springfield, USA

121 Department of Psychology, University of Oklahoma, Norman, Oklahoma, US

122 The School of Health, The School of Health, the University of the Sunshine Coast, 1 Moreton Parade, Petrie QLD 4502, Australia, Morton Bay, Australia

123 Department of Psychology, Department of Psychology, Faculty of Arts and Sciences, Beijing Normal University at Zhuhai, Zhuhai, China, Zhuhai, China

124 Ivey School at Western University, London, Ontario, Canada

125 Department of Experimental Psychology, Ghent University, Ghent, Belgium

126 Department of Psychology, Sapienza University Of Rome, Rome, Italy

127 School of Human Sciences, University of Greenwich, London, United Kingdom

128 Faculty of Psychology, Ruhr University Bochum, Bochum, Germany

129 Psychology, University of Hong Kong, Hong Kong SAR, Hong Kong SAR

130 Department of Management, Technology, and Economics, ETH Zürich, Zürich, Switzerland

131 Department of Dynamic and Clinical Psychology and Health Studies, Sapienza University of Rome, Rome, Italy

132 Department of Psychology, Ashland University, Ashland, Ohio, United States

133 School of Psychology, University of Birmingham, Edgbaston, UK

134 Department of Psychology, University of Concepción, Concepción, Chile

135 Department of Brain and Behavioral Sciences, University of Pavia, Pavia, Italy

136 Psychology, Princeton University, Princeton, US

137 School of Social Sciences, Hellenic Open University, Patras, Greece

138 Centre for Comparative Psycholinguistics, University of Alberta, Edmonton, Alberta, Canada

139 Center for Sociocultural Research, HSE University, Moscow, Russia

140 Department of Psychology, University of Waterloo, Waterloo, Ontario, Canada

141 Marketing, ESSEC Business School, Cergy, France

142 IMT School for Advanced Studies Lucca, Lucca, Italy

143 The Education Department, Henan University, Kaifeng, China

144 Department of Psychology, Babes-Bolyai University, Cluj-Napoca, Romania

145 Psychology, University of Tehran, Tehran, Iran

146 Developmental Psychology, University of Amsterdam, Amsterdam, The Netherlands

147 Faculty of Philosophy, Applied Memory Research Laboratory, Institute of Psychology, Jagiellonian University, Krakow, Poland

148 Division of Social Science, Hong Kong University of Science and Technology, Kowloon, Hong Kong

149 Department of Media and Communication, City University of Hong Kong, Kowloon, Hong Kong SAR

150 Center for Liberal Arts, Fukuoka Institute of Technology, Fukuoka, Japan

151 Faculty of Philosophy, Jagiellonian University, Kraków, Poland

152 Department of Psychology, Japan Women’s University, Tokyo, Japan

153 George I.M. Georgescu Institute of Cardiovascular Diseases, Iași, Romania

154 Faculty of English, Adam Mickiewicz University, Poznań, Poland

155 Institute of Linguistics, Shanghai International Studies University, Shanghai, P. R. China

156 Department of Behavioral Sciences, York College, CUNY, New York, USA

157 Department of Linguistics, University of Alberta, Edmonton, Canada

158 Departamento de Fisiología, Biología Molecular y Celular, Universidad de Buenos Aires, Buenos Aires, Argentina

159 Independent Researcher, The Netherlands

160 School of Psychology, Dublin City University, Dublin, Ireland

161 Department of Cognition, Emotion, and Methods in Psychology, University of Vienna, Vienna, Austria

162 Department of Psychology, Faculty of Arts, Pavol Jozef Šafárik University in Košice, Košice, Slovakia

163 School of Applied Psychology, Griffith University, Mt Gravatt, Australia

164 Department of Psychology, Sungkyunkwan University, Seoul, South Korea

165 Department of Health and Functioning, Western Norway University of Applied Sciences, Bergen, Norway

166 IDN Being Human, Institute of Psychology, University of Wrocław, Wrocław, Poland

167 International Research Team on Internet and Society, Masaryk University, Faculty of Social Studies, International Research Team on Internet and Society, Joštova 10, Brno, Czech Republic, Brno, Czech Republic

168 Department of Psychology, Senshu University, Kawasaki, Japan

169 Faculty of Management, University of Warsaw, Warsaw, Poland

170 Department of British and American Studies, Pavol Jozef Šafárik University in Košice, Slovakia, Košice, Slovakia

171 Psychology Department, Aydın Adnan Menderes University, Aydın, Türkiye

172 Psychological Assessment, University of Marburg, Marburg, Germany

173 Faculty of Psychology, SWPS University, Kraków, Kraków, Poland

174 ERI-Lectura and Department of Methodology, Universitat de València, Valencia, Spain

175 Centre for Research on Linguistics and Language Studies (CRLLS), The Education University of Hong Kong, Tai Po, Hong Kong

176 Department of Psychology, The Education University of Hong Kong, Hong Kong SAR, Hong Kong SAR

177 Affective Physiology and Interoception (API) Group, MoMiLab, IMT School for Advanced Studies Lucca, Lucca, Italy, Lucca, Italy

178 Cognitive Science, Occidental College, Los Angeles, USA

179 MIT Sloan School of Management, Massachusetts Institute of Technology, Cambridge, MA, USA

180 Human Cognitive Neuroscience, Department of Psychology, University of Edinburgh, Edinburgh, United Kingdom

181 Olomouc University Social Health Institute, Olomouc University Social Health Institute, Palacký University Olomouc, Olomouc, Czech Republic, Olomouc, Czech Republic

182 Departamento de Psicología, Universidad Católica de Temuco, Temuco, Chile

183 Department of Psychology, University of Milano-Bicocca, Milano, Italy

184 Department of Psychology, University of Navarra, Pamplona, Spain

185 Psychology, University of Waterloo, Waterloo, Canada

186 Department of Education, Literatures, Intercultural Studies, Languages and Psychology, University of Florence, Florence, Italy

187 Facultad de Psicología, Centro de Estudios en Neurociencia Humana y Neuropsicología, Universidad Diego Portales, Santiago, Chile

188 Department of Dynamic and Clinical Psychology, and Health Studies, Sapienza University of Rome, Rome, Italy

189 Social Health Institute, Palacký University Olomouc, Social Health Institute, Olomouc, Czech Republic, Olomouc, Czech Republic

190 IDN Being Human, Institute of Psychology, University of Wroclaw, Wroclaw, Poland

191 Institute of Biological Sciences, Federal University of Pará, Belém, Brazil

192 School of Psychology, University of Auckland, Auckland, New Zealand

193 Facultad de Ingeniería y Ciencias, Universidad Adolfo Ibáñez, Viña del Mar, Chile

194 School of Health, University of the Sunshine Coast, Petrie, Australia

195 Psychology, University of Grenoble Alpes, Univ. Savoie Mont Blanc, LIP/PC2S, Grenoble, France

196 ELTE Eötvös Loránd University, Institute of Psychology, Budapest, Hungary

197 Faculty of English, Adam Mickiewicz University, Poznan, Poznan, Poland

198 Department of Psychology, Alex Ekwueme Federal University, Ndufu-Alike, Nigeria

199 Department of Psychology, University of Nebraska-Lincoln, Lincoln, NE, USA

200 Olomouc University Social Health Institute, Olomouc University Social Health Institute, Palacký University Olomouc, Olomouc, Czech Republic

201 Psychology Department, Alex Ekwueme Federal University Ndufu-Alike Nigeria, Ebonyi State, Nigeria

202 Department of Management and Entrepreneurship, Indiana University Kelley School of Business, Bloomington, IN, United States

203 School of Psychology, Manchester Metropolitan University, Manchester, UK

204 Psychology, Universidad Diego Portales, Santiago, Chile/South America

205 Department of Experimental Psychology, Division of Psychology and Language Sciences, University College London, London, United kingdom

206 Institute of Psychology, University of Silesia in Katowice, Katowice, Poland

207 Institute of Medical Psychology and Behavioral Neurobiology, University of Tuebingen, Tuebingen, Germany

208 Psychology and Educational Science, Shahid Beheshti University, Tehran, Iran

209 Faculty of Letters, Department of Psychology, Ege University, Izmir, Türkiye

210 Department of Methodology, Universitat de València, Valencia, Spain

211 Psychological Science, Central Connecticut State University, New Britain, USA

212 Department of Linguistics and Modern Language, Department of Linguistics and Modern Languages, The Chinese University of Hong Kong, Hong Kong, Hong Kong

213 Department of Psychology, University of Konstanz, Konstanz, Germany

214 School of Psychology, The University of Queensland, Brisbane, Australia

215 Department of Brain and Behavioural Sciences, University of Pavia, Pavia, Italy

216 Chair of Cognitive and Experimental Psychology, Institute of Psychology, RWTH Aachen University, Aachen, Germany

217 Department of Philosophy, Macquarie University, Sydney, Australia

218 Department of Psychology and Psychotherapy, Witten/Herdecke University, Witten, Germany

219 Foreign Language Education Department, Pamukkale University, Denizli, Türkiye

220 Institute for Molecular Medicine Finland (FIMM), University of Helsinki, Helsinki, Finland

221 CIS-Iscte, Instituto Universitário de Lisboa (Iscte-IUL), Lisboa, Portugal

222 Department of Psychology, Kadir Has University, İstanbul, Türkiye

223 Faculty of Informatics, Kansai University, Takatsuki, Japan

224 Department of Psychology, Ashland University, Ashland, OH, USA

225 Psychology Department, Bahçeşehir University, İstanbul, Turkey

226 Institute for Sustainability Psychology, Leuphana University Lüneburg, Lüneburg, Germany

227 Instute of Psychology, RWTH Aachen University, Aachen, Germany

228 Department of Psychology, University of Essex, Colchester, United Kingdom

229 Institute of Psychology, University of Wrocław, Wrocław, Poland

230 Department of Psychology, Bournemouth University, Bournemouth, United Kingdom

231 School of Psychology, University of Birmingham, Birmingham, United Kingdom

232 Division of Psychology, University of Chester, Chester, United Kingdom

233 Department Psychology and Psychodynamics, Karl Landsteiner University of Health Sciences, Krems an der Donau, Austria

234 Humanities Department, Icam School of Engineering, Toulouse, France

235 Department of Anthropology, Hirszfeld Institute of Immunology and Experimental Therapy, Polish Academy of Sciences, Wrocław, Poland

236 Psychological Sciences Research Institute, Université catholique de Louvain, Louvain-la-Neuve, Belgium

237 Department of Psychology, Oklahoma State University, Stillwater, United States

238 Institute of Psychology, Jagiellonian University, Krakow, Poland

239 Psychology, Manisa Celal Bayar University, Manisa, Türkiye

240 Felsefe, Pamukkale Üniversitesi, Denizli, Türkiye

241 Graduate School of Human-Environment Studies, Kyushu University, Fukuoka, Japan

242 Department of Psychology, University of Oslo, Oslo, Norway

243 School of Economics and Management, Beijing Jiaotong University, Beijing, China

244 Olomouc University Social Health Institute, Palacký University Olomouc, Olomouc, Czech Republic

245 Department of Psychology, Federal University of Sergipe, Aracaju, Brazil

246 Psychology, The University of Alabama-Tuscaloosa, Alabama, United States

247 Centro de Investigación en Ciencias Cognitivas, Talca, Chile

248 Department of Psychology, Panteion University of Social and Political Science, Athens, Greece

249 Psychology, Université de Toulouse, Toulouse, France

250 Institute for Sustainability Psychology, School of Sustainability, Leuphana University Lüneburg, Lüneburg, Germany

251 Department of Cognitive Psychology, Trier University, Trier, Germany

252 Department of Psychology, Arizona State University, Tempe, AZ, USA

253 Department of Experimental Psychology, University College London, London, United Kingdom

254 Psychology Department, Ithaca College, Ithaca, USA

255 Department of Psychology, LAPCOS, Université Côte d’Azur, Nice, France

256 Department of Psychological Sciences, Central Connecticut State University, New Britain, CT, United States of America

257 Institute of Sustainability Psychology, Leuphana University of Lüneburg, Lüneburg, Germany

258 School of Digital Ecomomics and Management, Suzhou City University, Suzhou, China

259 Harvard Kennedy School, Harvard University, Cambridge, USA

260 Department of Psychology, Faculty of Health and Life Sciences, Northumbria University, Newcastle-upon-Tyne, UK

261 Department of Psychology and Psychodynamics, Karl Landsteiner University of Health Sciences, Krems an der Donau, Austria

262 Psychology Department, School of Philosophy & Language Sciences, University of Edinburgh, Edinburgh, United Kingdom

263 Faculty of Arts and Science, Kyushu University, Fukuoka, Japan

264 Institute of Psychology and Behavior, Henan University, Kaifeng, China

265 Psychology, The Education University of Hong Kong, Hong Kong, Hong Kong

266 The School of Psychology and Cognitive Science, East China Normal University, Shanghai, China

267 Department of Psychology, University of Hong Kong, Hong Kong Special Administrative Region, China

268 Department of Psychology, New York University, New York, U.S.

269 Department of Psychology, Pamukkale University, Denizli, Turkey

270 Network for Economic and Social Trends, Western University, London, Canada

271 Department of Psychologystanbul, Turkey, Kadir Has University, İstanbul, Turkey

272 Department of Psychology, Marmara University, İstanbul, Türkiye

273 Laboratory of Neurotechnology, Ural Federal University, Ekaterinburg, Russia

274 Psychology, University of Alabama- Tuscaloosa, Tuscaloosa, USA

275 Medicine, Harvard Medical School, Boston, United States

276 Institut de Psychologie, Université Paris Cité, Laboratoire de Psychologie Sociale, Paris, France

277 Padova Neuroscience Center, University of Padova, Padova, Italy

278 Departamento de Psicología, Universidad de Palermo, Buenos Aires

279 Department of Vision Sciences, University of Leicester, Leicester, United Kingdom

280 Instituto de Lingüística, Facultad de Filosofía y Letras, Universidad de Buenos Aires, CONICET, Buenos Aires, Argentina

281 Department of Psychology, Ege University, Izmir, Türkiye

282 Social and Affective Neuroscience Institute, Brasília, Brazil

283 Department of Psychology, NTNU, Trondheim, Norway

284 Department of Psychology, Babeș-Bolyai University, Cluj-Napoca, Romania

285 Universidad Torcuato Di Tella, Escuela de Negocios, Laboratorio de Neurociencia, Buenos Aires, Argentina

286 Faculty of Education, Charles University, Prague, Czechia; Faculty of Humanities and Social Sciences, University of Jyväskylä, Jyväskylä, Finland

287 Escuela de Gobierno, Universidad Torcuato Di Tella, Buenos Aires, Argentina

288 Institute of Psychology, University of Pécs, Pécs, Hungary

289 Centro de Investigación Nebrija en Cognición (CINC), Universidad Antonio de Nebrija, Madrid, Spain

290 PsychGen Center for Genetic Epidemiology and Mental Health, Norwegian Institute of Public Health, Oslo, Norway

291 Cognitive Neuroscience Center, Adam Mickiewicz University, Poznan, Poland

292 Institute of Cognitive Sciences and Technologies, Italian Research Council, Rome, Italy

293 Escuela de Psicología, Center for Cognition Research, Universidad Adolfo Ibáñez, Santiago, Chile

294 Department of Psychology, Cornell University, Ithaca, New York, USA

295 The School of Psychology, The University of Queensland Brisbane QLD 4072 Australia., Brisbane, Australia

296 Beijing Key Laboratory of Applied Experimental Psychology, National Demonstration Center for Experimental Psychology Education, Faculty of Psychology, Beijing Normal University, Beijing, China

297 Social Neuroscience Laboratory, IRCCS Santa Lucia Foundation, Rome, Italy, Rome, Italy

298 Institute for Lifecourse Development, University of Greenwich, London, United Kingdom

299 Faculty of Philosophy, Doctoral School in the Social Sciences​, Jagiellonian University​, Krakow, Poland

300 Alexandru Ioan Cuza university, Iași, Romania

301 Key Laboratory of Language Science and Multilingual Artificial Intelligence, Shanghai International Studies University, Shanghai, P. R. China

302 Dept. of Psychology, CUNY Graduate Center, New York, USA

303 Cognitive Neuroscience Center, Adam Mickiewicz University, Poznań, Poland

304 Center for Neuroscience Imaging Research, Institute for Basic Science, Suwon, South Korea

305 Mohn Medical Imaging and Visualization Centre, Bergen, Norway

306 Psychology Department, Durham University, Durham, United Kingdom

307 Centro de Investigación Nebrija en Cognición (CINC), Universidad Nebrija, Madrid, Spain

308 Centre for Psychosocial Health, The Education University of Hong Kong, Hong Kong SAR, Hong Kong SAR

309 School of Anthropology & Museum Ethnography, University of Oxford, Oxford, United Kingdom

310 Centre for Brain Research, University of Auckland, Auckland, New Zealand

311 Institut Universitaire de France, Paris, France

312 Center for Brain, Biology, and Behavior, University of Nebraska-Lincoln, Lincoln, NE, USA

313 School of Psychology, Social Work and Public Health (PSP), Oxford Brookes University, Oxford, UK

314 Penn Center for Neuroaesthetics, University of Pennsylvania, Philadelphia, USA

315 Centro de Investigación Nebrija en Cognición, Universidad Nebrija, Madrid, Spain

316 School of Law and Justice, University of Southern Queensland, Ipswich, Australia

317 Cognitive Psychology Unit, IRCCS Mondino Foundation, Pavia, Italy

318 Division of Psychology, University of Stirling, Stirling, UK

319 Center for Language Evolution Studies, Nicolaus Copernicus University in Toruń, Toruń, Poland

320 Department of Psychology, University of Maryland, College Park, USA

321 Psychology, Université du Québec à Trois-Rivières, Trois-Rivières, Canada

322 Department of Psychology, Southern New Hampshire University, Manchester, NH, United States of America

323 Psychology Department, Centre for Applied Behavioural Sciences, School of Social Sciences, Heriot-Watt University, Edinburgh, United Kingdom

324 Department of Psychology, University of Michigan, Ann Arbor, MI, USA

325 Department of Psychology, Erzurum Technical University, Erzurum, Türkiye

326 Department of Psychology, Üsküdar University, İstanbul, Türkiye

327 Psychology, Ashland University, Ashland, USA

Abstract

Semantic priming has been studied for nearly 50 years across various experimental manipulations and theoretical frameworks. Although previous studies provide insight into the cognitive underpinnings of semantic representations, they have suffered from several methodological issues including small sample sizes and a lack of linguistic and cultural diversity. Here, we measured the size and the variability of the semantic priming effect across 19 languages (*N* = 25,163 participants analyzed) by creating the largest available database of semantic priming values based on an adaptive sampling procedure. Differences in response latencies between related word-pair conditions and unrelated word-pair conditions showed evidence for semantic priming. Model comparisons showed inclusion of a random intercept for language improved model fit, providing support for variability in semantic priming across languages. This study highlights the robustness and variability of semantic priming across languages and provides a rich, linguistically diverse dataset for further analysis.

# 

Measuring the Semantic Priming Effect Across Many Languages

Semantic priming is a well-studied cognitive phenomenon whereby participants are shown a cue word (e.g., DOG) followed by either a semantically related (e.g., CAT) or unrelated (e.g., BUS) target word1. Semantic priming is defined as the decrease in response latency (i.e., reduced linguistic processing or facilitation) for target words that are semantically related to their cue words in comparison to unrelated cue words1. Semantic priming research spans nearly 50 years of study as a tool to investigate cognitive processes, such as word recognition, and to elucidate the structure and organization of knowledge representation2, often by using results from these studies to develop theoretical and computational models that capture empirical effects3–6. Priming has also been used in studies of attention7,8, studies of bi/multilingual people9,10, on neurodivergent individuals such as those affected by Parkinson’s disease, aphasia, or schizophrenia, and in a large body of neuroscience studies11–13. The purpose of this study is to leverage the power and network of the Psychological Science Accelerator (PSA)14 to create a cross-linguistic normed dataset of semantic priming, paired with other useful psycholinguistic variables (e.g., frequency, familiarity, concreteness). The PSA is a large network of research laboratories committed to large-scale data collection and open scholarship principles.

Experimental psychologists have long understood that the stimuli in research studies are of great importance, and that controlled sets of normed information hold significant value for study control and allow for precision in measurement of effects. Often, stimuli are created in small pilot studies and then reused in many subsequent projects. However, both Lucas15 and Hutchison16 provided evidence that these small pilot data should be carefully interpreted given larger, more reliable datasets. In recent years, researchers have begun to more frequently publish large datasets with experimental stimuli for reuse in future work17. These datasets include lexical frequency18,19, large collections of text (e.g., corpora)20, response latencies,21–23 and subjective ratings from participants on semantic dimensions such as emotion24–26, concreteness27, or familiarity28. Recent advances in computational capability, the growth of large-scale online data collection, and the focus on replication and reproducibility may advance this research area. The importance of normed stimuli for research cannot be overstated. Not only do they provide methodological standardization for studies using the stimuli, but the stimuli themselves can also be studied to gain insight into cognitive architecture and processes, such as attention, memory, perception, and language comprehension or production.

Normed datasets provide a wealth of information for studies on semantic priming. Facilitation in priming is based chiefly on semantic similarity or the related word-pair condition as contrasted to the unrelated word-pair condition. Traditionally, word-pairs were simply grouped into pairs that were face-value similar (e.g., DOG-CAT) and unrelated (e.g., BUS-CAT), which was determined through pilot studies where word-pairs provided the expected statistical results. However, for reproducibility and methodological control, semantic similarity values should be defined before the results are known29. Semantic similarity has various conceptual and computational definitions that all generally describe the shared meaning between two words or texts5. The most common forms of similarity are feature-based similarity (i.e., number of shared features between words)30–32, association strength (i.e., the probability of a first word eliciting a second word when simply shown the first word)33,34, or text co-occurrence (i.e., words are similar because they frequently appear in similar contexts)35–37. Each of these computational definitions of similarity can be calculated from normed datasets or text corpora to provide a continuous measure of similarity from 0 (unrelated) to 1 (perfectly related).

The Semantic Priming Project comprised both a large-scale database collection and a semantic priming study that used defined stimuli to create related word pairs21. This project provided data for lexical decision and naming tasks for 1,661 English words and nonwords, along with other psycholinguistic measures for future research. The results of the Semantic Priming Project showed 23 ms to 25 ms decreases in word response latencies (i.e., lexical decision or naming speed) for the related word-pair conditions compared to unrelated word-pair conditions. The proposed study seeks to expand this dataset and address three key limitations of the Semantic Priming Project: reliability of item level effects, small sample sizes per item, and the focus on English words and English-speaking participants.

First, Heyman et al.38 explored the split-half reliability of item-level priming effects from the Semantic Priming Project, finding low reliability for the effects. This result corresponds with Hutchison et al.’s39 study, showing low reliability for priming effects; however, they demonstrated that priming effects can still be predicted at the item-level, albeit with a smaller dataset. Relatedly, for the second limitation, Heyman et al.40 noted that the required sample size necessary for reliable priming effects was much larger than the sample size used in the study, potentially explaining the differences between results as well as demonstrating the need for a larger dataset.

Last, the Semantic Priming Project only contains English data. If semantic priming provides a window into the structure of knowledge, the dominant focus on specific languages, such as English, has limited our understanding of the influence of linguistic variation on representation. Languages differ in script, syllables, morphology, and semantics, as well as the cultural variations that occur across language users. Related concepts that one may consider universal, such as LEFT and RIGHT, are not coded into all languages. Studies with more than one language within the same study often focus on bi/multilingual individuals to elucidate the potential shared structure of knowledge across languages41,42. Therefore, claims about human language are often based on a small set of languages, limiting the generalizability of these claims43. Even with the increase in publication of normed datasets in non-English languages17, conducting cross-linguistic studies on the same concepts is challenging, as large-scale data in this area are sparse.

Although it is challenging, using newer computational techniques44,45 and recently published corpora20,46, a broader coverage dataset in up to 43 languages is possible. Therefore, this study aims to provide data that complement and extend the published data, which would encourage research on methodology, item characteristics, models, cross-linguistic consistency in priming, and other theoretical areas that semantic priming has been applied to previously. The data will address the proposed limitations by increasing sample size to hopefully improve reliability and expanding beyond the English language within the same target stimuli. From these openly shared data, two research questions will be assessed as detailed in Table 1:

1. Is semantic priming a non-zero effect? To assess this research question, we will examine the confidence interval of the semantic priming effect to determine if the lower limit of the confidence interval is greater than zero using an intercept-only regression model estimating across all languages. Therefore, we predict semantic facilitation with reduced response latencies for related word-pair conditions in comparison to unrelated word-pair conditions.
2. Does the semantic priming effect vary across languages when examining the same target stimuli? We will add a random intercept of language to the model estimated in Hypothesis 1 to estimate the variability of priming across languages. We will conclude there is variability between priming effects for languages when the AIC for the random-intercept model is two or more points less than the AIC for the model in Hypothesis 147. To contextualize these results, we will provide a forest plot of the priming effects for languages to demonstrate the pattern of variability. For Hypothesis 2, we do not specify predicted directions for the effects but do expect potential variability in priming effects across languages. It is logical to expect differences in language due to culture, orthography, alphabet, etc., and empirical data suggest meaningful differences between languages48,49.

This research crucially supplements the literature outlined above by focusing on several key components of psycholinguistic research. For sampling, we will use accuracy in parameter estimation to ensure precision in our estimates50,51 to address the known reliability issues in item-level responding38,40 to support Hypothesis 1. The items will be selected using new computational techniques for addressing semantic similarity44,45 with recently available large corpora of movie subtitles20 to appropriately match comparable items across languages. As noted in Buchanan et al.17, research in non-English languages is expanding; however, stimuli matching is still sparse across published databases. By using large corpora, items are matched not only in their similarity levels, but also for their frequency of use. Thus, differences in priming can be attributed to differences in linguistic structure or culture, rather than translation or poor item matching, supporting Hypothesis 2.

**Table 1**. **Pre-registered Design Table**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Question | Hypothesis | Sampling plan (e.g., power analysis) | Analysis Plan | Interpretation given to different outcomes |
| Is semantic priming a non-zero effect? | HA: Response latencies will be faster for related word-pairs in comparison to unrelated word pairs.    H0: Response latencies for related word-pairs will be slower or equal to those for unrelated word-pairs. | We will sample participants on items until they reach a desired accuracy in parameter estimation confidence interval width (*SE* = 0.09). | We will calculate the mean and 95% confidence interval for the priming effect subtracting related word conditions from unrelated word conditions at the item level by using an intercept-only regression model.    These calculations will be repeated for the data with 2.5 *Z*-score outlier trials excluded and 3.0 *Z*-score outlier trials excluded. | The results will support HA when the lower limit of the confidence interval is positive and non-zero > 0.0001    The results will be inconclusive when the lower limit of the confidence interval is negative or zero ≤ 0.0001. |
| Does the semantic priming effect vary across languages? | HA: Priming response latencies will be variable between languages (i.e., heterogeneous).    H0: Priming response latencies will not be variable between languages (i.e., homogenous). | We will sample participants on items until they reach a desired accuracy in parameter estimation confidence interval width (*SE* = 0.09). | We will add a random-intercept of language to the previous intercept-only model to assess overall heterogeneity.    These calculations will be repeated for the data with 2.5 *Z*-score outlier trials excluded and 3.0 *Z*-score outlier trials excluded. | The results will support HA when the ΔAIC (intercept-only minus random-intercept) is ≥ 2 points.      The results will be inconclusive when the ΔAIC (intercept-only minus random-intercept) is < 2 points. |

**Method**

All deviation sections are listed directly after their pre-registered description in the method section. These are single spaced to help distinguish them from the pre-registered plan.

**Power analysis**

For our power analysis, we first detail the background on how we estimated sample size, explain accuracy in parameter estimation, provide two simulations based on previous research, and the final proposed sample size. We end this section by specifying why this procedure was superior to previous methods and the requirements for publication.

***Background***

One concern is how to estimate the sample size required for cue-target pairs, as the previous literature indicates variability in their results40. Sample sizes of N = 30 per study have often been used in an attempt to at least meet some perceived minimum criteria for the central limit theorem. We focused on the lexical decision task for our procedure, wherein participants are simply asked if a concept presented to them is a word (e.g., CAT) or nonword (e.g., GAT). The dependent variable in this study was response latency, and we used lexical decision data from the English Lexicon Project22 and the Semantic Priming Project21 to estimate the minimum sample size necessary for each item, as previous research has suggested an overall sample size may lead to unreliability in the item-level responses40. The English Lexicon Project contains lexical decision task data for over 40,000 words, while the Semantic Priming Project includes 1,661 target words.

***Accuracy in parameter estimation (AIPE)***

**AIPE description**. In this approach, one selects a minimum sample size, a stopping rule, and a maximum sample size. A minimum sample size was defined for all items based on data simulation below. For the stopping rule, we focused on finding a confidence interval around a parameter that would be “sufficiently narrow”50–52. These parameters are often tied to the statistical test or effect size for the study, such as correlation or contrast between two groups. In this study, we paired accuracy in parameter estimation with a sequential testing procedure to adequately sample each item, rather than estimate an overall effect size. Therefore, we used the previous lexical decision data to determine our sufficiently narrow confidence by finding a generalized standard error one should expect for well measured items. After the minimum sample size, each item’s standard error was assessed to determine if the item had met the goals for accuracy in parameter estimation as our stopping rule. If so, the item was sampled at a lower probability in relation to other items until all items reach the accuracy goals or a maximum sample size determined by our simulations below.

**Estimates from the English Lexicon Project**. First, the response latency data for the English Lexicon Project were z-scored by participant and session as each participant has a somewhat arbitrary average response latency53. The data were then subset for only real word trials that were correctly answered. The average sample size before removing incorrect answers was 32.69 (*SD* = 0.63) participants with an average retention rate (i.e., number of correct responses) of 84% and 27.41 (*SD* = 6.43) participants after exclusions. The retention rates were skewed due to the large number of infrequent words in the English Lexicon Project, and we used the median retention rate of 91% for later sample size estimations. The median standard error for response latencies in the English Lexicon Project was 0.14, and the mean was 0.16. Because the retention rates were variable across items, we also calculated the average standard error for items that retained at least 30 participants at 0.12. This standard error rate represented the potential stopping rule.

The data were then sampled with replacement to determine the sample size that would provide that standard error value. One hundred words within the data were randomly selected, and samples starting at *n* = 5 to *n* = 200 were selected (increasing in units of five). The standard error for each of these samples was then calculated for the simulation, and the percent of samples with standard errors at or less than the estimated population value was then tabulated. In order to achieve 80% of items at or below the proposed standard error, we will need approximately 50 participants per word. This value was used as our minimum sample size for a lexical decision task, and the accuracy standard error level was potentially set at 0.12.

**Estimates from the Semantic Priming Project**. This same procedure was examined with the Semantic Priming Project’s lexical decision data on real word trials. The priming response latencies were expected to be variable, as this priming strength should be predicted by other psycholinguistic variables, such as word relatedness. Therefore, we aimed to achieve an accurate representation of lexical decision times, from which priming could then be calculated. However, it should be noted that accurately measured response latencies do not necessarily imply “reliable” priming or difference score data54, but larger sample sizes should provide more evidence of the picture of item-level reliability. We used these data paired with the English Lexicon Project to account for the differences in a lexical decision only versus priming focused task. The average standard error in the Semantic Priming Project was less at 0.06, likely for two reasons: the data in the Semantic Priming Project are generally frequent nouns and only 1,661 concepts, as compared to the 40,000 in the English Lexicon Project. The retention rate for the Semantic Priming Project was less skewed than the English Lexicon Project at a median of 97% and mean of 96%. Using the same sampling procedure, we estimated sample sizes of *n* = 5 to *n* = 400 participants increasing by units of 5. In this scenario, we found the maximum sample size of 320 participants for 80% of the items to reach the smaller standard error of 0.06. Therefore, we used 320 as our maximum sample size, and the average of the two standard errors found as our stopping rule, i.e., 0.09.

**Final sample size**. Given our minimum, maximum, and stopping rule, we then estimated the final sample size per language based on study design characteristics. Participants completed approximately 800 lexical decision trials per session, and each participant only completed 150 of these concepts (75 targets in the related condition, 75 targets in the unrelated condition; cue words were not analyzed) that were the target of this sample size analysis (see below for more details on trial composition). Therefore, the target number of items (*n* = 1000 concepts) was multiplied by the minimum/maximum sample size, and conditions (related word pair versus unrelated word pair) and divided by the total number of critical lexical decision trials per participant times the data retention rate (a conservative estimate of 90%). The final estimate for sample size per language was 741 to 4741 [(1000\*50\*2) / (150\*.90); (1000\*320\*2) / 150\*.90]. The complete code and description of this process are detailed in our supplemental documents.

This sample size estimation represents a major improvement from previous database collection studies, as many have used the traditional *N* = 30 to guess at minimum sample size. Because the variability of the sample size was quite large, we employed a stopping procedure to ensure participant time and effort were maximized, and data collection was optimized. To summarize, the minimum sample size was 50 participants per word and the maximum for the adaptive procedure was 320, which results in 741 to 4741 participants per language based on expected usable trials. Therefore, the total sample size was proposed to be 7410 to 47410 participants for ten languages. After 50 participants who answered a real word item, each concept was examined for standard error, and data collection for that concept was decreased in probability when the standard error reached our average criterion of 0.09. Item probability for selection was also decreased when they reached the maximum proposed sample size (*n* = 320). This process was automated online and checked in a scheduled subroutine.

**Languages**

Forty-three languages were originally identified for possible data collection based on the information available from the OpenSubtitles20 and subs2vec46 projects. We translated stimuli and collected data from at least one participant in the following 30 languages/dialects (languages with asterisks were included in our pre-registered minimum data collection plan): Arabic, Brazilian Portuguese, Czech\*, Danish, Dutch, English\*, Farsi, French, German\*, Greek, Hebrew, Hindi, Hungarian, Italian, Japanese\*, Korean\*, Norwegian, Polish, Portuguese (European)\*, Romanian, Russian\*, Serbian, Simplified Chinese\*, Slovak, Slovenian, Spanish\*, Thai, Traditional Chinese, Turkish\*, and Urdu. Table 2 provides a summary of the data collection for each language with respect to the number of included participants (based on the pre-registered data inclusion rules), the number of participants excluded, the proportion of correct answers for participants[[1]](#footnote-1) included, and the median completion time for included participants in minutes. A complete breakdown of gender, education, age, and stimuli completion can be found in the supplementary materials. The following 19 languages met the minimum data collection requirements and will be analyzed in this manuscript: Brazilian Portuguese, Czech, Danish, German, Greek, English, French, Hungarian, Italian, Japanese, Korean, Polish, Portuguese (European), Romanian, Russian, Serbian, Simplified Chinese, Spanish, and Turkish. The stimuli for European and Brazilian Portuguese overlapped by 90%; data were combined such that each unique target (unrelated and related trials) obtained the minimum number of participant answers[[2]](#footnote-2). All data are available online, including those languages that did not meet the pre-registered minimum data collection criteria for analysis. For each language, we also provide data checks and a summary of the number of participants, trials, items, and priming trials during data processing (see Supplementary Materials).

**Table 2. Language Data Collection Sample Sizes, Accuracy, and Median Study Completion Time in Minutes**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Language | *N*  Include | *N*  Exclude | Proportion  Correct | *Mdn* Time  (Minutes) |
| Arabic | 133 | 102 | 0.92 | 18.67 |
| Czech | 1074 | 362 | 0.94 | 19.76 |
| Danish | 829 | 167 | 0.93 | 18.70 |
| Dutch | 184 | 25 | 0.93 | 17.60 |
| English | 5122 | 1607 | 0.92 | 17.64 |
| Farsi | 192 | 110 | 0.95 | 17.71 |
| French | 869 | 142 | 0.95 | 17.68 |
| German | 2628 | 469 | 0.94 | 19.02 |
| Greek | 689 | 130 | 0.94 | 18.48 |
| Hebrew | 247 | 74 | 0.92 | 16.63 |
| Hindi | 1 | 2 | 0.82 | 27.39 |
| Hungarian | 718 | 180 | 0.94 | 17.94 |
| Italian | 1085 | 142 | 0.95 | 18.10 |
| Japanese | 1165 | 680 | 0.94 | 18.69 |
| Korean | 975 | 601 | 0.91 | 17.59 |
| Norwegian | 85 | 17 | 0.93 | 20.08 |
| Polish | 1188 | 318 | 0.94 | 19.15 |
| Portuguese (Combined) | 1178 | 332 | 0.93 | 18.25 |
| Romanian | 741 | 174 | 0.94 | 19.65 |
| Russian | 1806 | 956 | 0.94 | 19.68 |
| Serbian | 681 | 109 | 0.94 | 21.01 |
| Simplified Chinese | 729 | 291 | 0.93 | 17.75 |
| Slovak | 381 | 391 | 0.94 | 18.68 |
| Slovenian | 31 | 10 | 0.95 | 18.89 |
| Spanish | 1468 | 284 | 0.94 | 18.04 |
| Thai | 65 | 20 | 0.95 | 18.34 |
| Traditional Chinese | 174 | 67 | 0.92 | 18.05 |
| Turkish | 2218 | 790 | 0.93 | 17.83 |
| Urdu | 315 | 381 | 0.88 | 22.15 |

*Note*. *Mdn* = median.

**Ethics and research labs**

We did not collect any identifiable private or personal data as part of the experiment; therefore, all information about participants should be interpreted as participant sessions. This project was approved by Harrisburg University of Science and Technology, conforming to all relevant ethical guidelines and the Declaration of Helsinki, with special care to conform to the General Data Protection Regulation (GDPR; eugdpr.org). No global exclusion criteria for participating in the study were used, except for a minimum age requirement of 18 years. See the analysis section below for other participant data and trial-level exclusion criteria related to analyses.

A total of 133 labs completed ethics documentation for data collection, and 126 labs in 41 geopolitical regions collected data for the study. Each of the final data collection labs obtained local ethical review (81), relied on the ethical review provided by Harrisburg University (31), or provided evidence that no ethical review was required (14). The supplementary materials provide links to the IRB approvals hosted on the Open Science Framework (OSF) and a table of participating labs with their data collection information, which includes languages sampled, geopolitical region of the team, compensation procedure and amount, online versus in-person testing, and testing type (individual participants or classroom type settings). This information can be matched to study data using the lab code that is present in the participant and trial-level files. See Figure 1 for a visualization of the entire sample during data collection.

A map of the world

Description automatically generated

**Figure 1**. Binned sample sizes based on research lab geopolitical region and data collection language demonstrating the full data available for reuse from the project.

**Participants**

In this section, we describe both the full sample available for download and the analyzed dataset. 35,904 participants opened the study link, with 31,645 participants proceeding to complete at least one study trial (i.e., past the practice trials). Of these participants, 26,971 were retained for analysis because they met our three participant-level inclusion criteria: 1) at least 18 years of age, 2) completed at least 100 trials, and 3) scored at least 80% correct. All exclusion criteria are summarized in the results section for clarity (across both participant and trial-level exclusions). The pre-registered plan calculated accuracy as in the planned scripts; however, an administrative team discussion revealed that the pre-registered report’s definition of accuracy could alternatively be interpreted as . If accuracy were defined using this alternative formula, 28,162 participants would have been included for analysis. This report uses the stricter criterion of accuracy for analysis, while an analysis using the rescored accuracy can be found in the supplementary materials. The analyses reported below examine only those languages that met the minimum data criteria, which includes 32,897 total participants, 29,155 of whom completed at least one trial, 25,163 met the strict inclusion criteria, and 26,197 met the rescored version of the inclusion criterion for accuracy. The descriptive statistics of the participant data are provided below for the 25,163 participants who met the strict inclusion criteria.

**Materials**

The following details the important facets of the materials. We first explain the types of word-pair conditions in a semantic priming study (i.e., related, unrelated, and nonword). Next, we detail how the related word-pair conditions were created using the OpenSubtitles corpora, new computational modeling techniques, and the selection procedure.

***Word-pair conditions***

In a semantic priming study, there are three types of word-pair conditions. In the related word-pair condition, cue-target pairs are chosen for their similarity or relatedness. Cosine distance is similar to correlation in representing relatedness; however, cosine distance is always positive. Therefore, a cosine distance (when used for similarity purposes) of 1 represents the same numeric vectors (perfect similarity), while a cosine distance of 0 represents no similarity between vectors. To create the unrelated condition, cue-target pairs were shuffled so that the cue word was combined with a target word with which it had a negligible cosine distance similarity (i.e., < .15).

**Unrelated-pair cosine value deviations**. For English, cosine similarity for unrelated pairs were shuffled until all but one pair was less than .15. The pair (ONE-TORTURE) that did not achieve this criterion had a cosine similarity of .20, as the word ONE is a high-frequency word with high cosine similarity values to all targets. For Korean, we increased the unrelated cosine criterion to .20 to find the lowest possible cosine values, as below .15 was not possible for approximately 100 pairs due to the smaller word set size. For Czech, the maximum cosine for unrelated pairs was ~ .16. For Japanese, nearly all pairs were related at very high levels (i.e., *M* = .80 for cosine). The Japanese model (*fastText*) was created in the same way as described in the subs2vec paper46 (as it was not available in the subs2vec dataset), but these cosine values are improbable. We shuffled the pairs for the unrelated trials and picked the lowest possible combination for running the study. For Serbian, Simplified Chinese, and Traditional Chinese, the same problem occurred in that all word pairs were very highly correlated. We followed the same procedure as described for Japanese.

Nonword pair conditions were created by using the Wuggy-like algorithm55 for non-logographic languages. For logographic languages, we consulted with at least two native speakers to change one stroke or radical such that the character(s) were a pronounceable word with no meaning by starting from known nonword lists56. Any disagreements between native speakers were resolved by discussion between these speakers. Each cue and target word were first hyphenated using the *sylly* package and LaTeX style hyphenation57. If words were not hyphenated, as they were one syllable or the syllables were not clear, we created bigram character pairs for replacement purposes. The 100,000 most frequent words for each language from the OpenSubtitles data were also hyphenated in this style. From the OpenSubtitles data, we calculated the frequency of each pair of possible hyphenation combinations (e.g., NAPKIN → [\_, NAP], [NAP, KIN], [KIN, \_]) as the transition frequency from Wuggy. For each cue and target, we selected a set of character replacements that: kept or matched closely to the same number of characters as the original word, minimized transition frequency (i.e., the frequency of the replacement was very close to the frequency of the original pair of hyphenated characters), and matched the number of character changes to the number of syllables. At least two native speakers examined each programmatically generated word to ensure they were pronounceable (i.e., phonologically valid) and not pseudo-homophones (i.e., wherein the pronunciation sounds like a real word, KEEP → KEAP)55. In cases of disagreement, the native speakers discussed and resolved these inconsistencies. When they marked a nonword for exclusion, a new nonword was generated until speakers agreed it met the rules for nonwords. Native speakers also suggested alternatives, which the lead author checked to ensure that they matched the desired nonword characteristics.

**Nonword deviations**. Translators suggested new nonword options from the computationally generated list. Given that the translators were native speakers, we relied upon their expertise for this component. These suggestions were implemented before data collection. After implementation of trials into the online experiment, a few words were found to be incorrectly marked as nonwords or were misspelled in the dataset. These trials were corrected during data collection or post-data collection in the data processing scripts. These deviations and issues are noted in the data processing files found online.

To control the ability of participants to anticipate or guess the answers, we ensured that half the trials should be answered with a word and half with a nonword. Therefore, we used 150 related trials (150 word / 0 nonword; 75 pairs), 150 unrelated trials (150 word / 0 nonword; 75 pairs), 200 word-nonword trials (100 word / 100 nonword, this could have been word-nonword or nonword-word combinations to control for answer chaining; 100 pairs), and 300 nonword-nonword trials (0 word / 300 nonword; 150 pairs). These trials were randomly presented to control the transition probability between word and nonword trials (i.e., random presentation should ensure trials do not present a word-word-nonword-nonword style pattern that allows participants to mindlessly guess the answers). Therefore, the yes-no probability was 50% for words-nonwords across all trials, and the relatedness proportion for pairs was 18.8%. The exact trial proportions for each language can be found online in our data processing summary, as not all participants completed all trials, which can change proportions for each language.

***Similarity calculation***

**Corpora**. As described in the introduction, the choice of related words based on similarity was key for the study. There are multiple measures of semantic similarity including the cosine similarity between overlapping features32, free association probabilities33,34,58, and local/global coherence values from network models. However, the underlying data for these calculations are inconsistent across languages. Therefore, one solution is to use the data present in the OpenSubtitles datasets20 (i.e., a large collection of movie subtitles) to calculate word frequency and cosine similarity values. These datasets have been used to calculate word frequencies for the SUBTLEX projects, which have validated their use as strong predictors of cognitive related phenomena18,59–66. Cosine similarity was selected over other similarity measures because of the availability of possible languages and models for this project, as described below.

The OpenSubtitles data includes 62 languages or language combinations (e.g., Chinese-English mix). We used the 10,000 most frequent nouns, adjectives, adverbs, and verbs from each potential language without lemmatization (i.e., converting words into their dictionary form RUNS → RUN). The *udpipe* package67 is a natural language processing package that contains more than 100 treebanks to assist in part of speech tagging (i.e., labeling words as noun, verb, etc.), parsing (i.e., separating blocks of text into words and their relationship to other words in a text), and lemmatization. This package was selected for its large coverage of languages with reliable part-of-speech tagging. Cross-referencing the available languages in *udpipe* with the OpenSubtitles data allowed for the possibility of 43 different languages in this project. See Figure 2 for the model selection process.

A diagram of a software model

Description automatically generated

**Figure 2.** Flow chart of thestimuli selection method. Circles represent the data or models used in the decision tree. Diamonds represent a decision criterion for the data selected. Squares represent coding processes or data reduction for the final stimuli set.

**Modeling**. The subs2vec project46 used the OpenSubtitles data to create *fastText*68 computational representation for 55 languages. *fastText* is a distributional vector space model, an extension of *word2vec*44,45, wherein each word in a corpus is converted to a vector of numbers that represents the relationship of that word to a number of dimensions. These dimensions can be imagined as a thematic or topic representation of the text. The relationship between these vectors represents the similarity between concepts, as words that have similar or related meanings will appear in similar places and dimensions in a text, and will, therefore, have similar numeric vectors4,5. We used the existing models from subs2vec to extract related word concepts for the most frequent concepts identified using the top cosine distance between word vectors. When the model was not present in subs2vec, we recreated the same model using their parameters on the relevant OpenSubtitles data.

**Cue selection procedure.** The procedure for stimuli selection can be reviewed in our supplementary materials and is displayed graphically in Figure 2. If the language was available via subs2vec, the provided subtitle frequency counts were examined. If the language has more than 50,000 unique concepts represented in the subtitle data, we used the subtitle model only. If the subtitles do not provide enough linguistic information (i.e., fewer than 50,000 concepts in the corpus), we used the combined Wikipedia and subtitle model46. subs2vec contains models with only the OpenSubtitles data, only Wikipedia for a given language, and a combined model of both. The subtitle data has shown to best represent a language18,59; however, not all subtitle projects contain a large enough corpus for the subtitles to cover the breadth of the possible concepts within that language (e.g., Afrikaans subtitles only represent approximately 18,000 words).

The selected token list was then tagged for part-of-speech using *udpipe*, selecting tokens that were tagged as nouns, adjectives, adverbs, and verbs. From the *udpipe* output, the lemma for each token was selected to control for high similarity between lemma-token forms (e.g., RUN is highly related to RUNS). All stopwords (i.e., commonly used words in a language with little semantic meaning such as THE, AN, OF), words with fewer than three characters for non-logographic languages, and words with numeric characters were eliminated (i.e., 1 would be eliminated but not ONE). The stopword lists can be found in the stopwords package using the Stopwords ISO dataset69. This procedure covered all but two languages in our list of 43 possible languages. For the final two languages, we used *udpipe* to tag the OpenSubtitles directly and calculate word frequency. Additionally, *fastText* models using the same parameters as subs2vec were trained for similarity calculation. The 10,000 most frequent concepts were selected at this point.

**Target selection procedure**. Using the *fastText* models for each language, we selected the top five cosine distance similarity values for each concept in each language independently, resulting in 50,000 possible cue-target pairs. These were cross-referenced across languages using Google Translate to create a master list of potential cue-target pairings. The related word pairs (n = 1000) were selected from this list using each cue or target only once, favoring pairs with translations in most languages. Therefore, the selection procedure was based on the most common cue-target pairs across languages, rather than selecting similar words in one language and then translating. This procedure was programmatic, using Google Translate, which may not produce the most appropriate translation for a word. Therefore, native speakers ensured the accurate translation of word pairs using the PSA’s translation network for the final selected set in a similar manner as described above. They suggested a more common or appropriate word for items they thought were unusual, and in cases of disagreement, group discussion between the two translators took place. In some instances, translation may have indicated that a particular language does not have separate concepts for the cue-target pairing. In this instance, we changed the cue word to a related word for that language from the five selected in the original list. Thus, all targets were matched across languages, and as many cues as possible while avoiding repetition within a cue-target pair as best possible.

***Selection deviations*.** We planned to filter OpenSubtitles for words with at least three characters (excluding logographic languages). This process was completed, and all cue words were at least three characters in length; however, when we matched cues to high-cosine targets, several two-letter words were included. Additionally, due to translation suggestions and cross-referencing, some other two-letter words were also included. For example, in English, MAKE-GO, DOWN-UP, and ENTER-GO were included as potential related cue-target pairs for target selection.

**Procedure**

We describe the important components to the procedure in this section. First, we detail the implementation of the study, focusing on the timing software and adaptive stimuli section, as not all participants see all items. We then discuss the study procedure in order, as shown in Figure 3. First, participants completed a demographic questionnaire, followed by the lexical decision task. We explain how our data compliments the Semantic Priming Project and finally, discuss additional data that researchers can combine with the current dataset.

A diagram of a language

Description automatically generated

**Figure 3.** Flow chart of the procedure for the study. Within the lexical decision task, participants were given short breaks after 100 trials. The answer choices for that language were always displayed at the bottom of the screen during the lexical decision task.

**Implementation**

***Timing software***

While participants were naïve to the word pairings, the principal investigator knew the pair combinations during data collection and analysis. A small demonstration of the experiment can be found at:<https://psa007.psysciacc.org/> or recreated from our supplemental materials. The study was programmed using *lab.js*70, which is an online, open-source, study-building software. Precise timing measurement was required for this study, and the *lab.js* team has documented the accuracy of measurement within their framework71, and previous work has shown no differences between lab and web-based data collection for response latencies72. In addition, SPALEX, a large lexical decision database in Spanish, was collected completely online23. We recommended that research labs suggest Chrome as their browser for participants completing the study due to recommendations from the *lab.js* team. However, meta-information about the browser and operating system were saved when participants took the experiment to examine for potential implementation differences.

Participants were directed to an online web portal to complete the study, and all data were retained in the online platform with regular backups to the server. Participants were required to complete the study on a computer with a keyboard, rather than on a device with only a touch screen. This requirement allows for tracking of the display of the device which indicates important aspects about screen size, browser, and timing accuracy. In order to enforce this requirement, participants were asked to hit the spacebar to continue the study.

***Adaptive stimuli selection***

At the start of data collection, all presented items were randomly selected from the larger item pool by equalizing the probability of inclusion for all words and nonwords (p = 1/1000 concepts)[[3]](#footnote-3). After the minimum sample size was collected, each word’s standard error was checked to determine if the sample size for that item had reached our accuracy criteria. If so, the probability of sampling that item was decreased by half. Once a concept has reached the maximum required sample size, the probability of sampling will also be decreased by half. This procedure will allow for random sampling of the items that still need participants without eliminating words from the item pool. Therefore, we ensured that there were always words to randomly select from (i.e., to keep the same procedure and number of trials for all participants) and that the randomization was a sampled mix of words that reach accuracy quickly and words that need more participants (i.e., participants do not only see the unusual words at the end of data collection). Once all words reached the stopping criteria or maximum sample size, the probabilities were equalized. We set minimum, maximum, and a stopping rule for the initial data collection; however, we allowed data collection after these were reached and will post updates to the data using a DOI service to allow researchers to cite the specific dataset they used for their research73 (modeled after the Small World of Words Project33, which is ongoing). All data are included in our dataset, and the analysis section describes how we indicated exclusion criteria. Therefore, data collection was a repeated-measures design in which participants did not see all of the possible stimuli, but did see all the possible conditions (related, unrelated, and nonword pairs). Participants were blinded to condition, and the explicit link between pairs was not explained to participants.

**Adaptive implementation deviations**. One potential issue with some data collection options labs wanted to use, such as MTurk and Prolific, was the speed of data collection. For example, a researcher can collect data from thousands of participants in an hour via these services. Our study was designed to collect data more slowly across time and to implement the stimuli randomization and selection algorithm. If hundreds of participants came to the study at the same time, we would unevenly collect data on the current stimuli because there is no time to update the stimuli counts. To control for the speed of collection using these sites and any other simultaneous participant runs (i.e., classroom testing), multiple versions of the study were programmed, and participants were assigned to a random version via Qualtrics randomizer. They were then redirected back to their paid provider. Each language continued to use the adaptive randomization and selection algorithm. A summary of data collection procedures by lab is available in the supplementary materials

For large paid samples funded by ZPID and Harrisburg University (<https://leibniz-psychology.org/>: Japanese, Russian, Turkish, Czech, and Korean), we created 14 different randomizations that evenly distributed the pairs across the study with a small overlap because the important trial combinations (word–word) do not evenly distribute. These were static during the data-collection process to ensure that we obtained 50+ participants in the paid samples for each word–word trial combination. After initial large-scale data collection, the algorithm was turned back on for PSA labs collecting data in those languages.

Additionally, to allow randomization to be more frequent during early stages of data collection, we ran the algorithm randomization process every five minutes once the data collection for a language started. As data size increased, we increased the time interval, to account for the time it took for the algorithm code to run, so that each randomization could finish before the next one was scheduled to start. This process also ensured that the .json files of randomized stimuli were not overwritten or corrupted if two processes were running at once.

An error in the stimulus-writing process led to partial data collection from some participants who appeared to have completed the experiment. The error involved a failure to write new stimuli to the folder used to run the experiment (and therefore, participants were given incorrect practical trials for the first six real blocks followed by two correctly formatted trial blocks before we recognized the error). These tests and inappropriate trials were excluded (please see the data check files for languages and the number of trials affected). Other coding-related issues included a typo that showed one trial pair twice at the beginning of the study (affected languages were Czech, English, Japanese, Korean, Russian, and Turkish), instances of garbled items in non-Latin language scripts (e.g., where symbols were shown instead of the Cyrillic characters in Russian), and typos in word spellings. These issues were fixed as soon as they were discovered.

Last, when examining data-collection progress, we noticed that Korean did not have all matched related-unrelated pairs. This error happened during the shuffle to get low cosine values, resulting in too many unrelated trial combinations. Thirty-three new trial combinations were added to ensure each related target had a corresponding unrelated target. In Arabic, the research labs requested that we exclude specific word pairs due to their taboo nature; this request was honored, and thus, the total number of possible stimuli is lower in that language.

***Study Procedure***

**Demographics**. Participants were given a language specific link for each research lab. Participants were asked to indicate their gender (i.e., male, female, other, prefer not to say), year of birth, and education level (i.e., none, elementary school, high school, bachelors, masters, doctorate; or their equivalent in the target country of data collection) as demographic variables. They provided their native language in an open text box and selected left or right as their dominant hand for the mapping of word-nonword answer keys (see below). A flow chart of the procedure is provided in Figure 3.

**Lexical decision task**. Instructions on how to complete a lexical decision task were shown on the next screen, followed by 10 practice trials. Each trial started with a fixation cross (+) in the middle of the screen for 500 ms. The stimulus item was then displayed in the middle of the screen in lowercase Sans-serif 18-point font (i.e., Arial font, dog). On the bottom of the screen the possible responses were shown as the traditional keys next to the Shift key depending on the most common keyboard layout for that language (i.e., Z and / on a QWERTY keyboard or < and - on a QWERTZ keyboard or numbers 1 and 9 for languages that had many keyboard layouts). Response keys were mapped such that the “nonword” response option is on the non-dominant hand side of the keyboard, and the “word” response option is on the dominant hand side74. Participants made their choice for each concept, and during the practice trials, they received feedback if their answer was correct or incorrect. The next stimulus appeared with an intertrial interval of 500 ms (i.e., the time between the offset of the first concept response and onset of the next concept, when the fixation cross was showing). Responses timed out after three seconds and moved on to the next trial. After 10 trials, participants saw the instruction screen again with a reminder that they would now be doing the real task.

After 100 trials, the participants were shown a short break screen with the option to continue by hitting the spacebar after 10 seconds. This break timed out after 60 seconds. After eight blocks of 100 trials (800 word-nonword decisions), the experiment ended with a thank you screen. On this screen, participants were given instructions on how to indicate that they had completed the study to the appropriate lab. Participants were allowed to take the study multiple times as items were randomly selected for inclusion. An estimate for the time required for the study was approximately 30 minutes inclusive of practice trials, reading all instructions, and breaks. This estimate was based on previous studies of lexical decision times22, and the final median completion time was approximately 18 minutes.

**Comparison to the Semantic Priming Project**. This procedure is a continuous lexical decision task wherein every concept (cue and target) is judged for lexicality (i.e., word/nonword). Many priming studies often present cue words for a short period of time prior to the presentation of target words for lexicality judgment. Evidence from the Semantic Priming Project suggests that the stimulus onset asynchrony (i.e., time between non-judged cue word and target word) does not affect overall priming rates (25 versus 23 ms for 200 ms and 1200 ms). Further, adding the lexicality judgment to each presented concept creates a less obvious link between cue and target to avoid potential conscious expectancy generation effects75,76. Even though they appear sequentially in the task, they are not explicitly paired by being a non-judged cue word followed by a judged target word. Therefore, this procedure varies from the data collected in the Semantic Priming Project; thus, extending their work to different conditions. Lucas15 provides evidence that priming effect sizes are relatively equal across task type (e.g., continuous, masked, paired, and naming), and therefore, we should expect similar results.

**Additional data.** We then combined available lexical and subject rating data with the priming data, and a tutorial is provided in the supplementary documentation on how to download data and combine with available norms. Lexical measures, such as length, frequency, part of speech, and the number of phonemes (i.e., sounds in a word) are easily created from the concept or the SUBTLEX projects59–65. Subjective measures are concept characteristics that are rated by participants, and we included age of acquisition77–80 (approximate age you learned a concept), imageability81,82 (how easy the concept comes to mind), concreteness83 (how concrete is the concept), valence (how positive versus negative is the concept), arousal (how excited or calm a concept makes a person), dominance (the word denotes something that is weak/subordinate or strong/dominant)24,26, and familiarity (how well a person knows a concept)84. These variables were selected from the list of most published databases for linguistic data17.

**Results**

We first detail the exclusion criteria from the pre-registered plan. Next, the descriptive statistics of the data are provided for participants, trials, items, and priming. The final section covers the hypothesis testing from Table 1. To reduce redundancy, we provide several overview tables of the descriptive results, and all pre-registered descriptives in the supplementary materials.

**Exclusion summary**

Data were excluded for the following reasons in this order (per the pre-registered plan):

1. Participant-level data: the entire participant’s data were removed from the analyses if:
   1. A participant did not indicate at least 18 years of age.
   2. A participant did not complete at least 100 trials.
   3. A participant did not achieve 80% correct.
2. Trial level data: individual trials were removed from the analyses in the following instances:
   1. Timeout trials (i.e., no response given in 3 s window)[[4]](#footnote-4).
   2. Incorrectly answered trials.
   3. Response latencies shorter than 160 ms85.
3. Trial level exclusions dependent on test: Participant sessions were *Z*-scored as described below, and trials were marked for exclusion in the dataset. Each analysis was tested with the full data and then without these values:
   1. Response latencies over the absolute value of *Z* = 2.5.
   2. Response latencies over the absolute value of *Z* = 3.0.

**Descriptive statistics**

***Participant (Session)-level data***

The following statistics are calculated by session, which generally represents one participant; however, participants could have taken the study multiple times. We will describe these sessions as participants for ease of reading. We present the full sample information and the analyzed sample information to demonstrate that the data analyzed are similar to the full dataset. The sample of participants self-identified as female (55.49%), male (37.39%), with the rest either missing data, not wanting to indicate their gender[[5]](#footnote-5), or other. If the data were filtered to select only participants that were included in the analysis, the participants self-identified as predominantly female (60.95%) or male (37.44%). Looking at the entire sample, participants indicated they had completed high school (42.77%), some college[[6]](#footnote-6) (7.63%), college (30.47%), a master’s degree (9.30%), and other options (less than High School, Doctorate, or missing). Participants included in the analysis also followed this pattern: high school (46.02%), some college (8.34%), college (31.97%), and a master’s degree (9.61%). Please note we use the terms here that were listed on the survey, but the terminology for education was localized to the data collection area.

The top twenty native languages represented in the data are shown in Table 3. Full language percent tables can be found in the supplementary materials. The data indicates that the pattern of native languages was similar in the full data and data used for analysis. The average self-reported age for all participants was *M* = 31.4 years (*SD* = 15.0), ranging from 18 to 104 years (*Mdn* = 24, *IQR =* 20 – 39). In the demographic questions, we asked the participants to enter their year of birth, and the high maximum values likely belonged to participants who entered the minimum possible year allowable in the data collection form. The data of the participants included in the analysis showed the same age pattern: *M* = 30.4 (*SD* = 14.2) ranging from 18 to 104 (*Mdn* = 24, *IQR =* 20 – 37).

**Table 3. Native and Browser Languages for the Overall and Analyzed Participants**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Native Language | | Browser Language | |
| Language | Overall % | Analyzed % | Overall % | Analyzed % |
| English | 15.83 | 17.19 | 27.35 | 27.65 |
| Turkish | 8.41 | 8.63 | 8.60 | 8.30 |
| German | 7.80 | 9.39 | 8.53 | 9.72 |
| Missing | 7.76 | 1.65 | 2.85 | 2.61 |
| Russian | 7.61 | 6.99 | 8.10 | 6.99 |
| Spanish | 5.39 | 6.13 | 4.85 | 5.35 |
| Japanese | 5.03 | 4.51 | 5.54 | 4.57 |
| Polish | 4.36 | 4.65 | 4.35 | 4.35 |
| Korean | 4.23 | 3.81 | 4.58 | 3.72 |
| Portuguese  (Combined) | 4.06 | 4.37 | 3.98 | 4.15 |
| Czech | 3.88 | 4.07 | 4.15 | 4.04 |
| Italian | 3.74 | 4.38 | 3.54 | 4.09 |
| French | 2.80 | 3.31 | 2.83 | 3.25 |
| Danish | 2.79 | 3.20 | 2.61 | 2.90 |
| Hungarian | 2.72 | 2.96 | 2.36 | 2.45 |
| Mandarin | 2.58 | 2.68 | NA | NA |
| Greek | 2.35 | 2.73 | 1.60 | 1.73 |
| Serbian | 2.27 | 2.66 | 0.45 | 0.50 |
| Romanian | 1.99 | 2.23 | 0.96 | 1.08 |
| Chinese | 0.62 | 0.57 | 2.43 | 2.24 |

*Note*. Native language was coded as Cantonese or Mandarin when the participant used those terms for more specificity. Participants also used a more generic term “Chinese”, and the more specific terminology and generic terms are both included in the table. Browser language meta-data only included “Chinese”, and therefore, is the terminology used here. Values are sorted in descending order by overall native language.

The majority of participants used a Windows-based operating system (76.91%), followed by Mac OS (18.45%), and Linux (1.80%), with some missing data (2.85%) based on browser meta-data. The distribution of operating systems was similar for the participants used in the analysis: Windows (76.82%), Mac (18.70%), Linux (1.86%), and missing (2.61%). Web browsers were grouped into the largest categories for reporting as the data provided includes specific version numbers. The majority of the participants used Chrome (58.96%), followed by Edge (14.92%), Safari (8.88%), Firefox (8.18%), Opera (3.09%), Yandex (2.37%), and other web browsers (3.60%). The results were similar when examining only the participants who were included in the analysis: Chrome (59.81%), Edge (14.23%), Firefox (8.18%), Firefox (8.43%), Safari (9.22%), Opera (2.99%), Yandex (2.03%), and other browsers (3.29%). The top twenty browser languages represented in the data are shown in Table 3, with full tables of browser languages in the supplementary online data. Generally, this pattern matched the demographics of the study, as well as the targeted languages, except that more participants had their browser set in English compared to the indicated native language, see Table 3.

Participants’ overall proportion of correct answers was calculated, and participants who did not correctly answer at least 80% of the trials or saw fewer than 100 trials were marked for exclusion within the participant and trial-level datasets (see below). The average percentage of incorrect responses in the Semantic Priming Project was between 4% to 5%, and the 80% criterion was chosen to only include participants who were engaged in the experiment. Additionally, as noted above, two definitions of accuracy were identified by the lead team, and consequently, both criteria are provided.

The study lasted an average of 26.40 minutes (*SD* = 303.61). If a participant’s computer went to sleep during the study, and they later returned to it (e.g., to close the browser), the last timestamp would include the final time the study was open. Therefore, the median completion time is likely more representative, *Mdn* = 17.88 minutes. The participants included in the analysis completed the study in 24.14 minutes on average (*SD* = 296.83, *Mdn* = 17.97 minutes).

***Trial-level data***

Each language was saved in separate files in the online materials. Supplementary files and code within *semanticprimeR* enable merging trials across concepts and pairings (e.g., CAT [English] → KATZE [German] → GATTO [Italian]). If a participant left the study early (e.g., Internet disconnected, computer crashed, closed the study), the data beyond that point were not recorded. Therefore, the trial-level data represents all trials displayed during the experiment, and new columns were added to denote different exclusion criteria at the trial level. We expected that participants would provide an incorrect answer on some trials, and these trials were marked for exclusion. All timeout trials were marked as missing values in the final data set. No missing values were imputed.

Trials were also marked for exclusion if they were under the minimum response latency of 160 ms85. Further, *lab.js* automatically codes timeout data with a special marker (i.e., data ended on response or timeout as a column), which excludes trials over 3000 ms as the maximum response latency. However, because of variations in browser/screen refresh rates, some trials were answered with response latencies over 3000 ms when a participant made a key press at the very end of the trial before timeout. Given the pre-registered exclusion rules, these were also marked for exclusion.

The response latencies from each participant’s session were then *Z*-scored following Faust et al.53 For privacy reasons, we did not collect identifying information to determine if a person took the experiment multiple times, but as these are considered different sessions, the recommended *Z*-score procedure should control for participant variability at this level. Therefore, the possibility of repeated participation was not detrimental to data collection, especially with the large number of possible stimuli for a participant to receive within each session. Both *Z*-score and raw response times are included in the provided data files. Table 4 includes the number of trials and values accuracy for each language, for all participants, and for analyzed participants. The mean *Z-*scores for all trials, regardless of item or related/unrelated condition, are presented in the summary files online. The analyses averaged over item statistics are presented below.

**Table 4. Total of Lexical Decision Task (LDT) Trials and Accuracy Proportion by Word-Nonword Trial**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | All Participants | | Analyzed Participants | | All Participants | | Analyzed Participants | |
| Language | Total Nonword Trials | Total Word Trials | Total Nonword Trials | Total Word Trials | Accuracy Nonword | Accuracy Word | Accuracy Nonword | Accuracy Word |
| Czech | 446,465 | 447,172 | 396,459 | 397,150 | 0.91 | 0.95 | 0.94 | 0.97 |
| Danish | 344,582 | 345,061 | 311,920 | 312,264 | 0.89 | 0.94 | 0.92 | 0.95 |
| English | 2,245,604 | 2,252,266 | 1,961,546 | 1,968,289 | 0.87 | 0.94 | 0.91 | 0.95 |
| French | 349,804 | 350,247 | 331,078 | 331,316 | 0.93 | 0.96 | 0.94 | 0.96 |
| German | 1,090,365 | 1,090,615 | 1,022,547 | 1,022,866 | 0.92 | 0.95 | 0.93 | 0.96 |
| Greek | 280,819 | 281,564 | 264,274 | 264,915 | 0.93 | 0.94 | 0.95 | 0.95 |
| Hungarian | 310,186 | 309,954 | 279,322 | 279,126 | 0.91 | 0.93 | 0.94 | 0.94 |
| Italian | 442,736 | 443,774 | 420,132 | 420,889 | 0.94 | 0.96 | 0.95 | 0.96 |
| Japanese | 445,883 | 444,659 | 379,645 | 378,968 | 0.90 | 0.92 | 0.94 | 0.96 |
| Korean | 388,661 | 390,327 | 321,070 | 322,260 | 0.87 | 0.92 | 0.91 | 0.94 |
| Polish | 492,714 | 492,552 | 448,989 | 448,941 | 0.92 | 0.95 | 0.94 | 0.96 |
| Portuguese (Combined) | 495,485 | 495,373 | 456,065 | 456,166 | 0.89 | 0.95 | 0.91 | 0.96 |
| Romanian | 304,296 | 304,271 | 278,125 | 278,246 | 0.92 | 0.96 | 0.93 | 0.97 |
| Russian | 795,078 | 793,816 | 652,446 | 652,149 | 0.91 | 0.93 | 0.95 | 0.96 |
| Serbian | 285,389 | 285,498 | 262,660 | 262,664 | 0.92 | 0.95 | 0.93 | 0.96 |
| Simplified Chinese | 327,479 | 327,869 | 274,613 | 274,870 | 0.88 | 0.93 | 0.92 | 0.95 |
| Spanish | 586,901 | 586,488 | 556,113 | 555,740 | 0.92 | 0.95 | 0.93 | 0.96 |
| Turkish | 898,853 | 897,783 | 788,613 | 788,008 | 0.91 | 0.94 | 0.94 | 0.95 |
| Overall | 10,531,300 | 10,539,289 | 9,405,617 | 9,414,827 | 0.90 | 0.94 | 0.93 | 0.96 |

***Item-level data***

The item-level data files can be matched with lexical information about all stimuli calculated from the OpenSubtitles20 and *subs2vec46* projects using the *semanticprimeR* package (see the supplementary materials for a tutorial)86. The descriptive statistics calculated from the trial-level data is separated by language for each item: mean response latency, average standardized response latency, sample size, standard errors of response latencies, and accuracy rate. No data points were excluded for being a potential outlier (i.e., no response latencies were excluded due to being an “outlier” after removal of excluded participants and trials mentioned above); however, we used a recommended cut-off criterion for absolute value *Z*-score outliers at 2.5 and 3.021, and we calculated these same statistics with those subsets of trials excluded. For all real words, when available, values for age of acquisition, imageability, concreteness, valence, dominance, arousal, and familiarity values can be merged with the item files. These values do not exist for nonwords. Tables 5 and 6 show the item statistics for average item sample size, average *Z*-scored response time, average *SE* for the Z-scored response latencies separated by item (nonword, word) type and language. These values exclude both participants and trials from the exclusions listed above, and scores are calculated by creating item means and then averaging all item means.

**Table 5. Total Number of Unique Trials and Average Trials Per Item**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  | All Trials | | *Z* < 2.5 | | *Z* < 3.0 | |
| Language | *N* Unique Nonword | *N* Unique Word | *M* Trials Nonword | *M* Trials Word | *M* Trials Nonword | *M* Trials Word | *M* Trials Nonword | *M* Trials Word |
| Brazilian Portuguese | 1,946 | 1,956 | 180.75 | 208.70 | 172.05 | 205.65 | 175.09 | 206.71 |
| Czech | 1,981 | 1,969 | 185.05 | 193.07 | 176.56 | 190.18 | 179.43 | 191.16 |
| Danish | 1,957 | 1,954 | 145.73 | 151.12 | 138.84 | 148.48 | 141.14 | 149.35 |
| English | 1,978 | 2,000 | 889.16 | 932.03 | 851.22 | 915.36 | 863.12 | 920.45 |
| French | 1,976 | 1,936 | 156.07 | 163.90 | 149.51 | 161.36 | 151.66 | 162.17 |
| German | 1,957 | 1,946 | 484.48 | 499.54 | 463.33 | 491.11 | 470.60 | 493.85 |
| Greek | 1,949 | 1,924 | 120.51 | 130.60 | 115.71 | 127.85 | 117.35 | 128.73 |
| Hungarian | 1,936 | 1,924 | 134.59 | 135.65 | 129.57 | 132.80 | 131.25 | 133.73 |
| Italian | 1,992 | 1,991 | 197.80 | 201.52 | 189.60 | 198.37 | 192.38 | 199.40 |
| Japanese | 1,989 | 1,953 | 177.24 | 183.63 | 170.69 | 179.39 | 172.89 | 180.63 |
| Korean | 1,857 | 1,938 | 154.96 | 154.65 | 149.13 | 151.40 | 150.93 | 152.33 |
| Polish | 1,985 | 1,949 | 211.16 | 219.87 | 202.23 | 216.29 | 205.28 | 217.44 |
| Portuguese  (European) | 1,965 | 1,956 | 183.61 | 209.07 | 174.44 | 206.09 | 177.64 | 207.10 |
| Romanian | 1,966 | 1,952 | 130.63 | 136.68 | 124.39 | 134.80 | 126.59 | 135.45 |
| Russian | 1,996 | 1,998 | 306.39 | 309.55 | 294.25 | 303.59 | 298.45 | 305.57 |
| Serbian | 1,960 | 1,957 | 123.51 | 128.09 | 117.67 | 126.54 | 120.04 | 127.15 |
| Simplified Chinese | 1,993 | 1,842 | 126.09 | 140.62 | 120.99 | 137.76 | 122.60 | 138.63 |
| Spanish | 1,989 | 1,941 | 259.36 | 273.35 | 247.93 | 269.43 | 251.68 | 270.71 |
| Turkish | 1,866 | 1,929 | 391.22 | 383.96 | 375.84 | 376.19 | 380.81 | 378.57 |
| Overall | 37,238 | 37,015 | 239.97 | 251.59 | 229.74 | 247.20 | 233.16 | 248.60 |

*Note. N* represents sample size.

**Table 6. Z-Scored RT Means, Standard Errors for Nonword and Word Trials by Language**

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | All Trials | | | | *Z* < 2.5 | | | | *Z* < 3.0 | | | |
| Language | *M* Z NW | *M* Z W | *SE* Z NW | *SE* Z W | *M* Z NW | *M* Z W | *SE* Z NW | *SE* Z W | *M* Z NW | *M* Z W | *SE* Z NW | *SE* Z W |
| Brazilian Portuguese | 0.29 | -0.26 | 0.08 | 0.06 | 0.12 | -0.32 | 0.06 | 0.04 | 0.17 | -0.30 | 0.06 | 0.05 |
| Czech | 0.31 | -0.25 | 0.07 | 0.06 | 0.15 | -0.31 | 0.05 | 0.04 | 0.19 | -0.30 | 0.06 | 0.05 |
| Danish | 0.28 | -0.22 | 0.08 | 0.07 | 0.11 | -0.29 | 0.06 | 0.05 | 0.15 | -0.27 | 0.06 | 0.05 |
| English | 0.26 | -0.20 | 0.03 | 0.03 | 0.09 | -0.28 | 0.02 | 0.02 | 0.13 | -0.26 | 0.03 | 0.02 |
| French | 0.27 | -0.23 | 0.08 | 0.06 | 0.12 | -0.30 | 0.06 | 0.05 | 0.16 | -0.28 | 0.06 | 0.05 |
| German | 0.26 | -0.20 | 0.04 | 0.04 | 0.11 | -0.27 | 0.03 | 0.03 | 0.15 | -0.25 | 0.03 | 0.03 |
| Greek | 0.20 | -0.14 | 0.09 | 0.07 | 0.05 | -0.22 | 0.07 | 0.06 | 0.09 | -0.20 | 0.07 | 0.06 |
| Hungarian | 0.18 | -0.13 | 0.08 | 0.07 | 0.05 | -0.22 | 0.06 | 0.06 | 0.08 | -0.20 | 0.06 | 0.06 |
| Italian | 0.26 | -0.24 | 0.07 | 0.06 | 0.12 | -0.31 | 0.05 | 0.04 | 0.15 | -0.29 | 0.05 | 0.05 |
| Japanese | 0.17 | -0.13 | 0.07 | 0.06 | 0.04 | -0.23 | 0.05 | 0.05 | 0.07 | -0.21 | 0.06 | 0.05 |
| Korean | 0.23 | -0.16 | 0.08 | 0.07 | 0.08 | -0.26 | 0.06 | 0.05 | 0.11 | -0.24 | 0.06 | 0.05 |
| Polish | 0.27 | -0.23 | 0.07 | 0.05 | 0.12 | -0.29 | 0.05 | 0.04 | 0.15 | -0.28 | 0.05 | 0.04 |
| Portuguese  (European) | 0.35 | -0.27 | 0.08 | 0.05 | 0.17 | -0.33 | 0.06 | 0.04 | 0.22 | -0.31 | 0.06 | 0.04 |
| Romanian | 0.32 | -0.28 | 0.09 | 0.07 | 0.16 | -0.33 | 0.06 | 0.05 | 0.20 | -0.32 | 0.07 | 0.05 |
| Russian | 0.21 | -0.22 | 0.05 | 0.05 | 0.08 | -0.29 | 0.04 | 0.04 | 0.11 | -0.27 | 0.04 | 0.04 |
| Serbian | 0.36 | -0.33 | 0.09 | 0.06 | 0.22 | -0.37 | 0.07 | 0.05 | 0.27 | -0.36 | 0.07 | 0.06 |
| Simplified Chinese | 0.23 | -0.18 | 0.09 | 0.07 | 0.08 | -0.27 | 0.06 | 0.05 | 0.11 | -0.25 | 0.07 | 0.06 |
| Spanish | 0.29 | -0.25 | 0.06 | 0.05 | 0.13 | -0.31 | 0.05 | 0.04 | 0.17 | -0.30 | 0.05 | 0.04 |
| Turkish | 0.22 | -0.17 | 0.05 | 0.04 | 0.07 | -0.25 | 0.04 | 0.03 | 0.10 | -0.24 | 0.04 | 0.03 |
| Overall | 0.26 | -0.21 | 0.07 | 0.06 | 0.11 | -0.29 | 0.05 | 0.04 | 0.15 | -0.27 | 0.06 | 0.05 |

*Note*. *M* = mean, *SE* = standard error, NW = nonwords, W = words.

***Priming-level data***

In separate files, we prepared information about the priming results in two forms: 1) priming trials that were converted from long data (i.e., one trial per row) to wide data (i.e., cue-target priming trial combinations paired together on one line), and 2) summary data, which includes the list of target words, average response latencies, averaged *Z*-scored response latencies, sample sizes, standard errors, and priming response latency. For each item, priming was defined as the average *Z*-scored response latency when presented in the unrelated minus the related condition. Therefore, the timing for DOG-CAT would be subtracted from BUS-CAT to indicate the priming effect for the word CAT. The similarity scores calculated during stimuli selection are provided for merging, as well as other established measures of similarity if they are available in that language. For example, semantic feature overlap norms are also available in Italian87, German88, Spanish23, Dutch89, and Chinese90. The overall priming averages by language are shown in Figure 4 as part of Hypotheses 1 and 2.

**Priming calculation deviations***.* In some cases, a target word was repeated due to language translation. This repetition occurred when translators indicated that there were not separate words for targets within their language, resulting in repeated targets. We created pairs of translations (i.e., cue-target-related1, cue-target-unrelated1, cue-target-related2, cue-target-unrelated2) to ensure each pair only gets subtracted once. For example, if SPOON-CHEESE and TREE-CHEESE (unrelated) needed to be paired with MOUSE-CHEESE and CHEDDAR-CHEESE (related), we ensured each version was only combined once: SPOON-CHEESE minus MOUSE-CHEESE and TREE-CHEESE minus CHEDDAR-CHEESE.

For Korean, the extra unrelated pairs accidentally implemented (see above) were excluded in the priming calculation. When the unrelated target was repeated multiple times with no matching related target (i.e., one related target, three unrelated targets), we selected the lowest cosine unrelated target pair to be the comparison condition and discarded the rest of the unrelated pairs. This procedure also allowed us to control the slightly higher cosine values found (and noted above) for unrelated pairs in Korean.

**Reliability.** Item reliability was calculated by randomly splitting priming trials into two halves, calculating *Z*-score priming for each half, and correlating those scores by item. The results presented below were calculated on the original accuracy scoring for all trials, and the supplementary materials include the rescored accuracy versions. Participant-level reliability was calculated in a similar fashion by splitting participant related-unrelated trials in half and calculating priming as the average unrelated *Z*-scored response latency minus the related *Z*-scored response latency and correlating the two priming scores. The Spearman-Brown prophecy formula was applied to the average and median correlation across 100 random runs to estimate overall reliability. Table 7 shows the reliability estimates for participants and items. The average reliability was .56 for items (*Mdn* = .56), and.08 for participants (*Mdn* = .08). The discussion compares these results to previous findings.

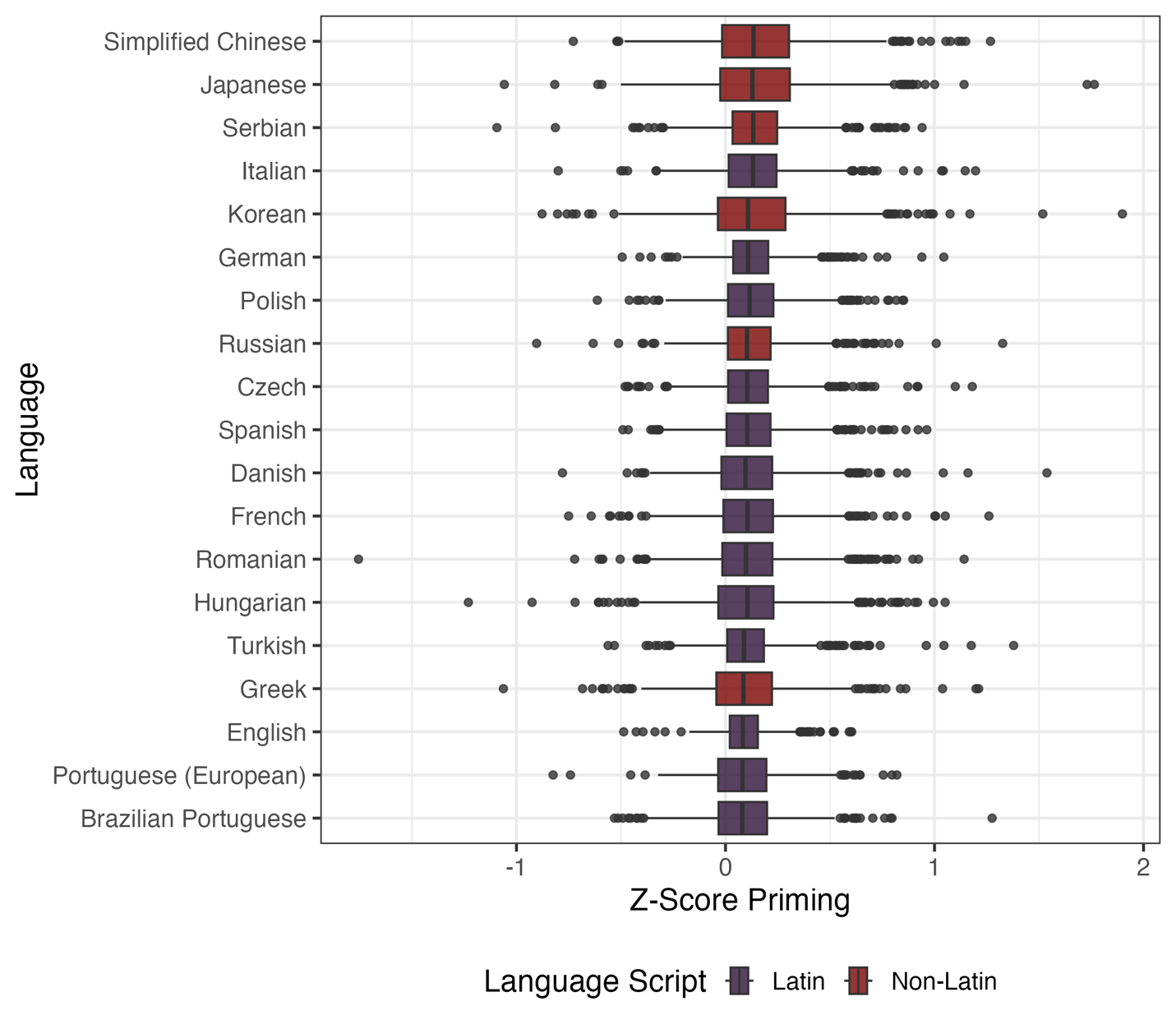
**Table 7. Mean Item and Participant Reliability for Priming Scores**

|  |  |  |
| --- | --- | --- |
| Language | Item Reliability | Participant Reliability |
| Brazilian Portuguese | .51 | .08 |
| Czech | .55 | -.01 |
| Danish | .47 | .14 |
| English | .72 | .06 |
| French | .46 | -.06 |
| German | .67 | -.01 |
| Greek | .41 | .01 |
| Hungarian | .47 | .03 |
| Italian | .54 | .12 |
| Japanese | .74 | .17 |
| Korean | .69 | .01 |
| Polish | .52 | .12 |
| Portuguese (European) | .45 | .12 |
| Romanian | .48 | -.04 |
| Russian | .71 | .17 |
| Serbian | .44 | .20 |
| Simplified Chinese | .53 | .10 |
| Spanish | .63 | .08 |
| Turkish | .66 | .01 |

**Hypothesis 1**

Hypothesis 1 predicted finding semantic facilitation wherein the response latencies for related targets would be faster than unrelated targets, as shown in Table 1. Hypothesis 1 was tested by fitting an intercept-only regression model using the *Z*-scored priming response latency as the dependent variable. The priming response latency was calculated by taking the average of the unrelated pair *z*-scored response latency minus the average related pair response latency within each item by language. Therefore, values that are positive and greater than zero (i.e., > 0.0001) indicate priming because the related pair had a faster response latency than the unrelated pair. The intercept and its 95% confidence interval represent the grand mean of the priming effect across all languages.

The overall *Z*-scored priming effect was *b0* = 0.12, *SE* = 0.001, *95%CI* [0.11, 0.12]. This process was repeated for average priming scores calculated without trials that were marked as 2.5 *Z*-score outliers and 3.0 *Z*-score outliers separately. These results were consistent with overall priming: *b0Z2.5* = 0.10, *SE* = 0.001, *95%CI* [0.10, 0.11], and *b0Z3.0* = 0.11, *SE* = 0.001, *95%CI* [0.10, 0.11]. Figure 4 denotes the distribution of the average item *Z*-score effects, ordered by the size of the overall priming effect for each language. The distributions of the priming scores are very similar with long tails and roughly similar shapes (albeit with more variance in some languages). For comparison to previous publications, the raw response latency priming was *b0* = 30.61, *SE* = 0.43, *95%CI* [29.78, 31.45], *b0Z2.5* = 27.12, *SE* = 0.36, *95%CI* [26.51, 27.92], and *b0Z3.0* = 28.08, *SE* = 0.37, *95%CI* [27.35, 28.81].



**Figure 4***.* Distribution of average priming effects for languages that met the minimum sample size criteria using boxplots. Order of languages is based on their average priming effect from smallest (bottom) to largest (top). The pre-registered language selection for the study included a requirement to ensure at least one non-Latin script within the language choices. The graph color codes these languages for convenience to highlight the diversity in included languages. This plot represents all data without outliers removed.

**Hypothesis 2**

Hypothesis 2 explored the extent to which these semantic priming effects vary across languages. Therefore, we calculated a random effects model using the *nlme*91 package in *R* wherein the random intercept of language was added to the overall intercept-only model for Hypothesis 1. Please see Table 8 for AIC values and their difference scores for comparison. The addition of this parameter improved model fit supporting significant heterogeneity as the value of AIC for the random effects model is two points or more lower than the value of AIC for the intercept-only model47. The standard deviation of the random effect was 0.02, *95% CI* [0.01, 0.03]. The pseudo-*R2* for the model was .0192. The random effect was useful in both Z-score 2.5 and 3.0 models wherein the random effect sizes were similar to the overall model: Z2.5 = 0.02, *95% CI* [0.01, 0.02], Z3.0 = 0.02, *95% CI* [0.01, 0.03].

**Table 8. AIC Values for Intercept-Only and Random-Effects Model**

|  |  |  |  |
| --- | --- | --- | --- |
|  | Overall | *Z* = 2.5 | *Z* = 3.0 |
| Intercept Only | -6,613.93 | -14,469.54 | -12,977.97 |
| Random Effects | -6,711.77 | -14,604.55 | -13,104.04 |
| Difference | 97.84 | 135.01 | 126.07 |

Figure 5 portrays the forest plot for the average priming effects by language, ordered by the size of the effect without the removal of outliers. The global priming average is presented on each facet to show how the priming effect changes based on the removal of outliers. In nearly all languages, the priming effect decreases slightly with the removal of outliers. This figure also shows that the priming effect does vary by language, as supported by the results from Hypothesis 2, but that the effect is likely small, given pseudo-*R2* was < .01.

A graph of different languages

Description automatically generated

**Figure 5**. Forest plot of average priming effects for each language ordered by priming average when no outliers are removed (least restrictive), *Z*-scores more than 2.5 are removed (most restrictive), and *Z*-scores more than 3.0 are removed. Error bars represent a 95% confidence interval. The plot indicates that all priming averages are positive, and their confidence intervals do not include zero, as the lower end of the graph is approximately *Z* = 0.07, even with the removal of the outliers shown in Figure 4. Triangles represent non-Latin languages for convenience, and languages are ordered based on average priming for the no *Z*-score removal condition from smallest (bottom) to largest (top).

**Discussion**

This study represents the largest cross-linguistic study on semantic priming to date, with data collection in 30 languages using a set of coordinated stimuli. Using computational models of word embeddings and expanded linguistic corpora, we selected a stimulus set that covered semantic similarity across languages, rather than in a single language to be translated into others. Using a continuous lexical decision task, more than 21 million trials were collected using an adaptive stimulus presentation algorithm that shifted data collection toward uncertainty after a minimum number of trials. Data collection requirements were completed for 19 languages/dialects, with more than 700 participants in each language and coverage of both Latin and non-Latin-based scripts. Given the large proportion of published linguistic research that is still WEIRD93, we provide a diversity of stimuli, participants, and data that can be reused to examine new hypotheses, control stimuli in new studies, and create cross-linguistic comparisons for previously found results.

In the 19 analyzed languages, we demonstrated consistent non-zero priming effects ranging from *Z* = 0.09 to 0.15, and this effect is robust to the removal of strong priming pairs with high *Z*-scores such as ROMEO-JULIET, GOLDEN-SILVER, MENTAL-EMOTIONAL, and BLIND-DEAF (i.e., highest positive *Z* priming scores across all languages, translated into their English counterparts). The *Z*-score removal also eliminates strong negative pairs, such as RESCUE-SAVE, FASHIONABLE-ELEGANT, and POSITION-STATUS. The English dataset provided one of the lowest priming averages, *Z* = 0.09, even with an average cosine relatedness of 0.55 for related pairs (*SD* = 0.11, min = 0.22, max = 0.90). For comparison, the results of the Semantic Priming Project21 demonstrated higher priming values when stimulus onset asynchronies were short (200 ms; *Z* = 0.21 for first associates, *Z* = 0.14 for other associates), but comparable values for longer stimulus onset asynchronies (1200 ms; *Z* = 0.16 for first associates, *Z* = 0.10 for other associates). Given that participants also made lexical decisions on cue words in our study, the results should most closely match the longer SOA conditions because there is a longer time before the target is seen; accordingly, our results generally align with the Semantic Priming Project’s results for other associates. Our results also demonstrate higher item reliability estimates than some estimates previously shown (.0440, .17-.3338) and are more in line with other estimates (.66 standardized LDT39). The participant reliability estimates are considerably lower than previous examinations of the Semantic Priming Project for first associates (.21-.27) but somewhat similar to results for other associates (.07-.0894) and other studies (-.06-.4395). The large sample sizes in this project likely boosted reliability results for item level reliability, as the largest samples show some of the strongest reliability coefficients. Researchers interested in predicting semantic priming at the item level are advised to focus on those languages that showed the highest item reliability estimates, most notably Japanese, English and Russian.

Our secondary hypothesis examined the potential heterogeneity of priming effects across languages and revealed small but non-zero differences in levels of priming across languages. One key takeaway from Figure 4 is the relatively similar distributions found for all languages. While Portuguese and Simplified Chinese show clearly non-overlapping confidence intervals in Figure 5 in each *Z*-score calculation, it is somewhat surprising that all means are within the confidence intervals of previous (English) *Z*-score estimates for priming (i.e., stimulus onset asynchrony 1200 ms; 95% *CI* [0.14, 0.18] for first associates, 95% *CI* [0.08, 0.12] for other associates) and how remarkably comparable the results are for each analyzed language. Given the potential differences in translation, script, processing, culture, and more, this result points to a generalizable cognitive mechanism for semantic priming. With the wealth of data provided in this project, researchers may begin to discern what variables predict differences found in the strength of priming effects at the language level, rather than within individual multilingual populations.

The limitations of this research include the necessity of picking a single design for semantic priming, but it does extend the available data to a new study type (i.e., the Semantic Project and others have used a paired (masked) priming task while this study used a continuous lexical decision task)2,21. The study design does provide abundant data for all types of word processing analyses, but it did not specifically target a single underlying cognitive mechanism for the explanation of priming effects (i.e., automatic versus controlled processes). Moreover, only a few self-reported individual demographic variables are present to explore potential reasons for participant variability[[7]](#footnote-7), and other studies may provide more individual differences measures, such as reading and vocabulary measures21. This limited demographic data collection allowed the study to be conducted easily in many geopolitical regions, as institutional review boards vary widely in their approval of studies that collect identifying measures, especially with overseas data management (i.e., they would rather the data be collected and stored locally). Further, this procedure with limited demographic variables represents the normal approach for mega-studies to combat fatigue and different privacy regulations across the globe96–98. Finally, not all translated languages completed initial data collection; however, the data are available for use, and ideally, new low-resource languages would be added to new publications of the dataset.

In summary, our results demonstrate semantic priming and its variability across languages and cultural contexts (as multiple languages were collected in different geopolitical regions), using a controlled set of stimuli comprising matching target words. Future research may further explore the sources of variability in semantic priming evident within individuals, items, and languages using the provided *semanticprimeR* package to merge datasets across other psycholinguistic variables. This study demonstrates the effectiveness of large-scale team collaboration in answering cross-linguistic questions, as well as providing resources for future reuse that are more “complete” (i.e., fewer missing values when combining databases) than individual lab contributions17. Although linguistics is largely still WEIRD, big team projects can continue to tackle sampling bias and generalizability problems within the field,43,93,99–101 using grassroots networks like the Psychological Science Accelerator14 and the ManyLanguages community102.

**Protocol Registration**

The pre-registration is at<https://osf.io/u5bp6> (updated 5/31/2022).

**Data Availability**

All raw and processed data will be available for download from GitHub: <https://github.com/SemanticPriming/SPAML> or Zenodo: <https://zenodo.org/records/10888833>.

**Code Availability**

All code used for study creation and delivery, data processing, and analyses are available on OSF (https://osf.io/wrpj4/) and GitHub (https://github.com/SemanticPriming/SPAML).

References

1. Meyer, D. E. & Schvaneveldt, R. W. Facilitation in recognizing pairs of words: Evidence of a dependence between retrieval operations. *Journal of Experimental Psychology* **90**, 227–234 (1971).

2. McNamara, T. P. *Semantic Priming*. (Psychology Press, 2005). doi:10.4324/9780203338001.

3. Mandera, P., Keuleers, E. & Brysbaert, M. Explaining human performance in psycholinguistic tasks with models of semantic similarity based on prediction and counting: A review and empirical validation. *Journal of Memory and Language* **92**, 57–78 (2017).

4. Cree, G. S. & Armstrong, B. C. Computational Models of Semantic Memory. in *The Cambridge Handbook of Psycholinguistics* (eds. Spivey, M., McRae, K. & Joanisse, M.) 259–282 (Cambridge University Press, 2012). doi:10.1017/CBO9781139029377.014.

5. McRae, K. & Jones, M. *Semantic Memory*. (Oxford University Press, 2013). doi:10.1093/oxfordhb/9780195376746.013.0014.

6. Rogers, T. T. Computational Models of Semantic Memory. in *The Cambridge Handbook of Computational Psychology* (ed. Sun, R.) 226–266 (Cambridge University Press, 2001). doi:10.1017/CBO9780511816772.012.

7. Frings, C., Schneider, K. K. & Fox, E. The negative priming paradigm: An update and implications for selective attention. *Psychon Bull Rev* **22**, 1577–1597 (2015).

8. Spruyt, A., De Houwer, J., Everaert, T. & Hermans, D. Unconscious semantic activation depends on feature-specific attention allocation. *Cognition* **122**, 91–95 (2012).

9. McDonough, K. & Trofimovich, P. *Using Priming Methods in Second Language Research*. (Routledge, 2011). doi:10.4324/9780203880944.

10. Singh, L. One World, Two Languages: Cross-Language Semantic Priming in Bilingual Toddlers. *Child Dev* **85**, 755–766 (2014).

11. Kiefer, M. *et al.* Neuro-cognitive mechanisms of conscious and unconscious visual perception: From a plethora of phenomena to general principles. *Advances in Cognitive Psychology* **7**, 55–67 (2011).

12. Steinhauer, K., Royle, P., Drury, J. E. & Fromont, L. A. The priming of priming: Evidence that the N400 reflects context-dependent post-retrieval word integration in working memory. *Neuroscience Letters* **651**, 192–197 (2017).

13. Liu, B., Wu, G., Meng, X. & Dang, J. Correlation between prime duration and semantic priming effect: Evidence from N400 effect. *Neuroscience* **238**, 319–326 (2013).

14. Moshontz, H. *et al.* The Psychological Science Accelerator: Advancing Psychology Through a Distributed Collaborative Network. *Advances in Methods and Practices in Psychological Science* **1**, 501–515 (2018).

15. Lucas, M. Semantic priming without association: A meta-analytic review. *Psychonomic Bulletin & Review* **7**, 618–630 (2000).

16. Hutchison, K. A. Is semantic priming due to association strength or feature overlap? A microanalytic review. *Psychonomic Bulletin & Review* **10**, 785–813 (2003).

17. Buchanan, E. M., Valentine, K. D. & Maxwell, N. P. LAB: Linguistic Annotated Bibliography – a searchable portal for normed database information. *Behav Res* **51**, 1878–1888 (2019).

18. New, B., Brysbaert, M., Veronis, J. & Pallier, C. The use of film subtitles to estimate word frequencies. *Applied Psycholinguistics* **28**, 661–677 (2007).

19. Gimenes, M. & New, B. Worldlex: Twitter and blog word frequencies for 66 languages. *Behav Res* **48**, 963–972 (2016).

20. Lison, P. & Tiedemann, J. Opensubtitles2016: Extracting large parallel corpora from movie and tv subtitles. (2016).

21. Hutchison, K. A. *et al.* The semantic priming project. *Behav Res* **45**, 1099–1114 (2013).

22. Balota, D. A. *et al.* The English Lexicon Project. *Behavior Research Methods* **39**, 445–459 (2007).

23. Aguasvivas, J. A. *et al.* SPALEX: A Spanish Lexical Decision Database From a Massive Online Data Collection. *Front. Psychol.* **9**, 2156 (2018).

24. Bradley, M. M. & Lang, P. J. Measuring emotion: The self-assessment manikin and the semantic differential. *Journal of Behavior Therapy and Experimental Psychiatry* **25**, 49–59 (1994).

25. Warriner, A. B., Kuperman, V. & Brysbaert, M. Norms of valence, arousal, and dominance for 13,915 English lemmas. *Behav Res* **45**, 1191–1207 (2013).

26. Bradley, M. M. & Lang, P. J. *Affective Norms for English Words (ANEW): Instruction Manual and Affective Ratings*. (1999).

27. Brysbaert, M., Warriner, A. B. & Kuperman, V. Concreteness ratings for 40 thousand generally known English word lemmas. *Behav Res* **46**, 904–911 (2014).

28. Stadthagen-Gonzalez, H. & Davis, C. J. The Bristol norms for age of acquisition, imageability, and familiarity. *Behavior Research Methods* **38**, 598–605 (2006).

29. Kerr, N. L. HARKing: Hypothesizing After the Results are Known. *Pers Soc Psychol Rev* **2**, 196–217 (1998).

30. Cree, G. S., McRae, K. & McNorgan, C. An Attractor Model of Lexical Conceptual Processing: Simulating Semantic Priming. *Cognitive Science* **23**, 371–414 (1999).

31. Zannino, G. D., Perri, R., Pasqualetti, P., Caltagirone, C. & Carlesimo, G. A. Analysis of the semantic representations of living and nonliving concepts: A normative study. *Cognitive Neuropsychology* **23**, 515–540 (2006).

32. Buchanan, E. M., Valentine, K. D. & Maxwell, N. P. English semantic feature production norms: An extended database of 4436 concepts. *Behav Res* **51**, 1849–1863 (2019).

33. De Deyne, S., Navarro, D. J., Perfors, A., Brysbaert, M. & Storms, G. The “Small World of Words” English word association norms for over 12,000 cue words. *Behav Res* **51**, 987–1006 (2019).

34. Nelson, D. L., McEvoy, C. L. & Schreiber, T. A. The University of South Florida free association, rhyme, and word fragment norms. *Behavior Research Methods, Instruments, & Computers* **36**, 402–407 (2004).

35. Landauer, T. K., Foltz, P. W. & Laham, D. An introduction to latent semantic analysis. *Discourse Processes* **25**, 259–284 (1998).

36. Landauer, T. K. & Dumais, S. T. A solution to Plato’s problem: The latent semantic analysis theory of acquisition, induction, and representation of knowledge. *Psychological Review* **104**, 211–240 (1997).

37. Lund, K. & Burgess, C. Producing high-dimensional semantic spaces from lexical co-occurrence. *Behavior Research Methods, Instruments, & Computers* **28**, 203–208 (1996).

38. Heyman, T., Hutchison, K. A. & Storms, G. Uncovering underlying processes of semantic priming by correlating item-level effects. *Psychon Bull Rev* **23**, 540–547 (2016).

39. Hutchison, K. A., Balota, D. A., Cortese, M. J. & Watson, J. M. Predicting Semantic Priming at the Item Level. *Quarterly Journal of Experimental Psychology* **61**, 1036–1066 (2008).

40. Heyman, T., Bruninx, A., Hutchison, K. A. & Storms, G. The (un)reliability of item-level semantic priming effects. *Behav Res* **50**, 2173–2183 (2018).

41. Perea, M., Duñabeitia, J. A. & Carreiras, M. Masked associative/semantic priming effects across languages with highly proficient bilinguals. *Journal of Memory and Language* **58**, 916–930 (2008).

42. Guasch, M., Sánchez-Casas, R., Ferré, P. & García-Albea, J. E. Effects of the degree of meaning similarity on cross-language semantic priming in highly proficient bilinguals. *Journal of Cognitive Psychology* **23**, 942–961 (2011).

43. Levisen, C. Biases we live by: Anglocentrism in linguistics and cognitive sciences. *Language Sciences* **76**, 101173 (2019).

44. Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S. & Dean, J. Distributed representations of words and phrases and their compositionality. in *Advances in neural information processing systems* 3111–3119 (2013).

45. Mikolov, T., Chen, K., Corrado, G. & Dean, J. Efficient Estimation of Word Representations in Vector Space. *arXiv:1301.3781 [cs]* (2013).

46. van Paridon, J. & Thompson, B. subs2vec: Word embeddings from subtitles in 55 languages. *Behav Res* **53**, 629–655 (2021).

47. Burnham, K. P. & Anderson, D. R. Multimodel Inference: Understanding AIC and BIC in Model Selection. *Sociological Methods & Research* **33**, 261–304 (2004).

48. Tzelgov, J. & Eben-ezra, S. Components of the between-language semantic priming effect. *European Journal of Cognitive Psychology* **4**, 253–272 (1992).

49. Kirsner, K., Smith, M. C., Lockhart, R. S., King, M. L. & Jain, M. The bilingual lexicon: Language-specific units in an integrated network. *Journal of Verbal Learning and Verbal Behavior* **23**, 519–539 (1984).

50. Kelley, K. Sample size planning for the coefficient of variation from the accuracy in parameter estimation approach. *Behavior Research Methods* **39**, 755–766 (2007).

51. Kelley, K., Darku, F. B. & Chattopadhyay, B. Accuracy in parameter estimation for a general class of effect sizes: A sequential approach. *Psychological Methods* **23**, 226–243 (2018).

52. Maxwell, S. E., Kelley, K. & Rausch, J. R. Sample Size Planning for Statistical Power and Accuracy in Parameter Estimation. *Annu. Rev. Psychol.* **59**, 537–563 (2008).

53. Faust, M. E., Balota, D. A., Spieler, D. H. & Ferraro, F. R. Individual differences in information-processing rate and amount: Implications for group differences in response latency. *Psychological Bulletin* **125**, 777–799 (1999).

54. Overall, J. E. & Woodward, J. A. Unreliability of difference scores: A paradox for measurement of change. *Psychological Bulletin* **82**, 85–86 (1975).

55. Keuleers, E. & Brysbaert, M. Wuggy: A multilingual pseudoword generator. *Behavior Research Methods* **42**, 627–633 (2010).

56. Tse, C.-S. *et al.* The Chinese Lexicon Project: A megastudy of lexical decision performance for 25,000+ traditional Chinese two-character compound words. *Behav Res* **49**, 1503–1519 (2017).

57. Michalke, M. sylly: Hyphenation and Syllable Counting for Text Analysis. (2020).

58. De Deyne, S., Navarro, D. J. & Storms, G. Better explanations of lexical and semantic cognition using networks derived from continued rather than single-word associations. *Behav Res* **45**, 480–498 (2013).

59. Brysbaert, M. & New, B. Moving beyond Kučera and Francis: A critical evaluation of current word frequency norms and the introduction of a new and improved word frequency measure for American English. *Behavior Research Methods* **41**, 977–990 (2009).

60. van Heuven, W. J. B., Mandera, P., Keuleers, E. & Brysbaert, M. Subtlex-UK: A New and Improved Word Frequency Database for British English. *Quarterly Journal of Experimental Psychology* **67**, 1176–1190 (2014).

61. Keuleers, E., Brysbaert, M. & New, B. SUBTLEX-NL: A new measure for Dutch word frequency based on film subtitles. *Behavior Research Methods* **42**, 643–650 (2010).

62. Cai, Q. & Brysbaert, M. SUBTLEX-CH: Chinese Word and Character Frequencies Based on Film Subtitles. *PLoS ONE* **5**, e10729 (2010).

63. Brysbaert, M. *et al.* The Word Frequency Effect: A Review of Recent Developments and Implications for the Choice of Frequency Estimates in German. *Experimental Psychology* **58**, 412–424 (2011).

64. Dimitropoulou, M., Duñabeitia, J. A., Avilés, A., Corral, J. & Carreiras, M. Subtitle-Based Word Frequencies as the Best Estimate of Reading Behavior: The Case of Greek. *Front. Psychology* **1**, (2010).

65. Mandera, P., Keuleers, E., Wodniecka, Z. & Brysbaert, M. Subtlex-pl: subtitle-based word frequency estimates for Polish. *Behav Res* **47**, 471–483 (2015).

66. Duchon, A., Perea, M., Sebastián-Gallés, N., Martí, A. & Carreiras, M. EsPal: One-stop shopping for Spanish word properties. *Behav Res* **45**, 1246–1258 (2013).

67. Wijffels, J. *et al.* udpipe: Tokenization, Parts of Speech Tagging, Lemmatization and Dependency Parsing with the ‘UDPipe’ ‘NLP’ Toolkit. (2021).

68. Bojanowski, P., Grave, E., Joulin, A. & Mikolov, T. Enriching Word Vectors with Subword Information. *arXiv preprint arXiv:1607.04606* (2016).

69. Benoit, K., Muhr, D. & Watanabe, K. stopwords: Multilingual Stopword Lists. (2021).

70. Henninger, F., Shevchenko, Y., Mertens, U. K., Kieslich, P. J. & Hilbig, B. E. *Lab.Js: A Free, Open, Online Study Builder*. https://osf.io/fqr49 (2019) doi:10.31234/osf.io/fqr49.

71. Henninger, F., Shevchenko, Y., Mertens, U. K., Kieslich, P. & Hilbig, B. E. Who said browser-based experiments can’t have proper timing? Implementing accurate presentation and response timing in browser. (2018).

72. Hilbig, B. E. Reaction time effects in lab- versus Web-based research: Experimental evidence. *Behav Res* **48**, 1718–1724 (2016).

73. Buchanan, E. *et al.* SemanticPriming/SPAML: SPAML v1 Data Release. [object Object] https://doi.org/10.5281/ZENODO.10888833 (2024).

74. Proctor, R. W. & Cho, Y. S. Polarity correspondence: A general principle for performance of speeded binary classification tasks. *Psychological Bulletin* **132**, 416–442 (2006).

75. Neely, J. H., Keefe, D. E. & Ross, K. L. Semantic priming in the lexical decision task: Roles of prospective prime-generated expectancies and retrospective semantic matching. *Journal of Experimental Psychology: Learning, Memory, and Cognition* **15**, 1003–1019 (1989).

76. Shelton, J. R. & Martin, R. C. How semantic is automatic semantic priming? *Journal of Experimental Psychology: Learning, Memory, and Cognition* **18**, 1191–1210 (1992).

77. Johnston, R. A. & Barry, C. Age of acquisition and lexical processing. *Visual Cognition* **13**, 789–845 (2006).

78. Ghyselinck, M., Lewis, M. B. & Brysbaert, M. Age of acquisition and the cumulative-frequency hypothesis: A review of the literature and a new multi-task investigation. *Acta Psychologica* **115**, 43–67 (2004).

79. Juhasz, B. J. Age-of-Acquisition Effects in Word and Picture Identification. *Psychological Bulletin* **131**, 684–712 (2005).

80. Brysbaert, M. & Ellis, A. W. Aphasia and age of acquisition: are early-learned words more resilient? *Aphasiology* **30**, 1240–1263 (2016).

81. Richardson, J. T. E. Imageability and concreteness. *Bull. Psychon. Soc.* **7**, 429–431 (1976).

82. Richardson, J. T. E. Concreteness and Imageability. *Quarterly Journal of Experimental Psychology* **27**, 235–249 (1975).

83. Paivio, A., Walsh, M. & Bons, T. Concreteness effects on memory: When and why? *Journal of Experimental Psychology: Learning, Memory, and Cognition* **20**, 1196–1204 (1994).

84. Wilson, M. MRC psycholinguistic database: Machine-usable dictionary, version 2.00. *Behavior Research Methods, Instruments, & Computers* **20**, 6–10 (1988).

85. Proctor, R. W. & Schneider, D. W. Hick’s law for choice reaction time: A review. *Quarterly Journal of Experimental Psychology* **71**, 1281–1299 (2018).

86. Buchanan, E. SemanticPriming/semanticprimeR: semanticprimeR package. [object Object] https://doi.org/10.5281/ZENODO.10697999 (2024).

87. Montefinese, M., Ambrosini, E., Fairfield, B. & Mammarella, N. Semantic memory: A feature-based analysis and new norms for Italian. *Behav Res* **45**, 440–461 (2013).

88. Kremer, G. & Baroni, M. A set of semantic norms for German and Italian. *Behav Res* **43**, 97–109 (2011).

89. Ruts, W. *et al.* Dutch norm data for 13 semantic categories and 338 exemplars. *Behavior Research Methods, Instruments, & Computers* **36**, 506–515 (2004).

90. Deng, Y. *et al.* A Chinese Conceptual Semantic Feature Dataset (CCFD). *Behav Res* **53**, 1697–1709 (2021).

91. Pinheiro, J., Bates, D., Debroy, S., Sarkar, D. & Team, R. C. nlme: Linear and nonlinear mixed effects models. (2017).

92. Bartoń, K. MuMIn: Multi-Model Inference. (2020).

93. Bochynska, A. *et al.* Reproducible research practices and transparency across linguistics. Preprint at https://doi.org/10.31222/osf.io/rcews (2022).

94. Yap, M. J., Hutchison, K. A. & Tan, L. C. Individual differences in semantic priming performance: Insights from the semantic priming project. in *Big data in cognitive science* 203–226 (Routledge/Taylor & Francis Group, New York, NY, US, 2017).

95. Stolz, J. A., Besner, D. & Carr, T. H. Implications of measures of reliability for theories of priming: Activity in semantic memory is inherently noisy and uncoordinated. *Visual Cognition* **12**, 284–336 (2005).

96. Siegelman, N. *et al.* Rethinking First Language–Second Language Similarities and Differences in English Proficiency: Insights From the ENglish Reading Online (ENRO) Project. *Language Learning* **74**, 249–294 (2024).

97. Mandera, P., Keuleers, E. & Brysbaert, M. Recognition times for 62 thousand English words: Data from the English Crowdsourcing Project. *Behav Res* **52**, 741–760 (2020).

98. Kuperman, V. *et al.* Text reading in English as a second language: Evidence from the Multilingual Eye-Movements Corpus. *Stud Second Lang Acquis* **45**, 3–37 (2023).

99. Andringa, S. & Godfroid, A. Sampling Bias and the Problem of Generalizability in Applied Linguistics. *Annual Review of Applied Linguistics* **40**, 134–142 (2020).

100. Sulpizio, S. *et al.* Taboo language across the globe: A multi-lab study. *Behav Res* **56**, 3794–3813 (2024).

101. Blasi, D. E., Henrich, J., Adamou, E., Kemmerer, D. & Majid, A. Over-reliance on English hinders cognitive science. *Trends in Cognitive Sciences* **26**, 1153–1170 (2022).

102. ManyLanguages. https://many-languages.com/.

**Acknowledgements**

* A.D.A. was supported by the South-Eastern Norway Regional Health Authority (#2020023)
* J.L.U. was supported by ANID/CONICYT FONDECYT Iniciación 11190673, Programa de Investigación Asociativa (PIA) en Ciencias Cognitivas (RU-158-2019), Research Center on Cognitive Sciences (CICC), Faculty of Psychology, Universidad de Talca, Chile
* P.K. was supported by APVV-22-0458
* M.M.E. was supported by Baily Thomas Grant
* S.W. was supported by DFG Heisenberg Programme (funding ID: 442405852)
* Y.A.N., M.H.C., and S. Pfattheicher were supported by the Interacting Minds Centre through the seed grant No. 26254
* M. Marelli was supported by ERC Consolidator Grant 101087053 (project “BraveNewWord”)
* A. Sepehri was supported by ESSEC Business School Research Center (CERESSEC)
* E.M.B. was supported by funding from the Einstein Foundation Award through the Psychological Science Accelerator, Harrisburg University of Science and Technology, and the Leibniz Institute for Psychology (ZPID)
* C.H. was supported by Fund for Scientific Research Flanders (FWO), grant number FWO G049821N
* P.A. was supported by Fundação para a Ciência e Tecnologia (FCT), through the Research Center CIS\_Iscte (UID/PSI/03125/2020)
* I.C. was supported by Funded by Comunidad de Madrid PhD grants: PIPF-2022/COM-24573
* M. Köster was supported by Funded by Deutsche Forschungsgemeinschaft (DFG) - grant number 290878970-GRK 2271
* M. Cavdan was supported by German Research Foundation DFG-project no. 502774891-ORA project “UNTOUCH”
* M.A. Vadillo was supported by Grant PID2020-118583GB-I00 from Agencia Estatal de Investigación (Spain)
* D. Grigoryev was supported by HSE University Basic Research Program
* S.C.R. was supported by IDN Being Human Inkubator; P.S. was supported by Incubator "Being Human"
* Y. Yamada was supported by JSPS KAKENHI (JP22K18263)
* K. Schmidt was supported by John Templeton Foundation
* R.M.R. was supported by John Templeton Foundation (grant ID: 62631)
* K.K. was supported by the Austrian Science Fund (FWF) [grant DOI: 10.55776/ESP286]
* K.B. and Ewa Ilczuk were supported by a grant from the National Science Centre, Poland (2019/35/B/HS6/00528)
* L.R. was supported by the National Recovery and Resilience Plan (PNRR), Mission 4, Component 2, Investment 1.1, Call for tender No. 104 published on 2.2.2022 by the Italian Ministry of University and Research (MUR), funded by the European Union—NextGenerationEU—Project Title “The World in Words: Moving beyond a spatiocentric view of the human mind (acronym: WoWo)”, Project code 2022TE3XMT, CUP (Rinaldi) F53D23004850006; and by the Italian Ministry of Health (Ricerca Corrente 2024)
* M. Kowal was supported by the Foundation for Polish Science (FNP) START scholarship
* D.M.-R. was supported by National Master’s Scholarship by the Agencia Nacional de Investigación y Desarrollo of Chile 3537/2023
* R.n.a.J. was supported by the National Science Center (2020/37/B/HS6/00610)
* M. Adamkovič was supported by PRIMUS/24/SSH/017; APVV-22-0458
* M. Perea was supported by Reference of Grant: CIAICO/2021/172, Funder: Department of Innovation, Universities, Science and Digital Society of the Valencian Government
* J.H.-w.H. was supported by Research Grant Council of Hong Kong (GRF #17608621 to Hsiao)
* A. Sorokowska was supported by Scientific Excellence Incubator "Being Human"
* F.T. was supported by Seed funding from the Interacting Minds Centre (Aarhus University)
* W.D. was supported by The Fund for Scientific Research Flanders (FWO), project number G049821N
* K. Wolfe was supported by The Leverhulme Trust (RPG-2020-035)
* T.V.P. was supported by The Ministry of Science, Technological Development and Innovation of the Republic of Serbia, according to the contract on the financial support of the scientific research of teaching staff at accredited higher education institutions in 2024, contract number: 451-03-65/2024-03/200105
* Z.P. was supported by The Ministry of Science, Technological Development and Innovation of the Republic of Serbia, as part of the financial support of the scientific research at the University of Belgrade – Faculty of Philosophy (contract number 451-03-66/2024-03/200163)
* D.A.S.E.-D. was supported by The researcher would like to thank Prince Sultan University for funding this project through [the Applied Linguistics Research Lab - RL-CH-2019/9/1]
* M. Comesaña was supported by The study corresponding to European Portuguese data was conducted at the Psychology Research Centre (PSI/01662), School of Psychology, University of Minho, and was supported by the Foundation for Science and Technology (FCT) through the Portuguese State Budget (Ref.: UIDB/PSI/01662/2020)
* Z.M. and R.Z. were supported by The work was supported from ERDF/ESF project TECHSCALE (No. CZ.02.01.01/00/22\_008/0004587)
* K.F. was supported by This project received funding via a Marie-Curie-Fellowship (882168)
* F.S. was supported by This research was promoted by the Austrian Research Promotion Agency (FFG)
* S.D.D. was supported by This study was supported by a Social Sciences and Humanities Research Council of Canada grant (SSHRC) [grant number 435-2021-1074]
* M. Montefinese was supported by the Investment line 1.2 'Funding projects presented by young researchers' (CHILDCONTROL) from the European Union - NextGenerationEU.
* I.S.P. was supported by a research project implemented as part of the Basic Research Program at the National Research University Higher School of Economics (HSE University)
* C. Blaison was supported by Two fundings: ANR-18-IDEX-0001, ANR-20-FRAL-0008
* T.N. was supported by University Excellence Fund of ELTE Eötvös Loránd University, Budapest, Hungary;
* D. Muller was supported by Université Grenoble Alpes, Institut Universitaire de France.

**Author contributions**

The authors made the following contributions. Erin M. Buchanan: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing; Kelly Cuccolo: Project administration, Supervision, Writing - review & editing; Tom Heyman: Conceptualization, Data curation, Methodology, Project administration, Validation, Writing - review & editing; Niels van Berkel: Methodology, Project administration, Software, Writing - review & editing; Nicholas A. Coles: Validation, Writing - review & editing; Aishwarya Iyer: Project administration, Writing - review & editing; Kim Peters: Project administration, Writing - review & editing; Anna E. van ’t Veer: Project administration, Writing - review & editing; Maria Montefinese: Conceptualization, Investigation, Methodology, Resources, Writing - original draft, Writing - review & editing; Nicholas P. Maxwell: Conceptualization, Investigation, Methodology, Writing - review & editing; Jack E. Taylor: Conceptualization, Methodology, Writing - original draft, Writing - review & editing; Kathrene D. Valentine: Conceptualization, Methodology, Writing - original draft, Writing - review & editing; Patrícia Arriaga: Funding acquisition, Investigation, Resources, Writing - review & editing; Krystian Barzykowski: Investigation, Resources, Supervision, Writing - review & editing; Leanne Boucher: Investigation, Resources, Supervision, Writing - review & editing; W. M. Collins: Investigation, Resources, Supervision, Writing - review & editing; David C. Vaidis: Investigation, Resources, Supervision, Writing - review & editing; Balazs Aczel: Investigation, Resources, Writing - review & editing; Ali H. Al-Hoorie: Investigation, Resources, Writing - review & editing; Ettore Ambrosini: Investigation, Resources, Writing - review & editing; Théo Besson: Investigation, Resources, Writing - review & editing; Debora I. Burin: Investigation, Resources, Writing - review & editing; Muhammad M. Butt: Investigation, Resources, Writing - review & editing; A. J. Benjamin Clarke: Investigation, Resources, Writing - review & editing; Yalda Daryani: Investigation, Resources, Writing - review & editing; Dina A. S. El-Dakhs: Investigation, Resources, Writing - review & editing; Mahmoud M. Elsherif: Investigation, Resources, Writing - review & editing; Maria Fernández-López: Investigation, Resources, Writing - review & editing; Paulo R. d. S. Ferreira: Investigation, Resources, Writing - review & editing; Raquel M. K. Freitag: Investigation, Resources, Writing - review & editing; Carolina A. Gattei: Investigation, Resources, Writing - review & editing; Hendrik Godbersen: Investigation, Resources, Writing - review & editing; Philip A. Grim II: Investigation, Resources, Writing - review & editing; Peter Halama: Investigation, Resources, Writing - review & editing; Patrik Havan: Investigation, Resources, Writing - review & editing; Natalia C. Irrazabal: Investigation, Resources, Writing - review & editing; Chris Isloi: Investigation, Resources, Writing - review & editing; Rebecca K. Iversen: Investigation, Resources, Writing - review & editing; Yoann Julliard: Investigation, Resources, Writing - review & editing; Aslan Karaaslan: Investigation, Resources, Writing - review & editing; Michal Kohút: Investigation, Resources, Writing - review & editing; Veronika Kohútová: Investigation, Resources, Writing - review & editing; Julija Kos: Investigation, Resources, Writing - review & editing; Alexandra I. Kosachenko: Investigation, Resources, Writing - review & editing; Tiago J. S. d. Lima: Investigation, Resources, Writing - review & editing; Matthew HC Mak: Investigation, Resources, Writing - review & editing; Christina Manouilidou: Investigation, Resources, Writing - review & editing; Leonardo A. Marciaga: Validation, Visualization, Writing - review & editing; Xiaolin M. Melinna: Project administration, Resources, Writing - review & editing; Jacob F. Miranda: Investigation, Project administration, Writing - review & editing; Coby Morvinski: Investigation, Resources, Writing - review & editing; Aishwarya Muppoor: Investigation, Resources, Writing - review & editing; Fatma E. Müjdeci: Resources, Validation, Writing - review & editing; Yngwie A. Nielsen: Investigation, Resources, Writing - review & editing; Juan C. Oliveros: Investigation, Resources, Writing - review & editing; Jaš Onič: Investigation, Resources, Writing - review & editing; Marietta Papadatou-Pastou: Investigation, Resources, Writing - review & editing; Ishani Patel: Investigation, Resources, Writing - review & editing; Zoran Pavlović: Investigation, Resources, Writing - review & editing; Blaž Pažon: Investigation, Resources, Writing - review & editing; Gerit Pfuhl: Investigation, Resources, Writing - review & editing; Ekaterina Pronizius: Investigation, Resources, Writing - review & editing; Timo B. Roettger: Investigation, Resources, Writing - review & editing; Camilo R. Ronderos: Investigation, Resources, Writing - review & editing; Susana Ruiz-Fernandez: Investigation, Resources, Writing - review & editing; Magdalena Senderecka: Investigation, Resources, Writing - review & editing; Çağlar Solak: Investigation, Resources, Writing - review & editing; Anna Stückler: Investigation, Resources, Writing - review & editing; Raluca D. Szekely-Copîndean: Investigation, Resources, Writing - review & editing; Analí R. Taboh: Investigation, Resources, Writing - review & editing; Rémi Thériault: Investigation, Resources, Writing - review & editing; Ulrich S. Tran: Investigation, Resources, Writing - review & editing; Fabio Trecca: Funding acquisition, Investigation, Writing - review & editing; José Luis Ulloa: Investigation, Resources, Writing - review & editing; Marton A. Varga: Investigation, Resources, Writing - review & editing; Steven Verheyen: Investigation, Resources, Writing - review & editing; Tijana Vesić Pavlović: Investigation, Resources, Writing - review & editing; Giada Viviani: Investigation, Resources, Writing - review & editing; Nan Wang: Investigation, Resources, Writing - review & editing; Kristyna Zivna: Investigation, Resources, Writing - review & editing; Chen C. Yun: Investigation, Resources, Writing - review & editing; Oliver J. Clark: Investigation, Writing - review & editing; Oguz A. Acar: Investigation, Writing - review & editing; Matúš Adamkovič: Investigation, Writing - review & editing; Giulia Agnoletti: Investigation, Writing - review & editing; Atakan M. Akil: Investigation, Writing - review & editing; Zainab Alsuhaibani: Investigation, Writing - review & editing; Simona Amenta: Investigation, Writing - review & editing; Olga A. Ananyeva: Investigation, Writing - review & editing; Michael Andreychik: Investigation, Writing - review & editing; Bernhard Angele: Investigation, Writing - review & editing; Danna C. Arias Quiñones: Investigation, Writing - review & editing; Nwadiogo C. Arinze: Investigation, Writing - review & editing; Adrian D. Askelund: Resources, Writing - review & editing; Bradley J. Baker: Resources, Writing - review & editing; Ernest Baskin: Investigation, Writing - review & editing; Luisa N. A. Batalha: Investigation, Writing - review & editing; Carlota Batres: Investigation, Writing - review & editing; Maria S. Beato: Investigation, Writing - review & editing; Manuel Becker: Investigation, Writing - review & editing; Maja Becker: Investigation, Writing - review & editing; Maciej Behnke: Investigation, Writing - review & editing; Christophe Blaison: Investigation, Writing - review & editing; Anna M. Borghi: Resources, Writing - review & editing; Eduard Brandstätter: Investigation, Writing - review & editing; Jacek Buczny: Resources, Writing - review & editing; Nesrin Budak: Investigation, Writing - review & editing; Álvaro Cabana: Investigation, Writing - review & editing; Zhenguang G. Cai: Investigation, Writing - review & editing; Enrique C. Canessa: Investigation, Writing - review & editing; Ignacio Castillejo: Investigation, Writing - review & editing; Müge Cavdan: Investigation, Writing - review & editing; Luca Cecchetti: Investigation, Writing - review & editing; Sergio E. Chaigneau: Investigation, Writing - review & editing; Feria X. W. Chang: Investigation, Writing - review & editing; Christopher R. Chartier: Investigation, Writing - review & editing; Sau-Chin Chen: Resources, Writing - review & editing; Elena Cherniaeva: Investigation, Writing - review & editing; Morten H. Christiansen: Investigation, Writing - review & editing; Hu N. Chuan-Peng: Investigation, Writing - review & editing; Patrycja Chwiłkowska: Investigation, Writing - review & editing; Montserrat Comesaña: Investigation, Writing - review & editing; Chin Wen Cong: Resources, Writing - review & editing; Casey Cowan: Investigation, Writing - review & editing; Stéphane D. Dandeneau: Investigation, Writing - review & editing; Oana A. David: Investigation, Writing - review & editing; William E. Davis: Investigation, Writing - review & editing; Elif G. Demirag Burak: Resources, Writing - review & editing; Barnaby J. W. Dixson: Investigation, Writing - review & editing; Hongfei Du: Investigation, Writing - review & editing; Rod Duclos: Investigation, Writing - review & editing; Wouter Duyck: Investigation, Writing - review & editing; Liudmila A. Efimova: Investigation, Writing - review & editing; Ciara Egan: Investigation, Writing - review & editing; Vanessa Era: Resources, Writing - review & editing; Thomas R. Evans: Investigation, Writing - review & editing; Anna Exner: Resources, Writing - review & editing; Gilad Feldman: Investigation, Writing - review & editing; Katharina Fellnhofer: Investigation, Writing - review & editing; Chiara Fini: Resources, Writing - review & editing; Sarah E. Fisher: Investigation, Writing - review & editing; Heather D. Flowe: Investigation, Writing - review & editing; Patricia Garrido-Vásquez: Investigation, Writing - review & editing; Daniele Gatti: Investigation, Writing - review & editing; Jason Geller: Validation, Writing - review & editing; Vaitsa Giannouli: Investigation, Writing - review & editing; Anna S. Gorokhova: Investigation, Writing - review & editing; Lindsay M. Griener: Investigation, Writing - review & editing; Dmitry Grigoryev: Investigation, Writing - review & editing; Igor Grossmann: Investigation, Writing - review & editing; Mohammadhesam Hajighasemi: Investigation, Writing - review & editing; Giacomo Handjaras: Investigation, Writing - review & editing; Cathy Hauspie: Investigation, Writing - review & editing; Zhiran He: Resources, Writing - review & editing; Renata M. Heilman: Investigation, Writing - review & editing; Amirmahdi Heydari: Investigation, Writing - review & editing; Alanna M. Hine: Investigation, Writing - review & editing; Karlijn Hoyer: Resources, Writing - review & editing; Weronika Hryniszak: Investigation, Writing - review & editing; Janet H.-w. Hsiao: Investigation, Writing - review & editing; Guanxiong Huang: Investigation, Writing - review & editing; Keiko Ihaya: Resources, Writing - review & editing; Ewa Ilczuk: Investigation, Writing - review & editing; Tatsunori Ishii: Resources, Writing - review & editing; Katarzyna Jankowiak: Investigation, Writing - review & editing; Xiaoming X. J. Jiang: Resources, Writing - review & editing; David C. Johnson: Investigation, Writing - review & editing; Rafał n. a. Jończyk: Investigation, Writing - review & editing; Juhani Järvikivi: Investigation, Writing - review & editing; Laura Kaczer: Investigation, Writing - review & editing; Kevin L. Kamermans: Resources, Writing - review & editing; Johannes A. Karl: Investigation, Writing - review & editing; Alexander Karner: Investigation, Writing - review & editing; Pavol Kačmár: Investigation, Writing - review & editing; Jacob J. Keech: Investigation, Writing - review & editing; M. Justin Kim: Validation, Writing - review & editing; Max Korbmacher: Resources, Writing - review & editing; Kathrin Kostorz: Investigation, Writing - review & editing; Marta Kowal: Investigation, Writing - review & editing; Tomas Kratochvil: Resources, Writing - review & editing; Yoshihiko Kunisato: Resources, Writing - review & editing; Anna O. Kuzminska: Investigation, Writing - review & editing; Lívia Körtvélyessy: Investigation, Writing - review & editing; Fatma E. Köse: Investigation, Writing - review & editing; Massimo Köster: Investigation, Writing - review & editing; Magdalena Kękuś: Investigation, Writing - review & editing; Melanie Labusch: Investigation, Writing - review & editing; Claus Lamm: Investigation, Writing - review & editing; Chaak Ming Lau: Resources, Writing - review & editing; Julieta Laurino: Investigation, Writing - review & editing; Wilbert Law: Investigation, Writing - review & editing; Giada Lettieri: Investigation, Writing - review & editing; Carmel A. Levitan: Investigation, Writing - review & editing; Jackson G. Lu: Investigation, Writing - review & editing; Sarah E. MacPherson: Investigation, Writing - review & editing; Klara Malinakova: Investigation, Writing - review & editing; Diego Manriquez-Robles: Investigation, Writing - review & editing; Nicolás Marchant: Investigation, Writing - review & editing; Marco Marelli: Investigation, Writing - review & editing; Martín Martínez: Investigation, Writing - review & editing; Molly F. Matthews: Investigation, Writing - review & editing; Alan D. A. Mattiassi: Investigation, Writing - review & editing; Josefina Mattoli-Sánchez: Investigation, Writing - review & editing; Claudia Mazzuca: Resources, Writing - review & editing; David P. McGovern: Investigation, Writing - review & editing; Zdenek Meier: Investigation, Writing - review & editing; Filip Melinscak: Investigation, Writing - review & editing; Michal Misiak: Investigation, Writing - review & editing; Luis C. P. Monteiro: Resources, Writing - review & editing; David Moreau: Resources, Writing - review & editing; Sebastian Moreno: Investigation, Writing - review & editing; Kate E. Mulgrew: Investigation, Writing - review & editing; Dominique Muller: Investigation, Writing - review & editing; Tamás Nagy: Investigation, Writing - review & editing; Marcin Naranowicz: Investigation, Writing - review & editing; Izuchukwu L. G. Ndukaihe: Investigation, Writing - review & editing; Maital Neta: Resources, Writing - review & editing; Lukas Novak: Investigation, Writing - review & editing; Chisom E. Ogbonnaya: Investigation, Writing - review & editing; Jessica Jee Won Paek: Resources, Writing - review & editing; Aspasia E. Paltoglou: Resources, Writing - review & editing; Francisco J. Parada: Investigation, Writing - review & editing; Adam J. Parker: Investigation, Writing - review & editing; Mariola Paruzel-Czachura: Investigation, Writing - review & editing; Yuri G. Pavlov: Investigation, Writing - review & editing; Saeed Paydarfard: Investigation, Writing - review & editing; Dominik Pegler: Investigation, Writing - review & editing; Mehmet Peker: Investigation, Writing - review & editing; Manuel Perea: Investigation, Writing - review & editing; Stefan Pfattheicher: Investigation, Writing - review & editing; John Protzko: Investigation, Writing - review & editing; Irina S. Prusova: Investigation, Writing - review & editing; Katarzyna Pypno-Blajda: Investigation, Writing - review & editing; Zhuang Qiu: Investigation, Writing - review & editing; Ulf-Dietrich Reips: Validation, Writing - review & editing; Gianni Ribeiro: Investigation, Writing - review & editing; Luca Rinaldi: Investigation, Writing - review & editing; S. C. Roberts: Investigation, Writing - review & editing; Tanja C. Roembke: Investigation, Writing - review & editing; Marina O. Romanova: Investigation, Writing - review & editing; Robert M. Ross: Investigation, Writing - review & editing; Jan P. Röer: Investigation, Writing - review & editing; Filiz Rızaoğlu: Investigation, Writing - review & editing; Toni T. Saari: Resources, Writing - review & editing; Erika Sampaolo: Investigation, Writing - review & editing; Anabela C. Santos: Investigation, Writing - review & editing; Fırat Ç. Sarıçiçek: Investigation, Writing - review & editing; Kyoshiro Sasaki: Resources, Writing - review & editing; Frank Scharnowski: Investigation, Writing - review & editing; Kathleen Schmidt: Investigation, Writing - review & editing; Amir Sepehri: Investigation, Writing - review & editing; Halid O. Serçe: Investigation, Writing - review & editing; A. Timur Sevincer: Investigation, Writing - review & editing; Cynthia S. Q. Siew: Investigation, Writing - review & editing; Matilde E. Simonetti: Investigation, Writing - review & editing; Miroslav Sirota: Investigation, Writing - review & editing; Agnieszka Sorokowska: Investigation, Writing - review & editing; Piotr Sorokowski: Investigation, Writing - review & editing; Ian D. Stephen: Investigation, Writing - review & editing; Laura M. Stevens: Investigation, Writing - review & editing; Suzanne L. K. Stewart: Investigation, Writing - review & editing; David Steyrl: Investigation, Writing - review & editing; Stefan Stieger: Investigation, Writing - review & editing; Anna Studzinska: Investigation, Writing - review & editing; Mar Suarez: Investigation, Writing - review & editing; Anna Szala: Resources, Writing - review & editing; Arnaud Szmalec: Investigation, Writing - review & editing; Daniel Sznycer: Investigation, Writing - review & editing; Ewa Szumowska: Investigation, Writing - review & editing; Sinem Söylemez: Investigation, Writing - review & editing; Bahadır Söylemez: Investigation, Writing - review & editing; Kaito Takashima: Resources, Writing - review & editing; Christian K. Tamnes: Resources, Writing - review & editing; Joel C. R. Tan: Investigation, Writing - review & editing; Chengxiang Tang: Investigation, Writing - review & editing; Peter Tavel: Investigation, Writing - review & editing; Julian Tejada: Investigation, Writing - review & editing; Benjamin C. Thompson: Investigation, Writing - review & editing; Jake G. Tiernan: Investigation, Writing - review & editing; Vicente Torres-Muñoz Torres-Muñoz: Investigation, Writing - review & editing; Bastien Trémolière: Investigation, Writing - review & editing; Monika Tschense: Investigation, Writing - review & editing; Belgüzar N. Türkan: Investigation, Writing - review & editing; Miguel A. Vadillo: Investigation, Writing - review & editing; Caterina Vannucci: Investigation, Writing - review & editing; Michael E. W. Varnum: Investigation, Writing - review & editing; Martin R. Vasilev: Investigation, Writing - review & editing; Leigh Ann Vaughn: Investigation, Writing - review & editing; Fanny Verkampt: Investigation, Writing - review & editing; Liliana M. Villar: Investigation, Writing - review & editing; Sebastian Wallot: Investigation, Writing - review & editing; Lijun Wang: Investigation, Writing - review & editing; Ke Wang: Resources, Writing - review & editing; Glenn P. Williams: Investigation, Writing - review & editing; David Willinger: Investigation, Writing - review & editing; Kelly Wolfe: Investigation, Writing - review & editing; Alexandra S. Wormley: Investigation, Writing - review & editing; Yuki Yamada: Resources, Writing - review & editing; Yunkai Yang: Resources, Writing - review & editing; YUWEI ZHOU: Investigation, Writing - review & editing; Mengfan Zhang: Investigation, Writing - review & editing; Wang Zheng: Investigation, Writing - review & editing; Yueyuan Zheng: Investigation, Writing - review & editing; Chenghao Zhou: Resources, Writing - review & editing; Radka Zidkova: Investigation, Writing - review & editing; Nina M. Zumbrunn: Investigation, Writing - review & editing; Ogeday Çoker: Investigation, Writing - review & editing; Sami Çoksan: Investigation, Writing - review & editing; Sezin Öner: Investigation, Writing - review & editing; Asil A. Özdoğru: Investigation, Writing - review & editing; Seda M. Şahin: Investigation, Writing - review & editing; Даурен Казанов: Investigation, Writing - review & editing; Savannah C. Lewis: Investigation, Project administration, Supervision, Writing - review & editing.

**Competing interests**

The authors declare no competing interests.

**Links to Supplementary Materials**

Please note: all files are synced to OSF through GitHub. We have also included the folder you can find files in if the GitHub add-on is not working on OSF. Since you cannot link directly to a folder on OSF storage, we also indicated where on OSF to find the folder.

**Complete Files**

* Open Science Framework: <https://osf.io/wrpj4/>
* GitHub: <https://github.com/SemanticPriming/SPAML>
* Zenodo: <https://zenodo.org/records/10888833>

**Ethics**

* Ethics Component OSF Link: <https://osf.io/ycn7z/>
* Ethics/Lab Table Summary: <https://osf.io/ty4hp>
  + GitHub: 06\_Analysis > supplemental

**Power Analysis**

* Power analysis code: <https://osf.io/v2y9e>
  + Github: 02\_Power

**Method**

* Materials separated by language:
  + OSF: 03\_Materials
  + Github: 03\_Materials
  + The readme explains the stimuli selection and creation procedure: <https://osf.io/mz7p4>
* *lab.js* Scripts to recreate the experiment:
  + OSF: 04\_Procedure
  + Github: 04\_Procedure
* Language Table Information: <https://osf.io/y3dk7>
  + GitHub: 06\_Analysis > supplemental
* Deviation Guide: <https://osf.io/mwuv3>
  + GitHub: 06\_Analysis > supplemental
* Translation Information: <https://osf.io/vdme5>
  + Github: 03\_Materials readme

**Data**

* Zenodo: <https://zenodo.org/records/10888833>
* Data Release: <https://github.com/SemanticPriming/SPAML/releases>
* Data Processing Scripts:
  + OSF: 05\_Data > data\_processing
  + Github: 05\_Data > data\_processing
* Data Processing Checks/Summary: <https://osf.io/zye59>
  + Github: 05\_Data
* Codebooks:
  + OSF: 05\_Data > codebooks
  + Github: 05\_Data > codebooks
  + Codebook full data: <https://osf.io/xz6nk>
  + Codebook item data: <https://osf.io/5u9t6>
  + Codebook participant data: <https://osf.io/9a368>
  + Codebook priming trial level data: <https://osf.io/49nzq>
  + Codebook priming summarized level data: <https://osf.io/sx26p>
    - Summary table of the sample size calculations: <https://osf.io/kv6am>
  + Codebook trial data: <https://osf.io/s2kqd>
* semanticprimeR tutorial: <https://osf.io/yd8u4>

**Analyses**

* Scripts:
  + OSF: 06\_Analysis
  + Github: 06\_Analysis
  + Method: <https://osf.io/bqpk2>
  + Descriptive Statistics
    - Participants: <https://osf.io/vdgkr>
    - Trials: <https://osf.io/baem5>
    - Items: <https://osf.io/rvt8f>
    - Priming: <https://osf.io/m8kjv>
  + Hypothesis testing: <https://osf.io/rmkag>
  + Supplemental Meta-Analysis: <https://osf.io/rke82>
    - Github: 06\_Analysis > supplemental
* Supplemental Tables/Summaries:
  + Note: A summary of labs and languages is also in this folder, but linked above
  + Github: 06\_Analysis > supplemental
  + Native Language:
    - Overall Native Language Frequency: <https://osf.io/ta6wf>
    - Analysis Participants Native Language Frequency: <https://osf.io/652h8>
    - Rescored Analysis Participants Native Language Frequency: <https://osf.io/b3y6r>
  + Browser Language:
    - Overall Browser Language Frequency: <https://osf.io/93kep>
    - Analysis Participants Browser Language Frequency: <https://osf.io/3yab7>
    - Rescored Analysis Participants Browser Language Frequency: <https://osf.io/adhbe>
  + Lab Reports:
    - Native Language by Lab: <https://osf.io/hnrgk>
    - Operating System by Lab: <https://osf.io/gud6v>
    - Web Browser by Lab: <https://osf.io/egk9w>
    - Language Locale by Lab: <https://osf.io/wt3xn>
  + Language Reports:
    - Native Language by Language: <https://osf.io/5b72x>
    - Operating System by Language: <https://osf.io/9dwqb>
    - Web Browser by Language: <https://osf.io/bn7uv>
    - Language Locale by Language: <https://osf.io/dyh4e>
  + Reliability data files:
    - Item Reliability: <https://osf.io/r4fym>
    - Participant Reliability: <https://osf.io/jf28q>

**Manuscript**

* Pre-registration: <https://osf.io/u5bp6>
* Registered Report: <https://osf.io/preprints/osf/q4fjy>
* Tenzing chart: <https://osf.io/uv27t>
  + Github: 08\_Credit

1. Participant accuracy scores were calculated, and then the average of participant accuracy scores for each language were calculated. [↑](#footnote-ref-1)
2. We present the combined results when discussing trials or global information but separate them when examining item- or priming-level effects. [↑](#footnote-ref-2)
3. For each trial type combination: word-word unrelated, word-word related, nonword-nonword, nonword-word, word-nonword. Some combinations have higher probabilities of being selected, as the trial type combination is more frequent, but the individual trials have a 1/1000 probability. [↑](#footnote-ref-3)
4. This value was chosen to ensure that the experiment was completed in under 30 minutes on average, while giving an appropriate amount of time in a lexical decision study to answer (using the Semantic Priming Project as rubric for general trial length). [↑](#footnote-ref-4)
5. We use *female, male, other,* and *prefer not to say* because these were the English labels on the survey. We asked participants to indicate their gender. Current norms suggest we should have used *woman* and *man* instead. We report the labels that were on the survey. [↑](#footnote-ref-5)
6. College was used to indicate university-type experience (community college or otherwise). “Some college” indicated that they had not completed a degree but had completed some credits. [↑](#footnote-ref-6)
7. Given low participant reliability scores, one may not be able to predict this value anyway. [↑](#footnote-ref-7)